Mathematical Analysis of RubClean and Elastowett Production Capacity in the Manufacturing Industry: A Case Study

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Abstract: *The polymer and rubber compounding industry faces challenges in optimizing production efficiency while minimizing bottlenecks. This study applies queuing theory to analyze the productivity of RubClean and Elastowett manufacturing processes, with a focus on workstation efficiency and reducing lead time. This study evaluated conventional queuing models (M/M/1, M/M/2, and M/G/1) using observational data and statistical validation, including the Chi-square goodness-of-fit test. Findings indicate that inefficiencies arise from blocking in the cutting workstation and starvation in the packing process. The proposed improvements, such as parallel processing and the addition of a punching machine, reduce queue time from 92% to 32%, significantly enhancing system stability and throughput. Empirical validation confirms the accuracy of queuing models in predicting production performance. This study presents a structured approach to mitigating production inefficiencies; however, its findings are limited by the assumptions inherent in steady-state data. Future research should investigate the integration of real-time data to refine adaptive queuing models for dynamic manufacturing environments, thereby enhancing the accuracy and effectiveness of these models.*
Keywords: *Production productivity; Manufacturing optimization; Queuing theory; Rubber products*

1. Introduction

The manufacturing industry has long been recognized as a key driver of global economic growth, playing a vital role in industrialization, job creation, and technological advancement. Within this sector, the polymer and rubber compounding industries have gained increasing attention due to their complexity, reliance on specialized materials, and growing demand for customized products. These industries are particularly challenged by production environments that require consistency, precision, and responsiveness to market fluctuations [1][2].

To address these challenges, scholars and practitioners have developed numerous mathematical and statistical models to improve production system efficiency [3][4][5]. Among these, queuing theory has emerged as one of the most widely utilized analytical frameworks for modelling, analysing, and optimizing production processes [6][7][8]. Zhang et al. [9] demonstrated the usefulness of queuing models in analysing and improving throughput in rolling mill operations, while Seyyedhasani et al. [10] applied queuing theory in collaborative human-robot production environments, achieving notable efficiency gains. These studies support the relevance of queuing theory but also highlight its need for adaptation to more complex systems. Queuing theory facilitates the identification of system bottlenecks, supports optimal allocation of limited resources, and enables decision-makers to simulate different operational scenarios to evaluate performance outcomes. Its core strength lies in its ability to abstract complex manufacturing systems into analysable models that capture the stochastic nature of arrivals, service times, and queue behaviours. Koo et al. [11] use the relative error parameter to validate the use of queuing theory by setting a limit of 10% as a validation requirement, and Dilworth [12] sets the requirements for the validity of the use of queuing theory based on the queue time value between 80% to 95%.

Classical queuing models, such as M/M/1, M/M/2, and M/G/1, have been extensively studied in the academic literature. The M/M/1 model assumes a single server with Poisson arrivals and exponential service times, making it suitable for stable and straightforward production systems [13]. The M/M/2 model extends this framework to include two parallel service channels, providing a more realistic representation of systems that utilize redundancy or parallel processing. The M/G/1 model introduces general service time distributions, making it more flexible and applicable to complex manufacturing environments such as rubber-based production, where variability in processing times is significant due to differences in raw materials, operator behaviour, or machine performance [14].

Despite their widespread use, these models have limitations when applied to real-world production settings. Traditional queuing theory models typically assume steady-state conditions, do not account for phenomena such as blocking or starvation, and often ignore feedback loops, rework cycles, or variability in operator efficiency. These limitations become particularly evident in the manufacturing of rubber-based products such as RubClean and Elastowett, where production lines are subject to a high degree of variability, tight process constraints, and the need for rapid response to quality deviations [15][16].

To address the limitations of classical queuing theory, recent research has incorporated simulation techniques and empirical validation methods to improve model accuracy and relevance. Simulation enables researchers and practitioners to replicate complex manufacturing environments and test the performance of various queuing models under diverse operational scenarios. For instance, Pan et al. [17] developed an active queue management algorithm that dynamically adjusts to real-time changes in queue length, thereby improving overall system responsiveness. Khasanah et al. [18] employed Monte Carlo simulations to model queuing behaviour in manufacturing systems and optimize key operational metrics, including cycle time and throughput. These approaches provide deeper insights into system behaviour and support more robust decision-making.

Bera et al. [19] extended this line of inquiry by applying kinetic modelling to rubber moulding processes, validating the theoretical models against real-world observations. Their work emphasized the importance of using actual production data to refine model assumptions and improve accuracy. Empirical validation ensures that theoretical predictions align with the realities of the production floor, allowing manufacturers to implement tailored process improvements based on data-driven insights.

Statistical techniques also play a pivotal role in validating queuing models and ensuring their applicability. One commonly used method is the Chi-square goodness-of-fit test, which is employed to determine whether empirical data conform to theoretical distributions such as Poisson arrivals and exponential service times [20]. This test is critical in assessing the validity of queuing model assumptions and in identifying potential discrepancies between theory and practice. Rolke [21] noted, however, that the test's accuracy depends heavily on sample size, the number of observations, and the appropriateness of the classification intervals used. Consequently, robust data collection and preprocessing are essential to avoid statistical errors and misleading conclusions.

In the broader context of manufacturing systems research, the integration of simulation, mathematical modelling, and real-time data analytics has gained considerable momentum. Recent studies have demonstrated the effectiveness of combining simulation-based optimization with queuing theory to develop comprehensive frameworks for improving production system performance [22]. These integrated approaches allow for the exploration of multiple performance indicators, including cycle time reduction, buffer capacity optimization, and overall equipment effectiveness (OEE). Furthermore, such methodologies enable the evaluation of trade-offs among competing objectives, such as minimizing waiting time versus maximizing throughput, which is essential in complex systems like those producing specialized rubber products [23].

Nevertheless, despite the growing body of research, several critical gaps remain. First, there is a lack of industry-specific studies that focus on the unique operational characteristics of the rubber compounding and polymer sectors. Most existing models are based on general manufacturing environments and do not account for the specific constraints, material properties, and production sequences involved in the manufacturing of rubber-based products [24]. Second, there has been limited comparative analysis of different queuing models—such as M/M/1, M/M/2, and M/G/1—in the context of real-world rubber production systems [25]. Without such comparisons, it is difficult to determine which models offer the most accurate predictions and practical benefits in these specialized environments.

Third, while simulation and statistical validation methods have been increasingly adopted, their integration with real-time data analytics and adaptive control systems remains underdeveloped. As manufacturing systems become more digitized and interconnected, the ability to collect, analyse, and respond to real-time production data will be essential for achieving higher levels of efficiency and responsiveness [26]. Ultimately, there is a growing need to develop hybrid modelling frameworks that integrate queuing theory, control theory, and machine learning algorithms to capture both the stochastic and adaptive aspects of modern manufacturing systems. Prior research into the production of RubClean and Elastowett underscores the importance of consistency in processing conditions, material quality, and operational precision. These products require careful control over variables such as temperature, mixing ratios, and curing times. Studies have shown that even minor deviations in these parameters can result in significant reductions in product quality and increased rejection rates [27][28]. As such, production systems must be designed and managed to minimize variability and respond quickly to deviations from expected performance.

This study aims to address the gaps identified in the literature by developing an empirical framework for evaluating and optimizing queue management strategies in the production of RubClean and Elastowett. By comparing the performance of M/M/1, M/M/2, and M/G/1 models using real production data, the study seeks to determine the most appropriate queuing model for these specialized environments. Additionally, the research incorporates statistical validation techniques and simulation tools to ensure that the models are both theoretically sound and practically applicable.

The expected contribution of this research is twofold: first, to provide a deeper understanding of how queuing theory can be adapted and applied in rubber-based manufacturing systems; and second, to offer practical insights and data-driven recommendations for improving production efficiency, reducing lead times, and enhancing overall system reliability. By doing so, the study aims to bridge the gap between theoretical modelling and practical application, thereby contributing to the advancement of manufacturing systems engineering and the optimization of complex production environments.

2. Research Methodology

This study rigorously investigates production productivity in a real-world manufacturing environment by integrating mathematical modelling, queuing theory, and empirical validation. The researchers surveyed a mid-sized manufacturing firm, Company X, which specializes in industrial rubber compounding and polymer-related products. This study focuses on the production processes for RubClean and Elastowett, segmenting the production line into four primary workstations: mixing, length cutting, width cutting, and packing.

2.1 Research Approach and Design

The research employs a mixed-methods approach, integrating quantitative mathematical modelling with empirical data collection and statistical validation. This approach is well-suited to the study's objective of analysing production productivity by applying queuing theory while ensuring that the developed models reflect actual production conditions. The design is primarily quantitative, leveraging mathematical models such as the M/M/1 queuing system to simulate the behaviour of individual workstations. This study models each production stage—mixing, length cutting, width cutting, and packing—separately, assuming a Poisson arrival pattern and exponentially distributed service times. The study deliberately treats the processes as isolated queuing systems, a decision motivated by the complexities and practical challenges encountered when attempting to model an interconnected queuing network in a dynamic production environment. This design choice is justified by the empirical observation that the practical constraints of the production facility render network analysis unwieldy, thereby necessitating a simplified yet robust isolated model approach. The research framework also incorporates a validation mechanism where the theoretical cycle times computed from the queuing models are compared with standard data provided by Company X. This comparative analysis, which involves calculating the relative error between theoretical and observed values, serves as the cornerstone for determining the applicability and accuracy of the queuing models. In addition to mathematical analysis, the research design integrates qualitative observations from the production floor to capture aspects that are not readily quantifiable, such as operational practices and job control dynamics. This mixed-method strategy ensures that numerical precision and contextual understanding are achieved, thereby comprehensively evaluating production productivity.

The overall design is structured in sequential stages. The first stage involves an extensive review of production data and operational practices at Company X, establishing a baseline understanding of the current production system. The second stage focuses on the mathematical modelling of each workstation using established queuing theory frameworks, where parameters such as arrival rates, service rates, and queue discipline (First-Come, First-Served) are defined based on direct observations. The third stage involves the application of statistical tools, including the Chi-square goodness-of-fit test, to verify the validity of the assumed arrival and service distributions. In the fourth stage, cycle times are computed by subtracting the average waiting times from the total time spent in the system, and these calculated values are then compared with the standard data provided by the company. Finally, potential improvement strategies—such as introducing parallel processing at specific workstations—are evaluated by comparing performance metrics (e.g., percentage waiting time, utilization factor) across different model configurations. Each of these stages is carefully designed to ensure that the theoretical constructs are continually informed and refined by empirical evidence, thereby enhancing the overall robustness and credibility of the research findings.

2.2 Data Collection Techniques

Data collection for this study is multifaceted, incorporating both primary and secondary sources to ensure a comprehensive understanding of the production system. Primary data are obtained through direct observation and measurement on the production floor of Company X, where detailed records of arrival times, service times, and cycle times are collected at each of the four workstations. Observational techniques, such as time-motion studies and process mapping, are crucial for capturing real-time operational dynamics and identifying potential sources of delay or inefficiency. Structured observations are supplemented by informal interviews with operators and production supervisors, which provide contextual insights into operational practices and the underlying causes of queuing phenomena. Secondary data are sourced from the company's internal records and standard production data, which serve as benchmarks for validating the mathematical models. These data include historical records of production cycles, machine utilization rates, and quality control reports that have been maintained over a significant period of time.

The data collection process is meticulously planned to capture the inherent variability in production operations. A data collection schedule is implemented over several weeks to ensure that both peak and off-peak production periods are adequately represented. This temporal coverage is critical for obtaining a representative sample of production performance, as variability in arrival rates and service times can differ significantly over different shifts and operational conditions. The use of digital tools, such as time-tracking software and automated sensors, enhances the accuracy of the data collected, while manual verification processes are employed to ensure data integrity. Each workstation is instrumented with monitoring devices that record the exact times at which workpieces arrive, begin processing, and exit the system. These devices are calibrated regularly to mitigate measurement errors and to ensure consistency across different collection periods.

Additionally, the study utilizes a structured questionnaire distributed to production staff to gather qualitative data on their perceptions of operational challenges and potential areas for improvement. The questionnaire is designed to capture detailed information about daily operational practices, the frequency and causes of machine downtime, and the impact of job specialization (or lack thereof) on productivity. This qualitative data is analysed alongside the quantitative metrics to provide a holistic view of the production environment. The triangulation of data from multiple sources—observational, quantitative, and qualitative—ensures that the subsequent analysis is both comprehensive and robust. Ethical guidelines for data collection are strictly adhered to, with informed consent obtained from all participants and assurances that data will be anonymized to protect confidentiality. This multi-dimensional approach to data collection not only strengthens the validity of the research findings but also provides a rich dataset that captures the complex interplay of factors influencing production productivity.

2.3 Data Analysis Procedures

The data analysis phase is integral to the research, as it involves applying mathematical models and statistical techniques to interpret the collected data and test the study's hypotheses. The analysis is conducted in several sequential steps, beginning with processing and cleaning raw data, then applying queuing theory models, and concluding with a comprehensive statistical evaluation of the results. The primary focus of the analysis is to model the production system using the M/M/1 queuing framework for each workstation, based on the assumption that arrivals follow a Poisson distribution and service times are exponentially distributed. The first analytical step involves calculating key parameters, such as the arrival rate (λ) and the service rate (μ), for each workstation. These parameters are derived from the empirical data collected during the observation period and are critical inputs for the queuing models.

Subsequently, the Chi-square goodness-of-fit test is employed to validate the assumed arrival and service distributions. This statistical test is crucial for determining whether the observed data conforms to the theoretical distributions posited by the queuing models. The test involves comparing the observed frequency of arrivals and departures with the expected frequencies, with any significant deviation indicating potential issues with the underlying assumptions. Once the distributions are validated, the queuing models are applied to calculate key performance metrics, including the average waiting time (Wq), the average time spent in the system (Ws), and the cycle time for each workstation. These metrics are calculated using standard equations from queuing theory, such as $Wq = \lambda/(\mu(\mu-\lambda))$ for the M/M/1 model. The computed cycle times are then compared with the standard production data provided by Company X to evaluate the accuracy of the models.

The next phase of the analysis involves conducting a relative error analysis, where the percentage error between the model-predicted cycle times and the actual observed cycle times is computed. A relative error below the threshold of 10% is considered acceptable, providing a quantitative justification for the use of queuing theory in this context. The analysis also includes scenario-based simulations, where alternative configurations (e.g., shifting from a single-server M/M/1 system to a dual-server M/M/2 system) are modelled to evaluate potential productivity improvements. These simulations help identify the impact of modifications such as the addition of parallel processing units or the implementation of job specialization at key workstations. By comparing performance measures such as the percentage of time spent in queues (%Wq) across different configurations, the study provides insights into the most effective strategies for reducing delays and enhancing throughput.

3. Results and Discussion

This study focuses on the queuing phenomenon during the mixing, length cutting, width cutting, and packing processes. In addition, the assumptions and limitations set in this study are that instant recycling of used goods is not permitted, and transient state queuing will be ignored. Open queueing networks can be applied as the best models for analysing production systems. However, the company's actual production environment and practices made queuing network analysis a challenging task. Hence, for simplicity, the four main processes will be modelled as four isolated queuing systems rather than a single queuing network. The queuing system schematics are illustrated below.

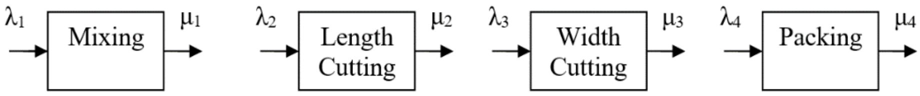

Fig. 1.The schematic of the Queuing theory

A Chi-square goodness of fit test was used to determine the arriving pattern and leaving distribution. The Chi-square goodness-of-fit test provided the essential information to determine mathematically the arrival and departure distribution. The rest of the queue elements, however, will be determined through observations. The queue seizes, and the source from which arrivals are generated is considered infinite. Based on actual production practice in the company, the queue discipline is assumed to be first-come, first-served. The number of service channels or servers in each workstation is one, and it is a single stage. The elements and notation for each process are shown in Table 1.

Table 1: Queue's elements

Process	Description
Mixing process	Single server, unlimited Markovian Queue
Length cutting process	Single server, unlimited Markovian Queue
Width cutting process	Single server, unlimited Markovian Queue
Packing process	Single server, unlimited Markovian Queue

The industrial standard value for queue time is around 80% to 95%. As shown in Table 2, the results of this study indicate that most processes fall within and close to this range, except for the packing process. These values were obtained from steady-state data.

Table 2: Queueing performance of measures

Workstation	Mean time for arrivals spent in the system, Ws	Mean Time for Arrivals Spent in Queue, Wq	Mean % for Arrival Spent in Queue
Mixing process	108 minutes	95 minutes	78
Length cutting process	243 minutes	226 minutes	92
Width cutting process	382 minutes	364 minutes	91
Packing process	116 minutes	103 minutes	66

Theoretically, any process with a short queue time will result in faster production lead time; nevertheless, some workstations might need to have longer queues to prevent them from running out of work. To determine the cycle time for each process, the average time spent in the system, Ws, is subtracted from the respective average time spent in the queue, Wq. The results are shown in Table 3.

Table 3: Cycle time for each workstation

Workstation	Cycle time
Mixing process	13 minutes
Length cutting process	17 minutes
Width cutting process	18 minutes
Packing process	13 minutes

Blocking occurred in the cutting length because infinite product batches are always available from the cooling buffer. Cutting width experienced the same blocking problems because the cutting length and cutting width processes are highly interdependent. Another important factor that caused blocking in these two processes is machinery constraints. Currently, both length and width cutting processes utilize conventional cutting tools. As a result, both workstations were operated ineffectively. The packing process often encounters starvation because the processing time is faster than the width-cutting process, causing the workstation to shut down earlier while other workstations are still operating.

The value obtained using queuing theory in Table 3 needs to be validated by comparing it with the value in the standard data owned by Company X. After this comparison process, the value of the relative error can be identified. The found relative error percentage will be used to justify the use of queuing theory in analysing production systems in this study. The maximum relative error percentage value allowed is 10%.

Table 4 presents the relative error in this study, calculated based on the data in Table 3 and compared to the standard data. This standard data is confidential, but in this study, some data can be informed to researchers by Company X. Based on the data in Table 4, it can be justified that the use of queuing theory is relevant in analysing production systems in the manufacturing industry because the relative error value in each process is less than 10%.

Table 4: The relative error of the cycle time for each workstation

Workstation	Cycle Time (Queuing Theory)	Cycle Time (Standard Data)	Relative Error
Mixing process	13 minutes	12 minutes	8.33%
Length cutting process	17 minutes	16 minutes	6.25%
Width cutting process	18 minutes	17 minutes	5.88%
Packing process	13 minutes	12 minutes	8.33%

4. Improvement Suggestion

4.1 Cutting Length Workstation

Improvements for the cutting length workstation include adding an extra parallel cutting length server (Cutting Length Machine) to the existing workstation. Since the arrival and leaving rates remain the same, the suggested system will become the M/M/2 queuing system. Table 5 compares performance measures between single-server and two-server workstations.

Table 5: Improvement comparison for the cutting length process

No	Number of Servers, C	$\%W_q$
1	2	32%
2	1	92%

As the comparison indicates, the product batch lead time percentage will be reduced from 92% to 32%, which will, in turn, decrease the work-in-progress inventory stored in the cooling buffer. Another advantage of this solution is its capability to improve queue stability. The previous analysis showed that for a single server, 3 periods of interval time have a utilization factor of more than 1 ($\rho>1$, system in transient state), and we expect that, as time goes by, the size of the queue will increase without binding (assuming there is no refusal of customer entry). By adding an extra parallel server, the queue will achieve a steady state, making it easier to monitor and control.

Job control is another factor that can help improve the productivity of this workstation. Operators at this workstation have no job specialization. The job schedule for pre-cut and cut lengths is unclear. For instance, operators will first concentrate on the pre-cut process (for specific batches while leaving the length-cutting machine idle), then only switch to cut length (and leave the pre-cut idle). This situation will create idle time at another station whenever it is in use. To achieve optimal productivity, it is preferable to process both pre-cut and cut lengths concurrently. The workforce at the workstation should be assigned to job specialization, i.e., pre-cut operator and cut length operator. Additionally, detailed working procedures for each workstation should be prepared and implemented to ensure better control and management.

4.2 Cutting Width Workstation

Machinery is the primary factor that blocks this workstation. The best solution is to improve technology or add another server to the wide-cutting workstation. In this case, Company X has ordered and plans to install a new punching machine to replace the current machinery. To identify what a new server and punching machine can contribute to the system, a comparison between the following three situations is necessary:

- Current system single-width cutting workstation (M/M/1)
- Proposed parallel width cutting workstation (M/M/2)
- New punching machine (M/G/1)

Table 6 shows the improvement in the cutting width process. The result shows that with the parallel server, the waiting percentage is reduced to 27%, while a single punching machine would have a 60% waiting percentage. The parallel server system is more efficient than operating the punching machine. The punching machine can also reduce the waiting percentage. The company has already ordered the punching machine, so the best solution would be to continue running the current system while waiting for a new punching machine to be installed.

Table 6: Improvement in the cutting width process

No	Description	$\%W_q$
1	Current System	92%
2	Additional parallel server	27%
3	Single new punching machine	60%

5. Conclusion

This study demonstrates the applicability of queuing theory in analysing and optimizing production systems, specifically for the manufacturing processes of RubClean and Elastowett. By employing queuing models such as M/M/1 and M/M/2, the research effectively quantifies critical performance metrics, including waiting times, cycle times, and workstation utilization. The findings highlight that inefficiencies in queue management have a significant impact on production lead time, contributing to bottlenecks and the accumulation of work-in-progress inventory. The study also confirms that traditional single-server models may not be sufficient for complex production environments, as demonstrated by the need for parallel processing in cutting workstations. The empirical validation, performed through statistical analysis and comparative evaluations with actual production data from Company X, confirms the model's reliability and practical applicability in real-world manufacturing settings. The results showed that queuing models align well with actual production performance, with relative errors of less than 10%, affirming their reliability in predicting system behaviour.

Additionally, the research identified key operational challenges, such as blocking in the cutting processes and starvation in the packing workstation, which adversely affect overall production efficiency. To address these inefficiencies, the study proposes process improvements, including the introduction of a parallel server in the cutting length workstation and the deployment of a new punching machine for width cutting. The proposed interventions are expected to significantly reduce queue times and enhance overall system stability. Moreover, workforce specialization and structured job control are recommended to optimize production flow further and minimize idle time. Overall, this study offers valuable insights into optimizing production systems and provides a robust framework for enhancing efficiency in manufacturing environments.

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