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A Simulation-Based Approach for Production Lead-Time Analysis in Leather Processing: A Case Study at Nakara, Namibia



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A Simulation-Based Approach for Production Lead-Time Analysis in Leather Processing: A Case Study at Nakara, Namibia

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ABSTRACT

Purpose: A study was conducted to analyze production lead time challenges in the leather processing industry by use of simulation techniques.

Methodology: The study was able to successfully develop a simulation model that predicts the production lead time by using past data that was obtained from the case factory and using discrete event simulation method in Arena Software. A case study undertaken at a worldly recognized leather manufacturing factory in Namibia called Nakara proved that there are challenges faced when estimating the production lead time.

Findings: The research highlighted the significance of leather manufacture's ability to know their processing facility's production lead time as it proved to be a huge boost in client attraction and degree of satisfaction.

Unique Contribution to Theory, Practice and Policy: Many leather manufacturing factories in the world experience high difficulties when estimating their production lead time, therefore the study contributes to theory, practice and policy by developing a simulation model for production lead-time estimation. Moreover, a good production lead time reflects an efficient and effective production system.

Key words: Production lead-time, Corrected grain leather, Tannery, Arena.



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1. INTRODUCTION

Production lead time (PLT) plays a key role in many organizations, from job procurements to end product delivery. It is defined as the time it takes for a placed order to go through the production process from start to finish (Solomon, Jilcha, & Berhan, 2015). The leather industry is one of the largest market share holders worldwide, shockingly surpassing other industries such as the meat, coffee, and rice industries in recent years (Negussie, 2014). Due to the above discovery, the research was focused on PLT analysis in leather processing to solve challenges found in struggling leather processing organisations. A case study was performed at Nakara, a large-scale leather processing organisation in Namibia that was experiencing analytic PLT challenges. The research aimed to introduce a realistic, reliable, and accurate simulation model for PLT analysis. A simulation approach was considered favourable since the research target was to analyse the PLT, even if there was no actual processing facility. Hence, by simulation, any leather processing organisation would be able to analyse its attained PLT. It makes it difficult to use other analytic methods that would lead to a lengthy presentation of the outcomes (Solomon, Jilcha, & Berhan, 2015). The model would be used as a significant abetting tool in the PLT analytic process.

1.1 Problem Statement

Many industries, such as the leather processing industry, face challenges in knowing their accurate production lead time. In most cases, the lead time was inaccurately estimated, undesirable, and could be improved (Karmarkar, Kekre, Kekre, & Freeman, 1985). As leather processing industries continue to face challenges when estimating production lead time, it was important to develop more realistic and reliable methods for production lead time analysis. Developing appropriate simulation approaches for accurate production lead time analysis and prediction was imperative. Negative impacts of poor production lead time analysis methods include poor service delivery rating, high production costs, and over-processing. Hence, the urgency of addressing lead time nervousness is of the essence to Nakara and the leather processing industry at large.

2. LITERATURE REVIEW

2.1. Nakara, a leather processing tannery in Namibia

Nakara is a leather tannery in Namibia that produces finished leather products from raw animal skins. Nakara produces many different types of leather, with corrected-grain leather being the top seller and most frequently ordered. Nakara is in the country's capital city, Windhoek, and is the leading tannery in the country. Nakara employs a total of 160 employees, comprising both the administration and production departments. Nakara has a production lead time of 60 hours for CG leather production (Jaos, 2019). The tannery is the biggest and key role player in the Namibian leather processing industry, with very little competition in the local sector. Nakara supplies about 95% of all local shoe and upholstery leather goods manufacturers in the country and is also involved in supplying beyond the borders of Namibia. Due to the firm's ability to export and feed export markets, Nakara has become a significant role player in the Namibian economic growth



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sector, through its export of finished leather hides and wet blue hides (Jaos, 2019). Wet blue hides are hides which have not been fully processed but only up to a certain stage, they then sold to customers who wish to process them to a finished level at their tanneries. This gives them full control over the finish, and in turn gives them a competitive edge since the finish is treated as a kind of secret recipe. Nakara has won many local awards since its founding, but the most fascinating award was when they proved to be one of Africa's largest tanneries after receiving the regional tannery of the year for Africa award in the year 2011 (Reporter, 2011).

2.2 Lead time significance

It is very important to consider the total lead time taken to manufacture a finished product, and this has been a central problem in many manufacturing processes. Longer lead times inflict costs due to higher work in process, larger safety stocks, requirement nervousness, and poor or reduced performance to due dates (Karmarkar, 1987). Manufacturing lead times are a significant measure of measuring manufacturing performance that has not been greatly recognized in literature. There are many factors affecting lead times including capacity, loading, batching and scheduling, and they affect many aspects of costs, and control (Karmarkar, 1993). A study carried out by (Liao & Shyu, 1991) articulated that lead time is not prescribed and therefore it is subject to control in many practical situations. They further elucidated that lead time can be shortened at the expense of extra costs to improve customer service, system responsiveness and reduce inventory investment, in safety stocks. Literature indicates that when lead time is not included in the planning process, planners tend to underestimate the effects of time delays and become more concentrated on the due date for delivery without a contingency plan and due to change dynamics can find themselves in almost irreversible situations making it very difficult for them to recover the time loss. It is thus of the essence to plan for lead times to avoid failure of projects. Planning in time for lead time also enables the planner to create a secondary plan for probable unexpected scenarios (Duffie, Bendul, & Knollmann, 2017). Production managers and researchers have suggested that the significance of reducing production lead time has become one of the highest necessities for manufacturing firms to stay competitive at the world-class level. The study done by (Sheu & Wacker, 1997) empowers a notion directed to all manufacturers that for any manufacturer to compete at the highest-level in-service delivery the entity must attain what has been proclaimed as a world-class manufacturing status. It has highlighted the crucial requirement for firms to implement a variety of programmes to lower the production lead time.

2.3 Leather processing Industry

According to (Ben, 2019) the leather industry is one of the biggest industries in the world with its largest feeder, the ever-flourishing meat industry and its lure the ever-increasing consumer demand. According to the Global Leather Goods Market 2017-2021 Report, conducted by Technavio analysts, the global leather market is projected to raise at a multiple annual growth rate of almost 5% from 2017-2021. In 2017, the total market value was \$217.49 billion. It is projected



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to arrive at \$271.21 billion by 2021. This sector is probable to represent an incremental growth of more than \$53.72 billion during the anticipated period. The sub-sector of global footwear market was worth \$126.99 billion in 2016. In 2016, the Americas registered the highest leather revenue of \$83.67 million. The global leather goods market size was \$95.4 billion in 2018. It is estimated to arrive at \$128.61 billion by 2022 at 4.36% during the targeted period. In addition, a recent market report by Technavio claims that the global leather market will register profits of almost \$289 billion by 2022.

2.4 Leather types and the production process

There are many types of leather each with distinct characteristics that define them and their purpose. The most used leather type is called the corrected grain (CG) leather which has found its high demand through the large variety of use by most consumers. CG leather is the leather that is easily found and mostly used in our everyday life. Finished products such as leather furniture, clothing, shoes, handbags, belts and even book covers and many leather pouches are made from it. The other leather types that make up the types of leather comprise of Full grain leather, Top grain leather and split leather as illustrated in Fig. 1 below.



Figure 1: Different types of Leather

The leather production process is a highly sophisticated and lengthy process that yields its inevitable quality. According to (Tussah, 2014) the process starts with treating the raw hides what is called tanning. The raw skin is submerged in water to clean and soften thoroughly. Next salt is added on the hide extremely reducing its moisture content. This prevents bacteria growth and



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enables the hide to fight against deterioration. Once the hide has been salted enough it is re soaked in water to remove completely the excess salt. The next process called the liming process weakens the hair then the hide undergoes multiple treatments through other various processes until the PH level of the hide has reached the desirable level for completion of the tanning process. The hide is then cured, and the top grain is treated to give the hide a topcoat finish which includes coloring the hide and adding a pattern. Fig. 2 below highlights a diagram presented by (Ben, 2019) supporting the leather production process.





2.5 Types of leather defects

According to a study on an automated approach for the classification of types of defects experienced in the leather industry, a study by (Choonjong, Jose, & VenturaKarim, 2000) found there are five types of defects on leather hides namely: lines, holes, stains, wears, and knots. These



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defects are set to be part of the production process's objective to remove and correct to successfully produce a quality hide.

2.6 Discrete simulation method

There are three types of simulation: discrete event simulation (DES), continuous, and Monte Carlo. DES (based on Nance (1993)) is a model (mathematical and logical) of a physical system that has changes at precise points in simulated time. Customers waiting for service, the management of parts inventory or military combat are typical types of DES (Mike & Albrecht, 2010).

2.7 Simulation software

According to (Mike & Albrecht, 2010), selecting Simulation and Modeling packages in conducting a simulation modeling study, one or more software tool is needed. There are many (87+) packages available for DES. Selecting the appropriate package for your study can be a study of its own. Tools for this selection are generally scarce. A survey conducted by (Mike & Albrecht, 2010) in (2007) Simulation Software using several sources was performed to identify current simulation software. The survey identified 87 discrete event simulation and modeling tools, which included simulation application packages currently available. Of these five are not currently available (AWESIM, KAMELEON, MODSIM III, Silk, and Visual SLAM). Thirty-three are either academia supported, or open source supported. The remaining forty-nine are commercial offerings. Three of the commercial offerings (Arena, Extend, and SIGMA) have academic versions used for teaching simulation courses. Due to this finding the current research has opted to utilize the Arena Simulation Software (ASS) since it has an academic version allowing the researcher to download and use the software for free with limited but adequate features suitable for academic purposes. A Simulation checklist selection guide by: Hlupic, Irani, and Paul (1999) present a list of vital areas of consideration when comparing and selecting the simulation software to use (Mike & Albrecht, 2010).

2.8 Research Gaps

Current literature does not have any simulation approach to lead time analysis for the leather processing industry. The research tackles an existing production lead time problem that has been persistent for many years. The suggested simulation model is useful to the leather processing industry for accurate production lead time analysis and planning. The simulation model contributes to existing body of knowledge in leather processing. Research states that a noble production lead time improves an organization's overall performance level, creates additional job opportunities and makes the organisation extra competitive (Karmarkar, Kekre, Kekre, & Freeman, 1985).

3. METHODOLOGY

The research used a mixed method design which combines qualitative and quantitative approaches to gain a more comprehensive understanding of the research problem. The target population include interview questions, secondary data collection, a site visit and use of simulation software.



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The interview questions comprised of key questions to aid the research. The interview required the presence of one member, preferably the company's Head of Operations. The secondary data set required a five-year period for effectiveness which comprised of past lead times, and how they were obtained, delivery notes, orders, records of deadlines not met, rework orders, defects, events of over-production, machine breakdown records, number of employees and machinery involved in the various production lines. A site visit to the factory was necessary to familiarize the researcher with the leather production process. The Arena Simulation Software was used to perform the simulation model for this research. The software was selected due to its availability, wide use in many parts of the world, and its accessibility option of a free student version. The data was analyzed and used to feed the simulation model where the results are presented.

3.1 Interview questions

A set of questions was prepared by the researcher targeting the hierarchy of Nakara staff to obtain a more in-depth understanding of the firm's stature. The interview only required one individual who sits at the top of Nakara's management hierarchy, a General Manager (GM) or company Chief Executive Officer (CEO), to sit on a one-on-one session with the researcher and provide answers to the interview questions. Some of the main interview questions are listed in Table 1 below:

NO.INTERVIEW QUESTION1What role do you play in the Namibian leather industry?2How do you rate your company's service delivery level in terms of on-time delivery?3What is your average production lead time?

Table 1: Main interview questions

3.3. Secondary Data

Past data will comprise, but not be limited to, past lead times and how they were determined, delivery notes, orders, records of deadlines not met, rework orders, defects, events of overprocessing, machine breakdown records, the number of employees and machinery involved in the various production lines. The research requires that a sample size of five years must be obtained and analyzed to offer a more fulfilling outcome. This was decided based on past research, like our study, which faced challenges when the data sample was shorter. The availability of the data also plays an important role; however, for this research in a large-scale manufacturing firm, the need to capture and analyze data is of the essence. The secondary data collected should provide the current and past PLT of the tannery spanning 5 years back.



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3.4. Observations

The purpose of this exercise was to visit Nakara leather processing tannery and make physical observations, to observe the process flow, current setup of machinery, processing stages, workers' utilization, perform time and distance measurements, note current challenges, look for bottlenecks, and understand the production process.

3.8. Developing the Simulation Model

The simulation model would be developed using the current and past data obtained. The modeling would be done in the Arena Simulation Software (ASS) package with the free student version option available. The researcher would study the model using the model booklet guide found in the help tab of the software, learn how it works, and compute the simulation model of the Nakara tannery. The model must contain all the processes involved in the production process and attain all attributes for each process. The model must be set up in such a way that the simulation outcomes provide the results required to achieve the research objective. Fig. 3 below shows the ASS interface and the restrictions on the model making it strictly only for academic purposes. The ASS makes it easier to create simulation as the software takes care of the lengthy mathematical calculations that go into generating a feasible simulation involving in depth statistical formulas and equations. This software has been developed to aid users in producing reliable models.



Figure 3: Arena Simulation Software



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4. RESULTS AND DISCUSSION

4.1 Interview answers

The interview questions were obtained through a questionnaire. The interview was conducted between the researcher as the interviewer and the CEO of Nakara, Mr. Theo Jaos, as the interviewee. The interview took place on 10 May 2019 in Nakara's boardroom at their tannery located in the northern industrial area in Windhoek, Namibia.

4.2 Secondary data obtained

Secondary data was successfully obtained from Nakara for the purpose of this research. Table 2 below shows Nakara's performance about identified key performance indicators (KPI).

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Table 2: Key Performance Indicators

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The percentage values for each KPI average has been indicated below and the data is presented in the form of a bar graph (Fig. 4).



Figure 4: A Bar graph representing the KPI's

Table 3 below shows the average production lead times (PLTs) achieved by Nakara for the past five years, from the year 2014 to date.

Table 3:	Average	PLTs for	the past	t 5 years
	0			~

Nakara Namibia	cc	
Production lead t	ime for the past 5 years	
1 Batch = 100 hide	28	
YEAR 2019	BATCH ORDER QTY	AVE. PRODUCTION LEAD TIME (HOURS)
January	1	60.5000
February	1	62.0000
March	2	100.0000
April	1	59.0000
Best PLT	5	59.0000
2018	Batch order Qty	Ave. Production lead time (hours)
January	1	61.5000
February	1	60.5000
March	1	63.0000
April	1	60.0000
May	2	100.0000

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July 1 60.0000 August 1 60.0000 September 1 61.0000 October 1.5 42.0000 November 1 68.0000 December 0.5 33.0000 Best PLT Image: September 2017 Batch order Qty Ave. Production lead time (hours) January 0 0.0000 February 0 0.0000 March 1 75.0000 May 1 70.5000 June 1 71.0000 July 1 68.0000 May 1 70.5000 June 1 68.0000 May 1 66.0000 July 1 68.0000 September 1 68.0000 October 2 100.0000		-	00.0000
August 1 60.0000 September 1 61.0000 October 1.5 42.0000 November 1 68.0000 December 0.5 33.0000 Best PLT 13 60.0000 2017 Batch order Qty Ave. Production lead time (hours) January 0 0.0000 February 0 0.0000 March 1 75.0000 April 1 68.0000 June 1 70.5000 June 1 66.0000 August 1 68.0000 September 1 68.0000 June 1 68.0000	July	1	60.0000
September 1 61.000 October 1.5 42.000 November 1 68.000 December 0.5 33.000 Best PLT 13 60.0000 2017 Batch order Qty Ave. Production lead time (hours) January 0 0.0000 February 0 0.0000 March 1 75.0000 April 1 68.0000 June 1 70.5000 June 1 66.0000 May 1 66.0000 June 1 68.0000 Jourder 1 68.0000 June 1 68.0000 June 1 68.0000 Jourder 1 0.00000	August	1	60.0000
October 1.5 42.000 November 1 68.000 December 0.5 33.000 Best PLT 13 60.0000 2017 Batch order Qty Ave. Production lead time (hours) January 0 0.0000 February 0 0.0000 March 1 75.0000 May 1 70.5000 June 1 66.0000 July 1 66.0000 July 1 68.0000 Jourget 1 68.0000 July 1 68.0000 July 1 68.0000 July 1 68.0000 November 2 100.0000	September	1	61.0000
November 1 68.000 December 0.5 33.000 Best PLT 13 60.0000 2017 Batch order Qty Ave. Production lead time (hours) January 0 0.0000 February 0 0.0000 March 1 75.0000 April 1 68.0000 June 1 70.5000 July 1 66.0000 August 1 68.0000 September 1 68.0000 November 2 100.0000	October	1.5	42.0000
December 0.5 33.000 Best PLT 13 60.0000 2017 Batch order Qty Ave. Production lead time (hours) January 0 0.0000 February 0 0.0000 March 1 75.0000 April 1 68.0000 June 1 70.5000 July 1 66.0000 August 1 68.0000 September 1 68.0000 October 2 100.0000	November	1	68.0000
Best PLT 13 60.000 2017 Batch order Qty Ave. Production lead time (hours) January 0 0.0000 February 0 0.0000 March 1 75.0000 April 1 68.0000 May 1 70.5000 June 1 71.0000 July 1 66.0000 August 1 68.0000 September 1 68.0000 October 2 100.0000	December	0.5	33.0000
Best PLT 13 60.0000 2017 Batch order Qty Ave. Production lead time (hours) January 0 0.0000 February 0 0.0000 March 1 75.0000 April 1 68.0000 June 1 70.5000 July 1 66.0000 September 1 68.0000 November 2 100.0000			
2017 Batch order Qty Ave. Production lead time (hours) January 0 0.0000 February 0 0.0000 March 1 75.0000 April 1 68.0000 May 1 70.5000 June 1 66.0000 July 1 66.0000 September 1 68.0000 November 2 100.0000	Best PLT	13	60.0000
2017 Batch order Qty Ave. Production lead time (hours) January 0 0.0000 February 0 0.0000 March 1 75.0000 April 1 68.0000 May 1 70.5000 June 1 70.000 July 1 66.0000 August 1 66.0000 September 1 68.0000 Voceber 2 100.0000			
January 0 0.0000 February 0 0.0000 March 1 75.0000 April 1 68.0000 May 1 70.5000 June 1 71.0000 July 1 66.0000 September 1 68.0000 September 1 68.0000 November 2 100.0000	2017	Batch order Qty	Ave. Production lead time (hours)
February 0 0.0000 March 1 75.000 April 1 68.0000 May 1 70.5000 June 1 71.0000 July 1 66.0000 August 1 68.0000 September 1 68.0000 October 2 100.0000	January	0	0.0000
March 1 75.000 April 1 68.000 May 1 70.5000 June 1 71.0000 July 1 66.0000 August 1 66.0000 September 1 68.0000 October 2 100.0000	February	0	0.0000
April 1 68.000 May 1 70.5000 June 1 71.0000 July 1 66.0000 August 1 68.0000 September 1 68.0000 October 2 100.0000	March	1	75.0000
May 1 70.5000 June 1 71.0000 July 1 66.0000 August 1 68.0000 September 1 68.0000 October 2 100.0000 November 2 100.0000	April	1	68.0000
June 1 71.0000 July 1 66.0000 August 1 68.0000 September 1 68.0000 October 2 100.0000 November 2 100.0000	May	1	70.5000
July 1 66.000 August 1 68.0000 September 1 68.0000 October 2 100.0000 November 2 100.0000	June	1	71.0000
August 1 68.0000 September 1 68.0000 October 2 100.0000 November 2 100.0000	July	1	66.0000
September 1 68.0000 October 2 100.0000 November 2 100.0000	August	1	68.0000
October 2 100.0000 November 2 100.0000	September	1	68.0000
November 2 100 0000	October	2	100.0000
	November	2	100.0000
December 1 65.0000	December	1	65.0000
Best PLT 12 65.0000	Best PLT	12	65.0000
2016 Batch order Qty Ave. Production lead time (hours)	2016	Batch order Qty	Ave. Production lead time (hours)
January 2 85.0000	January	2	85.0000
February 1 75.0000	February	1	75.0000
March 1 75.0000	March	1	75.0000
April 1 75.0000	April	1	75.0000
May 1 69.0000	May	1	69.0000
June 1 75.0000	June	1	75.0000
July 1 95.0000	July	1	95.0000
August 1 81.0000	August	1	81.0000
September 0 0.0000	September	0	0.0000
October 1 79.0000	October	1	79.0000
November 1 76.0000	November	1	76.0000
December 0 0.0000	December	0	0.0000

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Best PLT	11	69.0000
2015	Batch order Qty	Ave. Production lead time (hours)
January	0	0.0000
February	1	85.0000
March	0	0.0000
April	1	80.0000
May	0	0.0000
June	1	84.0000
July	0	0.0000
August	1	81.0000
September	1	81.0000
October	1	80.0000
November	0.5	43.0000
December	0	0.0000
Best PLT	6.5	80.0000
2014	Batch order Qty	Ave. Production lead time (hours)
January	0	0.0000
February	0	0.0000
March	0	0.0000
April	0	0.0000
May	0	0.0000
June	0	0.0000
July	1	100.0000
August	0	0.0000
September	0	0.0000
October	0	0.0000
November	1	98.0000
December	0	0.0000
Best PLT	2	98.0000

The best average PLTs per year (Table 4) and a bar graph was plotted to give a more informed representation of the results. The year 2019 has the best average PLT of 59 hours for 100 hides of 1 batch of corrected grain leather.



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YEAR	BEST AVE. PRODUCTION LEAD TIME (HOURS)
2019	59.0000
2018	60.0000
2017	65.0000
2016	69.0000
2015	80.0000
2014	98.0000

Table 4: B	Best Average	Production	Lead Time	for the	past 5 ve	ars
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4.3 Observations made

A thorough walk-through the Nakara production system was carried out by the researcher, and observations made during the visit included: Familiarization and introduction to the Nakara tannery, Step-by-step observations of the production process operations, and Man and Machine involvement in each process. The production process for corrected grain leather observed at Nakara's tannery is shown in the Process Map (PM), (Fig. 5) below:



Figure 5: Nakara Tannery Process Map for CG Leather production

4.4 Conceptual model

The modular must first design the conceptual model of the case in the simulation model after obtaining all necessary information. The conceptual model enables the researcher to return to the tannery and present the model for approval, if the model makes sense or not. In this study the modular the researcher presented the conceptual model (Fig. 6) to Nakara, and it was approved.



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4.5 Model Assumptions

The study represents a discrete event simulation with the following assumptions: The tannery's work time is 9 hours per day on weekdays, working 6 days a week, with Saturdays working only a 6-hour shift. The machines are available all the time and all workers produce equal output within an equivalent time. Transportation time is included in the processing time at all times and there are no power interruptions. There are always 50 hides (half a batch) queuing every time a new batch of 100 hides is loaded and the production capacity is fixed to take in only a new batch when half a batch has been completed. The mean value for the Random exponential required in creating the simulation random numbers is 0.5 and the raw materials are available in sufficient quantities and all times. Therefore we are interested in; Simulating the system 20 times/replication to obtain a close to accurate average Production Lead-time (PLT) value.

4.6 Model formulation

Considering the definitions and assumptions given in the prior section, the model was developed using this data (Table 5).

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Ta	ble	5:	Data	used	to	compute t	he	conceptual	mod	le	l
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MODEL SYMBOL	DESCRIPTION	MODEL DECIDER	SOURCE
Production processes 1 – 16	These are all the production processes involved in the system	The 3 triangular distribution variable times (a, b, and c) for Each process in hours were used in each process	Process times and the TDM (Table 8)
Jobs in queue 1 – 8	These are jobs that are still in the production process at the point where a new batch is fed into the system	Each JIQ uses the Random (Expo) value of 0.5 and its allocated JIQ quantity as the maximum arrival quantity	Process times and the TDM (Table 8)
Start and finish points	At the starting point, the raw skins are fed into the system. At the finish point, the finished leather hides are dispatched	The start point uses the Random (Expo) value of 0.5 and the value 100 as the maximum arrival quantity. The finish point is a receiving point, hence there are no deciders	The Random (Expo) value is in the model assumption section
Quality control point at the end of the production process	The finished product is inspected for quality, and it is determined whether the product is defective or not at this stage	The percentage of truth is 85%. This means 15% of the production is defective. The defects will be inspected in the next step	The 85% value was obtained from Nakara's data (Table 4), the KPI's average value per month.
Defects reprocessing	This is a logic that takes the defects that can be reprocessed back into the system	The percentage of truth is 75%. This means only 25% of the defects can be reprocessed, and the remainders are complete defects	The 75% value was obtained from Nakara's data (Table 4) KPI's average value per month
Initial defects	At this stage, some defects can be reprocessed	Since this is a receiving point, there are no deciders	Expected simulation output
Complete defects	Unfixable defects are complete waste products	Since this is a receiving point, there are no deciders	Expected simulation output

The simulation model can be seen (Fig. 7) below after it was computed.



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Figure 7: Simulation model at zero replications

Fig. 8 shows the results after simulating the system 20 times/replications. The results have been plotted on a line diagram. It is seen on the line diagram that the average value is closer to the minimum value than the maximum value. We notice that replications 4, 6, 12, 18, and 20's maximum values are way out from the rest; henceforth, they were regarded as outcasts. This is seen after we plotted the line of best fit in red colour (Fig. 8).



Figure 83: Simulation results after 20 Replications



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4.7 Model Validation

In this study, the model was validated by comparing the actual data with the results generated by the simulation model (Fig. 9). The results (Fig. 10) indicate the model has been well designed and is reliable. This was notable when comparing the process average times; the actual average PLT from the data has a value of 59.0000 hours, and the simulated average PLT has a value of 60.1937. These values are in high proximity with a mere offset of only 1.1937, which, if the values were rounded off to the nearest 10, would be the same as the value of 60.0000.



Figure 9: Actual Average. PLT vs. Simulation Ave. PLT

Figure 10: Simulation model results

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5. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

The simulation method for the analysis of this study was successful. The research was able to model Nakara's production system in a simulation model. Two models were created, one using Nakara's current setup and data and another model using the lean improvement tools called the original model and improved model, respectively. The interview held with Nakara's CEO indicate lack of lean knowledge at Nakara. Nakara's production process includes 16 processes with quality controls done at every process, manpower of 96 employees is directly involved in the production process with 24 machines. Key KPI's observed in the form of order delays (20%), machine breakdowns (23%), re-work (25%), over-production (8%), and defects (15%) experienced a monthly average percentage respectively. Nakara's current production lead time for 1 batch of 100 hides of CG leather is 59 hours, and it currently stands as their best PLT since their founding. Formulating the simulation model constituted some assumptions, including the random number generation exponential used of 0.5 to deduce the random numbers for the simulation model, which was one of the key assumptions of the model. The simulation model was simulated 20 times, or replications, to give a leaner and close to accurate result. For validation of the model, the results obtained after simulation were compared to the secondary data. The actual average PLT from the secondary data was 59.0000 hours, and the simulated average PLT was found to be 60.1937 hours with a difference of 0.1937 hours. Since the values are in close proximity the simulation model was deemed satisfactory and reliable.

5.1 Further Research Directions

Future research that could be very helpful to the leather processing industry and its stakeholders include but not limited to: Simulation modeling study considering the total lead time and not only the production lead time to include factors influencing the lead time, including the supplier and end user or client effect. Another is simulation modeling, including different types of leather production – multi-leather type production to help deduce production lead times. Research looking at the organizational work environment setup of leather processing tanneries and the human behavior factor could also be essential. Lastly automated leather processing would be a very important study as the process is automated, providing an accurate production lead time.

Conflicts of Interest: The author declare no conflicts of interest.

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