DATA ANALYTICS SUPPORTING LEAN MANUFACTURING TOWARDS INDUSTRY 4.0 THROUGH SIMULATION: A REVIEW

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Abstract: The Lean Manufacturing (LM) system has been increasingly used in many industrial applications, worldwide, in the last 3 decades. The LM system is based on sound philosophy and includes several tools and principles, which permit its usage in eliminating wastes and decreasing production costs. Though the conventional LM is helpful, the new paradigm, i.e., Industry 4.0, has started challenging the system. The traditional LM system cannot analyze the complex issues present in the existing competitive market on its own. This is because the Industry 4.0 is based on data that is more diverse, complex and fast. In this review, the researchers have attempted to identify the solution for the current scenario. A literature survey showed that simulation was a relevant tool that could be used for addressing the complexity-based issues related to the new concept. Though the combination of the simulation and LM system helped in understanding the problems, there still existed a gap in the LM system with regards to the merging of the 2 technologies of Industry 4.0.

Keywords: Data analytics, simulation, Industry 4.0.

1. Introduction

Currently, a new paradigm, i.e., Industry 4.0 is being used worldwide, which is based on Data Analytics (DA). This paradigm is used as a platform that connects the Cyber and Physical Systems (CPS). This Industry 4.0 concept was first developed and used in November 2011 by the German government, who aimed to develop a flexible production model for digital and personalized services and products, which enabled a real-time interaction amongst products, devices, and people during production [1]. It has been predicted that Industry 4.0 would affect all the countries in the world, act as a driving force that would change the conventional techniques used in industrial production and will also guide the future manufacturing processes. On the other hand, in this Industry 4.0 era, the further use of the Lean Manufacturing (LM) system would help in addressing the manufacturing-related challenges.

This leads to the new question, how this developmental system could support one another? For addressing this issue and after considering the fact that DA is increasing exponentially day by day, in this paper, the researchers have studied the different ways in which the DA factors could support the LM system in the Industry 4.0 era.

2. The history of Lean Manufacturing (LM)

The LM concept was developed by Toyota, the Japanese automotive company, who introduced the Toyota Production System (TPS) [2]. The TPS was proposed by Eiji Toyoda and Taiichi Ohno in the company, after World War II. The success of the Toyota brand in Japan highlighted its excellent image in the U.S. automotive sector. As a result, when the US automotive industries were facing a crisis and were losing their market shares, they began implementing the lean processes for improving their manufacturing procedures [3]. TPS was synonymous with the terms like “lean manufacturing” and “lean production”, which were coined by the researchers at the Massachusetts Institute of Technology (MIT),
who were working in the International Motor Vehicle Program [4].

In the past 30 years, LM has been widely used in many industrial applications worldwide [5]. The LM is backed by a stable philosophy which aims to eliminate all the waste and decrease production costs. This has improved the effectiveness, efficiency and the profitability of the industries. LM presents 5 steps as its guideline, known as the Lean Principles. These include: specify a value; identify a value stream; establish the flow, pull value and strive for perfection [6]. These Lean Principles have been described in Table 1 [7].

| Step | Principles                  | Description                                                                 |
|------|-----------------------------|-----------------------------------------------------------------------------|
| Step 1 | Specify Value               | Problem-solving in LM requires effort through teamwork which consists of managers, engineers, production control and technical staff. To understand the definition of value, it is everything reflects the customer whether internal or external. Consequently, LM proposed the seven types of wastes called MUDA. MUDA comprise into seven. There are overproduction, inventory, motion, defects, over-processing, waiting and transport. |
| Step 2 | Identify value stream       | After the value has been specified, the team should address any processes and materials necessary to fulfill customer’s requirements. Lean thinkers should identify the value stream to analyze delays, inefficiencies and production limitations as well as value-creating steps. In LM, the process or steps are defined as VA (Value Added activity) and NVA (Non-Value-Added activity). Any activities which do not create value should be eliminated from the current process. |
| Step 3 | Establish flow              | After removing the wastes from the value stream, the next action is to ensure that the flow of the remaining steps run smoothly without interruptions or delays. Some strategies for ensuring that value-adding activities flow smoothly include breaking down steps, reconfiguring the production steps, creating cross-functional departments, and training employees to be multi-skilled and adaptive. |
| Step 4 | Pull value                  | Lean manufacturing principles are core to eliminating excess waste. Establishing a pull is no different. Once a flow is introduced, customers will begin to pull value from the next upstream activity. Pull creates a just-in-time or on-demand model. |
| Step 5 | Strive the Perfection       | Wastes are prevented through the achievement of the first four steps: 1) identifying value, 2) mapping value stream, 3) creating flow, and 4) adopting a pull system. However, the fifth step of pursuing perfection is the most important among them all. It makes Lean thinking and continuous process improvement a part of the organizational culture. Every employee should strive towards perfection while delivering products based on customer needs. The company should be a learning organization and always find ways to get a little better each and every day. |

Furthermore, the Lean Manufacturing Tools (LMT) help in achieving all the objectives presented by the various LM principles [8]. The various LMTs and techniques include the Single Minute Exchange of Dies (SMED), Overall Equipment Effectiveness (OEE), 5S, Kaizen, Value Stream Mapping (VSM), Jidoka, Poka Yoke, Kanban, Line Balancing and Andon [9]. In this paper, the researchers regarded the LM system as a challenging process that required a lot of data and involved several principles.

3. LM Challenges which affect the implementation of Industry 4.0

In the Industry 4.0 era, the production processes in the manufacturing industries face a lot of issues, like a lack of proper communicating interconnection, either vertical or horizontal, during data analysis. This indicated that the complexity issues would increase with an enhancing technology [10].
The data collected from the process engineering techniques like value chain data, structured data, and external data is increasing and is called data analytics (DA). Fig. 1 presents the growth of the sample data and its forecast for the period ranging between 2015 and 2020 that was collected from Cisco’s Visual Networking Index (VNI). This data showed exponential growth. It was seen that consumer mobile data traffic would reach 26.1 exabytes every month in 2020.

All the circumstances make the decision-making process very difficult to judge. Many factors affect the implementation of LM for resolving the complex issues [12]. A few earlier studies have focused on one aspect of LM, while some others focused on its integration for improving the system. LM is primarily implemented for optimizing all resources by reducing costs and waste. This phenomenon has forced the manufacturers to reshape or reconsider their strategies during the new Industry 4.0 era [13]. This has further increased the pressure of production. A few researchers have called this a “productivity paradox” [14].

4. Data Analytics

Industry 4.0 depends on the data which is faster, complex, vast, efficient and diverse. In the new digital era, data needs to be more accessible and it increases exponentially in several industries, which leads to the problem of ‘big data’. Input data used in the data analytics is derived from several channels like sensors, devices, log files, networks, video/audio, transactional applications, web along with the social media feed. In the big data environment, all datasets are large and very complex to be handled by the traditional DA software [15]. Hence, the industries and other researchers have proposed investigating the companies that have a lot of shop-floor and operational data.

For decreasing the complexity issues, some researchers have focused on two methods, i.e., data-driven simulation and modular simulation. The data-driven simulation creates models where the input data could be externally manipulated without any programming. These models help the users create, operate and update the simulation models based on different data categories, i.e., historical process data, automated model generation, and the factory status information.

The historical process data is based on the data that is derived from a production line and is used as the input during the simulation. This data would be fast but also inaccurate as it was outdated. On the other hand, the users need to make fewer efforts for collecting the data for simulation. The data is used for verifying or validating the simulation model before actually applying the conditions. The factory data refers to the ‘real-time’ information regarding the actual status of the production systems like product output plans or schedule and the machine circle time, etc. This information can be automatically or manually captured and used for optimization. This data includes information like the number of machines being used, production output, resources (operators) or the stock.
Table 2. Application of the simulation process for resolving the problems in the LM

| Researcher | Improvement | LM Activities |
|------------|-------------|---------------|
| [20]       | A simulation was applied at an assembly line to assist in the decision during LM implementation. | LM manufacturing at the assembly system. |
| [21]       | A simulation was used in designing a multi-stage, multi-buffer electronic device assembly line. | Design assembly line |
| [22]       | A simulation was used to analyze the benefit of LM Manufacturing and value stream mapping. | Value stream mapping (VSM). |
| [23]       | Improvement of LM manufacturing systems was designed using a simulation model. | LM Manufacturing systems. |
| [24]       | This study evaluates the role simulation-based modeling can play in assisting SMEs in ERP implementation. | Enterprise Resource Planning (ERP) |
| [25]       | LM principles and simulation optimization are collaborated on solving a combined hospital emergency department (ED) layout design and staff assignment problem. | LM principles |
| [26]       | Using experimental design and a simulation an optimizing tool, to measure the important factor in fishing net manufacturing | Apply simulation optimization in LM production system |
| [27]       | LM thinking and simulation-based approach are cooperated to improve the efficiency of warehousing and routing operations. | To improve warehouse. |

The automated model generation process allows the users to carry out an automated configuration of the simulation elements that reflect the changes occurring within the input parameters like the Computer-Aided Design (CAD) and the Computer-Aided Manufacturing (CAM) files. This approach could be used for flexible manufacturing wherein the domain was subjected to frequent changes. A simulation process could be used for resolving the complexity issues. In this review, the researchers used a simulation tool for planning the decision-making process and assessing the complex system, thereby evaluating the effect of different scenarios, prediction and assumptions. This tool helped in quantifying the improved performance which was determined after applying the LM manufacturing process [16]. During the Industry 4.0 era, the production process that faces issues without the establishment of a proper vertical communication interconnection during analysis is not organized. This indicated that the complexity issue increased when all technologies were further enhanced. A simulation was extensively used for resolving the behavior of the complex manufacturing system, especially to choose the best decision for the problems.

On the other hand, the simulation helps in innovation and maintaining flexibility while tackling the complexity issues. Different simulation models are used for problem-solving and decision-making, even under various scenarios [17]. Mohamad and Ito defined simulation as a process that helped in understanding and studying the behavior of a system (within the limit that was imposed by the criteria), as it helped in developing a model for the system and enabled experimentation using the model of the operating system [18]. This simulation model was seen to be a cost-effective tool that helped in exploring various solutions for the real systems that did not need an actual change [19]. This helped the users experiment and study the ‘what if’ conditions so that they could note all the changes occurring in the system. A successful application of this simulation process has shown its effectiveness in solving different issues affecting the manufacturing sector. Table 2 describes all the survey articles published in the literature concerning the application of the simulation process in the LM manufacturing systems.

5. Review of the framework simulation process and Industry 4.0 elements involved in the manufacturing industries

In 2011, several researchers began investigating the different emerging technologies that were being used after the introduction of Industry 4.0. Table 3 describes the framework consisting of the innovative ideas which were related to this concept. For generating the framework, the simulation
process was regarded as the primary concept, wherein the LMT was used for resolving the issues. For instance, VSM and analysis of 7 wastes were used for determining the existing issues. These parameters were used as input in the simulation process. A case study that described the server manufacturing system was presented [28]. In their study, Gurumurthy and Kodali reviewed the use of the simulation process with the VSM [29]. Mohamad et al. [30] proposed a novel framework that consisted of lean practitioners [30]. Wy et al. [31] described a generic simulation modeling framework that could decrease the time needed for developing a simulation model. Data was used in a framework before a simulation process was initiated [31].

Lee et al. [32] developed a framework wherein all the machines were interconnected to form a collaborative community [32]. This type of evolution needed the uses of some advanced prediction tools, which helped in the automated processing of data into information, explaining the uncertainties and making better and informed decisions. The Cyber-Physical Production System (CPPS)-based service and manufacturing innovations were seen to be inevitable challenges and trends that were used in the manufacturing industries. This framework helped in addressing the trends related to the manufacturing service transformation in the case of a big data environment. It also helped in developing smart predictive tools that helped in managing the big data, thus, increasing productivity and transparency. Rane et al. [33] reviewed all the existing tools and techniques that could be used for improving the assembly line. They claimed that the LM process was generally useful for such purposes, and could be used for analyzing the additional techniques which helped in acquiring the Lean configurations, i.e., Simulation and Simulation-based Optimisation (SBO). In their review, they primarily focused on the various case studies which used these techniques in the manufacturing applications, especially in the vehicle assembly lines. Nunes [34] designed a new framework that could help the managers through the DMAIC (Design, Measure, Analyse, Improve and Control) cycle [34]. This framework helped them select and apply the methods and tools that were used by the Ergonomics and Lean Six Sigma (LSS) paradigm. It further helped the managers identify the different improvement opportunities along with the recommended course of action. In the case of the system DSS conduct data collection process, the analysis and the decisions supported the activities that were based on the output that was required.

Fanti et al. [35] generated a framework consisting of 5 major elements, i.e., data components, interface components, model components, and decision components. The major modules of the proposed DSS were the optimization and simulation modules. The simulation module was based on the discrete event simulation, whereas the optimization module made use of the Particle Swarm Optimisation (PSO) metaheuristic algorithm in combination with an Optimal Computing Budget Allocation (OCBA) scheme. An integrated use of these modules helped the decision-makers make appropriate decisions by optimizing all the proper performance indices. Furthermore, Salama et al. [36] described a DSS architecture, wherein the decision-making process included 3 interconnected components, i.e., decision-makers, central cloud storage database, and a decision support system. In this framework, the decision-makers could use the knowledge and intuition and suggest a few steps to obtain the most appropriate proposal based on the predefined performance indicators [36].

Goutam et al. [37] investigated the effect of the Stochastic Linear Programming (SLP)-based DSS, wherein the values of the stochastic solution (VSS) and the Expected Value of Perfect Information (EVPI) were merged. The SLP-based DSS was described using the real data and it helped in managing the demand uncertainty and carrying the futuristic integrating planning [37]. Uriarte et al. [38] described the lean principles, which could be designed and the production changes could be studied through Simulation-based Multi-Objective Optimisation (SMO) [38].

Ferrer a et al. [39] developed a MAESTRI Total Efficiency Framework (MTEF) that defined the sustainability of the process and manufacturing industries. It described the management system and presented a scalable and flexible platform and methodologies. MTEF was seen to be an effective management system.
that was targeted towards constant process improvement. The major element was the IoT platform, which facilitated the data transfer from the systems, machines, and the sensors to the end-user software applications and tools at all industrial sites. This study enabled an easy data exchange and integration amongst the business systems, tools, and shop-floors.

**Table 3** All review articles which combined the simulation and IR4.0 elements involved in the manufacturing industries

| Authors | LM | Industry 4.0 elements | Database /Server | Cloud Computing |
|---------|----|-----------------------|------------------|-----------------|
|         |    | Data Analytics IoT CPPS Simulation |                |                 |
| [28]    | X  | X                     | X                | X               |
| [29]    | X  | X                     |                  |                 |
| [30]    | X  | X                     | X                | X               |
| [31]    | X  | X                     |                  |                 |
| [32]    | X  | X                     | X                |                 |
| [33]    | X  | X                     | X                | X               |
| [34]    | X  | X                     |                  |                 |
| [35]    | X  | X                     |                  |                 |
| [36]    | X  | X                     | X                |                 |
| [37]    | X  | X                     | X                |                 |
| [38]    | X  | X                     | X                | X               |
| [39]    | X  | X                     | X                | X               |
| [40]    | X  | X                     |                  | X               |
| [41]    | X  | X                     | X                | X               |

In their study, Tao et al. [40] proposed a novel data-driven manufacturing framework, wherein the system included 4 modules, i.e., manufacturing module, data driver module, real-time monitor module, and problem processing module [40]. Goodall et al. [41] developed a novel data-driven simulation approach which predicted the material flow behaviour of the remanufacturing operations. It used data from various digital manufacturing systems [41]. Table 3 presents a summary of all the review articles that combined the LM, simulation and the IR4.0 elements.

**6. Conclusion and Future works**

The literature included many studies that combined the LM and simulation techniques which further helped in solving several issues in the field of manufacturing. This trend started in 2011 wherein the emerging technologies related to Industry 4.0 like DA, Internet of Things (IoT), database, Cyber-physical systems (CPS), cloud computing, etc. could be used in the existing framework. It highlighted the role played by simulation in the industrial revolution along with its application as the major factor which could help the Industry 4.0 become a reality. The studies presented in Table 3 show the evolution of the increasing combination of the simulation and combination. It could be noted that there is a significant interest in this area, especially in the past 20 years. However, there is a gap in the combination of the various LM processes, simulation and Industry 4.0 elements. In future studies, the researchers would focus on analyzing the concepts that could support the various decision support systems presented by the companies, especially with regards to the real-world cases which were mentioned earlier.

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