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# Process Optimization in Manufacturing Industries Using Simulation Technologies

**Olanrewaju M. Okuyelu [a*], Bakhtiyar Doskenov [a] and Remilekun Aribike [a]**

[a] *California State University, Northridge, United States.*

***Authors' contributions***

*This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.*

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## ABSTRACT

The industrial application and importance of simulation technologies for process optimization in manufacturing industries cannot be underestimated. Adequate monitoring of raw materials processing to finished products and their conveyance to the end users is required together with profits and cost optimization to ensure the company attained the set goals. Thus, it is imperative to adopt the use of simulation-based optimization tools. This paper succinctly discussed the importance of simulation-based optimization technologies as effective techniques in manufacturing industries. The concept of process optimization, simulation and simulation techniques as related to manufacturing were discussed. Various techniques of simulation-based optimization in manufacturing were presented. These include Monte Carlo simulation, discrete event simulation and system dynamics. Also, typical examples of manufacturing optimization techniques were stated. These include Just-in-Time, statistical process control, total quality management, six sigma, value stream mapping and computer numerical control. Various applicable areas of simulation-based

**Corresponding author: E-mail: Olanrewaju.okuyelu.840@my.csun.edu, mookuyelu@gmail.com;*

optimization technologies in manufacturing were also addressed. However, resistance to change, lack of expertise, lack of data, unintended consequences, over-reliance on technology and insufficient testing are the associated problems to simulation-based optimization in manufacturing. In conclusion, relevant simulation-based optimization technologies should be adopted by various manufacturing companies to ensure profit maximization while still keeping the chain between production of good and supply to customers intact.

*Keywords: Process optimization; simulation techniques; scheduling; sequencing; technology; monte carlo simulation; manufacturing; industrial engineering.*

## 1. INTRODUCTION

### 1.1 Historical Background and Manufacturing Evolution

A manufacturing system is as a set of interconnected machines to perform a sequential operations and tasks on a material (either processed or unprocessed) in order to obtain or assemble a product [1]. Historically, the existence of manufacturing industry started in the 1850s and the first assembly line was created by Henry Ford in 1913 using mass-production philosophy. During this period, production of specific product at large volumes was the major focus of assembled production lines and machines. Thus, the idea of Dedicated Manufacturing Systems was introduced [2]. After some years, transition manufacturing paradigm to mass customization philosophy was experienced which enhanced and increased variability of products. This was supported and catalyzed by lean principles and Computer Numerical Control formulation. This helps manufacturing companies in the production of products of different kinds [3].

The evolution of manufacturing paradigm to mass customization philosophy started prevailing and spreading across the world to meet consumers' demand calling for the manufacturing of large products with different variability [4]. This made manufacturing companies to place high priority on the development of new manufacturing system types which can effectively handle cost with the experienced changes in demand. The concept of Reconfigurable Manufacturing System was introduced in the early 20s the economic and rapid growth conditions attached to uncertainties such as product changes and unforeseen market situations [5]. After several decades of industrial development, modelling and simulation technologies have become another vital means of optimizing industrial processes in manufacturing industries [6].

### 1.2 Process Optimization

In manufacturing industries, the main target of the producer is to minimize the production costs and at the same time maximize the profits realized without jeopardizing the product quality. Thus, process optimization is basically a positive and intrinsically human perception of maximization or minimization in order to achieve the best or most favorable outcome while putting all other factors that surround into consideration [7]. Designing systems and products requires a deep understanding of influences that surround the desirable performance. There is need for an efficient and systematic decision-making approach that drives the need for optimization strategies. The industry's general manufacturing process optimization based on a data-driven methodology is presented as Figure 1. "Collection of data in the database comes first which consists of financial and process information data. In the demand analysis, the data-driven manufacturing model simplifies allocating and arranging factory assets to meet changing demand" [8]. "However, product creation performance cannot be improved when compared with the conventional manufacturing model because the challenges of optimizing the complex and variable production system has not been addressed. Two approaches can be considered in maximizing the efficiency of production after business conversion into a decentralized network of resource agents. The resource data model proactively identifies production systems by extracting the database for information and joining it with the expertise of the producing process to make the best possible decision about how to balance demand with supply" [9].

"The associated manufacturing service is automatically formed and added to the database if the agent possesses production expertise. Alternatively, it sends the demand information to the agents responsible for the relevant resources. In the producing service, the resource agent utilizes the defect diagnostic and efficiency assistance to know if the service agents can work together to carry out the production customizations" [10]. "If some manufacturing resources lack the required assistance, a new resource agent is identified, and overall productivity is calculated correctly to detect the fault. In the end, the improved data-driven model is executed more methodically in the form of manufacturing choices. A unique industrial data management technology has been integrated into a dispersed storage and computation environment. After the quality of each machine has been verified, the operation's data are sent to the performance analysis module, which thoroughly analyzes the current state and predicts critical performance indicators at each stage of the process. If the requirements of the request are satisfied, the precise control and execution module will transform the associated data into a workable manufacturing and distribution management plan" [11].

### 1.3 Simulation in Manufacturing

Manufacturing is a multifaceted process that involves, quite literally, tons of moving parts. Industrial process simulation purposely permits engineers to recognize the stable and reproducible operating conditions required to reach satisfactory reaction yields, product purities and cycle times. In manufacturing processes, safety and environmental regulations together with process economics estimation are key factors. Process simulations give companies the insight needed to comply and achieve the aforementioned. Batch and semi-batch processes require dynamic simulation while continuous processes are usually studied with steady-state simulation. The execution of a series of runs, sensitivity studies, and optimizations enhanced forecasting dynamic behavior using steady-state simulations. The only shortcoming is that a detailed study of all interactions is not allowed. The actual plant behavior in a manufacturing industry can be represented by dynamic simulations based on real-time or accelerated-time principles. The distinct feature of a dynamic simulator is the ability to manipulate industrial and manufacturing properties and components with respect to time. It comprises dynamic unit operations such as capacity characteristics and dead time.

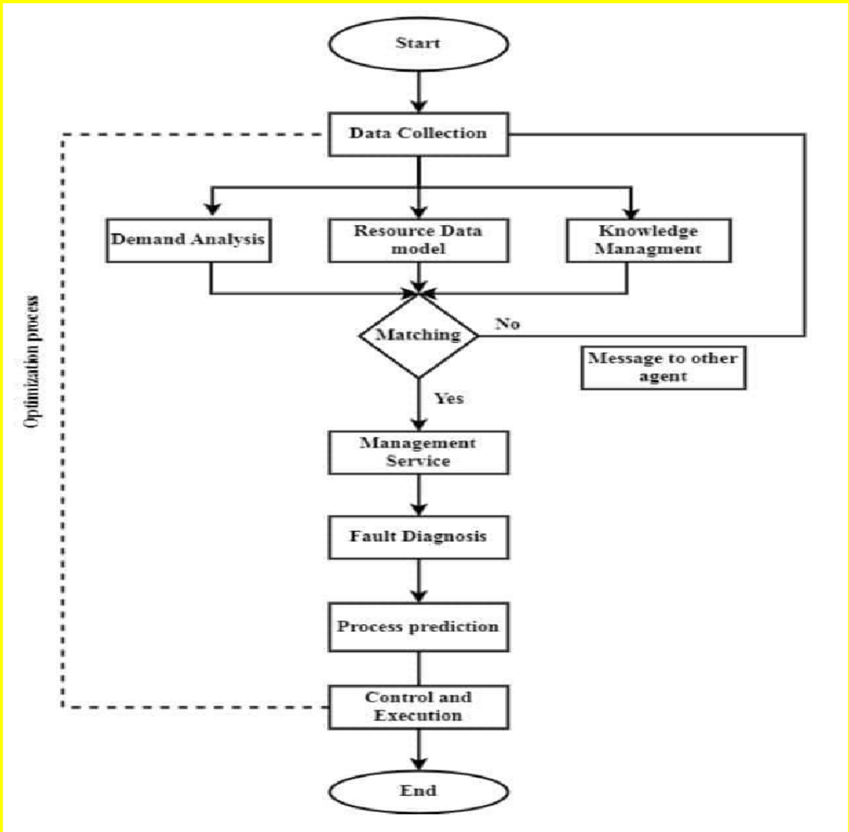


**Fig. 1. Manufacturing optimization process based on data-driven model in industry [8]**

The major functions of dynamic simulations in manufacturing industries include modelling of process routing, transfer of material in a pipe network, sequential operations in a batch process, equipment failure risk assessment, identification of hazardous conditions, emergency relief and blow-down systems and many more [12]. For a continuous process, a dynamic model can specify varying throughput impact; feed and composition changes; startup and shutdown; troubleshooting; real-time optimization and control loop tuning. For a batch process, a dynamic simulation can be adopted to investigate thermal performance and kinetics of reaction in a stirred-tank reactor; batch distillation cut decisions and control strategies effect; and emergency relief systems suitability [7].

### 1.4 Simulation Techniques in Manufacturing

Recently, the use of different simulation techniques for the successful modelling, designing and improvement of manufacturing systems is becoming prevailing. Simulation techniques are adopted to investigate the attributes of a system for different set of input variables via running a simulation model over a period of time. A set of models can be built and evaluated in order to determine the set of variables that perform excellently from among the different available combinations of input variables which are essential to be tested. However, the number of input variables increases exponentially as these systems become larger and more complex which makes the process becomes computationally unrealistic [13]. The only way to ascertain that everything runs as perfectly and efficiently as possible in manufacturing is process optimization. Therefore, the combination of simulation and optimization is highly imperative to find an optimal set of values for certain input variables [14-15]. This is called simulation-based optimization which allows a decision-maker to systematically search a large decision space for an optimal or near-optimal system design without being constrained to a few pre-specified alternatives [16-17]. Simulation-based optimization is commonly used in the manufacturing systems setting to optimize production measures such as Work in Lead Time (LT), Process (WIP), Throughput (THP) and storage capacities obtained from a simulation engine [18]. Thus, the importance of simulation-based optimization in manufacturing cannot be underestimated for effective smooth running from products processing to their delivery to the end users. This forms the basis for writing this critical paper on simulation-based optimization in manufacturing. Fig. 2 represents the block diagram showing the sequential steps of a simulation-based optimization utilized in manufacturing industries.

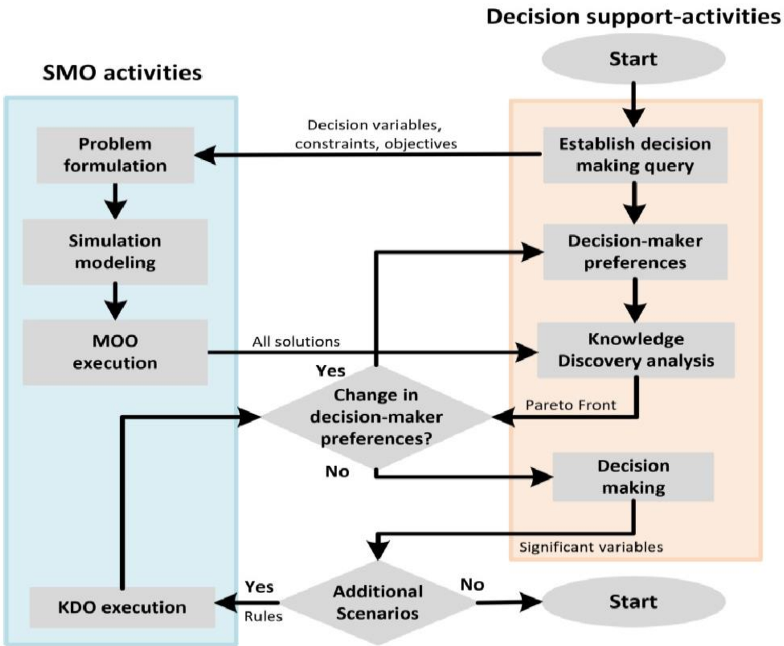


**Fig. 2. Sequential steps of a simulation-based optimization utilized in manufacturing industries [18]**

## 2. SIMULATION-BASED OPTIMIZATION IN MANUFACTURING

“When manufacturing is in design stage, simulation models are typically adopted for computational and data processing such that decision makers have enough time to collect data and run simulations to attain statistically valid conclusions. However, the explosive progress in computing power in recent times has significantly minimized the limitations of simulation-based decision-making as a result of computational cost concerns. Simulation-based optimization is now an active area of specialization in academic research. In over a decade ago, simulation optimization solvers have been incorporated to produce commercial simulation software packages for manufacturing purposes” [19]. “With simulation optimization, the decision maker can systematically search a huge decision space for an optimal system design without being constrained to a few pre-specified options. This new optimization proficiency greatly widens the scope of simulation as an analysis instrument for complex system design. A detailed review and explanation of simulation optimization research and applications in manufacturing has been presented” [16].

“Simulation optimization is exposed to more strict requirements when applied to dynamic operational control in complex stochastic systems. Decisions need to be made in a much shorter time-window in response to dynamically evolving situations. Data need to be collected and processed in near-real-time to detect disruptions in operating conditions. In most current simulation optimization applications, by contrast, data sets are collected over a long period of time and then used to estimate probability distribution models from which random variates are generated to drive the stochastic simulations. Arguably, the two fundamental limitations that hinder the utilization of simulation optimization in the control of complex stochastic systems are computational efficiency and data requirements” [20].

### 2.1 Techniques of Simulation-Based Optimization in Manufacturing

Different techniques of simulation stands as a powerful tool which enables project managers to estimate project expenses by generating virtual representations of real-world conditions. These techniques comprise the usage of mathematical and statistical models to simulate project scenarios and evaluate their financial implications. Each simulation technique, to be mentioned, possesses distinct advantages, and the selection of most applicable technique is a function of the project's attributes and objectives [21]. Some commonly used simulation techniques include:

#### 2.1.1 Monte carlo simulation

In this technique, multiple random scenarios are generated based on probability distributions for different kinds of project variables. By running simulations continually, project managers can study the range of possible outcomes and associated costs. Monte Carlo simulation usually reveals the likelihood of cost overruns and enables project managers to plan for unexpected and miscellaneous expenses [10].

#### 2.1.2 Discrete event simulation

In discrete event simulation, activities flow in a project are modelled followed by subsequent simulation of their sequence and events timing. By combining various resource constraints and cost factors, project managers can estimate the impact of different scenarios on project expenses. This simulation-based optimization technique is particularly beneficial for optimizing resource allocation and detecting potential bottlenecks that may inflate costs [17].

#### 2.1.3 System dynamics

This technique emphasizes on understanding the dynamic relationships existing between different project variables. By modeling causal relationships and feedback loops, the long-term consequences of cost-related decisions can be simulated by the project managers. System dynamics simulation enables project managers to detect the underlying drivers of project expenses and develop strategies to control costs effectively [22].

## 3. PROGRESS AND EVOLUTION OF SIMULATION-BASED OPTIMIZATION IN MANUFACTURING

The evolution of technology has greatly influenced the advancements of simulation-based optimization in predictability of manufacturing processes. By doing this, simulation techniques have revolutionized cost variance analysis. This gives different organizations the opportunity to gain even more perfect insights into cost variances [23]. The future trends in predictability simulation techniques include but not limited to:

### 3.1 Integration with Artificial Intelligence and Machine Learning

"Artificial intelligence and machine learning algorithms are expected to be integrated by predictability simulation techniques. This will allow more accurate predictions and real-time analysis of cost variances".[15]

### 3.2 Big Data Analytics

"The use of big data analytics will enable organizations to leverage vast amounts of data for more comprehensive and accurate cost variance analysis. This will provide businesses with deeper insights into the factors that affect cost variances" [20].

### 3.3 Real-Time Simulation

"Technological evolution will enhance real-time simulation. This gives room for organizations to analyze cost variances as they exist. This will enable businesses to make instant adjustments and control risks in real-time" [19].

### 3.4 Visualization Tools

"Improved visualization tools will motivate the interpretation and better understanding of simulation results. Businesses will be able to visualize cost variance patterns, trends, and potential impacts more efficiently. This creates the opportunity for decision-making to be more rigorous" [21].

With the continual evolution of these trends, predictability simulation techniques will be integrated and become more efficient and imperative for cost variance analysis. Organizations that embrace these improvements will gain a competitive advantage in managing costs and optimizing their resources.

## 4. TYPICAL EXAMPLES OF MANUFACTURING OPTIMIZATION TECHNIQUES

### 4.1 Just-in-Time

This is a manufacturing philosophy that entails products production when they are needed only. With this, there is minimization of inventory, waste reduction and improvement in efficiency. In order to further increase production processes, other optimization techniques such as Lean manufacturing can be combined with Just-in-Time [17].

### 4.2 Statistical Process Control

This is a statistical technique adopted in order to track and control production processes. It entails evaluating process variability and utilizing statistical methods to detect and correct sources of variation. Statistical Process Control can influence improvement in product consistency, increase efficiency and minimize waste [15].

### 4.3 Total Quality Management

This is a management approach that stresses more on quality in every aspects of a company's operations. Total Quality Management involves uninterrupted improvement, customer focus and employee participation. It can equally help to increase product quality, diminish defects, and improve customer satisfaction [6].

### 4.4 Six Sigma

Six Sigma is a data-driven method to process improvement that targets defects reduction and variability in production processes. In this, statistical methods are utilized to identify and remove variation sources in order to increase product consistency and quality. It is typically a data analysis process [14].

### 4.5 Value Stream Mapping

It is an instrument used to analyze and optimize production processes via mapping out materials flow and information from raw materials to the finished products, developing strategies for improvement and identifying bottlenecks and waste [18].

### 4.6 Computer Numerical Control

Under this, production processes are automated using computer-controlled machines to enhance manufacturing processes. Computer Numerical Control is good for improving the efficiency and accuracy in manufacturing with decrease in waste [22]

## 5. PROBLEMS WITH SIMULATION-BASED OPTIMIZATION IN MANUFACTURING

### 5.1 Resistance to Change

The introduction, adoption and utilization of simulation-based optimization in manufacturing usually calls for changes. However, managers and employees may be resistant to changes in processes or procedures, especially if they have been doing things the same way for a long time. This can cause defiance or even sabotage of the optimization process [23]

### 5.2 Lack of Data

Optimization efforts often require data analysis to identify areas for improvement. If the organization does not have access to the necessary data or if the data is unreliable or incomplete, it can be difficult to accurately identify and address problem [23].

### 5.3 Unintended Consequences

Optimization efforts can sometimes have unintended consequences such as increased complexity, higher costs and reduced quality. These consequences may not become apparent until after the optimization process has been implemented [3].

### 5.4 Over-Reliance on Technology

**“**While technology can be a powerful tool for optimization, it can also be a source of problems. Over-reliance on technology can lead to reduced flexibility, increased costs, and increased risk of downtime or system failures” [24].

### 5.5 Insufficient Testing

**“**Before implementing new processes or technologies, it is important to thoroughly test them to ensure that they are effective and reliable. If testing is insufficient or skipped altogether, it can lead to unexpected problems or failures down the road” [18].

## 6. APPLICATIONS OF SIMULATION-BASED OPTIMIZATION TECHNOLOGIES IN MANUFACTURING

Manufacturing processes are usually complex in nature and requires many variables and dependencies. Simulation techniques can be highly instrumental in optimizing manufacturing operations and improving their efficiencies. The simulation of different cases by a manager or employer can optimize resource allocation, identify process bottlenecks and improve overall productivity in businesses. Some of the specific ways by which simulation techniques can be adopted in manufacturing processes include:

## 7. PRODUCTION LINE OPTIMIZATION

Production line layouts, workflow processes and equipment utilization can be optimized using simulation techniques. Simulation of different configurations and layouts can facilitate businesses to identify the most efficient set-up with minimum bottlenecks and maximum throughput [25]. Design of product process is a serious activity in the product life cycle. The reason being that it plays the connection role between the product design task and production. It is essential to simulate designed plan process before the execution such that the effectiveness and efficiency of the process plan are ascertained. This allows the reduction of unwarranted factors surrounded in the process plan and thereby enhance the process plan [26]. For instance, the use of Computer Numerical Control machine as simulation tool for a manufacturing process involves tool path simulation, motion detection interference, machining process characteristic and machining accuracy. The evaluation and optimization of the welding technological parameters, modelling and numerical analysis can be employed in simulating the welding process simulation in a welding manufacturing industry. The use of Simulation-Based Optimization technique in designing process causes cost and time reduction; and also generate improvement in process design quality.

## 8. SCHEDULING AND SEQUENCING

Simulation techniques can help in production schedules optimization and sequencing rules. By The simulation of different scheduling algorithms and rules in businesses can reveal the best efficient route to resources allocation, set-up time minimization and reduction of idle time between production runs. This helps the supply chain to be efficiently managed.

Though some studies have shown that the supply chain in manufacturing industries can be optimized by other technological techniques, the use of simulation-based technique still remains relevant [27-28]. Modelling and simulation-based optimization have been applicable in the aspect of real-time scheduling of optimization challenges in a unit enterprise entity. The advancement in scheduling performance and quick response to interfering activities, suitability and demonstrating effectiveness can be attained via using ever changing data-driven simulation technology. The use of simulation and modelling plays a vital role in production processes management such as process scheduling and production planning. It should be noted that during production processes, unforeseen event such as breaking down of machine may be experienced resulting into cancellation of real production plans and schedules. Thus, it is necessary to use deterministic techniques in tackling the problem attached to scheduling in manufacturing.

Simulation-based optimization and modelling has been identified as one of the best effective means of finding solution to problems encountered in production dynamic scheduling. In order to minimize production time and ensure optimization of task implementation plan, the combination of simulation-based optimization with lean production in manufacturing system has been the most effective [17]. For the selection of process improvement ideas, discrete event simulation is the best technique to be adopted. By doing this, suitable conditions for online simulation technology is created as a result of drastic reduction in the simulations running time due to significant rise in the computing power. The simulation model is connected with the real manufacturing system for the execution of online simulated-based scheduling. This can then be modified to the manufacturing system real-time data. Based on the availability of this data, the model can be simulated such that the outcome can be utilized to enhance the available scheduling strategies in the real time domain. Nonetheless, the transmission of the simulation outcome to the machine operators through terminal devices increase their efficiency of responding to the disruptions. In spite of the efficacy of this technology in solving problems, there is still existence of some challenges in complex manufacturing systems. The incorporation of other simulation-based scheduling studies with expert systems and intelligent optimization algorithms has been so helpful [12].

## 9. LOGISTICS

The importance of logistics services in many manufacturing companies cannot be underestimated especially those handling fast moving commodity goods. It is imperative that goods are transported as at when due to the customers and thus, demand and supply chain should be adequately monitored. Ideal logistics services should be adequately selected to ensure that Just-in-Time delivery of manufactured goods to service demanders is attained. Studies have shown that in a manufacturing setting, approximation algorithm is the best simulation-based optimization technique for the optimal selection of logistics scheduling in tackling issues related to batching and transportation. In another rstudy, complex arrangement of a reverse logistics system was tackled using a mixed-integer linear programming for system analysis and optimization [29]. An integrated radio frequency identification sensor network system was additionally adopted as a tool in solving related problems attached to logistics in manufacturing. However, there is need for further studies on the execution of simulations to verify the built models to solve logistic problems [30].

## 10. MACHINING PROCESS IN MANUFACTURING

Machining process simulation can be executed in manufacturing for either a single unit or agglomeration of units via the development of simulation models possessing dynamics and kinematics characteristics of the process. The continual change in physical features and parameters can be monitored visually by the production engineers on duty by running of the simulation model. To achieve this, Computerized Numerically Controlled (CNC) machining simulation is usually adopted which is basically for CNC program verification, tool motion simulation and comparison of entities. Process simulation technology can be merged with Virtual Reality (VR) technology to form Virtual Machining (VM) which can be adopted to execute the simulation real control system and matching process via a virtual environment [31].

## 12. INVENTORY MANAGEMENT AND QUALITY CONTROL

The optimization of inventory levels in businesses and manufacturing companies can be executed via lowering the carrying costs by using simulation techniques. The optimal safety stock levels, reorder points and order quantities that reduce stock outs can be determined by the organizations by simulating different inventory policies while avoiding excessive inventory holding costs. Also, for quality control of products from manufacturing companies, simulation-based optimization techniques can be adopted to assess the influence of different quality control strategies on the overall manufacturing efficiency. The optimal balance between defect detection rates and inspection costs can be identified in businesses via the simulation of different inspection policies. By so doing, this can lead to reduction in re-work and also improve the quality of products in manufacturing companies [32].

## 13. CONCLUSION

In this paper, the importance of simulation-based optimization technologies as effective techniques in manufacturing industries has been presented and Monte Carlo simulation, discrete event simulation and system dynamics were stated as relevant techniques of simulation-based optimization in manufacturing. Examples of manufacturing optimization techniques are Just-in-Time, statistical process control, total quality management, six sigma, value stream mapping and computer numerical control. Production line optimization, scheduling and sequencing, logistics, machining process, inventory management and quality control are the major areas where simulation-based optimization technologies are applicable in manufacturing. However, there are some short-comings attached to these technologies such as resistance to change, lack of expertise, lack of data, unintended consequences, over-reliance on technology and insufficient testing. In conclusion, simulation-based optimization technologies should be adopted to ensure profit maximization while maintaining the chain between production of good and supply to customers intact.

## COMPETING INTERESTS

Authors have declared that no competing interests exist.

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