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Unleashing Manufacturing Potential: A Simulation-Based Journey Towards Optimal Efficiency

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Abstract

In the increasingly competitive landscape of manufacturing, companies are continuously striving to enhance their production processes, minimize expenses, and uphold stringent quality standards. A valuable approach to achieving these objectives involves the utilization of plant simulation software which enables businesses to analyze, plan, and simulate their manufacturing operations, facilitating optimization and cost reduction while maintaining superior quality levels. This study aims to explore the application of plant simulation in a large company, with a focus on identifying areas for optimization and increased efficiency of the whole product lifecycle. The research will involve simulating a real-life manufacturing process, including both production and service kits, using simulation software. The performance of the simulated plant system will be analyzed to evaluate its effectiveness. By doing so, this study will contribute to the existing knowledge base of product lifecycle management and plant simulation and provide valuable insights to manufacturers seeking to enhance their production processes and achieve their business objectives. Furthermore, it will showcase the capabilities and accuracy of plant simulation technologies, equipping manufacturers with the necessary information to make informed decisions regarding future production goals and estimates.

Keywords: Simulation; Optimization; Digital Twins Manufacturing; Plant; Product Lifecycle Management

1. Introduction

In the contemporary manufacturing landscape, companies face relentless pressure to enhance their production processes, reduce operational costs, and uphold stringent quality standards [1]. The contemporary manufacturing landscape poses formidable challenges for companies, demanding a constant quest for enhanced production processes, cost reduction, and the maintenance of superior quality standards [1]. The pressure to adapt to dynamic market demands, coupled with the need for sustainable practices, amplifies the complexity of this environment [2]. To navigate this competitive environment successfully, a strategic approach involving the integration of advanced technology is imperative [2]. Among the tools available, plant simulation software has emerged as a pivotal resource for manufacturers [3]. By facilitating in-depth analysis, meticulous planning, and realistic simulation of manufacturing operations, digital twins offer a platform for optimizing processes, reducing costs, and maintaining exceptional quality levels [4].

Simulation of certain systems is a specific form of knowledge process. The basic principle is drawing conclusions using experiments and simulations under defined systems for objects and their movement and interaction [5]. The simulation model can be characterized as a system that mimics the actual idea of the simulated system and its movement and defines the artificial material objects [5]. The use of digitalization technologies enabled virtual product and process planning and large amounts of data processed, analyzed, and evaluated by simulation and optimization tools for planning in real time [4].

However, the existing literature is rich with examples of plant simulation applications, making it imperative to clearly define the specific problem or challenge this study aims to address. This study discusses the practical implementation of...
plant simulation within a large-scale industrial enterprise, with a core focus on identifying avenues for process optimization and efficiency improvement. The research revolves around simulating an authentic manufacturing process and employs sophisticated simulation software. Subsequently, the performance of the simulated plant system undergoes a rigorous evaluation to gauge its effectiveness. In doing so, this study aims to enrich the current corpus of knowledge on plant simulation, offering valuable insights to manufacturers as they strive to optimize their production processes and achieve their business objectives. Moreover, it serves as a testament to the capabilities and precision of plant simulation technologies, empowering manufacturers to make informed decisions regarding future production goals and resource allocation. The fundamental problem addressed by this research is the optimization of manufacturing processes and the alignment of product design and engineering with manufacturing aimed at increasing competition, cost constraints, and the demand for high-quality production. By focusing on a real-life manufacturing process and employing sophisticated simulation software, we aim to not only optimize immediate production processes but also contribute to a more comprehensive understanding of how such optimization strategies impact the broader product lifecycle. To tackle this challenge, this study sets forth several key research objectives:

- To evaluate the performance of the simulated plant system and assess its effectiveness.
- To contribute to the existing body of knowledge regarding plant simulation and its practical applications in manufacturing.
- To offer valuable insights for manufacturers aiming to optimize their production processes and achieve their business objectives in the entire product lifecycle.
- To demonstrate the capabilities and precision of plant simulation technologies, enabling manufacturers to make well-informed decisions concerning future production goals and resource allocation.

Our research aligns with the broader objectives of lifecycle engineering by not only optimizing immediate manufacturing processes but also by providing valuable insights that can inform strategic decision-making throughout the entire product lifecycle. This holistic approach contributes to the sustainability and efficiency goals inherent in lifecycle engineering.

1.1. What is PLM (Product Lifecycle Management)?

In the realm of intelligent manufacturing, which is propelled by artificial intelligence technology, the fusion of computer and information science with manufacturing processes has ushered in an era of flexible and intelligent production systems that can swiftly adapt to dynamic market demands [6,7]. The incorporation of cutting-edge information technologies like the Internet of Things (IoT) and edge computing has resulted in the accumulation of valuable data within the manufacturing sector. The effective utilization of this data throughout the product lifecycle process holds immense significance in augmenting the value chain of the industry [2,8]. Data-driven product design plays a pivotal role in comprehending how products interact with the external world [9]. By delving into product data through analysis and mining, decision-makers can unveil concealed patterns and refine product and system configurations [10]. This data-driven design methodology spans the entire product life cycle and substantially enhances product quality by leveraging operational data within the system [6,11].

Product Life-Cycle Management (PLM) is a critical information strategy for knowledge-intensive processes [8]. The proficient management of design knowledge and data stands as a linchpin for companies aspiring to retain their competitive edge while reducing product development timelines [7]. Data-driven design paves the way for the digitalization of production processes, ameliorates design efficiency, and bolsters management capabilities in alignment with user feedback and market demands [12].

Researchers have embarked on numerous studies focusing on data-driven design methods, applications, and illustrative case studies [6,13]. Nevertheless, the intricate interplay between data-driven design and PLM necessitates further in-depth exploration concerning design methodologies and knowledge classification systems [8]. A comprehensive review study by Feng et al. [6] underscores the substantial progress made in developing a comprehensive theoretical framework for product data-driven design over several decades. However, a dearth of studies persists in terms of the thorough mining of implicit customer requirements that are not explicitly articulated [14]. The advent of text mining and natural language processing technologies has opened up new horizons for extracting concealed requirement data, which now forms an essential facet of customer requirement analysis [8,15].

Moreover, collaborative conceptual design extends beyond the purview of experts from various fields to encompass an array of stakeholders, ranging from customers and designers to manufacturers [11]. This collaborative conceptual design integrates multidisciplinary knowledge that is essential for the complex conceptualization of products. Managing diverse product data and knowledge while resolving conflicts within collaborative conceptual design is now emerging as a core challenge. Hence, conventional engineering optimization methods often depend on subjective experience to address design uncertainties. Future research endeavors are expected to focus on integrating uncertainty parameters described by models into data-driven uncertainty optimization models. This study delves into theoretical foundations and methodological advancements. The aim is to provide insights with broad applicability across product lifecycle sectors, going beyond the immediate industry context.

1.2. Plant Simulation

Digital twins are not limited to just simulating initial designs; they also offer real-time monitoring capabilities. IoT sensors can continuously collect data from physical assets, which are then mirrored in the digital twin. This real-time data allows for predictive maintenance, as deviations or anomalies can be detected early [16]. For instance, in the aerospace industry, digital twins are used to monitor aircraft engines and predict maintenance needs, reducing unplanned downtime and
improving safety. While the advantages of digital twins and plant simulation are significant, their implementation comes with challenges [17]. Companies need to invest in IoT sensors, data infrastructure, and software tools. Additionally, personnel need to be trained to effectively operate and maintain these technologies. Ensuring data security and privacy is another challenge, especially in healthcare and other sensitive industries.

Plant simulation is a powerful software tool that plays a pivotal role in the manufacturing industry by offering the capability to simulate production systems within a dynamic 3D virtual environment [4]. This technology is instrumental in the design, analysis, and optimization of various aspects of manufacturing systems, including layout, workflow, and system performance. Its versatility makes it a valuable asset across a wide array of industries, spanning automotive, aerospace, electronics, media, medical devices and pharmaceuticals, food and beverage, and more [18]. With plant simulation software, users can effortlessly construct 2D and 3D digital models of their production systems. These models serve as a foundation for simulating the behavior of a system that can encompass machines, workers, or a combination of both [19]. The simulations are highly adaptable, allowing for the integration of several factors, such as material flow, machine behavior, robotic operations, and workforce interactions. Moreover, plant simulation software is an indispensable tool for evaluating various scenarios, enabling users to explore changes in system layout, the introduction of new machinery, or the implementation of different processes [20].

Tecnomatix, developed by Siemens, is a prominent name in the realm of plant simulation software [21]. As a global technology company, Siemens specializes in bridging the digital and physical domains to deliver benefits to both customers and society. Tecnomatix provides an array of advanced simulation and optimization tools tailored for manufacturing processes [5]. It encompasses aspects like production lines, logistics, and assembly processes, offering an extensive toolkit that includes 2D/3D simulation, virtual commissioning, and advanced analytics. Furthermore, Tecnomatix stands out for its ability to seamlessly integrate with various software tools and systems, rendering it a versatile solution suitable for manufacturing companies of all sizes, and has been chosen for this empirical study. Hence, this academic exploration contributes theoretical and methodological insights for simulating production systems. The goal is to offer knowledge with broader applicability across manufacturing domains.

2. Case Study

The case company, a family-owned organization founded in 1956, is dedicated to advancing sustainability in the food and agricultural sectors. With the global population increasing, food demand is expected to rise significantly. The objective is to derive knowledge that transcends the specific industry context, offering insights into sustainable practices in diverse industrial settings. The case company aims to foster innovation, ensuring product quality, fair compensation, efficiency, and waste reduction. Manufacturing, research, and development facilities in different locations around the world enable the case company to meet global demand effectively. Their solutions are distributed and supported through subsidiaries in 32 countries and more than 75 global distributors.

The case study is in the process of building more than 10 new plants due to expansions. In this study, we will focus on and analyze one specific part of the plant called kitting process. Kitting involves workers selecting various components based on specific orders and placing them in designated positions within a kitting box. These boxes may be intended for production orders, where they are used in manufacturing, or for service orders, where they are sold to customers for support purposes. The service order kitting process involves additional steps such as bagging, labeling, and including instructional notes. To achieve an accurate simulation of the kitting process, it is crucial to conduct thorough data analysis using reliable and relevant data that reflects real-world operations. Before delving into the analysis, it's essential to establish a clear understanding of the whole product lifecycle and manufacturing within the context of the case company. The rigorous data analysis, simulation modeling, and evaluation of the simulated plant system are conducted following sound scientific principles. Our findings are intended to augment the existing body of knowledge in product lifecycle management and plant simulation.

2.1. Data analysis

For the data analysis, the case company relies on historical master data from a Citrix Workspace, which enables data extraction into Excel files. The data obtained is complex and interconnected across different Excel sheets. The primary objective is to clarify the data's meaning, explain column names, and establish the crucial links between various sheets, including the identification of materials, their quantities, and categorization into production or service kits.

To estimate the fundamental functions and tasks involved in the manufacturing process, we rely on historical master data accumulated over several years. A Python programming code is utilized with a focus on the Pandas library to filter the data and classify orders into these categories. Different attributes are considered, including movement types, material codes, and internal/external production sources. This analysis encompasses the data from different sections in the entire product lifecycle. The analysis results provide a foundation for estimating the time required for different kitting processes, considering the quantity of materials and specific process details. This data analysis process allows for the development of a more accurate simulation of the manufacturing process. In this study to understand manufacturing processes, a rigorous analysis of historical master data over an extended period in the product lifecycle is conducted. The intent is to derive insights generalizable and applicable to a broad spectrum of manufacturing industries.

2.2. Defining Scenarios

Before delving into the intricacies of defining scenarios and simulating the manufacturing process, it's essential to gain a
comprehensive understanding of the facility's layout, as illustrated in Figure 1. Our primary objective is to simulate the kitting process within the designated kitting area, a process that can be divided into two distinct parts of production and service orders.

The kitting area operates in close coordination with the Automated Boxed Storage system, relying on designated ports for the efficient delivery of materials. These ports serve as the interface between the kitting area and the storage system, enabling the seamless transfer of various materials necessary to fulfill orders. When materials arrive at the kitting area, often delivered in boxes through the gate, they are presented to the workers stationed nearby. The workers play a crucial role in completing the orders by assembling the required components.

Upon the fulfillment of an order, the worker returns the box to the port. For service kits, the automated box storage system takes over. In the case of production orders, the worker transports the box to the loading point. From there, the box can be further conveyed to the Modules or Instruments area using a conveyor system. This systematic approach ensures the efficient flow of materials within the manufacturing facility. In our project, we were tasked with creating various scenarios to accurately represent the kitting process. The presented scenarios are differentiated primarily based on the time required for workers to pick and place parts during order execution.

Table 1. The example of low process time scenario

<table>
<thead>
<tr>
<th>Service kits</th>
<th>Production kits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Times min (examples)</td>
<td>Frequency %</td>
</tr>
<tr>
<td>28, 26, 21</td>
<td>10</td>
</tr>
<tr>
<td>96, 80, 60, 58, 48</td>
<td>45</td>
</tr>
<tr>
<td>6, 6.5, 7</td>
<td>15</td>
</tr>
<tr>
<td>10, 11, 2, 13</td>
<td>30</td>
</tr>
</tbody>
</table>

- **Low process time scenarios**: In this category, we assume that a worker takes 10 seconds to pick one part, with an additional 2-3 seconds for each additional part when dealing with production kits. For service kits, we assume that picking one part requires 30 seconds.
- **High process time scenarios**: In this category, we allocate 30 seconds for each material picked, with an additional 10 seconds for each extra quantity for production kits. When dealing with service kits, we assume that picking one part takes 1 minute, with an additional 30 seconds for each additional quantity. Additionally, high process time scenarios include a 1-minute recovery time for workers at each station after completing an order.

An example for low process time scenario is demonstrated in Table 1.

We have planned to create a total of six scenarios, each incorporating different numbers of ports and configurations. These scenarios are devised to provide a thorough representation of the kitting process and its various possibilities. In Scenario A, a simulation is created with six ports, each having a dedicated worker for handling both production and service kit orders. Scenario B retains the existing six ports and introduces an additional two ports exclusively designated for service kit orders, resulting in eight ports with one worker each. The remaining four scenarios utilize high process time assumptions. Scenario C, similar to Scenario B in terms of port configuration, features differences primarily in process times. Scenario D entails ten ports, with six capable of supporting both production and service kits, while the remaining four are dedicated solely to service Kits. Scenario E comprises twelve ports, with half allocated for production kits and the other half for service kits. Lastly, Scenario F utilizes twelve ports, with six for service kits, two for production kits, and four capable of facilitating both production and service kits. These scenarios will serve as the foundation for our kitting process simulations, enabling a detailed exploration of operational possibilities and their impacts on efficiency and order fulfillment.

3. Results

In the process of creating a visually appealing simulation model in Tecnomatix, we begin by constructing the factory environment. This layout represents the overarching structure of the simulated environment, with careful attention to details like color schemes and company branding elements. Before we delve into building Scenario A, which is the first of six scenarios, we'll provide a comprehensive guide to the steps and configurations involved. It's crucial to understand that each scenario involves a single shift from 6 AM to 2 PM and utilizes sources to generate boxes for the kitting process. These boxes may represent production kits for final instruments or be directed to customers for service support.

For Scenario A, characterized by low process times, we simulate the kitting process with six ports, each capable of handling both production and service kits. To represent real-life situations, we use sources to generate parts under specific conditions, emulating workers' requests for materials from the Autostore to fulfill orders. The routing path for the worker is illustrated in Figure 2, where the worker retrieves a box from a...
designated buffer and processes it at Station 1. The worker begins by retrieving the Box from the designated buffer marked as A1 and proceeds to Station 1, where the kitting process takes place. If the box corresponds to a production kit, it will be delivered to buffer P1. On the other hand, if it is a service kit, the worker will transport it back to the Autostore through the buffer located at point A2. The worker decides whether the box is a production kit or a service kit and routes it accordingly. Implementing a self-method and a global variable ensures that the source only generates new boxes when the previous ones are completed. Additionally, the processing times are configured based on data-derived timings. Worker actions are controlled by a method that uses the color attribute of the box to determine its destination. The WorkerPool settings incorporate additional buffers to prevent errors due to workers ending their shifts while carrying boxes. The remaining ports follow similar methods and configurations with some variations. The completed Scenario A model is illustrated in Figure 3.

In Scenario A, configured with low process times, we have six ports capable of handling both Production and Service kits. After an 8-hour simulation representing a single shift, we obtained the following results: 205 Production Kits and 30 Service Kits, with an average of 38-40 orders per Port. In Figure 4, we generated the main statistics table for Scenario A, with each column providing specific information. To clarify, let's briefly explain each column's purpose. "Drain 1" represents the final destination of Production kits (Modules Area), while "Drain 2" is for Service kits (Autostore). "Mean Life Time" denotes the duration from box generation to reaching the drain, including any waiting time. "Throughput" reflects the number of boxes produced in 8 hours, and "TPH" shows the boxes produced per hour. "Production," "Transportation," and "Storage" columns indicate the percentages of a box's life cycle spent on these tasks.

Figure 5 provides an overview of the occupation and percentage of time that each worker spends on specific tasks, such as working and walking. It is evident that all the workers exhibit a similar pattern in their task distribution. However, worker 6 stands out with slightly higher percentages in "Carrying" and "Walking" tasks. This can be attributed to the fact that worker 6 is responsible for delivering the boxes from the Modules Area back to Autostore, requiring more movement and transportation compared to the other workers.

Upon the completion of our simulation and analysis, our study has successfully met the outlined objectives, providing a comprehensive exploration of a real-life manufacturing kitting process through advanced plant simulation software. The insights gleaned from this research extend well beyond the confines of the specific case company, offering valuable guidance to a broader audience of manufacturing enterprises. The findings contribute substantially to the existing knowledge base in plant simulation, demonstrating the applicability and precision of these technologies. Importantly, our study serves as a foundation for understanding and optimizing production processes in diverse manufacturing settings considering the data from the product lifecycle. The methodologies and lessons learned can be generalized and applied by manufacturers across various industries, underlining the broader impact of our research.

While our study focuses on the application of plant simulation to enhance manufacturing efficiency, it is crucial to note that our simulation model, like any computational model, is a simplified representation of the real-world system. To enhance the credibility of our findings, future research could incorporate more extensive validation procedures. First, we compared the simulation outputs with real-world based on the current available plants and discussed any discrepancies and potential reasons for variations between simulated and actual results. Second, benefiting from constant consultations with domain experts and practitioners has highlighted adjustments based on expert insights. Third, we conducted sensitivity analysis by identifying the key parameters, determining the parameters ranges, running multiple simulations, and examining the variation in simulation results across the different parameter values.

4. Conclusion

In the ever-evolving landscape of manufacturing, businesses are confronted with the ceaseless challenge of refining their production processes, curtailing expenses, and preserving the high standards of quality that have become synonymous with success. Within this dynamic environment, the adoption of plant simulation software has emerged as a powerful strategy to navigate this complex terrain [1,22]. By affording companies
the capacity to meticulously analyze, strategically plan, and rigorously simulate their manufacturing operations, plant simulation software has proven to be instrumental in optimizing efficiency, reducing costs, and upholding superior quality standards [6,23]. This study embarked on an exploration of the multifaceted world of plant simulation, with a specific emphasis on its application within a large company. The core objective was to uncover avenues for optimization and efficiency enhancement by delving into the intricate workings of a real-life manufacturing kitting process. This involved the simulation of both production and service kits using cutting-edge simulation software, followed by a comprehensive evaluation of the performance of the simulated plant system. The insights yielded from this research endeavor hold significant value, extending far beyond the confines of the specific kitting process under scrutiny. They contribute substantively to the collective reservoir of knowledge surrounding product lifecycle, providing a comprehensive view of its efficacy in real-world manufacturing contexts. This newfound knowledge equips manufacturers with a potent toolset to augment their production processes and attain their overarching business objectives.

Moreover, this study underscores the profound capabilities and precision of plant simulation technologies, illuminating their capacity to replicate and elucidate the intricacies of manufacturing processes with remarkable accuracy. Armed with this knowledge, manufacturers are bestowed with the discernment required to make well-informed decisions regarding future production goals and estimates. Consequently, they can adapt, evolve, and thrive in the face of ever-increasing competition and exacting standards. While this study sheds light on the application of plant simulation in manufacturing, it is constrained by its specific focus on a particular kitting process in a large company, limiting the generalizability of its findings. Assumptions and simplifications were made to facilitate the simulation, which may not fully capture the complexities of real-world manufacturing processes. Data constraints could have affected the model's accuracy. Future research could encompass broader comparative studies across different manufacturing domains, enhanced accuracy through real-time data integration, advancements in AI and big data-driven simulation software, cost-benefit analyses, investigations into human factors, worker training, and ergonomics, as well as sustainability efforts to optimize resource usage and eco-efficiency. These future research avenues promise to provide a more comprehensive understanding of plant simulation's potential in manufacturing and its implications for efficiency, and sustainability.

References


