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OPTIMIZING PRODUCTION COSTS: A REVIEW OF MODERN TOOLS AND TECHNIQUES IN MANUFACTURING

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Abstract: Finding efficient ways to maximize production expenses has become even more vital given the rising complexity and competitiveness of world manufacturing. This study examines the most recent techniques and instruments employed to reduce costs without compromising operational efficiency or product quality. Although conventional techniques like lean manufacturing, Six Sigma, and just-in-time (JIT) approaches remain crucial, new developments in digital technology are altering the cost optimization method used. Real-time observation, predictive maintenance, and smart decision-making in production systems are made possible by new technologies including big data analytics, the Internet of Things (Iot), machine learning, and digital twins. Moreover, sophisticated cost models are increasingly generated and resource allocation is improved using computational intelligence techniques such as neural networks and genetic algorithms. This study provides a comprehensive review of both technology-based and conventional cost optimizing methods, evaluating their applicability for various sectors, effectiveness, and implementation difficulties. The review emphasizes significant trends and knowledge gaps by combining recent study with business practices, therefore offering a road map for future developments in cost-effective manufacturing. Particularly in the framework of Industry 4.0, the findings seek to help researchers, decision-makers, and practitioners select and apply suitable instruments for specific manufacturing environments and smart manufacturing systems.
Keywords: Optimization, Production Costs, Cost-efficient manufacturing, decision-makers, Tools and Techniques

Introduction

In today's fiercely competitive industrial environment, manufacturers consider reducing production costs as a vital focus in order to achieve profitability, enhance operational efficiency, and boost market presence. The rising costs of raw materials, increased energy prices, higher labor costs, and the growing need for personalized products have put more pressure on manufacturers to create effective strategies for cost reduction (Gunasekaran *et al.*, 2001). Consequently, companies are utilizing a variety of contemporary tools and methods aimed at cutting waste, improving how resources are used, and streamlining processes while still ensuring product quality and satisfying customers.

Modern production cost reduction includes both conventional methods like lean manufacturing, Six Sigma, and just-in-time (JIT) systems, along with innovative technologies such as machine learning, big data analysis, digital twins, and the Internet of Things (IoT) (Womack & Jones, 2003; Lee *et al*. , 2015). These resources offer real-time tracking and predictive insights that help manufacturers make knowledgeable choices and manage production resources effectively. In particular, techniques in Computational Intelligence (CI) have gained popularity for their potential to model intricate manufacturing systems and facilitate economical decision-making through smart automation (Jain *et al.*, 2018).

Even with a rising number of tools available, choosing the right and most effective techniques suitable for particular manufacturing settings is still difficult because of variations in production size, complexity, and levels of technology adoption. Hence, conducting a thorough examination of modern cost optimization methods and tools is crucial to grasp their functions, constraints, and implementation difficulties. This analysis intends to provide a detailed summary of present practices, shine a light on upcoming trends, and pinpoint areas lacking in current literature, thus offering helpful insights for both researchers and industry professionals aiming to enhance production costs in the age of smart manufacturing.

Inventory Management

In the present competitive business world, organizations need to manage inventories with efficient policies especially when the distribution network is dealing with deteriorating inventories (Ahlaqqach *et al.,*2020). Sometimes due to high demand or season or the deteriorating nature of inventories, manufacturers increase their production and therefore need rented warehouse (RW) facility to manage a large number of inventories (Chang *et al.*, 2020). Once the organization rents an extra facility to keep the extra number of inventories, the problem that they face is which inventories should be used first for minimum cost and minimum deterioration of inventories (Chang et *al.*, 2020). The green supply chain is also a need as carbon factor is increasing in the environment and business firms are also responsible for carbon generation by manufacturing, transportation, warehousing, etc.; therefore, it needs to be controlled by effective policies. Government and policymakers initiate policies such as carbon tax, carbon cap, and trade and offset policies to control carbon factors (Ahlaqqach et *al.*, 2020). The deterioration process is a natural process that cannot be stopped but it can be minimized if deteriorating nature inventories are managed properly.

Inspection is one such policy that is effective for deteriorating nature inventories. According to Bai *et al.,* (2016), deteriorated inventories are removed from the supply chain at the initial stage, then it will not deteriorate other inventories by contact and the decaying process can be minimized to some extent. In the same way, separated deteriorated inventories can be utilized to earn revenue and also solve the problem of the disposal of decaying inventories. An inspection policy helps to reduce carbon emissions and helps to turn a supply chain into a green supply chain. Deterioration is a natural activity that must happen with decaying types of inventories (Pal *et al.*, 2015). It cannot be stopped but it can be minimized with some tools. Many researchers, policymakers, and organizations have given distinct policies, tools, and management areas that could be profitable for the firms to handle such inventories. Many works have been conducted in this area with different policies. Pal *et al.,* (2015), in their work defined a prepayment policy for retailers as a financial arrangement where customers are required to make a payment in advance before receiving goods or services. This policy is often used to manage credit risk, ensure cash flow, and reduce the risk of non-payment. Retailers might implement prepayment policies for various reasons, such as when dealing with new or untrusted customers, high-value products, or customized orders. It can also be used as a way to secure commitments from customers and manage inventory more effectively.

Bai et *al.,* (2016) is of the opinion that inspection policy for deteriorating inventories involves setting guidelines for the inspection, disposal, or handling of items that are prone to deterioration, spoilage, or obsolescence. This is particularly relevant for perishable goods, products with expiration dates, or items that lose value over time. Implementing an inspection policy can help reduce losses from holding inventory that is no longer usable or saleable due to deterioration.

Muriana, (2016) stated that the actual behavior of the distribution network after applying an inspection policy can vary based on factors such as the nature of the products, the effectiveness of the policy implementation, the accuracy of demand forecasts, and the overall distribution structure. After applying an inspection policy for deteriorating inventories in a supply chain, several behaviors and outcomes may occur. The implementation of an inspection policy allows for more rigorous control over the quality and condition of inventory items. This helps to identify deteriorated items early enough and this prevents their inclusion in sales and reducing customer dissatisfaction (Bai *et al.,* 2016). Also by identifying and disposing of deteriorating items promptly, the supply chain can minimize losses associated with holding inventory that can no longer be sold. The insights gained from the inspection policy can inform better demand forecasting and ordering decisions. This can lead to optimized inventory replenishment and reduced chances of overstocking items that might deteriorate (Panda and Modak, 2017). Avoiding the sale of deteriorated items can enhance customer satisfaction and maintain the retailer's reputation for providing quality products. Also preventing the sale of deteriorated items can save costs related to customer complaints, returns, and refunds. Data collected through the inspection policy can be used to fine-tune inventory management strategies, including reorder points, safety stock levels, and replenishment schedules (Jing and Mu, 2019). According to Pand and Modak, (2017), implementing an inspection policy may require adjustments to processes and workflows to accommodate the identification, segregation, and disposal of deteriorating items. Khakzad and Gholamian, (2020) studied the prepayment policy for the retailer and the behaviour of distribution network after applying an inspection policy for deteriorating inventories. They were able to optimize the cost associated with the finished goods inventory. Halim *et al.,* (2021) discussed a production opening inventory model for deteriorating items under overtime concept with price and available inventory focused demand. According to them, in the present combative and developing business world, it is a very challenging and tough task to manage decay type inventories without any loss. Moreover, a manufacturer may find it very costly to own a more spacious and well-established warehouse. In this situation, if the amount of manufactured inventories is more than the holding susceptibility of the owner warehouse (OW), the manufacturer will require a rented warehouse (RW) (Halim *et al*., 2021). Sometimes manufacturers feel the need for extra

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production due to higher demand of inventories in the market and when manufacturer are dealing with deteriorating types of inventories, it necessary that production size be larger than demand of the market (Halim *et al*., 2021). Sometimes some seasonable products are manufactured before the season so as to fulfil market demand without delay. Some organizations manufacture inventories in RW and keep them in OW. Therefore, after placing them in RW, the next important policy is how to utilize these inventories, which means determining which inventories must be used first for maximum profit. Though it somewhat depends on factors such as the nature of the inventories and the rent of RW. Distinct supply chains adopt different policies but there are some policies that are established by policy makers and researchers. As well, these are also used by the market. Organizations are required to choose a dispatching policy that fits their supply chain and that can fulfil customer demand with minimum cost, less deterioration of inventory, and utilization of whole inventory without any loss (Maihami *et al.*, 2019).

For this, manufacturers should have enough knowledge about dispatching policies that suit their supply chain and provide maximum profit. Some of these policies are:

(a) LIFO (last in first out) policy. This policy works with the concept that RW inventories should be used first as it reduces extra rent, which leads to minimum cost because it is an extra cost burden (Chakraborty *et al.*, 2018).

(b) FIFO (first in first out). This policy works with the concept that OW inventories should be used first as it reduces the deterioration rate, because the inventory that comes first is manufactured first so it will become deteriorated first, hence, when used first, it reduces the deterioration cost (Yu, 2019). There is one more concept behind this policy that some RWs provide better storage policies compared to OW which reduces deterioration. In RW, inventories can be kept fresh for a longer period and it minimizes deterioration cost and indirectly maximizes profit instead of greater cost of RW. In the FIFO policy, inventories that are kept first, must be utilized first. There are some RWs that charge less with a good quality of storage facilities that reduce deterioration so that it is more profitable for firms to use OW inventories. Many organizations work with this policy to make sure better originality of the stored inventory (Xu *et al.*, 2017).

(c) MFIFO (mix first in first out) policy. This works with the concept of the FIFO policy but with some modifications. In this policy, deteriorated inventories are replaced with RW so RW inventories are also simultaneously utilized. Xu *et al.,* (2017) worked on this policy with a constant demand rate.

(d) MLIFO (mix last in first out) dispatching policy. This policy works upon the LIFO policy with some modification. In this policy RW inventories are used first. Inventories from RW are sent to OW and then to the market. Some of the manufactures manufacture inventories in RW and then place them in owner warehouse. Notably, Xu *et al*., (2017) worked with this policy on deteriorating inventories. They also considered all the above policies and compared them using mathematical modeling in each case.

(e) Mixed FIFO and LIFO policy. In this policy, both inventories are utilized simultaneously depending on the customer's demand (Minner and Transchel, 2017). In this policy, OW inventories are utilized first but some fraction of inventories is replaced from RW. Thus, under this policy, both warehouses are used simultaneously and inventories are finished at the same time. Green supply chain means "integrate environmental thinking into

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supply chain". At the present time world business manufacturers, policymakers, and researchers are attracted to the problem of carbon emission during supply chain (Mishra *et al.*, 2020). If the supply chain is dealing with deteriorating types of inventories then this problem requires more involvement. Policymakers and governments established a few policies to solve these problems such as carbon tax, cap and tax, offset policy and trade and cap etc. Huang. and Fang (2019) established a model considering the carbon emission regulation policy by using the game theory approach. Yu *et al.,* 2020) studied and established a model with preservation technology for carbon emission considering demand as the function of stock and price. According to them, it was difficult to manage these inventories at a low cost but if these inventories deal with some special policies, then it is profitable. Inspection during supply chain to remove deteriorating inventories is one such tool that helps. Inspection policy is a kind of tool that converts a normal supply chain into a green supply chain. If during each cycle the inspection process is adopted, then these inventories can be separated at the initial stage (Mishra *et al.,* 2020). This will help firms in two ways; one is that deteriorating inventories will not deteriorate other fresh inventories and the rate of decay can be minimized. The second is, if these deteriorating inventories are separated initially then it can be utilized for any purpose which helps to generate revenue. Inspection policy also helps in reducing emission (Yu *et al*., 2020). The separated products can be used for any other purpose based on the product or it can be sold as a product in the market at a low price so that it solves the disposal problem and reduces emissions. Thus, with this policy, the supply chain becomes a green supply chain.

Simulation and Optimization Models

Simulation optimization (SO) is simply refers as the optimization of an objective function subject to constraints, where both can be evaluated through stochastic simulation (Satyajith *et al.,* 2016). Simulation optimization involves the search for those specific settings of the input parameters to a stochastic simulation such that a target objective, the function of the simulation output, is minimized. Simulation and optimization models are valuable tools used in cost optimization in manufacturing. These models enable manufacturers to analyze complex systems, simulate various scenarios, and identify optimal solutions for cost reduction and operational improvement. Simulation models replicate real-world processes using mathematical and statistical techniques (Satyajith *et al*., 2016). They simulate the behavior of a manufacturing system by capturing the interactions among various variables, such as resources, activities, and constraints. Simulation models can be used to assess the impact of different factors on costs, identify bottlenecks, and evaluate the effectiveness of potential cost optimization strategies. Key characteristics of simulation models are outlined by Andradottir (2006) as:

1. Input Variables: Simulation models incorporate input variables such as production volumes, resource availability, demand patterns, and process parameters.

II. System Representation: The model represents the manufacturing system's structure and processes, including production lines, workstations, material flows, and scheduling rules.

III. Replication and Iteration: Simulation models are often run multiple times to generate statistical output and assess system performance under different scenarios.

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IV. Analysis and Optimization: Simulation models enable the analysis of cost-related metrics, such as production costs, cycle times, inventory levels, and resource utilization. They can also be used to optimize system performance by identifying improvement opportunities and testing different cost-saving strategies**.**

Optimization models form a significant area of research in various disciplines, including mathematics, operations research, engineering, and computer science. These models aim to find the best possible solution for a given problem by optimizing certain objective functions and subject to specific constraints (Deng and Ferris 2007). One widely studied category of optimization models is linear programming (LP), which involves linear relationships between variables and constraints. The simplex algorithm, proposed by George Dantzig in 1947, is a fundamental method used to solve LP problems (Dolan and More 2012). Nonlinear programming (NLP) extends optimization to handle non-linear objective functions and constraints. NLP models are commonly solved using techniques such as gradient-based methods, interior-point methods, or evolutionary algorithms. Integer programming (IP) deals with optimization problems where the decision variables must take integer values. These models are often more challenging to solve compared to linear programming. Additionally, there are specialized optimization models such as network optimization, stochastic optimization, dynamic programming, and convex optimization, each with their own specific techniques and applications. Optimization models use mathematical algorithms and techniques to determine the best allocation of resources and optimize decision-making (Dolan and More 2012). These models aim to find optimal solutions that minimize costs, maximize efficiency, or achieve other desired objectives. Optimization models can be used to address various cost optimization problems in manufacturing, including production planning, scheduling, capacity allocation, inventory management, and supply chain optimization. Optimization models define an objective function that quantifies the goal to be achieved, such as minimizing costs or maximizing profit. It also has decision variables which represent the decision options available, such as production quantities, resource allocations, or inventory levels. Optimization models incorporate constraints that reflect the limitations and requirements of the manufacturing system, such as capacity constraints, demand constraints, or resource availability constraints. Optimization models employ mathematical programming techniques, such as linear programming, integer programming, or dynamic programming, to find the optimal solution.

It can be used to perform sensitivity analysis, which helps understand the impact of changes in input parameters on the optimal solution and cost outcomes (Wang and Pasupathy 2012).

Simulation and optimization models offer several benefits for cost optimization in manufacturing. These models help identify cost-saving opportunities, optimize resource allocation, and streamline processes, leading to overall cost reduction.

Optimization models optimize resource allocation, production planning, and scheduling to minimize costs and maximize operational efficiency.

Simulation and optimization models can be integrated with other cost optimization techniques, such as activity-based costing, lean manufacturing, or Six Sigma, to provide a comprehensive approach to cost optimization. For example, simulation models can evaluate the impact of lean initiatives or Six Sigma projects on costs and process performance (Wang, 2012). Simulation and optimization models are powerful tools in cost optimization. They enable manufacturers to analyze complex systems, simulate scenarios, and identify optimal solutions for cost reduction, process improvement, and resource optimization. By leveraging these models, organizations can make data-driven decisions to enhance their cost competitiveness and operational efficiency. Fu *et al.,* (2011) provides a comprehensive survey of the field and its scope in solving manufacturing cost problems. The paper listed different ways in which optimization and simulation interact and provides a very basic simulation output analysis and convergence theory for simulation optimization. Hong and Nelson (2009) classify simulation optimization problems into those with a finite number of solutions, continuous decision variables and discrete variables that are integer-ordered in cost problems. Birge and Louveaux (2011) maintained that simulation optimization, like stochastic programming attempts to optimize under uncertainty. However, stochastic programming differs in that it makes heavy use of the model structure itself. Derivative-free optimization (DFO) is sometimes referred to as black-box optimization method. Output variability is the key factor that distinguishes SO from DPO. As explained by Conn *et al.,* (2009), some DPO algorithm under certain assumptions, expect rates that are closer to linear than quadratic and therefore early termination may be suitable. Policy gradient methods (Peters *et al.,* 2013) are a subfield of reinforcement learning, where the set of all possible sequences of actions make up the policy space which is estimated and a gradient ascent-type method is then used to move to a local optimum. Discrete event simulations have been successfully used to model many real-world systems such as operations managements, queues and networks. The occurrence of events is modeled using probabilistic distributions in modelling the randomness (Peters *et al.,* 2013).

Cost Optimization tools and techniques in Manufacturing

Cost optimization is a very important aspect of manufacturing operations (Chang. *et al.*, 2020). The significance is presented in the following ways: It helps to improve profitability, competitive advantage, enhanced efficiency, sustainable operations, better decision making and adaptability of market changes (Zeng *et al.*, 2020). Zeng *et al.*, (2020) further explained thus:

(i) Improved Profitability: Cost optimization directly impacts a company's profitability. By identifying and implementing measures to reduce production costs, companies can increase their profit margins and financial stability. This is especially crucial in industries with tight profit margins or intense competition.

(ii) Competitive Advantage: In today's global marketplace, companies face intense competition. Implementing cost optimization strategies can provide a competitive edge by allowing companies to offer products at more competitive prices. This can help attract more customers and increase market share.

(iii) Enhanced Efficiency: Cost optimization in manufacturing operations often involves streamlining processes, reducing waste, and improving efficiency. By identifying and eliminating inefficiencies, companies can improve production cycle times, reduce lead times, and enhance overall operational performance.

(iv) Sustainable Operations: Cost optimization often involves reducing resource consumption, waste generation, and environmental impact. By implementing sustainable practices, companies can align their operations with environmental regulations and customer expectations, leading to improved brand reputation and customer loyalty.

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(v) Better Decision-Making: Cost optimization requires a comprehensive understanding of production costs and factors influencing them. By analyzing cost data and implementing computational intelligence techniques, companies can gain insights that help in informed decision-making. This can involve identifying cost drivers, optimizing supply chain operations, or evaluating the cost-effectiveness of different manufacturing processes.

(vi) Adaptability to Market Changes: Manufacturing companies must be agile and adaptable to changing market conditions, including fluctuating raw material costs, market demand shifts, or economic uncertainties. Cost optimization strategies enable companies to quickly respond to market changes by adjusting production processes, sourcing strategies, or pricing structures. Cost optimization in manufacturing operations is essential for improving profitability, competitiveness, operational efficiency, and sustainability. It allows companies to optimize their resources, enhance decision-making capabilities, and align their operations with market demands, leading to long-term success in the manufacturing industry (Mohammadi *et al.*, 2015).

1. Activity-Based Costing (ABC)

Activity-Based Costing (ABC) is a cost optimization technique that provides a more accurate and detailed understanding of costs by tracing them to specific activities within an organization. It is a valuable tool for identifying cost drivers, allocating resources effectively, and making informed decisions regarding product pricing, process improvements, and resource utilization (Ittner and Larcker 2011).

Activity-Based Costing (ABC) emerged as a response to the limitations of traditional cost allocation methods, such as the volume-based allocation used in traditional costing systems. ABC recognizes that activities, rather than simple volume metrics, drive costs. It allocates costs based on the activities that consume resources and cause costs to be incurred. Ittner and Larcker (2011) argued that methodology of ABC involves the following steps:

a. Identifying Activities: Activities are the fundamental actions or processes that occur within an organization, contributing to the creation of a product or service.

b. Assigning Costs to Activities: Direct and indirect costs are assigned to each activity based on their consumption.

c. Determining Cost Drivers: Cost drivers are the factors that influence the frequency or intensity of an activity. They provide a basis for allocating costs to cost objects (e.g., products, services, and customers) based on their utilization of activities.

d. Allocating Costs to Cost Objects: Costs are allocated to cost objects using cost drivers and activity consumption data.

Benefits of Activity-Based Costing:

Enhanced Cost Accuracy: ABC provides a more accurate understanding of costs by attributing them to specific activities, enabling better cost control and cost reduction decisions (Ittner and Larcker 2011). ABC highlights the relationship between activities and costs, making it easier to identify areas of excessive costs or inefficiencies. Ittner and Larcker (2011) in their work, allocate resources more effectively and prioritize activities based on their impact on costs and performance of a manufacturing operations. They applied ABC facilitates in analysis of profitability at the product, customer, and market segment level, helping organizations focus on high-value products or customers which provides valuable cost information for decision-making, such as pricing decisions, product mix optimization, process improvement initiatives, and outsourcing evaluations (Gunasekaran and Ngai 2004).

Implementing ABC requires significant effort in collecting accurate and reliable data on activity costs and their drivers. It can be challenging to obtain data from various sources and departments within the organization. Implementing ABC can be resource-intensive, requiring investments in technology, training, and data collection systems. The initial costs of implementing ABC may deter some organizations from adopting this approach (Ittner and Larcker 2011). Subjectivity in Cost Driver Selection: Choosing appropriate cost drivers involve subjective judgments and incorrect driver selection can lead to distorted cost allocations. Implementing ABC may face resistance from employees who are accustomed to traditional costing methods. Proper change in management and communication strategies is necessary to overcome this resistance (Gunasekaran and Ngai 2004).

Integration with Other Techniques:

ABC can be effectively integrated with other cost optimization techniques and tools to enhance decision-making and improve cost management. For example, ABC data can be integrated with simulation and optimization models to identify cost-efficient process configurations and resource allocations. Activity-Based Costing is a powerful cost optimization technique that provides organizations with a detailed understanding of costs and their drivers (Gunasekaran and Ngai 2004). By allocating costs based on activities, ABC enables informed decision-making, better resource allocation, and improved profitability. However, implementing ABC requires careful planning, data collection, and consideration of organizational dynamics to overcome challenges and leverage its benefits effectively.

Target Costing

Target costing is a cost optimization technique that focuses on setting cost targets during the product design phase (Cooper and Slagmulder 2008). It is a proactive approach that aims to achieve desired profitability by considering customer requirements, competitor analysis, and market dynamics. Target costing involves a systematic process of cost planning, cost management, and value engineering throughout the product lifecycle. The primary objective of target costing is to determine the target cost for a product or service that will allow the organization to achieve its desired profitability while considering market conditions and customer expectations. Target costing provides understanding of customer needs, preferences, and price expectations through market research and customer feedback. Target costing enables setting a target price based on the market analysis, considering factors such as customer value perception, competition, and profitability goals (Gidiagba 2023).

Benefits of Target Costing:

According to Gidiagba (2023), the benefits of target costing include but not limited to the following:

- Enhanced Cost Management: Target costing provides a systematic framework for managing costs throughout the product lifecycle, allowing organizations to proactively identify and control costs.
- Customer Focus: By incorporating customer requirements and market dynamics into cost planning, target costing ensures that products are designed to meet customer needs and price expectations.

- Competitive Advantage: Target costing enables organizations to achieve cost leadership by optimizing costs while maintaining product quality and value.
- Profitability Improvement: By aligning cost targets with profit objectives, target costing helps organizations improve profitability by achieving the desired profit margin.
- Cross-Functional Collaboration: Target costing promotes collaboration between design, engineering, procurement, and manufacturing teams, leading to better cost control and innovation.

Cost Optimization Techniques and Tools

Simulation and Optimization Models

Simulation and optimization models are valuable tools used in cost optimization in manufacturing. These models enable manufacturers to analyze complex systems, simulate various scenarios, and identify optimal solutions for cost reduction and operational improvement (Von- Ronne 2012). Simulation models replicate real-world processes using mathematical and statistical techniques. Simulation modelling and analysis is the process of creating and experimenting with a computerized mathematical model of a physical system (Chung 2010). They simulate the behavior of a manufacturing system by capturing the interactions among various variables, such as resources, activities, and constraints. Simulation models can be used to assess the impact of different factors on costs, identify bottlenecks, and evaluate the effectiveness of potential cost optimization strategies. Key characteristics of simulation models according to Van-Ronne (2012) include:

1. Input Variables: Simulation models incorporate input variables such as production volumes, resource availability, demand patterns, and process parameters.

II. System Representation: The model represents the manufacturing system's structure and processes, including production lines, workstations, material flows, and scheduling rules.

III. Replication and Iteration: Simulation models are often run multiple times to generate statistical output and assess system performance under different scenarios.

IV. Analysis and Optimization: Simulation models enable the analysis of cost-related metrics, such as production costs, cycle times, inventory levels, and resource utilization. They can also be used to optimize system performance by identifying improvement opportunities and testing different cost-saving strategies**.** Simulation models are categorized based on three dimensions, namely randomness, data organization and timing of change (Mourtzis *et al.*, 2014). Simulation consists of an indispensable set of technological tools and methods for the successful implementation of digital manufacturing since it gives room for the experimentation and validation of process, configuration as well as system design. Simulation methods and tools are factory layout design, material and information flow design, manufacturing networks design, manufacturing systems planning and control, manufacturing networks planning and control, augmented and virtual reality in product and process design, planning and verification, ergonomics, robotics etc (Mourtzis *et al.*, 2014). Out –bound manufacturing operations has a big challenge of identifying the benefits of collaboration. Confusion around the optimum number of partners, investment in collaboration and duration of partnership are some of the barriers of healthy collaborative arrangements that should be surpassed (Ramanathan 2014). Out-bound manufacturing operations is the value-

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adding of activities from the initial raw materials to the ultimate consumption of the finished product spanning across multiple supplier- customer links (Dugal *et al.,* 2011).

Optimization models form a significant area of research in various disciplines, including mathematics, operations research, engineering, and computer science. These models aim to find the best possible solution for a given problem by optimizing certain objective functions and subject to specific constraints (Fazli-Khalaf *et al.,* 2019). One widely studied category of optimization models is linear programming (LP), which involves linear relationships between variables and constraints. The simplex algorithm, proposed by George Dantzig in 1947, is a fundamental method used to solve LP problems. Nonlinear programming (NLP) extends optimization to handle non-linear objective functions and constraints. NLP models are commonly solved using techniques such as gradient-based methods, interior-point methods, or evolutionary algorithms. Integer programming (IP) deals with optimization problems where the decision variables must take integer values (Mourtzis and Nicholls 2020). These models are often more challenging to solve compared to linear programming. Additionally, there are specialized optimization models such as network optimization, stochastic optimization, dynamic programming, and convex optimization, each with their own specific techniques and applications. Optimization models use mathematical algorithms and techniques to determine the best allocation of resources and optimize decision-making (Mourtzis. and Nicholls 2020). These models aim to find optimal solutions that minimize costs, maximize efficiency, or achieve other desired objectives. Optimization models can be used to address various cost optimization problems in manufacturing, including production planning, scheduling, capacity allocation, inventory management, and supply chain optimization. Key characteristics of optimization models according to Mourtzis and Nicholls (2020) include:

Objective Function: Optimization models define an objective function that quantifies the goal to be achieved, such as minimizing costs or maximizing profit.

Decision Variables: These variables represent the decision options available, such as production quantities, resource allocations, or inventory levels.

Constraints: Optimization models incorporate constraints that reflect the limitations and requirements of the manufacturing system, such as capacity constraints, demand constraints, or resource availability constraints.

Solving Techniques: Optimization models employ mathematical programming techniques such as linear programming, mixed-integer programming and dynamic programming to find optimal solutions.

Sensitivity Analysis: Optimization models can be used to perform sensitivity analysis, which helps understand the impact of changes in input parameters on the optimal solution and cost outcomes. Simulation and optimization models offer several benefits for cost optimization in manufacturing. These models help identify cost-saving opportunities, optimize resource allocation, and streamline processes, leading to overall cost reduction. Simulation and optimization models provide decision-makers with valuable insights and data-driven recommendations for making informed cost optimization decisions. Simulation models allow manufacturers to assess the impact of uncertainties, such as demand fluctuations or supply disruptions, on costs and performance. Simulation models assist in identifying process bottlenecks, inefficiencies, and improvement areas (Mourtzis and

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Nicholls 2020). Optimization models optimize resource allocation, production planning, and scheduling to minimize costs and maximize operational efficiency. Simulation and optimization models can be integrated with other cost optimization techniques, such as activity-based costing, lean manufacturing, or Six Sigma, to provide a comprehensive approach to cost optimization. For example, simulation models can evaluate the impact of lean initiatives or Six Sigma projects on costs and process performance (Chang 2010). Simulation and optimization models are powerful tools in cost optimization. They enable manufacturers to analyze complex systems, simulate scenarios, and identify optimal solutions for cost reduction, process improvement, and resource optimization. By leveraging these models, organizations can make data-driven decisions to enhance their cost competitiveness and operational efficiency (Mourtzis and Nicholls 2020).

Conclusion

Manufacturers aiming to stay competitive have therefore an essential aim in lowering production costs. Great promise for cost reduction and efficiency improvement exists by mixing classic methods—such as lean manufacturing and Six Sigma—with modern technologies such as Io, machine learning, and big data analytics. Still, accomplishing this effectively calls for a tailored approach addressing issues particular to every sector. Future research should focus on improving these technologies and exploring their potential for collaborative use to maximize modern manufacturing systems for cost savings. Achieving continuous operational excellence in manufacturing will ultimately depend on a customized approach to cost control.

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