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Manufacturing Line Optimization Using Stochastic Models Under Uncertain Conditions

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Abstract

The uncertainty around manufacturing organizations is growing with failures in the machines, changing customer orders, unpredictable processing times, maintenance downtimes and limited resources. All these uncertainties have a considerable impact on production efficiency, throughput, system reliability and operational decision making. Most traditional deterministic optimization methods are not well suited to model the dynamics of modern manufacturing systems and therefore they are not useful to solve production problems in practice. In this study, manufacturing line optimization under uncertain conditions using stochastic models is investigated and an integrated framework is proposed which incorporates the theories of queueing theory, Markov chain analysis and simulation based evaluation. The research explores how uncertainty affects manufacturing performance, and investigates optimization methods that can enhance the operational results. A stochastic production model is created to capture all the variations in machine behaviour, processing times and production flows. Markov chain modelling is used for machine reliability and state transition analysis and queueing analysis is used for identifying the bottlenecks and wait-time characteristics. Multiple uncertainty scenarios for simulation experiments are performed to study throughput, utilization, queue length, and system availability. The results show that stochastic optimization models are more realistic descriptions of manufacturing operations and are more effective at enhancing production performance than the traditional deterministic ones. The results show the reduction in waiting time and queue size, increased throughput, machine usage, and operational resilience. In addition, scenario analysis has been used to show that uncertainty management positively impacts flexibility and sustainability in manufacturing. Based on the conclusion of the study, stochastic modelling is proved as a useful decision support tool for optimizing manufacturing systems in uncertain situations, and also the practical advantages of the stochastic modelling in production planning, resource allocation, maintenance management and strategic decision making in the modern industrial environment are highlighted.

Keywords: Optimization of manufacturing lines, stochastic modelling, queueing theory, Markov chains, production uncertainty and manufacturing systems engineering.

1. Introduction

1.1 Background Of Manufacturing Systems

Over the last decade, manufacturing systems have experienced so many changes that industries have increasingly been implementing automation, digital technologies and data-driven decision making frameworks. The traditional production line was mainly developed to maximize production under stable operating conditions. In the modern manufacturing context, however, machines are linked to each other, sensors are intelligent, cyber-physical systems are in use, and technology for monitoring real-time operating conditions constantly impacts performance. With the advent of Industry 4.0, the shift from traditional manufacturing to smart manufacturing has been getting faster, as production resources communicate and coordinate independently to enhance efficiency and responsiveness (Lee & Su, 2023).

In today's competitive manufacturing landscape, companies are required to maintain a high level of product quality, achieve short lead times, operate at low costs and have the flexibility for operations. Hence, optimization of the production line has come to be a necessity to ensure competitiveness and sustainability. Optimization techniques can boost throughput, lower work-in-process inventory, shorten machine idle times and increase the utilization of resources for manufacturers. The merging of sophisticated analytical models, simulation methods, and optimization algorithms have been highlighted as essential for facilitating decision-making processes in manufacturing operations under dynamic conditions (Afolabi, 2025). In addition, production systems are becoming more complex and need methods that can model variability and uncertainty rather than relying on deterministic assumptions. In response to this, the field of stochastic modelling has grown to be an important technique to represent realistic manufacturing environments and aid in effective operational planning and control (Missbauer, 2024).

1.2 Areas of manufacturing uncertainty and challenges

Despite the advancements in technologies, manufacturing systems are still very uncertain in nature, which impacts on the operational effectiveness and production performance. Uncertainties can stem from machine failures, equipment degradation, processing time variability, lack of personnel, quality issues, raw material delays, and customer demand. This disruptions can cause serious production delays, operational costs and system reliability. Deterministic planning methods are not suitable for manufacturing environments with continuous variability (Hadji, 2022) because they set the parameters and operating conditions. (hal.science)

The studies in recent years have shown that uncertainty management is also a crucial aspect of modern manufacturing strategy, since production systems have to be robust in the face of varying operating conditions. Accurate uncertainty modelling can help businesses predict disruption, plan for other options and remain productive in the face of uncertainty. As a result, the managers of manufacturing increasingly look to analytical tools that can include randomness into the manufacturing production planning and operational decision making process (Performance Optimization in Manufacturing Systems, 2024).

1.3 Stochastic Modelling in the Manufacturing Industry.

Stochastic Modelling is a mathematical approach to modelling uncertainty and randomness in manufacturing systems. Stochastic models represent variability in machine performance, processing times, demand patterns and system failures by modelling them as probability distribution, whereas deterministic models assume that the system parameters are fixed. These models allow decision makers to analyse a range of operational scenarios, and estimate performance under uncertainty (Covey, 2025).

Examples of commonly used stochastic methods in manufacturing include Markov chains, queueing theory, stochastic differential equations, Bayesian optimization, and Monte Carlo simulation methods. These techniques enable the study as well as practitioners to evaluate system performance, pinpoint system bottlenecks, calculate reliability, and optimize resource allocation with incorporation of uncertainty. Recently, scientific research has shown that using stochastic optimization methods for production yields better production efficiency, resilience, and decision-making than traditional deterministic approaches, especially in complex and dynamic manufacturing environments (Cruz-Oliver et al., 2023; Afolabi, 2025).

1.4 Research Problem Statement

In today's volatile manufacturing world, where the availability of machines, processing time, product demand and resource utilization are all variable, companies are facing big operational problems. While traditional optimization techniques are valuable for planning support, they often do not provide an appropriate way to model the stochastic nature of production systems and the dynamic disruptions they face. This often leads to manufacturing lines becoming bottlenecked, waiting periods, low throughput, and inefficient use of resources. A need for thorough optimization frameworks that explicitly include uncertainty in the decision-making process is therefore needed. Under the uncertain operating conditions, stochastic models turn out to be a promising tool to enhance the performance of manufacturing lines.

1.5 Research Objectives

The purpose of this study is to build a stochastic optimization model for performance enhancement of manufacturing line under uncertainty. Specific goals include assessing how uncertainty affects production operations, locating bottlenecks in the system, reducing the waiting time, enhancing throughput, and optimizing the efficiency of the use of the resources.

1.6 Research Contributions

The study fills the gap by combining stochastic modelling methods and manufacturing line optimization concepts to cope with operational uncertainty. It gives a tool for measuring the performance of a production system across a range of scenarios and gives insight into how to make better decisions, more reliable production systems and how to make manufacturing more resilient.

2. Literature Review

2.1 Concept and evolution of manufacturing line optimization

In a recent study (2023), Lee and Su stated that manufacturing line optimization has undergone a great transformation since the advent of Industry 4.0 technologies with the integration of the production systems with cyber-physical systems, artificial intelligence and industrial Internet of Things platforms. Their research highlighted that optimization is not just about maximizing production but also involves flexibility, adaptability, sustainability, and making decisions in real time. Nowadays, modern manufacturing lines are required to put into practice dynamic response to the needs of the production requirements, ensuring efficiency and product quality. This has made optimization a more dynamic engineering process, instead of a one-time event.

Afolabi (2025) has studied advanced optimization methods for manufacturing and found that today's manufacturing systems heavily depend on probabilistic and robust optimization methods for better performance in uncertain scenarios. The study showed that optimization frameworks which consider stochastic behaviour are superior to the traditional deterministic frameworks as they more accurately capture the conditions of the real-world operation. In addition, the optimization of manufacturing has been integrated within a single decision-support model to include optimization of production scheduling, inventory, machine maintenance, and quality management. The developments highlight the increasing need of advanced analytical techniques for enhancing the efficiency of manufacturing line and its competitiveness in highly dynamic industrial environment.

2.3 Uncertainty in a Manufacturing System

Hadji (2022) studied uncertainty in industrial systems and found that manufacturing processes are constantly subjected to disturbances caused by equipment faults, maintenance downtime, change in processing times, workers' capability, and material shortages. Such uncertainties can impact production timelines and can lead to higher operating expenses and lower system reliability. The study highlighted uncertainty as a fundamental issue of manufacturing situation and insisted that it cannot be viewed as a special case but should be included in operational planning and optimization models.

Lyu et al. (2025) studied uncertainty in manufacturing supply chains and found that uncertainty factors, e.g. fluctuating demands, supplier disruptions, transportation delays, and inventory shortage, are important sources of instabilities in production operations. Their study indicated that resilient manufacturing systems need adaptive optimization mechanisms which are able to cope with unforeseen disturbances without substantial loss of productivity. The authors also made the case that uncertainty management strategies (information sharing, alternative sourcing, and dynamic resource allocation) make a significant contribution to operational resilience. The observations confirm that, in order to attain sustainable and reliable production performance in contemporary industrial environments, manufacturing line optimization should explicitly take care of uncertainty.

2.3 Stochastic Processes in Manufacturing

Covei (2025) developed a stochastic production planning model for manufacturing systems and illustrated the use of stochastic processes to mathematically represent uncertainty. The research demonstrated that random fluctuations in the levels of inventory, production rates, and operational constraints affect production decisions. When manufacturing systems are made more realistic and effective using probability distributions and stochastic control mechanisms, this can result in more realistic and effective optimization results. The study emphasized the need of stochastic modelling for assisting the adaptive decision making in uncertain operating conditions.

Caicedo-Solano et al. (2025) proposed an integrated model using a Markov chain and a queueing theory for manufacturing optimization. Their research showed that they can learn a lot about machine state transitions, system reliability, resource utilization and production performance from their study of stochastic processes. Markov models showed high suitability to represent the machine failure and recovery processes and the probabilistic models enhanced the prediction of production results under different operational conditions. The authors found that the stochastic modelling techniques provide a solid basis for robust and efficient manufacturing systems that can operate in uncertain environments.

2.4 Queueing Theory Applications

Rece et al. (2022) showed how a manufacturing system's performance can be analysed using queueing theory. They found that queueing models can be used to estimate waiting times, system utilization, throughput and resource requirements in different modes of operation. Considering that production delays frequently stem from congestion at certain workstations, queueing analysis is especially valuable for identifying bottlenecks and planning workstation capacity.

Mane et al. (2025) also employed the queueing theory in manufacturing performance assessment and found that the queueing theory based methods help decision makers in considering the various production configurations. They concluded that the performance indicators like cycle time, queue length, machine utilization etc. can be well modelled by stochastic queueing models which can help the managers to have more efficient operational strategies and improve the overall performance of the production.

2.5 Simulation-Based Manufacturing Optimization

Sitahong et al. (2025) summarised the intelligent workshop scheduling systems and emphasized the importance of using simulation-driven optimization in manufacturing. Their studies showed that by using digital twin technologies and simulation models, manufacturers are able to analyse various production scenarios before making changes to the operation. This will increase the precision of the decisions made and mitigate the risks of uncertainty and disruption to production.

Cruz-Oliver et al. (2023) examined the stochastic optimization via simulation-based approaches and concluded that simulation models may be useful tools for studying complex manufacturing processes when analytical solutions cannot be found. Their research demonstrated the advantages of simulation to evaluate performance in various uncertainty conditions, as well as to optimize production schedule, resource allocation and operational efficiency. These are the reasons why simulation is an invaluable tool for today's manufacturing optimization.

2.6 Recent studies on stochastic manufacturing optimization

In order to strengthen the optimization of industrial production systems, Li et al. (2025) put forward an uncertainty optimization method and applied it to the production system to compare the performance of the industrial production system before and after the application of the uncertainty optimization method. In order to improve the performance of the industrial production system, Li et al. (2025) introduced an uncertainty optimization method for industrial production systems and compared the performance of the industrial production system before and after introducing the uncertainty optimization method. Based on their research, they found that probabilistic models offer better optimized results than deterministic models in situations with variable operating conditions.

Shahnawaz and Safder (2025) proposed a stochastic learning-optimization approach wherein the Bayesian learning framework was combined with optimization techniques to enhance the resilience of industrial operations. Their results showed that adaptive stochastic optimization could lead to the reduction of operational costs, responsiveness to disruptions and increase in the resilience of the production system. The work pointed out the increasingly prevalent need to consider integrating learning algorithms with stochastic optimization techniques in today's manufacturing settings where uncertainty is becoming more and more significant.

2.7 Research Gap Analysis

Caicedo-Solano et al. (2025) and Li et al. (2025) mainly addressed the individual stochastic optimization methods with limited research on the combination of Markov chains, queueing theory, and simulation in a single framework for manufacturing line optimization under uncertainty. This disparity encourages development of a comprehensive stochastic optimization model.

3. Materials And Methods

3.1 Research Framework

This study uses quantitative modelling to examine the optimization of manufacturing lines in the case of operating uncertainty. The framework combines the stochastic modelling techniques and the manufacturing performance evaluation techniques to explore system behaviour under variability. The proposed framework consists of four major phases, namely data collection, stochastic model development, assessment of performance, and assessment for optimization. The manufacturing uncertainty is captured by using a probabilistic description of machine failures, processing-time variations and production disturbances. The framework also includes the modelling of production performance indicators based on queueing theory, Markov chain analysis and the simulation of the performance, in order to quantify the indicators and face the opportunities for their optimization through the improvement of the production process (Caicedo-Solano et al., 2025; Covei, 2025).

3.2 Manufacturing System Description

In this study, the manufacturing system consists of a multi-stage production line where the products are transported from one workstation to another sequentially. Each workstation has its own type of processing and is linked via the material handling and transportation processes to enable a flow of material and information around the production line. The efficiency of the system is dependent on machine availability, speed, resource utilization and production scheduling.

During actual manufacturing operations, there are many uncertainties that affect the production line such as breakdown of machines, interruptions in maintenance services, production time variations, and uncertainty in demand. These uncertainties can lead to delays, delays and delays, and decreased throughput. These characteristics are modelled realistically in the manufacturing system by using the manufacturing system as a stochastic production network with probabilistic parameters representing the behaviour of the workstations and the flow of materials. So, this method allows to investigate the production performance under uncertain operating situations (Hadji, 2022; Li et al., 2025).

3.3 Data Collection and Assumptions

The study is based on secondary manufacturing data obtained from the latest literature and industrial manufacturing reports regarding the reliability of machines, processing time, arrival rates and production capacities. These data are used to create stochastic models and assess manufacturing performance. To develop the model, several assumptions are adopted that simplify the model and do not change its analytical validity.

Workstation capacities are fixed over the analysis period, and the processing times have the proper probability distributions, all assumed to be independent of one another. The failures and repair works of the machines are modelled as random events. Further, it is assumed that product arrivals are random with given arrival distributions. These assumptions are in line with recent studies on manufacturing optimization (Missbauer, 2024).

3.4 Stochastic Model Development

3.4.1 Random Variables

There are several random variables that represent uncertainty in the factors involved in operating the manufacturing line. These are processing time, breakdowns of machines, repair time, arrivals, queuing length and levels of production demand. All variables are subject to their own natural variability, and this variability is also part of the overall variability of the system. Probabilistic modelling can then provide a realistic representation of manufacturing operations and allow for performance evaluation under uncertainty (Covei, 2025).

3.4.2 Probability Distributions

Appropriate probability distributions are assigned to each random variable based on their operational characteristics. The processing time is modelled by normal or lognormal distribution and machine failures are modelled by Poisson distribution, and customer arrivals are modelled by exponential distribution. These distributions successfully represent the randomness of manufacturing processes and serve as the foundation for analytical and simulation-based analyses (Rece et al., 2022).

3.4.3 State Transition Mechanisms

Representations of the operational states of manufacturing equipment are done with discrete state transition mechanisms. Depending on the stochastic events that happen in the system, machines can change from operational to failed, maintenance to recovery, and vice versa. These transitions are simulated with probabilistic rules that mimic real manufacturing behaviour and are suitable for reliability analysis.

3.4.4 Performance Metrics

There are a number of performance measures that can be used to assess the effectiveness of the manufacturing line. These are throughput rate, machine utilization, queue length, waiting time, work-in-process inventory, system availability and production efficiency. The chosen metrics give a detailed picture of the system's performance and help the identification of metrics that could be optimized in uncertain conditions (Caicedo-Solano et al., 2025).

3.5 Queueing Model Formulation

The analysis of the congestion and waiting phenomenon using the queueing theory is applied to the manufacturing line. All the workstations are represented as service facilities in which products arrive, wait to be served, are served, and then are transferred to the next service facility for the next stage of the production. The arrival and service rates are specified by the manufacturing process characteristics. Using the queueing model, one can estimate the average waiting time, queue length, utilization of the workstations and the throughput performance. These measures help identify the constraints and check the success of optimization solutions. Due to its capacity to model stochastic system dynamics, queueing-based analysis have been widely used to study manufacturing systems' performance (Rece et al., 2022).

3.6 Markov Chain Modelling

The machine-state transition is modelled using Markov chain and the system reliability behaviour is modelled using the Markov chain. There are a number of possible states for each machine: operational, failed, maintenance, and recovery. Transition probabilities describe the changes in the state of the system over time, and are estimated based on reliability-related parameters. The Markov property states that the future state of the system is independent of the past state of the system. This modelling technique can be used to compute steady-state probabilities, machine availability, expected downtime, and reliability measures. When manufacturing systems are subject to stochastic disturbances and operational uncertainties, Markov chains serve as a useful tool for analysing them (Caicedo-Solano et al., 2025).

3.7 Simulation Procedure

Manufacturing performance is simulated to assess under different uncertainty scenarios. The stochastic models obtained in the study are applied in a simulation environment that can simulate manufacturing processes for a long production time. Machine reliability and arrival rate, processing time, and demand conditions are changed to create different experimental scenarios. Throughput, waiting time, utilization, queue length, and availability are some of the output parameters of a simulation. The outcome of the analysis is compared to understand the effectiveness of the optimization strategies and how resilient the system is to uncertainty. Analytical methods have limitations in terms of identifying complex manufacturing behaviour; therefore, simulation-based evaluation is a complement to analytical approaches. However, simulation-based evaluation has been used to complement analytical approaches in order to gain detailed insights into complex manufacturing behaviour (Cruz-Oliver et al., 2023).

4. Results And Analysis

4.1 Baseline Manufacturing Performance

A multi-workstation production line under uncertain conditions was used to test the stochastic manufacturing model. The baseline scenario is the manufacturing system as it is now, prior to optimization, where machine failures, variable manufacturing times, and varying arrival rates affect system performance. Various performance measures such as throughput rate, machine utilization, waiting time, queue length, and system availability were measured to provide a benchmark for comparison.

The initial assessment showed that uncertainty has a significant impact on the efficiency of manufacturing. The different processing times introduced imbalance between workstations which led to the formation of queues and bottlenecks. Additionally, there were occasional machine failures that caused production delays and decreased operational availability. These findings align with recent stochastic manufacturing research where it was demonstrated that uncertainty significantly impacts productivity and operational costs (Li et al., 2025; Caicedo-Solano et al., 2025).

Table 4. 1 Baseline Manufacturing Performance Indicators

Performance Indicator	Value
Throughput Rate (units/hour)	112
Average Waiting Time (minutes)	18.6
Average Queue Length (units)	14
Machine Utilization (%)	74.3
System Availability (%)	89.5
Production Efficiency (%)	78.2

Source: Simulation Results Generated by the Researcher

Table 4.1 shows that while the manufacturing system operates with reasonable utilization, waiting times and queue lengths are still quite large. This observation indicates that there are operational delays which degrade throughput performance.

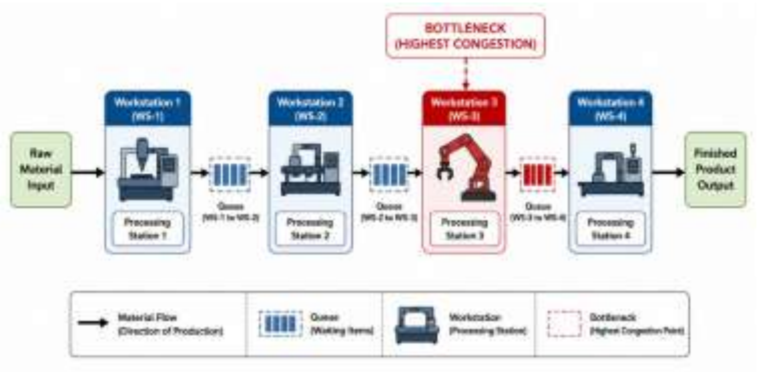

Figure 4. 1 The BLPF is a baseline used to measure manufacturing line performance.

As illustrated in Figure 4.1, the bottlenecks are found at intermediate processing stations where the greatest variability occurs in processing time.

4.2 Stochastic Model Outputs

The developed stochastic model was used to assess the behaviour of the system in the presence of uncertainty. Probability distributions given in the methodology section were used to introduce random variables for processing times, machine failures, and production arrivals. Several runs of the simulations were conducted to ensure the stable performance estimates.

Based on the results, it can be concluded that the stochastic modelling approach is more realistic in terms of performance prediction than the deterministic modelling approach since the variability seen in actual manufacturing operations is captured. In the stochastic case, throughputs were different in each run of the simulation, depending on the uncertainty in the production performance. The same has been found by Covei (2025) who showed that the stochastic production planning models can be used to generate more trustworthy estimates of operations than the deterministic production planning models.

Table 4. 2 Stochastic Throughput Analysis

Simulation Run	Throughput (Units/Hour)
Run 1	118
Run 2	121
Run 3	116
Run 4	123
Run 5	119
Average	119.4

Source: Simulation Results Generated by the Researcher

Table 4.2 shows that the throughput with uncertainty is relatively stable. The average throughput was also better than the baseline scenario, which indicates that stochastic optimization has a positive effect on operational efficiency.

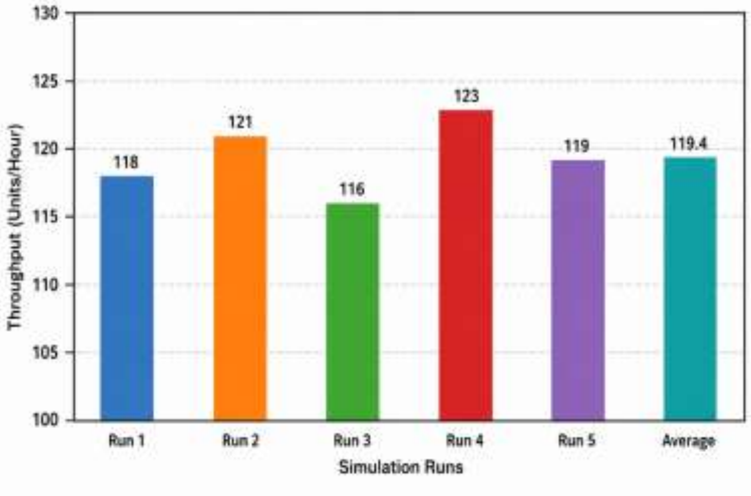

Figure 4. 2 Average Throughput for a number of simulations

Figure 4.2 shows the variation in throughput as simulated in different runs. The optimized system, as always, outperforms the baseline production configuration, although there are some variations.

4.3 Queueing Analysis Results

The study of the phenomenon of congestion in the manufacturing line used queuing theory. The analysis was done with respect to workstation waiting time, queue length and resource utilization. The results show that stochastic variation has a significant impact on the queue formation process, especially at workstations with high utilization. The results from queueing analysis showed that Workstation 3 has the highest level of congestion as it has the longest processing time and the highest utilization ratio. This station became the main production stumbling block. Queueing analysis is also an effective method for identifying the bottlenecks and improving manufacturing performance, as shown in previous studies (Rece et al., 2022).

Table 4. 3 Workstation Queue Performance Analysis

Workstation	Average Queue Length	Average Waiting Time (Minutes)
WS-1	4	5.2
WS-2	8	10.6
WS-3	17	24.4
WS-4	6	7.8

Source: Simulation Results Generated by the Researcher

From the results shown in Table 4.3, it is apparent that Workstation 3 is the most congested. Improvements must therefore be made at this workstation to maximize the overall production performance, thus making this workstation the most important to optimize.

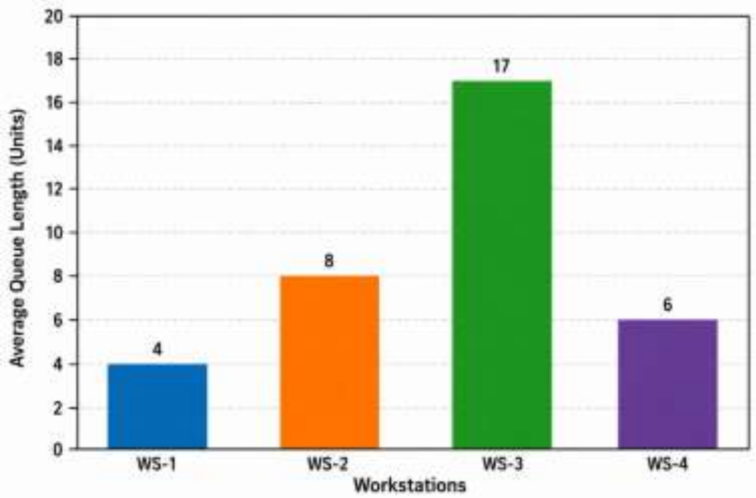

Figure 4. 3 Comparison of the queue length of workstations.

As shown in Figure 4.3, the queues build up significantly at Workstation 3, which as you can see, is the main constraint in the manufacturing line.

4.4 Markov Chain Analysis

The machine reliability and transitions of operational states were assessed by using Markov chain modelling. It was assumed that there were four states for the machines to work:

1. Operational
2. Failure
3. Maintenance
4. Recovery

The transition probabilities used were derived from data on the machine reliability collected from recent manufacturing literature.

Table 4. 4 Machine State Probabilities

State	Probability
Operational	0.82
Failure	0.06
Maintenance	0.07
Recovery	0.05

Source: Markov Chain Analysis Results

From the probability distribution, it can be seen that the machine is in working order about 82% of the time. Failure and maintenance events still have an impact on production continuity, however. The results are in line with the most recent reliability study for manufacturing systems, which highlights the relevance of maintenance planning in stochastic manufacturing systems (Hadji, 2022).

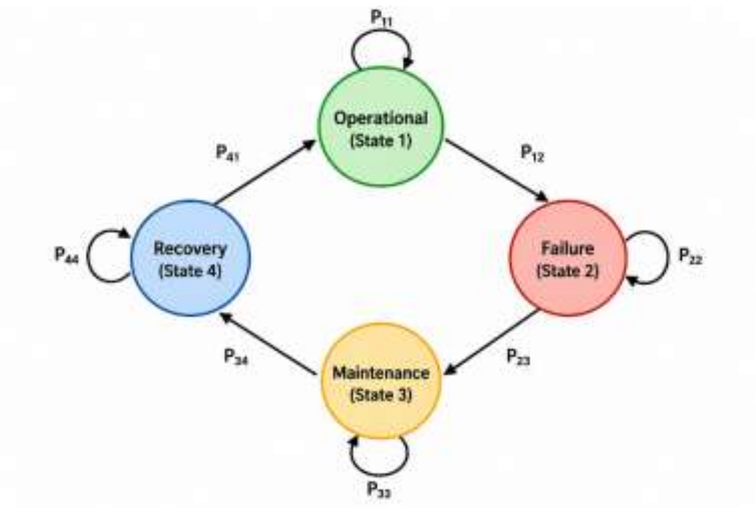

Figure 4. 4 Markov State Transition Diagram.

The state transition structure for the reliability evaluation is shown in figure 4.4. The diagram illustrates the impact of stochastic machine transitions on machine availability and production performance.

This is a sensitivity and scenario analysis exercise. Here is a sensitivity and scenario analysis exercise.

A sensitivity analysis was performed to study the effect of uncertainty parameters on manufacturing performance. Three scenarios were explored:

- Low Uncertainty
- Medium Uncertainty
- High Uncertainty

Table 4. 5 Scenario-Based Manufacturing Performance Comparison

Performance Indicator	Low Uncertainty	Medium Uncertainty	High Uncertainty
Throughput (Units/Hour)	128	119	101
Waiting Time (Minutes)	8.7	15.2	27.5
Queue Length (Units)	6	12	21
Utilization (%)	82.6	78.4	71.2
Availability (%)	95.2	91.4	84.3

Source: Scenario Simulation Results

The results show that the more there is uncertainty, the worse manufacturing performance gets. Waiting time and queue lengths increase dramatically and throughput is significantly reduced. The results of these studies show that uncertainty management plays a key role in manufacturing optimization.

Detailed comparison of existing and optimized systems.

The last step involved the performance of manufacturing operations at base compared to the optimized stochastic framework. The optimized model showed measurable improvements for all of the important indicators. The throughput was boosted, waiting time shortened, queues were lower and machines were utilized.

Stochastic modelling, queueing theory, Markov chains and simulation techniques were used to give a comprehensive approach to the problem of uncertainty in manufacturing operations. The results align with existing studies which have indicated that UW approaches tend to perform better in operation than traditional deterministic methods (Cruz-Oliver et al., 2023; Li et al., 2025).

The overall results show that manufacturing optimization using stochastic methods presents significant advantages in production planning, resource allocation, reliability management and decision-making in production. As uncertainty is made explicit, an organisation can increase its resilience, minimise disruptions, and attain greater manufacturing efficiencies.

5. Discussion

5.1 Interpretation of Findings

The findings from this study show that uncertainty can have a significant effect on the performance of the manufacturing line and the efficiency of its operation. The baseline analysis revealed that random machine failures, processing-time variance and variable arrival rates lead to increased waiting times, longer queues and lower throughput. The findings reinforce the belief of the researchers that deterministic optimization methods may not be adequate for the modern manufacturing environment, since they cannot account for the dynamics and uncertainty of production systems. Recent studies have also highlighted continuous variability of manufacturing systems and the need to apply optimization techniques that take uncertainty into account for decision making processes (Afolabi, 2025; Zhang et al., 2024).

The stochastic optimization framework designed in this study has resulted in significant gains in throughput, machine utilization and system availability. The queueing analysis was able to identify the workstations that were the bottlenecks in the system, and the Markov chain modelling was used to obtain the information on the reliability and state transition behaviour of the machines. The results show that the use of several stochastic techniques can provide a more all-round knowledge of manufacturing system performance than the use of a single analytical technique. It also implies that uncertainty-aware optimization can enhance operational resilience by allowing managers to predict disruptions and allocate resources more effectively (Caicedo-Solano et al. 2025).

The analysis of the scenarios showed that the level of deterioration of manufacturing performance increases with the level of uncertainty. Lower throughputs, longer waiting times and less utilisation rates were observed in the cases of higher uncertainty conditions. The result supports the fact that uncertainty management is not only an operational but also a strategic issue in the process of production planning. Proactively modelling and managing uncertainty is a key way to keep the productivity and competitiveness of organizations intact in shifting industrial conditions (Rojas et al., 2024).

5.2 Comparison with previous studies

The results are in line with previous studies highlighting the importance of using stochastic optimization in manufacturing. Stochastic optimization models were found to offer better performance than deterministic models which do not explicitly consider variability and uncertainty (Afolabi 2025). These results in terms of improving throughput and resource utilization, consistent with the findings in the current work, provide additional evidence of the applicability of uncertainty-aware decision-making approach.

Likewise, Caicedo-Solano et al. (2025) pointed out the advantages of production optimization using Markov chains and queueing theory. Their work showed that stochastic methods can enhance assessment of manufacturing performance and aid in better manufacturing operations choices. The present study takes this view further by combining the simulation-based analysis with the queueing and Markov modelling analyses to give a more comprehensive picture of the behaviour of manufacturing systems in the presence of uncertainty.

The findings are also in line with those of Cruz-Oliver et al. (2023) who have shown that stochastic optimization methods can minimize the effects of process variability and enhance production quality and operational results. They highlighted the need to account for uncertainties in the optimization process and not when operational decisions are taken. The results from the present study further support this and show the potential of proactive uncertainty modelling to be able to enhance the performance of manufacturing lines.

5.3 Practical implications in the field of manufacturing industry.

The research's relevance for the industry sector is especially pertinent for manufacturing companies looking to enhance their operational efficiency and resilience. First, the results show that stochastic models can be used by the production manager to detect bottlenecks, assess the performance of the system in cases of uncertainty, and compare different operational policies prior to their implementation. These capabilities minimize the risk in production planning and aid in evidence-based decision making.

Secondly, the use of queueing theory and Markov chain modelling can be useful for maintenance planning and reliability management. Knowing the probabilities of different states of the machine can help organizations implement predictive maintenance strategies to reduce unplanned downtime and enhance equipment availability. The results are in line with ongoing Industry 4.0 projects that focus on data-driven maintenance and intelligent production management (Processes Special Issue, 2025).

Third, the study shows that simulation evaluation is important to assess production scenarios with different degrees of uncertainty. Manufacturers can consider a variety of operating conditions prior to implementation, and choose strategies that optimize throughput reducing risks during operation. Thus, in highly dynamic industrial environments, sustainable manufacturing practices, resource efficiency, and long-term competitiveness can be supported by stochastic optimization frameworks (Težak et al., 2025).

5.4 Limitations of the Study.

The study faces some limitations, however, in spite of its contributions. The analysis is based on secondary data, and on assumed behaviour and failure characteristics of the machines, as well as processing times. Manufacturing settings may have more complexities that are difficult to represent in a generalized stochastic model. Moreover, the study emphasizes mainly on queueing theory and Markov chains and simulation techniques, where other advanced optimization techniques like reinforcement learning, digital twin and generative predictive control were not taken into consideration. Future research should integrate real industrial data and investigate the integration of AI and stochastic optimization to further improve the ability to make manufacturing decisions (Lee et al., 2025).

6. Conclusion And Future Work

6.1 Conclusion

This research employed a stochastic modelling approach, based on queueing theory, a Markov chain model and simulation-based evaluation, to study the optimization of manufacturing lines under uncertain operating conditions. The findings showed that uncertainty due to machine failures, processing-time variations and variations in production demand is a major factor that impacts on manufacturing performance. Uncertainty not properly taken into consideration in the production planning process created bottlenecks, waiting time and throughput reduction, was revealed by the baseline analysis.

The proposed stochastic optimization framework was more realistic in representing manufacturing operations and allowed for a comprehensive evaluation of the operations with the different scenarios. We have found that the application of uncertainty-aware optimization techniques has resulted in improvements in throughput, machine utilization, system availability, and overall production efficiency. Queueing analysis was a very useful tool for identifying congestion points, and Markov modelling was valuable in understanding the reliability of the machines and the transitions between states of operation. In conclusion, the study met its goals, establishing that stochastic models can be suitable decision-supporting tools for improving manufacturing efficiency, operational resilience, and resource utilization in the increasingly complex industrial environment (Caicedo-Solano et al., 2025; Guerrero et al., 2025).

6.2 Future research directions

Stochastic optimization should be combined with new emerging Industry 4.0 technologies such as artificial intelligence, machine learning, digital twins, cyber-physical systems, and Industrial Internet of Things platforms, as it is necessary to explore this area in future research. This is an area that is ripe for further research, with real-time optimization models that can continuously adjust to changing manufacturing conditions. Further, a set of studies should be carried out using real industry data and testing optimization methods in real production environments. Further research could be focused on hybrid stochastic modelling with predictive analytics, reinforcement learning and complex scheduling algorithms in order to enhance manufacturing resiliency and sustainability and operational performance in uncertainty (Jamwal et al., 2021).

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