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A Decision Support Tool for the Improved Processing of Yellowfin Sole Fillets at a Namibian Seafood Production Company

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Abstract

The fishing industry in Namibia contributes approximately 4.5% towards the Namibian GDP. Furthermore, the demand for sustainable processed Yellowfin Sole is increasing worldwide. This research focuses on the processing of Yellowfin Sole fillets which constitutes one of the main operations of a Namibian seafood production company. We present a decision support tool that provides quantitative guidelines for resource capacity allocation over a short-term planning horizon. The decision support tool consists of a software program based on established queueing theory principles to provide measurements and scenario testing of resource utilization, processing queue length as well and the waiting time of unprocessed fish in the processing queue. We test the validity of the decision support tool by means of a discrete event simulation model and predict the processing capacity based on various input values. The decision support tool enables the minimization of downtime, maximization of resource utilization, and improved overall efficiency while maintaining the sustainable processing of Yellowfin Sole fillets.

Keywords
Sustainable seafood production improvement, Decision support tool, Queueing theory, Discrete-event simulation, Resource allocation.

1. Introduction
The Namibian fishing industry holds significant economic importance, contributing around 4.5% to the country's GDP and constituting 15% of export earnings (Namibian Ministry of Fisheries 2018). While the overall Namibian fishing industry had a gross export value of $468 million in 2020 (The Growth Lab at Harvard University 2020), Yellowfin Sole (YFS), a key commodity in this industry, is not sourced from Namibian waters. Instead, it is caught in the Bering Sea and processed in Namibia. This presents a unique opportunity for European companies to invest in Yellowfin Sole

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processing in Namibia, especially as the cost of processing in China, where most Yellowfin Sole is currently processed (Ng 2007), has increased (Huang et al. 2021).

Yellowfin Sole populations are well managed, not subject to overfishing, and the 2021 stock assessment indicates a healthy state (Spies et al. 2020). With a total catch of 106,789 tons in 2021, Yellowfin Sole is abundant and sustainable (Spies et al. 2020). The biomass estimate has increased from 310,617 tons in 2010 to 510,029 tons in 2019, showcasing the species' resilience and the potential for continued fishing with proper conservation methods (Spies et al. 2020).

Market trends and demands in the global seafood industry are experiencing significant shifts. The global seafood trade has grown over 350% since 1970 (Food and Agriculture Organization of the United Nations, n.d.), with the seafood market valued at USD 310.75 billion in 2021 (Food and Agriculture Organization of the United Nations, n.d.). Projections suggest substantial growth, reaching USD 605.46 billion by 2029, driven by increased demand for ready-to-cook and processed seafood and a rising inclination toward pescetarianism (Food and Agriculture Organization of the United Nations, n.d.). These trends bode well for Yellowfin Sole, a commercially important flatfish species in the global seafood market.

The YFS processing facility consists of multiple processing stations that work in series to transform the raw material (whole frozen YFS) into YFS fillets that are sold on the international market. The processing line does not always run efficiently, as there are regular production backups and bottlenecks that form at certain processing stations. This leads to downtime at other processing stations and results in the resources of the facility being underutilized. This is seen in the daily production output of the facility, illustrated in Figure 1, as the production output per shift varies immensely.

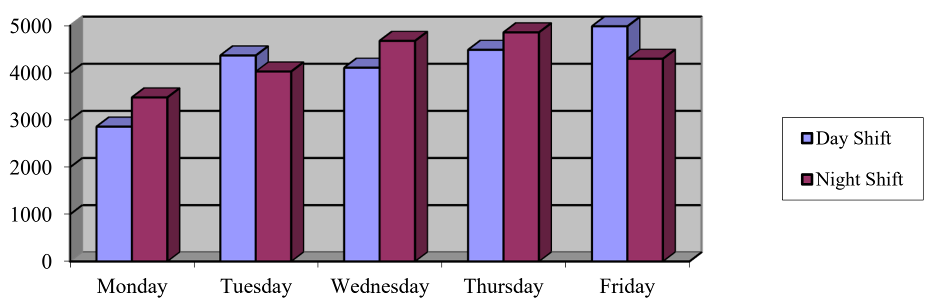

Figure 1. Sample production data

Furthermore, under the existing operational model of the Yellowfin Sole processing facility, a production of 4 metric tons of Yellowfin Sole fillets is achieved per shift. This falls short of the facility's maximum capacity and results in the production resources being underutilized.

The current positive market dynamics indicate a robust demand for Yellowfin Sole that can sustainably be harvested. The research aims to enhance the operational efficiency of a Namibian Yellowfin Sole processing company so that they can position themselves to meet the growing demand, maximize production, optimize resource utilization, and ensure product quality. This paper will delve into the intricacies of Yellowfin Sole processing, providing a tool for improved decision making, operational efficiency, and contributing to the sustainable growth of the industry.

This aim can be effectively addressed by firstly conducting a comprehensive analysis of the current operational model of the Namibian Seafood processing companies Yellowfin Sole processing facility. Thereafter, constraints, bottlenecks, and inefficiencies related to throughput, downtime and resource utilization can be identified. Finally, we develop a decision support tool that provides insight towards minimizing downtime, maximizing resource utilization and throughput while maintaining product quality and meeting their required production demands.

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2. Literature Review

This literature review provides an in-depth exploration of various key aspects that provide the foundation of knowledge for the development of a decision support tool aimed at enhancing operational efficiency of the Yellowfin Sole processing facility of the company.

Although the literature on the seafood processing industry in Southern Africa is not prolific, literature on operations management in production lines can successfully contribute towards achieving the aim of this research. Sims and Wan (2017) suggested that constraint identification and management should be the first steps in improving production processes. Other articles also propose the systematic use of Value Stream Mapping (VSM) and Theory of Constraints (TOC) to identify basic causes of production losses (Pereira Librelato et al. 2014; Pacheco et al.2019).

The foundation of TOC is the assumption that every system has at least one bottleneck, which is defined as any circumstance that prevents the system from performing at its highest possible performance level with respect to its objectives (Şimşit et al., 2014; Šukalová & Ceniga, 2015). TOC has an extremely wide range of industries where it is applied in. These industries include, but are not limited to, production, distribution, supply chain, project management and so forth (Şimşit et al., 2014). Goldratt and Cox proposed the Five Focusing Steps (5FS) that are the working process for ongoing process improvement. These steps are (Goldratt & Cox 1984):

1. Identify the system's constraint.
2. Decide how to exploit the system's constraint.
3. Subordinate everything else to the above decision.
4. Elevate the system's constraint.
5. If in any of the previous steps a constraint is broken, go back to step 1.

Research has shown the advantages of TOC in production settings as either a standalone practice (Situmorang and Matondang 2020) or integrated with other methodologies such as Time Driven Activity-Based Costing (TDABC) (Kefe and Tanış, 2023). Kefe and Tanış (2023) conducted a study in a manufacturing company who integrated TOC,with TDABC. This integration facilitated the identification of capacity constraints in specific resource centers, thereby aiding in capacity management and decision-making. Moreover, TOC plays a crucial role in optimizing production flow by eliminating constraints at bottleneck workstations, leading to enhanced overall system effectiveness. In a case study focused on the production of instant noodles, TOC was instrumental in overcoming constraints at mixing and cooking stations, ultimately improving production flow and efficiency (Situmorang and Matondang 2020). This optimization of production flow not only streamlines operations but also contributes to increased throughput and resource utilization. Furthermore, TOC offers a structured approach to manage production challenge and enables companies to make informed decisions regarding product mix, capacity management, and process improvement. By managing constraints effectively, companies can achieve maximum throughput and profitability (Saleh et al. 2019).

Drip loss is another factor that must be kept in mind in seafood processing. Drip loss is defined as the weight loss that is observed in fillets during storage and handling. Drip loss is an important factor that can significantly impact the overall yield and product quality (Love et al. 2015) of the YFS fillets. There are no studies on the specific rates of drip loss for YFS. However, a study conducted in 2018 showed that drip loss accelerated exponentially with longer holding time at room temperature (Yang et al. 2018). We therefore argue that the decision support tool that we develop will be more useful if a quantitative measurement of holding times between processes can be indicated.

Operations Research (OR) techniques are explored due to their ability to improve the efficiency of processes within an organization (Marcinkowski et al. 2021). They aid in finding optimal solutions to issues involving resource allocation, scheduling, and decision-making is the main goal of using OR approaches (Marcinkowski et al. 2021). Operations Research has the ability to solve real-world problems by formulating them as mathematical models. These models aid in understanding the dynamics of complex systems. They allow identification of constraints and variables, and provide quantifiable relationships between different components in a system. Formulating these complex models and solving them provides valuable insights and solutions that can be used to enhance productivity and streamline operations (Marcinkowski et al. 2021). In the context of the YFS processing line, OR methodologies can be instrumental in optimizing the Yellowfin Sole processing facility's operations. Employing OR techniques could lead to a more balanced production line and quantitative data of each component in the production process. OR can assist in maximizing throughput, minimizing downtime, and improving overall efficiency (Mcginnis 2014; Marcinkowski et al. 2021).

The YFS processing line is a series of processing stations, with a specified number of employees at each station. Bhosale and Pawar (2020) suggest that Queuing Theory is most suitable in such circumstances. Queuing Theory excels in scenarios where process optimization relies on identifying bottlenecks and maximizing throughput (Bhosale and Pawar 2020), which are precisely the goals of this project. Sztrik (2016) also describes Queuing Theory as a potent and adaptable branch of Operations Research, offering valuable insights into the behavior of waiting lines and resource utilization in diverse systems. Queuing Theory was also previously applied for capacity management of hospital beds (Bittencourt et al. 2018). Bittencourt et al. (2018) used Queuing Theory to determine operational measures such as utilization rate, waiting probability, estimated bed capacity, capacity simulations and demand behavior assessment. Their model provided a quantitative picture used to enhance decision-making for their specific use-case of capacity management in a hospital.

3. Methods

The YFS processing facility has 7 processing stations that determine the throughput in terms of changing the raw material to the final product. These processes are illustrated in Figure 2.

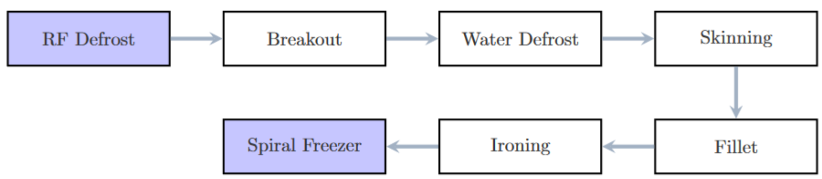

Figure 2. Flowchart of YFS processing facility

TOC was employed as a systematic approach to pinpoint the bottleneck within the production process. The following steps outline how TOC was utilized to identify the Spiral Freezer as the primary constraint:

1. *Identify the system's constraint:* The first step in TOC involves identifying the bottleneck. This was done by closely examining the existing operational model of the facility. Gemba walks were performed to understand the flow of production, resource allocation, and the sequence of processes involved in creating Yellowfin Sole fillets. By engaging with the production team, we came to the conclusion that the Spiral Freezer is the absolute constraint of the facility. The production team indicated that 800 trays is the maximum that the Spiral Freezer can process in an hour without being at risk of the trays overlapping and causing a shutdown of the Spiral Freezer.
2. *Decide how to exploit the system's constraint:* In the case of our facility, the Spiral Freezer was recognized as a critical component in the production process that determines the upper limit of what the facility can produce. Therefore, to maximize throughput, we would have to maximize the utilization of the Spiral Freezer.
3. *Subordinate everything else to the above decision:* The next step is to subordinate all other processes to facilitate the maximum utilization of the Spiral Freezer. This requires synchronizing all other processes with the maximum rate of production of the Spiral Freezer. This would minimize any downtime and reduce inefficiencies.
4. *Elevate the system's constraint:* Elevating the capacity of the spiral freezer is not currently an option, due to the fact that a larger capacity Spiral Freezer would require a large amount of capital, which does not fall within the scope of this project.

To maximize the throughput of the Spiral Freezer, all other processes must be able to process the equivalent of 800 trays per hour. With each tray containing 9 fillets weighing 75 grams each, the maximum total throughput that can be processed by the spiral freezer per hour can be calculated.

$$Max\ Throughput\ of\ Spiral\ Freezer\ =\ (800\ trays/hour)\ *\ (9\ fillets/tray)\ *\ (75\ grams/fillet)$$

$$Max\ Throughput\ of\ Spiral\ Freezer\ =\ 540\ kg/hour$$

Queuing Theory is then used to propagate backwards from the Spiral Freezer to the initial starting process (RF Defrost) to determine the throughput required from each process to sustain the Spiral Freezer at 100 % utilization. Among the various queuing models available, the M/M/c queue emerges as the most suitable choice due to its alignment with the characteristics of the production process and the specific objectives of this project. This is due to the fact that mean arrivals per hour is the context in which the items arrive at the Spiral Freezer. This indicates that a Poisson distribution is most applicable as it will accurately represent both the arrival and service times of each process station (He et al. 2014). The process stations can be modelled accurately with either a single server or multiple servers in a M/M/c queuing model. The following mathematical formulations are used to determine utilization, average waiting time in queue, and average number of items in queue for each process (Shortle et al. 2018):

- *Arrival Rate* (λ): The arrival rate (λ) represents the rate at which entities arrive at a process. It is a measure of how frequently new entities join the queue for processing.

  λ = (kg per hour or trays per hour)

- *Service Rate* (μ): The service rate (μ) denotes the rate at which entities are processed by the employees at each process station. It represents how quickly the servers (employees) perform their tasks on the fish.

  μ = (kg per hour or trays per hour)

- *Utilization* (ρ): Utilization (ρ) is the ratio of time a server (employee) is busy performing tasks to the total time. In this context, it represents the percentage of time that each employee at a process station is actively working on the fish.

$$\rho = \frac{\lambda}{c\mu}$$

  where:

  c = Number of Servers at the Process Station

- *Throughput* (X): Throughput (X) is the rate at which entities leave the system after being fully processed. It indicates the overall production rate of the system. The throughput of the system is equal to the arrival rate (λ), as long as $\rho < 1$.

- *Average Waiting Time* (Wq): Average waiting time (Wq) is the average time an entity spends waiting in the queue before being processed.

$$W_q = \frac{1}{c\mu - \lambda}$$

- *Queue Length* (Lq): Queue length (Lq) represents the average number of entities waiting in the queue to be processed by the servers (employees) at a given process station.

$$L_q = \lambda W_q$$

These equations, based on the M/M/c queue model, play a pivotal role in analyzing and optimizing the production process at each station on the production line. By calculating these performance metrics, the production team can analyze the employee allocations of each process station to determine whether resources are being used efficiently.

By using the throughput rate, determined previously for the Spiral Freezer, this rate can be propagated backward through the production process, calculating the required service rates for each process station. Figure 3 illustrates the order in which the service rates are propagated, from final product to raw material.

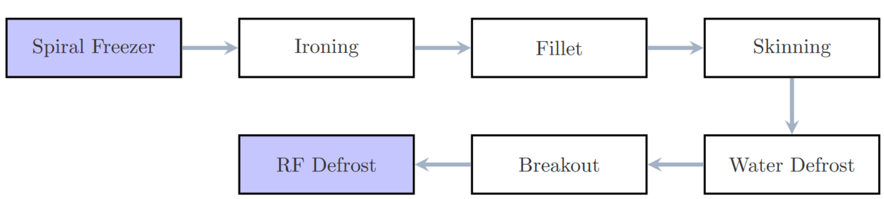

Figure 3. Flow of propagated rate calculation

Table 1 illustrates the calculated service rates that each process must be able to handle in order to sustain the Spiral Freezer at 100 % utilization. The facility currently employs Just-In-Time (JIT) manufacturing in its production line.

This is done with the goal of minimizing holding times between the different processes in the production line. By synchronizing production levels, holding times are decreased and waste can therefore be minimized. However, this does not provide flexibility in terms of resources allocated, since differing resource allocation would have a significant impact on the production levels of each process.

Table 1. Required service rates of each process

Process	Required Service Rate of Entire Process
Spiral Freezer	800 trays/hour
Ironing	540 kg/hour
Filleting	1 149 kg/hour
Skinning	1 149 kg/hour
Water Defrost	1 149 kg/hour
Breakout	1 149 kg/hour

Employing a dynamic software approach in conjunction with JIT manufacturing offers several advantages that can significantly enhance operational efficiency and flexibility. Firstly, a dynamic tool would provide real-time production rates aligned with the current resource allocation at each process. Unlike traditional static approaches, which assume constant resource allocation, a dynamic tool can adapt to changes in resource availability or demand fluctuations, allowing for more accurate and responsive production planning. A software model offers a systematic and structured approach to process optimization and resource management. Given the complexity of the production operations, manual methods for planning and scheduling would regularly fall short in addressing these kinds of dynamic production environments.

Furthermore, dynamic software enables resources to be allocated and reallocated dynamically based on changing production needs. This flexibility ensures that resources are optimally utilized across the production line, minimizing idle time and maximizing throughput. Moreover, by providing visibility into real-time production data and performance metrics, a dynamic software tool empowers managers to make informed decisions and proactively identify opportunities for optimization. For instance, managers can quickly identify bottlenecks or inefficiencies in the production process and take corrective actions to improve overall performance.

4. Data Collection

The data collection process involved conducting comprehensive time studies at each processing station within the Yellowfin Sole facility, these results are illustrated in Table 2. This meticulous approach aimed to capture the intricate details of the production workflow. Through rigorous observation and measurement, the mean time for each processing step was meticulously determined. This granular data forms the foundation for the subsequent analyses, enabling a detailed examination of the operational dynamics and facilitating precise insights into the time efficiency of individual processes.

Table 2. Service rate observations of each process

Process	Nr. Of Observations	Mean Service Rate	Unit
Breakout	75	6	minutes/bag/employee
Water Defrost	50	8	minutes/3 bins/tub
Skinning	125	98	seconds/bin/machine
Filleting	200	18	seconds/fish/employee
Ironing	125	42	seconds/tray/employee

Furthermore, the number of servers at each process was also documented, as seen in Table 3.

Table 3. Nr. of servers at each process

Process	Nr. Of Servers
Breakout	6
Water Defrost	3

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Skinning	2
Filleting	32
Ironing	16

5. Results and Discussion

The decision support tool is a sophisticated software program that is designed to aid the decision-makers to make informed decisions. The decision support tool harnesses the power of queuing theory to provide actionable data that will drive improvements. The decision support tool uses concepts from queuing theory as the mathematical backbone of the program. It calculates and provides the following key performance metrics:

- Utilization: Calculates the utilization of all relevant processes, to provide a measure of how efficiently the resources (employees) at each process are being used.
- Average Queue Length: Calculates the average number of items (fish/bins/trays) that will be waiting in a queue at each process. This allows the production team to have quantitative data to mitigate drip-loss and know where bottlenecks will occur.
- Average Time in Queue: Calculates the average time an item (fish/bins/trays) will spend waiting in a queue at a process. This also gives the production team quantitative data to mitigate drip-loss and determine bottlenecks.

The tool is designed so that changes can be made in terms of servers and service time for each process station. This allows the production team to have quantitative data on different configurations of the production line and the effects can be analyzed before being implemented. The User Interface (UI) is intuitive and easy-to-use, therefore the production team does not need any training prior to using the tool. Figure 4 illustrates the interface of the tool with the current operational model.

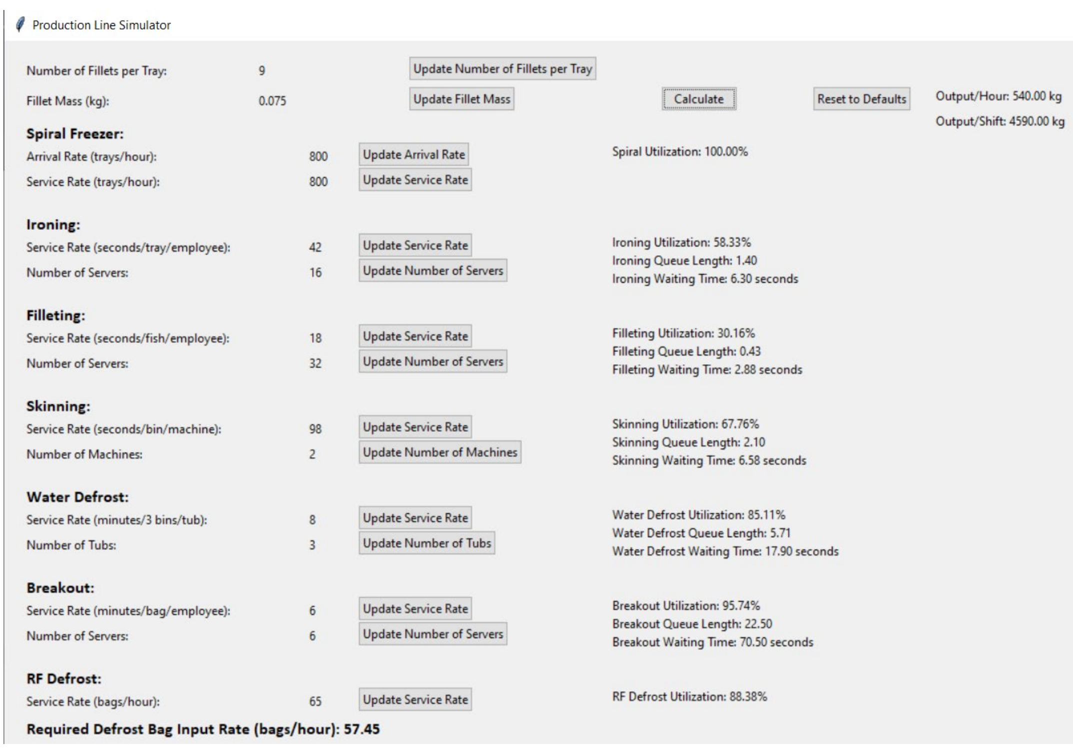

Figure 4. Tool UI with current operational model

5.1 Numerical Results

The tool indicates that a total fillet output of 4 590 kg per shift would be achieved if the spiral freezer is at constant 100 % utilization. The data provided by the tool indicates that with the current operational model, it would be highly unlikely that a constant 100 % utilization of the spiral freezer will be achieved. Table 4 provides the required utilization, inferred capacity status and queue length of all processes in order to achieve 100 % utilization of the spiral freezer.

Table 4. Summary of current process data acquired from DST

Process	**Utilization**	**Capacity Status**	**Queue Length**
RF Defrost	88.38 %	N/A	N/A
Breakout	95.74 %	High likelihood of delays and congestion	22.5 bags
Water Defrost	85.11 %	Possible staff falling behind	5.71 bins
Skinning	67.76 %	Staffed for required throughput	2.1 bins
Filleting	30.16 %	Staffed in excess of required throughput	0.43 fish
Ironing	58.33 %	Staffed for required throughput	1.4 trays

5.2 Proposed Improvements

Figure 5 illustrates an example of how the tool can be used to determine quantitative data about changing the servers at a process before investing resources in real-life.

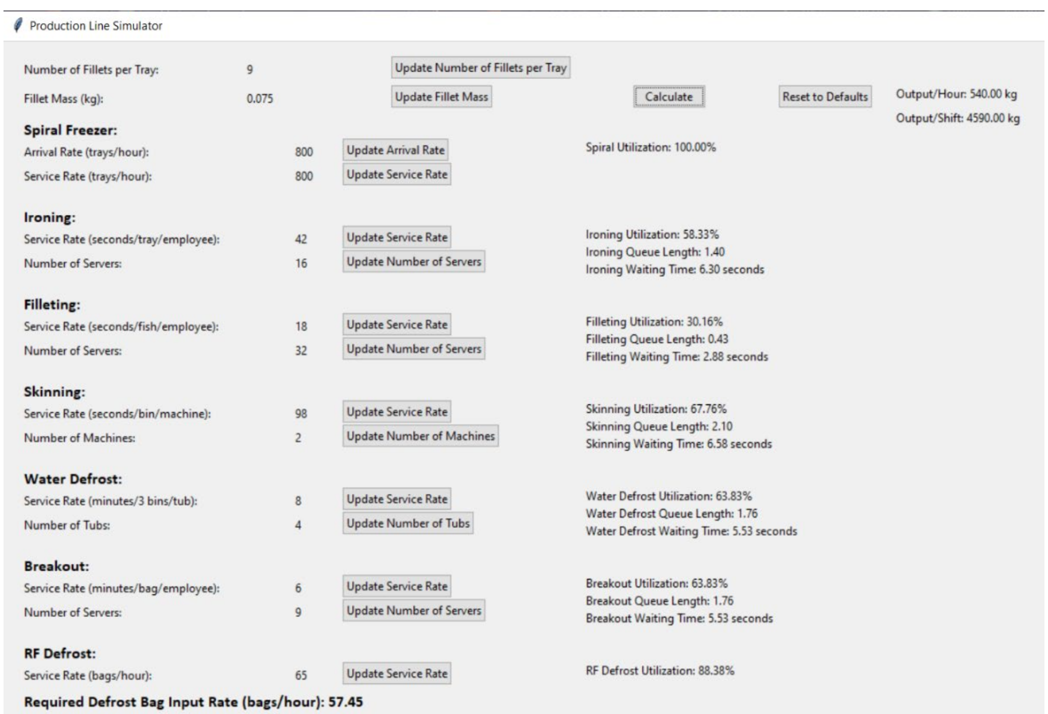

Figure 5. Tool UI with improved operational model

Only 2 changes are made to the current operational model, however it provides a picture that is far more plausible in terms of attaining 100 % utilization of the spiral freezer.

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- Breakout has 9 servers instead of 6. This provides a substantial decrease in utilization, queue length and queue waiting time. This indicates that with 9 servers, breakout would be sufficiently staffed to deliver the required throughput.
- Water defrost has 4 defrost tubs instead of 3. This also provides another substantial decrease in utilization, queue length and queue waiting time. This indicates that with 4 defrost tubs, this process would also have sufficient capacity to handle the required throughput.

By adding servers at 2 process stations, it becomes far more plausible for the facility to produce 4 590 kg of fillets per shift.

5.3 Validation

A discrete event simulation was constructed to determine the validity of the results obtained from the decision support tool. A discrete event simulation provides a realistic representation of the production process and allows changes to be captured dynamically (Salem and DeMelo, 2013). FlexSim was used to construct the simulation, due to its credibility and widespread use as industry standard software (Leks and Gwiazda, 2015; Aliyu and Mokhtar, 2021). Figure 6 provides a screenshot of the model that was developed in FlexSim.

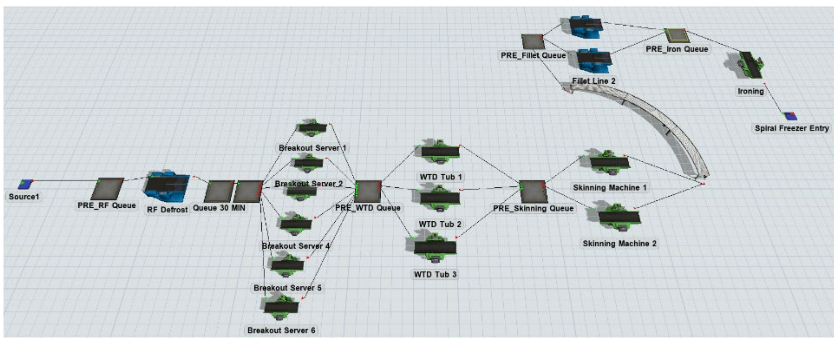

Figure 6. FlexSim simulation of current production model

FlexSim provides the obtained utilization rates of each process in dashboards, the data from these dashboards are illustrated in Table 5 below:

Table 5. Comparison of utilization rates obtained between DST and FlexSim

Process	Decision Support Tool	FlexSim	% Change
Breakout	95.74 %	93.97 %	1.77%
Water Defrost	85.11 %	82.61 %	2.50 %
Skinning	67.67 %	67.77 %	0.10 %
Filleting	30.16 %	38.43 %	8.27 %
Ironing	58.33 %	58.66 %	0.33 %
Mean Difference = 2.59 %			

Output

Object	Throughput
Spiral Freezer Entry	4580

Figure 7. FlexSim Spiral Freezer input volume

The FlexSim simulation indicates an output per shift of 4 580 kg, shown in Figure 7. This is comparable to the tools predicted output of 4 590 kg as it is only a 0.22 % difference. A mean difference in the utilization rates of 2.59 %, shown in Table 5, indicates that the tool is comparable to industry standard simulation software.

Table 6. Comparison of DST and historical production input rates

Production Input Rate	Production Output	Predicted Input Rate
51.05 bags per hour	4 080 kg	51.06 bags per hour
52.24 bags per hour	4 160 kg	52.06 bags per hour
52.94 bags per hour	4 250 kg	53.21 bags per hour

48 bags per hour	3 820 kg	47.82 bags per hour
49.41 bags per hour	3 910 kg	48.96 bags per hour

This validates the data obtained from the tool and proves that it can be used to infer real-world outcomes. Historical data is used to compare production input and output values to predicted input and output values obtained from the decision support tool. The historical data obtained from the company is illustrated in Table 6. The output values of the decision support tool is aligned with the observed production output to determine if the predicted input rate is the same as the observed input rate.

6. Conclusion

The aim of this research was to develop and test a decision support tool that will improve the operational efficiency of a Namibian Yellowfin Sole processing company. The project deliverable addresses this and provides a clear framework to increase the shift output to a capacity of 4 590 kg. The decision support tool provides a measurement of the utilization of all the processes in the production facility to allow the production team to prevent under-utilization of resources. The use of Queuing Theory to determine how a system will react to a specified outcome is an innovative approach that is not currently in scientific literature. In this case it allowed us to use Theory of Constraints in conjunction with Queuing Theory. By subordinating everything in the system to maximizing the utilization of the primary constraint, and then determining the behavior of the system, it provided a clear framework in terms of how the maximum throughput should be reached and why it currently isn't being reached.

References

Aliyu, R., & Mokhtar, A., Research Advances in the Application of FlexSim: A Perspective on Machine Reliability, Availability, and Maintainability Optimization, (48), 2021.

Bhosale, K. C., & Pawar, P. J. , Production planning and scheduling problem of continuous parallel lines with demand uncertainty and different production capacities. Journal of Computational Design and Engineering, 7(6), 761-774, 2020. https://doi.org/10.1093/jcde/qwaa055

Food and Agriculture Organization of the United Nations. (n.d.). GLOBEFISH - Information and Analysis on World Fish Trade. Retrieved from http://www.fao.org/in-action/globefish/en/

Goldratt, E. M., & Cox, J. (1984). The Goal: A Process of Ongoing Improvement. New York: North River Press.

He, D., Li, R., Huang, Q., & Lei, P., Maximum Entropy Principle Based Estimation of Performance Distribution in Queueing Theory. PLoS ONE, (9), 2014. https://api.semanticscholar.org/CorpusID:10358752

Huang, Y., Sheng, L., & Wang, G. , How did rising labor costs erode China's global advantage? Journal of Economic Behavior & Organization, 183, 632-653, 2021. https://doi.org/10.1016/j.jebo.2021.01.019

Kefe, İ., & Tanış, V. N. (2023). The Integration of the Theory of Constraints and the Time-Driven Activity-Based Costing System for the Improvement of Production Processes in an SME. Revista de Contabilidad. https://doi.org/10.6018/rcsar.413411

Leks, D., & Gwiazda, A. (2015). Application of FlexSim for modelling and simulation of the production process. In (Ed.), https://api.semanticscholar.org/CorpusID:208099916

Love, D., Fry, J., Milli, C., & Neff, R., Wasted seafood in the United States: Quantifying loss from production to consumption and moving toward solutions. Global Environmental Change, (35), 116-124, 2015. https://doi.org/10.1016/j.gloenvcha.2015.08.013

Marcinkowski, B., Narojczyk, S., Nowak, D., & Zalizko, V. (2021). Modern methods used in production-operations management. In (Ed.), https://doi.org/10.18559/978-83-8211-059-3/05

Namibian Ministry of Fisheries. (2018). Namibia Fisheries Policy: Ensuring fisheries and aquatic resources sustainability. Maximizing economic and social benefits to all Namibians. Available: https://mfmr.gov.na/documents/411764/2631681/Draft+Namibia+Sustainable+Blue+Economy+Policy.pdf/b4b334bd-b3e7-4e8b-442f-cbbc6fac34e2 , Accessed on January 22, 2024.

Ng, J. S. (2007). Development of China as the world's largest reprocessing centre of frozen fish products and future challenges for the industry. In Global Trade Conference on Aquaculture (Vol. 29, p. 221). Food and Agriculture Organization of the United Nations, Rome.

Pacheco, D. A. de J., Pergher, I., Antunes Junior, J. A. V., & Roehe Vaccaro, G. L. (2019). Exploring the integration between Lean and the Theory of Constraints in Operations Management. International Journal of Lean Six Sigma, 10(3), 718-742,2019. https://doi.org/10.1108/IJLSS-08-2017-0095

Pereira Librelato, T., Pacheco Lacerda, D., Henrique Rodrigues, L., & Rafael Veit, D. (2014). A process improvement approach based on the Value Stream Mapping and the Theory of Constraints Thinking Process. Business Process Management Journal, 20(6), 922-949. https://doi.org/10.1108/BPMJ-07-2013-0098

© IEOM Society International

Saleh, C., Immawan, T., Hassan, A. B., & Zakka, M. (2019). Profit Optimization Through the Application of Theory of Constraints (TOC): A Case Study in Printing Company. IOP Conference Series: Materials Science and Engineering, 530. https://doi.org/10.1088/1757-899X/530/1/012045

Salem, D. S., & DeMelo, A. C. (2013). On-the-fly verification of discrete event simulations by means of simulation purposes. Simulation. https://api.semanticscholar.org/CorpusID:267812563

Shortle, J. F., Thompson, J. M., Gross, D., & Harris, C. M. (2018). Fundamentals of Queueing Theory. John Wiley & Sons, Inc. https://doi.org/10.1002/9781119453765

Sims, T., & Wan, H., Constraint identification techniques for lean manufacturing systems. Robotics and Computer-integrated Manufacturing, (43), 50-58,2017. https://doi.org/10.1016/J.RCIM.2015.12.005

Şimşit, Z. T., Günay, N. S., & Vayvay, Ö. , Theory of Constraints: A Literature Review. Procedia - Social and Behavioral Sciences, 150, 930-936,2014. https://doi.org/10.1016/j.sbspro.2014.09.104

Situmorang, H. N., & Matondang, N. (2020). Production Flow Optimization By Using Theory of Constraints. https://doi.org/10.4108/eai.16-11-2019.2293240

Šukalová, V., & Ceniga, P., Application of the Theory of Constraints Instrument in the Enterprise Distribution System. Procedia Economics and Finance, (23), 134-13920,2015. https://doi.org/10.1016/S2212-5671(15)00445-1

Spies, I., Wilderbuer, T. K., Nichol, D. G., & Ianelli, J. (2020). Assessment of the yellowfin sole stock in the Bering Sea and Aleutian Islands. Stock Assessment and Fishery Evaluation Report for the Groundfish Resources of the Bering Sea/Aleutian Islands Regions. NOAA Fisheries, Alaska, AK.

Sztrik, J. (2016). Basic Queueing Theory. Retrieved from https://api.semanticscholar.org/CorpusID:114903987

The Growth Lab at Harvard University. (2020). The Atlas of Economic Complexity. Available: http://www.atlas.cid.harvard.edu , Accessed on March 19, 2023.

Yang, S., Hyldig, G., & Rustad, T., Drip loss characteristics of redfish (Sebastes marinus) and saithe (Pollachius virens) fillets. International Journal of Food Science, 2018. Hindawi.

Biography

Marthinus Marais is a recent graduate industrial engineer who obtained his qualification from the North-West University (NWU) in South Africa. He has extensive experience in the seafood processing industry. Mr. Marais has a special interest in Control Theory and Advanced Optimization. His further research focus includes mechanical engineering applied in motorsport, focusing on open-wheel race cars.

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