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Feasibility Analyses of Distributed Digital Factories Integrating Additive and Subtractive Manufacturing: A Case Study

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Nomenclature

DDF	Distributed Digital Factory
TF	Traditional Factory
SM	Subtractive Manufacturing
AM	Additive Manufacturing
DED	Directed Energy Deposition

Abstract

Various small and medium-sized manufacturing industries that use both additive and subtractive processes encounter difficulties in global competition due to the limited availability of cutting-edge machinery and substantial overhead expenses arising from frequent line changes. To address this difficulty, the idea of a Distributed Digital Factory (DDF) has evolved. For this purpose, a queuing model has been developed for feasibility analysis in traditional isolated, co-located factory environments and DDFs. The proposed model uses global balance conditions to obtain actual performance measurements to identify variables, efficiency, and correlations. Using the ARENA software, several manufacturing scenarios integrating additive and subtractive industries aim to pinpoint the threshold at which the distributed overhead impact decreases.

Through these scenarios, the specific factors at which the DDF setup becomes more efficient and cost-effective have been postulated. The outcomes show that the implementation of DDF resulted in a 29.0 % and 33.1 % reduction in queue time for distributed facilities when compared to the traditional method.

Keywords: Feasibility analysis; distributed digital factory; additive and subtractive manufacturing processes; traditional factories; queuing model; small and medium manufacturing industries.

1. Introduction

1.1 Introduction to Manufacturing System

A manufacturing system is a physical configuration that is made up of strategically arranged machines, workstations, robots, and other equipment connected or integrated physically through handling equipment and programmatically using computer control. The outputs of a manufacturing system can be divided into information and materials, such as scrap and finished products [1], [2]. Individual manufacturing companies are isolated, establishing their production systems at their factory locations and conducting business independently catering to either the local or global markets by incorporating themselves into the respective supply chain. In these manufacturing systems, people are an essential element, significantly contributing to the planning, design, operation, and control of these systems. Due to intense global competition and uncertain demands, the existing systems face several evolving hurdles: low levels of technological integration, lack of visibility into production and operations data, insufficient avenues to promote and implement creative solutions in product development, erroneous asset tracking procedures, and inefficient use of resources. Furthermore, after a system power outage or major failure event, the production line cannot be restarted until personnel manually trigger, test, and reconfigure it as needed, to ensure production quality and consistency, ultimately resulting in a significant loss of production [3], [4]. Unlike this traditional factory model, the proposed DDF model offers solutions to counter these hurdles of the past while fulfilling customer requirements, reducing lead time, and ensuring a resilient supply chain [5].

1.2 Rational Behind DDF

A DDF can be described as a decentralized model that connects multiple factories and small-to-medium enterprises to efficiently utilize distributed resources while economically and strategically deploying capital for generating goods. This type of system links factories across various geographically dispersed locations, enabling mobile production and rapid reconfiguration of production to situational demand. This allows for flexible, agile, and mass-customized manufacturing systems [5]. This system can merge both subtractive manufacturing (SM) and additive manufacturing (AM) processing to produce several parts in various locations where resources are available and bring them together to produce finished goods on par with and in many cases better than a traditional factory (TF) environment. Recent developments in digital twins and 3D printing can also help industries to optimize their product lines using distributed resources. These technological developments enable real-time monitoring, optimizing scheduling, and process modeling, enabling cost-saving products and higher utilization of capital equipment [6] addressing some of the shortcomings of a conventional factory environment.

AM and SM are two broad categorizations of manufacturing systems in most factory environments. While SM has many advantages related to tolerancing and finishing, AM has several advantages over SM because it reduces a product's lead time and material cost [7]. An inherent benefit of AM is its ability to effortlessly manufacture things with sophisticated geometries, fine details, and extremely small sizes [8]. Among the numerous classifications of AM, directed energy deposition (DED), and laser powder-based fusion are some of the most popular and offer several advantages. These methods create complex forms using a wide range of materials, all while employing a simplified CAD-to-product system. Due to this simplification and other advantages of AM, there is currently a growing trend in the adoption of AM and the optimization of input parameters for a variety of applications in sectors such as aerospace, nuclear power, medicinal and weaponry, automotive industries, and research [9], [10]. However, in traditional systems, all parts were produced independently in a single factory using SM or AM. As a result, changing the production line to produce multiple diverse product lines is time-consuming and costly [11]. In addition, the SM process requires a significant amount of time to produce certain parts due to the geometrical complexity of the product. Moreover, due to the limitations and unavailability of capital equipment, the production of a final part can take a significant amount of time [12]. Due to the lack of capital equipment and the complexity of the processes involved, small and medium-sized industries are unable to handle these types of orders. However, nowadays, most companies are shifting to modular parts to enable efficient product development and assembly

[13]. Therefore, it is feasible to manufacture some products using the SM process and some parts using the AM process, and then assemble them to finalize the products [14] for end use.

Producing such types of items as mentioned above by connecting various factories from various locations is complex, but it will help small and medium producers combine their resources to satisfy their customers as it can provide the quickest delivery or a cheaper price and compete in a global supply chain. Handling this kind of problem is similar to the queue problem in banks [15], hospitals [16], and other service sectors where various customers are coming to receive service, and facilitators provide them with proper service via a single server or multiple servers [17]. Therefore, queuing theory and computer simulation are important tools in system design and analysis, and they are quickly gaining popularity [18].

In this paper, we have constructed a queueing model to explore the adaptability of a DDF for manufacturing a diverse series of parts catering to different product lines. By applying queueing models, we have identified bottlenecks in various servers and optimized resource distribution, while minimizing wait times, leading to more accurate timeline predictions and improved production schedules. Through this analysis, we demonstrate how a DDF can dynamically adjust to demand fluctuations and resource availability, enhancing the responsiveness and scalability of the manufacturing process.

1.3 Leveraging DDF for AM Advancement

By bringing additive manufacturing closer to the consumer, DDF makes it possible to produce goods quickly and to their high standards. A DDF configuration also improves internet-based design and fast prototyping in AM, which contributes to reducing the duration of the product life cycle's product development phase. Prototypes may be swiftly manufactured, tested, and evaluated over several iterations of the product design phase of AM, which shortens the time to market and speeds up the innovation process. Because of this, this system makes use of AM to provide a great degree of customization and fast reaction times [19]. DDF guarantees the stability of a standardized manufacturing system, enabling AM to continue operating with high precision and consistency in a range of production domains. Furthermore, AM is renowned for its effective material usage. As a result, combining DDF with cutting-edge technology in AM improves productivity, flexibility, and sustainability of the production process [20]. Moreover, the ability of AM to produce parts locally reduces the extensive reliance on supply chains. In many cases, materials and finished goods do not need to be transported over long distances, resulting in cost savings in the supply chain and a reduced environmental impact [21]. Additionally, innovations and improvements made in one location can be easily shared and implemented across the entire supply chain network. Ultimately, the strong digital security and traceability provided by DDF enable AM to achieve greater energy and cost savings, consistent quality, and continuous innovation [22, 23].

1.4 Related Works

Queuing theory [24] involves studying and simulating models to predict the behavior of a manufacturing process that aims to accommodate sporadic demands in a manufacturing workstation. By applying this model, one can make decisions about the inefficiencies of wait times in queues, thereby enhancing productivity. The connections between cycle time, machine utilization, inter-arrival time statistics, and service have been demonstrated by engineers through the application of queuing theory results [24], [25]. Modeling the assembly process in a manufacturing plant using a suitable analytical framework for queuing theory is the primary target for applying queuing theory to manufacturing industries that have assembly processes. This model will yield several significant metrics that can be compared to the company's standard data. This then allows for the determination of how well the queuing model performs and provides recommendations for improving each server's performance and as a data source for increasing efficiency [26] in other servers and the production line. However, as products evolve into customized product-service systems, the current fiercely competitive business environment forces our existing product development processes to become more intricate. These models must be studied through simulation because the complexity of these systems makes it challenging to analyze them using just mathematical techniques or to enable computationally intense models to be assessed analytically.

Simulation is a powerful analytical tool that enables engineers and planners to make informed judgments accurately and timely regarding the configuration and performance of a system. The general functions of a simulation model consist of continuous improvement of new or existing facilities, problem-solving by measuring some parameters related to the system, and system design elements, as explained in Fig. 1 [27]. This requires the creation of an elaborate and complex production system. Gaining insight into these complex systems is achieved through simulation modeling and analysis. Conducting trials of novel operational or resource policies, ideas, or systems before putting them into practice [28], and, finally, information gathering and knowledge gathering without disrupting the real system [29] are also important aspects of this system.

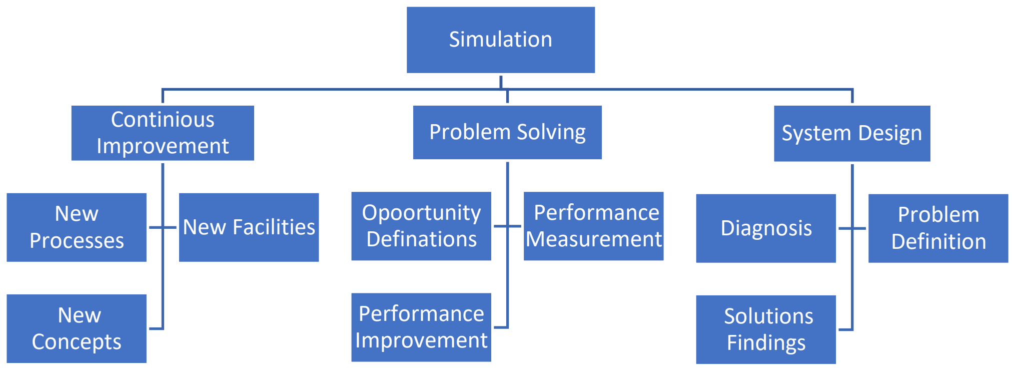


Figure 1. Manufacturing system design and operation through simulation; based on the data in Ref. [27].

A set of mathematical equations replicating a real phenomenon as closely as allowable, serves as the basis for the modeling process in simulation software [30], [31]. A simulation program lets users watch an operation happen virtually to understand bottlenecks and propose corrective improvements. Using simulation software to design machinery, procedures, or manufacturing systems can also help ensure that the final product and systems closely match the design specifications while avoiding costly process modifications. It is also one of the most used methods for manufacturing system analysis and design [32].

1.5 Problem Statement

Although DDF represents an emerging manufacturing model, it also needs to address challenges regarding productivity, handling uncertain demand, integrating different facilities, and conducting process capability analysis to become a viable economical alternative to existing manufacturing environments. Many researchers have researched technologies such as Industry 4.0 and digital twins to integrate isolated, dispersed factories under the DDF framework. However, comprehensive system analysis and investigation of the integrated DDF system are still lacking. It is well known that any changes made after the establishment of a DDF incur substantial costs and can sometimes be infeasible. In such cases, simulation can be a valuable tool for analysis. While simulation alone does not provide solutions, it can identify issues and quantitatively assess potential solutions [30]. Usually, simulation models are employed when developing an analytical approach to a studied problem that is challenging to numerically assess or empirically validate. Since these complex systems behave dynamically and there are not any "specialized" analytical models available for design, analysis, and optimization, simulation is a suitable way to tackle challenging issues associated with them. [33], [34], [35].

1.6 Proposed Work Motivation and Rational

The current paper addresses and expands on the challenges identified in earlier published works, reflecting the advancement of manufacturing systems, simulation techniques, and queuing theory. The queuing model and simulation's role in the planning and execution of manufacturing systems has changed significantly in recent years, opening new avenues for investigation and analysis. The primary focus of this paper though is to analyze the adaptability of DDF to enhance resource utilization and overall system efficiency, aiming to meet the growing demands of an ever-evolving market. Specifically, it looks at the feasibility of DDF using a queuing model and a simulation model that combines AM and SM to determine how well it works compared to traditional isolated manufacturing systems. In this research, mathematical models were developed: one for a single-line multistage system reflecting the traditional factory (henceforth called TF in this document) environment, and another for a multistage multiline system representing a DDF. Subsequently, the actual performances of these two systems are analyzed and demonstrated using simulation software. The main objectives of this study are to examine and simulate both the existing conventional factory system and the envisioned future manufacturing system within the framework of DDF. This evaluation is conducted using Arena Software to assess the feasibility and benefits of DDF compared to the traditional factory setup.

2. Methodology

2.1 Theoretical Background of Single Line Multistage Model

In this paper, a hypothetical scenario has been considered for a TF that has a single line with sequential machines, including a lathe machine, an AM machine, and a grinding machine on its production floor. Table 1 describes the summary of common terms and terminology used in queuing model describing the system.

Table 1. Common parameters of queuing theory

Queuing theory parameters	
Order arrival	Refers to the first-in-line orders that arrive.
Servers/ Counters	Refers to the machine-like AM/Lathe/Grinding machine
Queue number	Refers to the system's limitations based on the number of orders waiting in line.
Number of servers	Refers to the total number of machines serving the orders in line
Size of the client	Refers to the total number of orders in line
Queuing discipline	Refers to how many requests are delivered to the servers (includes first-in, first-out)
Production output	Refers to orders leaving after receiving service

This kind of production system can handle a single variety of products at a time. After completing a batch of such products, it will move on to the next step. When customers place a variety of orders, it can take a significant amount of time to make the necessary adjustments to start a new production quantity on the same line. As a result, there is a significant loss in production and a potential increase in waiting times and therefore associated costs for products with different specifications. Fig. 2 illustrates the system's process of receiving bulk orders as input. The system employs a sequential line of servers to serve these orders, and once all services are completed, they exit the production line. For analysis and insights into the above system and handling such a scenario, a single-line multistage model has been developed:

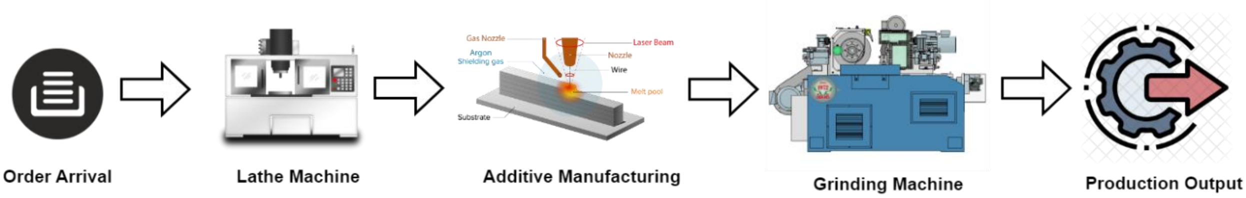


Figure 2. Single line multistage model.

The following standard terminology and notation is used henceforth:

- λ represents the average pace at which arrivals occur, measured as the expected number of arrivals per unit of time.
- The symbol μ represents the average pace at which the whole system completes service for each server, measured as the expected number of parts per unit of time.

- Pn represents the probability of precisely having n components in the queuing system.
- Ls represents the estimated number of pieces in a queuing system.
- Ws represents the anticipated duration that customers will spend waiting in the system.
- Lq represents the anticipated length of the queue.
- Wq represents the anticipated amount of time that customers will spend waiting in the queue.
- The symbol ρ represents the usage factor.
- k represents the number of stages.
- m represents the number of parallel lines.

The utilization factor, often known as the fraction of time, that servers are busy, is:

$$\rho = \lambda/\mu \tag{1}$$

The probability of having a specific number, n, of clients in the system may be calculated using the following expression:

$$P_0 = 1 - \lambda/\mu \tag{2}$$

$$P_n = (\frac{\lambda}{\mu})^n P_0 \tag{3}$$

The anticipated number of clients in the queue can be determined by:

$$L_q = \frac{k+1}{2k} \frac{\lambda^2}{\mu(\mu-\lambda)} \tag{4}$$

Expected number of clients in the system:

$$L_s = \frac{k+1}{2k} (\frac{\lambda}{\mu-\lambda}) \tag{5}$$

The mean duration of client wait time in the queue:

$$W_s = \frac{1}{\lambda} \frac{k+1}{2k} (\frac{\lambda}{\mu-\lambda}) \tag{6}$$

Anticipated customer wait time in the queue:

$$W_q = \frac{1}{\lambda} \frac{k+1}{2k} \frac{\lambda^2}{\mu(\mu-\lambda)} \tag{7}$$

2.2 Theoretical Background of Multi-Line Multistage Model

In a hypothetical DDF scenario, multiple factories are networked together, and each factory has a single line with sequential machines integrating AM and SM machines lined up in a product arrangement on the production floor. Different manufacturing lines from various industries can be used in this system to process many types of orders at once as shown in Fig. 3. When clients place several types of orders, the scheduling software presented here determines which production line from which factory will start production. Several types of systems can handle different orders, and there is no need to modify any single production line even to address the needs of multiple clients placing diverse product line orders. For analysis and insights into the above system and handling such a scenario, a single-line multistage model has been developed:

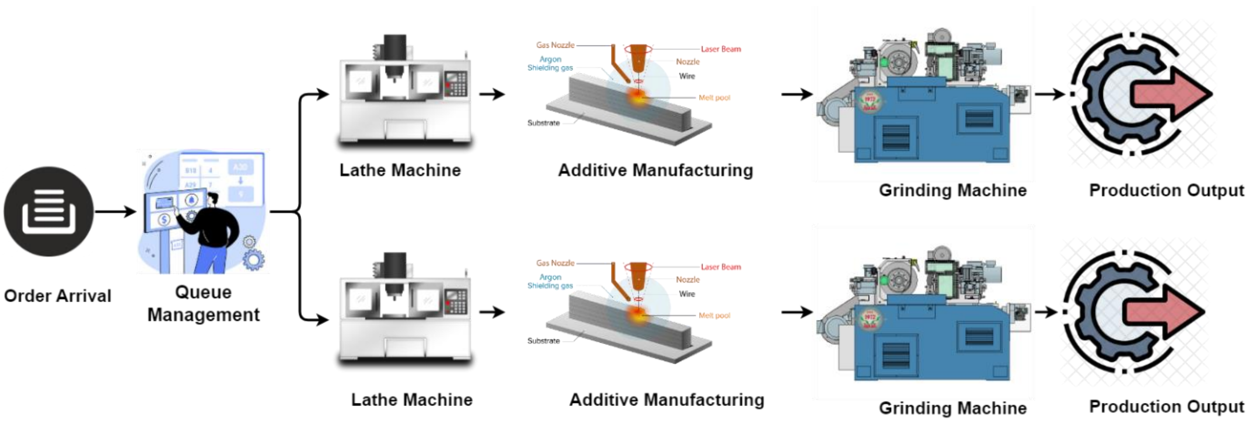


Figure 3. Dual line multistage model.

The utilization factor, often known as the fraction of time, that servers are busy, is:

$$\rho = \lambda/m\mu \tag{8}$$

The probability of having a specific number, n, of clients in the system may be calculated using the following formula:

$$P_0 = 1 - \lambda/m\mu \tag{9}$$

$$P_n = (\frac{\lambda}{m\mu})^n P_0 \tag{10}$$

The anticipated number of clients in the queue can be determined by:

$$L_q = \frac{k+1}{2k} \frac{\lambda^2}{m^2\mu(\mu - \lambda/m)} \tag{11}$$

Expected number of clients in the system:

$$L_s = \frac{k+1}{2k} \left(\frac{\lambda}{m(\mu - \frac{\lambda}{m})}\right) \tag{12}$$

The mean duration of client wait time in the queue:

$$W_s = \frac{k+1}{2k} \left(\frac{1}{\mu - \lambda/m}\right) \tag{13}$$

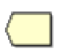
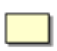
Anticipated customer wait time in the queue:

$$W_q = \frac{k+1}{2k} \frac{\lambda}{m\mu(\mu - \lambda/m)} \tag{13}$$

2.3 Simulation Model Description

Below Table 2 discusses the basic process panel that was used in describing the model of TF and DDF.

Table 2. Common panels used in ARENA.

Module	Basic Process Panel
 Part Arrival	Orders enter the simulation here.
 Output	Orders are removed from the simulation here.
 Process	An action that takes some time to finish and is often conducted by one or more resources.
 Decide	A branch in orders flow.
 Assign	Modify a parameter's value (during the simulation), such as the model variable or the kind of order.

2.3.1 Model Assumption

Both systems follow the following assumptions:

- Demand follows the exponential random variables or the exponential distribution.
- There is a non-value-added activity for transferring raw materials or existing parts to the next production factory; this process is called triangular distribution.

- Turning, drilling, and finishing processes follow the same distribution, which is the triangular distribution.
- Facilities follow 100.0 % reliability standards for both systems.
- Traditional Factory is considered a single-channel, multi-stage model.
- DDF is a dual-channel, multi-stage model.
- A demand that covers 33.0 % of operational capacity has a chance for special requirements, and the rest of the demand follows general production.

2.3.2 Existing TF

To replicate a real-life factory environment, a model, as shown in Fig. 4, is constructed that reflects every step of the manufacturing process in a traditional factory. As the process flows from left to right, the organization and categorization of entities in the factory's production line are crucial, as improper handling of the modules in the software used (ARENA) can impair the simulation's outcome. All five counters in the simulation model created for this case study are modeled using the ARENA software by copyright 2020, Rockwell Automation, Inc. version 16.10.0002. In the proposed ARENA simulation, the manufacturing system has been operated for a replication duration of 1000 hours. The first counter was used for part arrival, while the last counter was used for output, and the three counters located in between them are included to represent three dependent sequential operations in that process line. In addition, an assigned module has been inserted to recognize the products that were moving during production in individual counters, service capacities at individual counters, simulation durations, and replication counts, which are all considered input parameters for modeling.

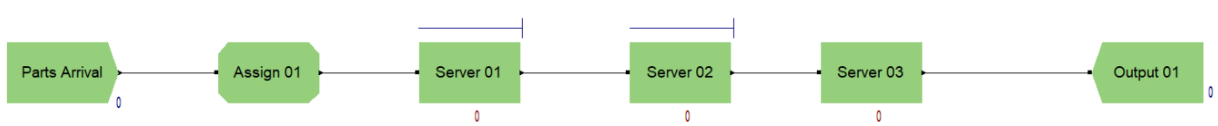


Figure 4. Overview of the TF.

After inputting all the parameters, Fig. 5 illustrates that the orders are arriving and engaging service from each counter and leaving the system after completion of the sequence of service operations. Besides, it was noticed after the simulation that there were queues in front of different service stations.

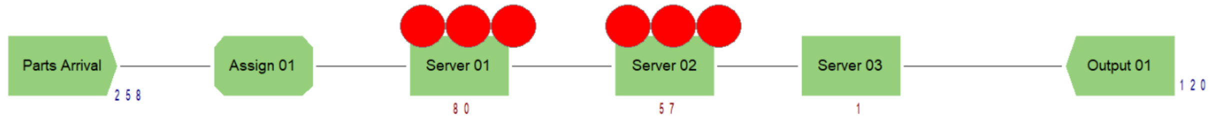


Figure 5. Queue conditions after simulation in a TF.

2.3.3 Proposed DDF Model Description

TFs maintain a fixed plant layout, necessitating production lines to adjust based on demand. The process of manufacturing new products or repairing parts takes place on the same production line [36]. Over time, significant changes must be made, leading to an increase in production lead time, mandating a significant amount of time to switch equipment along the production lines, and establishing and validating necessary modifications [37]. However, for the proposed DDF model, two scenarios have been considered: one where orders are for repairing existing parts, and another where orders are for new product development. These scenarios offer different perspectives; hence they are discussed separately in the following paragraphs.

2.3.3.1 Handling Repair Parts as a New Order for DDF: Case-01

In this scenario, the DDF comprises two distinct factories located in different regions but equipped with similar facilities and remotely connected. One factory serves as the source company where the decision-maker or job shop scheduler is located, while the other is situated in a separate region supporting and complementing the source company's production capacity. As a result, if the products need to be shipped, they need to be transported through a carrier. As a fair assessment, the model presented here incorporates a delay module to model realistic shipment scenarios. The design window screenshots shown in Fig. 6 and Fig. 7 illustrate a sequence of interconnected boxes representing the entities in the proposed model. These diagrams demonstrate the appropriate relationships between the entities depicted in Fig. 6 and Fig. 7. The process of each factory in this simulation is comprised of five primary parties: order arrival, lathe machine, AM, grinding machine, and output. Multiple product orders were created as a demonstration to detail a product's workflow through this environment. When multiple products are ordered, there is a box that acts as a scheduler and decision-maker (diamond-shaped) to send the products to various factories. The term "process module" refers to any square-shaped box named as various servers. The modules interconnected for measuring several factors should be assigned and documented.

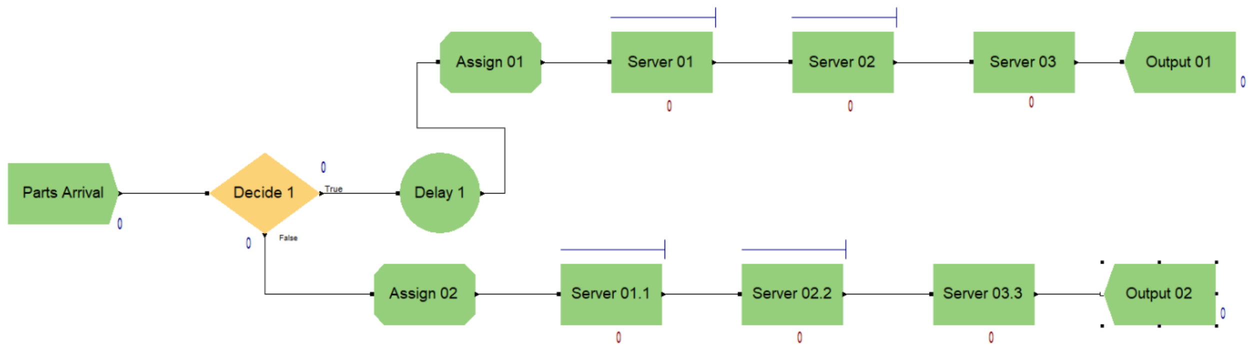


Figure 6. Overview of DDF (case-01).

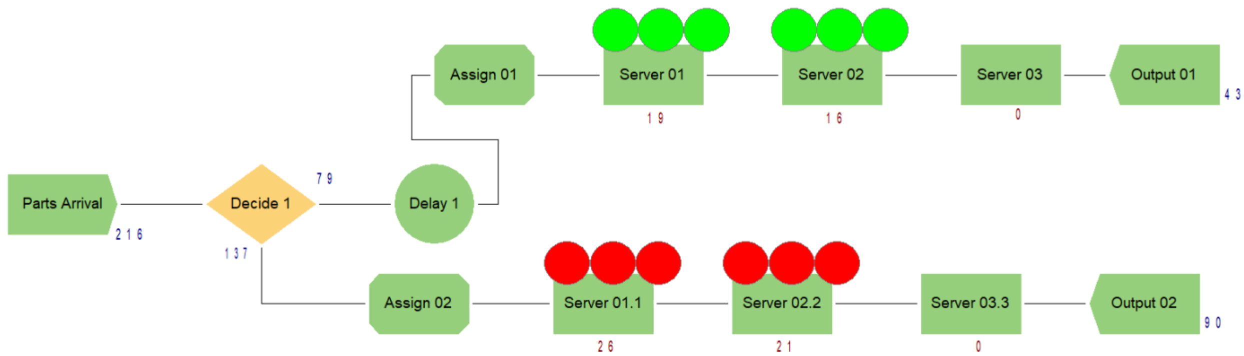


Figure 7. Queue conditions after simulation in DDF (case-01).

Fig. 7 depicts the production process scenario after simulating a DDF environment. As several product orders arrive; per the product specifications, production line availability, and response time consideration, the orders are assigned to different production lines that are in different geometric locations but are virtually connected through the scheduler proposed here.

2.3.3.2 Handling New Product Development as a New Order for DDF: Case-02

In this case, DDF consists of two different factories from two separate locations with the same facilities that are virtually connected. One factory is considered a source company in which the decider or job shop scheduler is located. The other factory is in a different area supporting the source company's operational capabilities. When a variety of orders enter this DDF, the scheduler sends the product orders to the appropriate production line. Using modern technological advancements such as digital twins, Industry 4.0, and the integration of machine learning models, we can visualize production from anywhere in the world. Additionally, the ARENA simulation tool was used to create and execute the process. The design window screenshot depicted in Fig. 8 exhibits a sequence of connected boxes that the entities in the proposed model depicted in Fig. 8 are related to. The process of each factory in this simulation is comprised of five primary parties:

order arrival, lathe machine, AM, grinding, and output. When multiple products are ordered, the scheduler and decision-maker send the products to various factories as in case 1 in DDF. After passing through the required number of process modules, finally it disposed of as a final output.

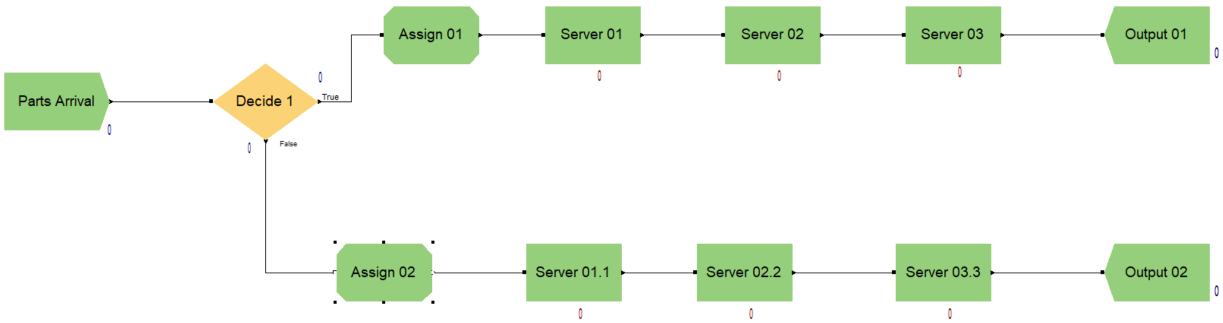


Figure 8. Overview of DDF (case-02).

2.4 Data Analysis

Hypothetical data was considered and kept the same for both TFs and DDFs. The study also included workstation sequential processes, types, and processing times, as well as production line capacity and other relevant information. Table 3 shows the necessary data and its probability distribution.

Table 3. Input data distribution for the developed ARENA model.

Module Name	**Distribution with data**
Parts Arrival	Random (exponential distribution) ($\boldsymbol{\lambda}$=4)
Decide	2-way by chance (33%)
Delay	Triangular (18,22,24)
Server 01(Lathe Machine)	Triangular (1,3,6)
Server 02(AM)	Triangular (1,3,6)
Server 03(Grinding Machine)	Triangular (1,3,6)

2.5 Model Verification and Validation

Verification assesses the accuracy of the formal depiction of the proposed model by examining computer programs and test runs, as well as checking for consistency in its statistics and validation operations, which are essential for establishing the credibility of the models. Simulation trials and scrutinized sample path trajectories have been conducted. Within a visual simulation environment, such as Arena, both code printouts and images were used to ascertain the accuracy of the underlying program logic. In simulation modeling, several sets of inputs are used to run each portion of the model. After adjusting various values and conducting actual tests, the results demonstrate the robustness of the model. For model validation, a number of replications have been completed to provide stochastic relevance. These replications have enabled the extraction of the statistical data samples from simulation runs while minimizing computational expenses.

3. Result Analysis

3.1 Value-Added Time and Non-Valued-Added Time Analysis

The process that directly contributes to making products for which customers are willing to pay is called a value-added activity, and the time spent on it is referred to as value-added time. During the machining process, the operations performed in front of different machines create value and are considered value-added time. However, other activities like moving, setting up jigs and fixtures, etc., are considered non-value-added activities. After completing the simulation, Fig. 9 indicates that in TF, the value-added time per part is 9.938 hours, with no non-value-added time as there is no transportation time involved because of only one factory. On the other hand, case-01 of DDF shows that the valued added time per part is 9.9251 hours, which alone is similar to the value-added time of TF, without even including the non-valued-added time per part. Also in TF, there is a wait time of 249.86 hours for each part, and there is no transfer time or other additional time involved. Conversely, the wait time for parts dropped to 180.40 hours, and an additional 6.8621 hours were required to transfer the product from the parent company to another company in DDF.

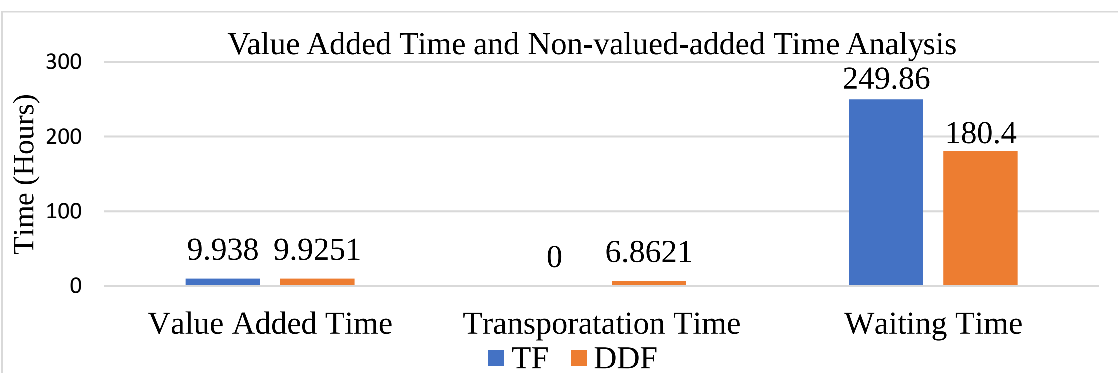


Figure 9. Result of value-added time and non-valued-added time after simulation.

3.2 Waiting Time Analysis in Queue

Fig. 10 depicts that Server 01's queue time is on average 106.14 hours, which is 29% lower than the TF queue time in Server 01; Server 01.1 queue time from another factory of DDF is on average 100.38 hours; and queue time in servers 02 and 02.1 of DDF is about 99.63 hours and 102.55 hours. The queue time is different between server 02 and server 02.1, because it processes distinct types of products despite having the resources of the server the same, however, DDF is reducing queue time by 33.1% lower than the TF queue time in server 02.

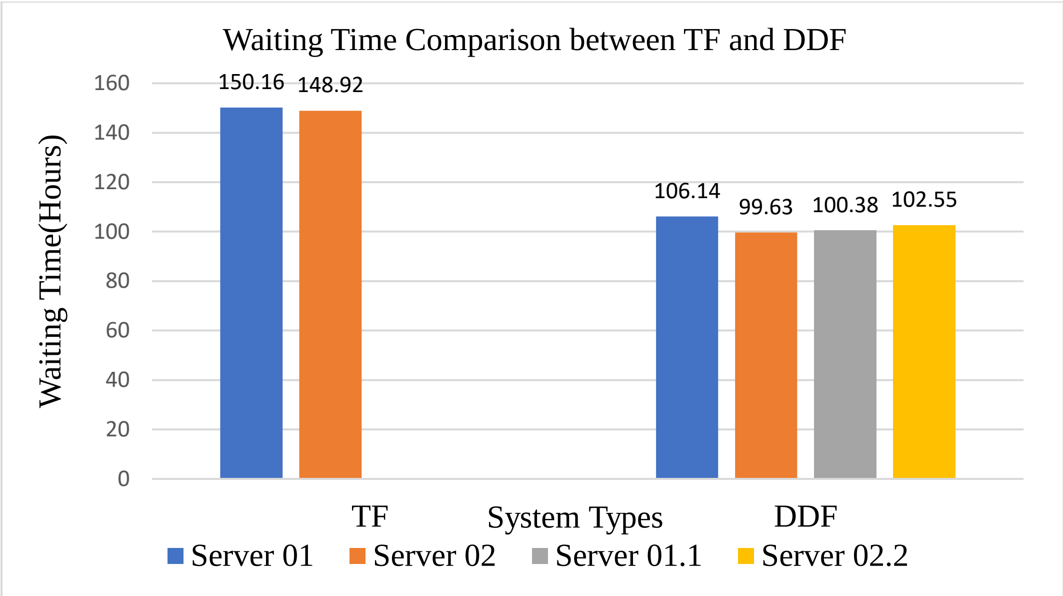


Figure 10. Result of waiting time after simulating.

3.3 Number of Parts in Queue

In TF, from Fig.11, it has been shown that 39 units are in queue in front of server 01, and 26 units are in queue in front of server 02. This puts a significant demand for these server units in TF ensuring significant delays in production time and long queues. Conversely, in DDF, it has been shown that only 8 units are in server 01's queue, while only 6 units are in server 02's queue. Besides, another factory in DDF shows that it can manage other types of products which have a queue of 14 units and 11 units before server 01.1 and server 02.2 consecutively.

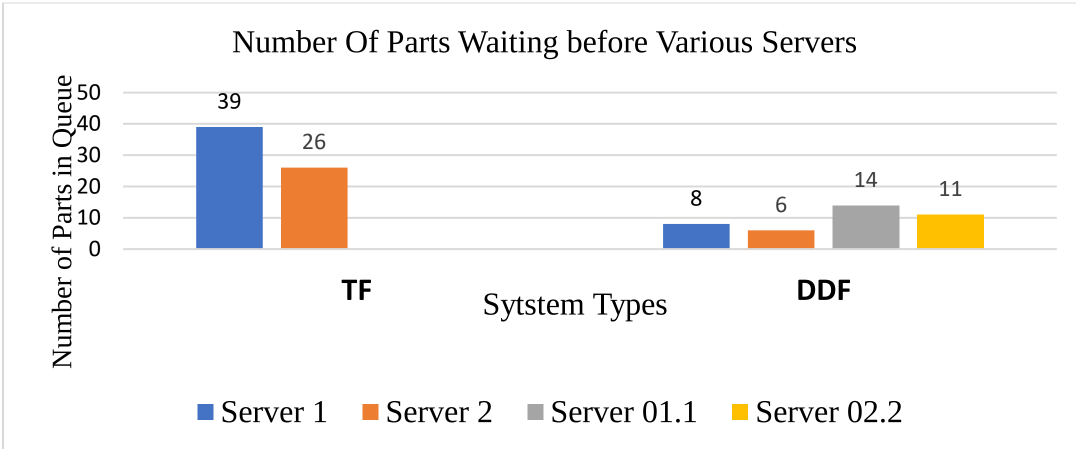


Figure 11. Parts are waiting before servers both in TF and DDF (case-01).

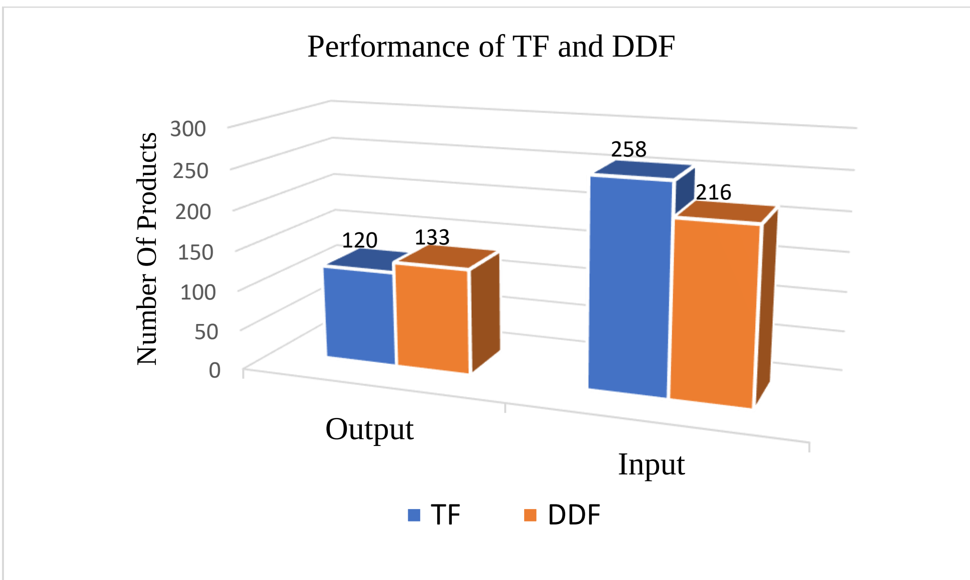


Figure 12. Output of TF and DDF (case-01).

The results presented in Fig. 12 below demonstrate that the total number of orders is about 258 units in TF, but due to capacity limitations and time constraints, the actual output is only 120 units. In DDF, although the total number of arrival orders is approximately 216 units, the output is still far better than that of TF, with an estimated output of 133 units. As the DDF model connected the two factories with the help of digital information advancement, Fig. 13 shows that the proposed DDF can manage varieties of demand by connecting several factories. The results show that the order is for 238 units, and after splitting the order as per the product variation in different factories, it has produced 237 units by effectively and efficiently utilizing the capacities of these factories.

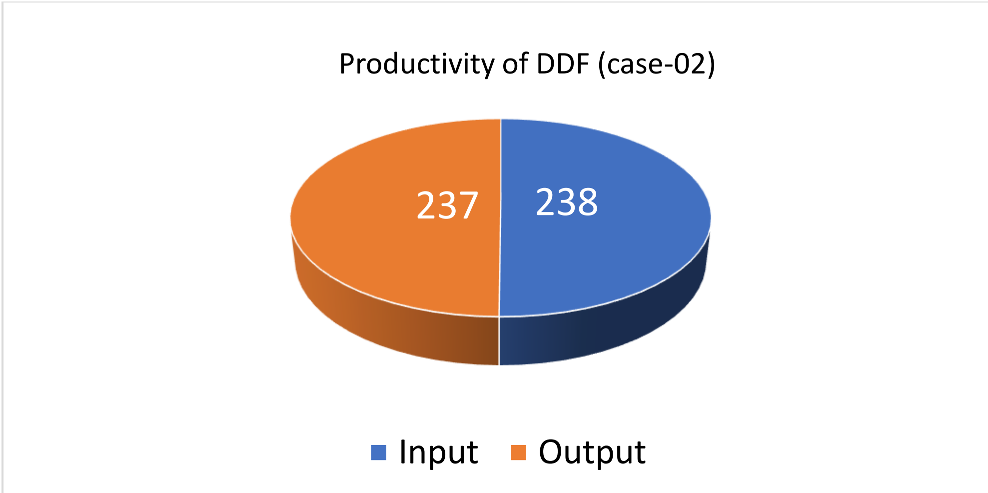


Figure 13. Results after simulating DDF (case 02).

Fig. 14 shows the behavior of the handling of repair products in both TFs and distributed digital factories. The line curve reveals that DDF manages repair product variety orders more successfully than TFs. Initially, when the production time and product variety are lower, the performance of both systems is quite similar. However, with increasing product variety and production time, DDF handles more number of products and different varieties of products as DDF has a different production line to handle those uncertain demands than TF.

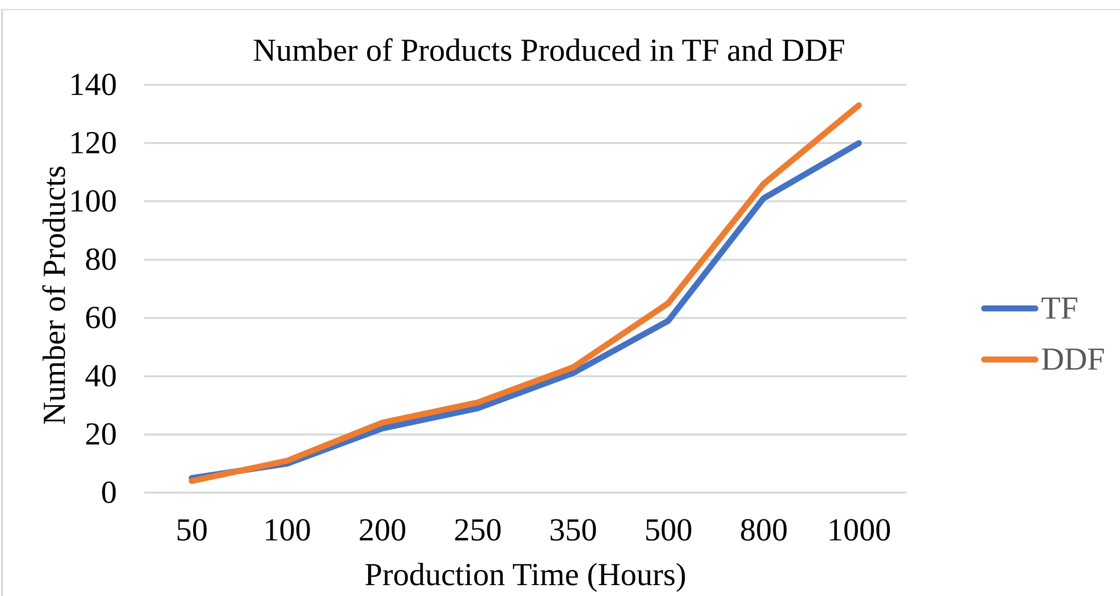


Figure 14. Comparison of repairing parts handling by DDF and TF.

Fig. 15 illustrates the handling behavior of repair products and new product development in both TFs and DDFs. From the line curve, it has been seen that more product variety orders are successfully managed by DDF than by TF. Initially, when the production time and product variety are lower, the performance of both systems is quite similar. However, with increasing product variety and production time, DDF outperforms the existing traditional system. Importantly, when a variety of orders consisting of higher production volume of distinct product development come in, DDF outperforms the other system because it connects multiple factories to manage demand and customer requirements.

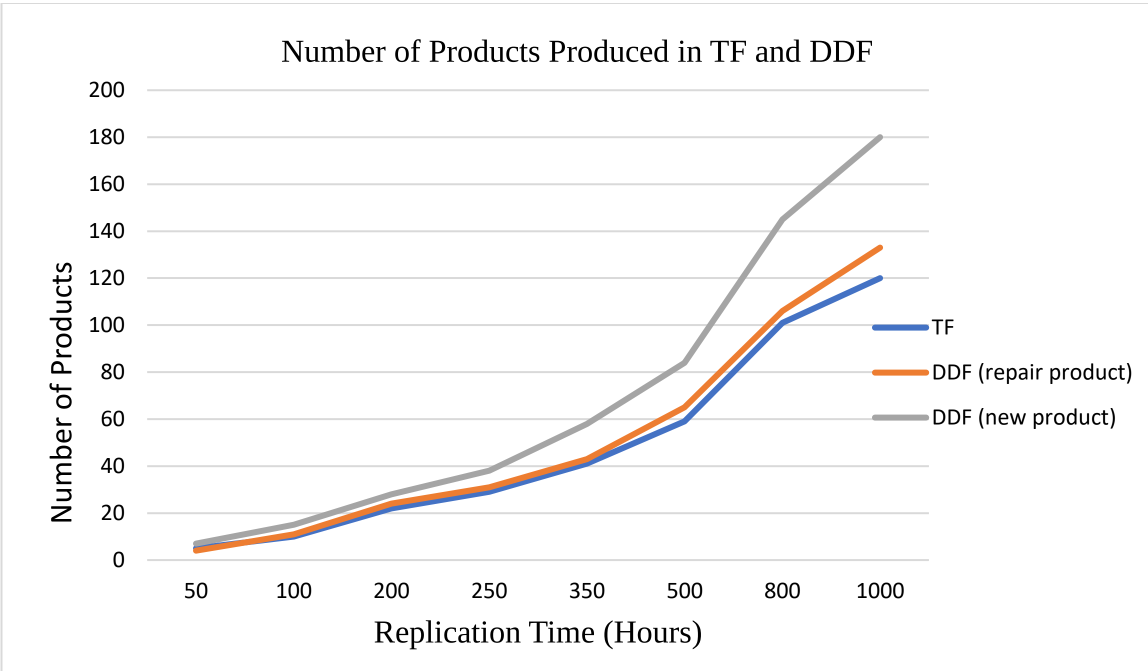


Figure 15. Comparison of repairing parts and new product development handling by DDF (both cases) and TF.

4. Conclusion

This paper has developed a queuing model for DDF and TF systems, not only to manage production complexity but also to analyze the feasibility of DDF compared to TF systems. The data and servers were considered the same both in the DDF and TF. Moreover, simulation results for TF and DDF (cases 01 and 02) show that DDF outperformed the TF in both cases when the orders showed more variability. The following conclusion has been made from the present study:

- For handling the demand for repair parts, DDF has reduced queue time in front of server 01 and server 02 by 29.0 % and 33.1 % to TF.
- In both case 01 and case 02, DDF handled a variety of demands with great productivity. In case-01, DDF repaired 133 units and in case-02, DDF manufactured 237 units where

TF handled only a single type of product orders and each time it manufactured 120 units.

- In case 02, DDF has considered a production scenario to produce new products where two factories were digitally connected. The result depicted that DDF handled a variety of orders, and it produced 237 units out of 238 units of products whereas TF handled the single type of orders, and it produced 120 units out of 258 units.

This work developed the queuing model as an analytical model but solved the current problems with a simulation model. From these case studies, it has been concluded that the advancement of information technology, and integration of SM and AM in DDF can be productive, and robust. The results also indicate that DDF can be a future manufacturing model as the business environment becomes more uncertain and competitive.

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