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Determining Process Variability Using Fuzzy Triangular Distribution in Dynamic Value Stream Mapping

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ABSTRACT

One of the lean tools is value stream mapping (VSM), which is used to visually map and analyze the flow of materials, information and processes required to deliver a product or service to the customer. VSM is widely used to streamline processes, reduce lead time and enhance overall operational performance. While VSM is a powerful tool, some challenges are associated with its conventional application in the manufacturing industry. Conventional VSM typically represents a snapshot of the value stream at a specific point in time. This static representation might not capture modern manufacturing environments' dynamic and evolving nature. Hence, this research addresses the problem of static representation of conventional VSM by applying Fuzzy Triangular Distribution (TFN) in the manufacturing industry by introducing a more flexible and dynamic approach. A conveyor manufacturing company was selected as a case study based on the wide variety and low volume type of manufacturing process. TFN approach was used to analyze variabilities in process parameters to identify their mean, minimum, and maximum values and remove all the outliers. Integrating TFN with VSM gives dynamic behavior to the conventional VSM. Based on the identifications, appropriate lean improvement tools were applied to develop an optimized future VSM. As a result, the future state map shows a 71.74% and 19.45% improvement ratio in terms of production lead time and value-added time, respectively, compared to the current VSM. This study can be further extended by investigating how the reduction of lead time and WIP inventory can help reduce costs for a company.

Keywords: Dynamic, lead time, triangular fuzzy number, value stream mapping, variability

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INTRODUCTION

In today`s competitive business landscape, organizations strive to optimize their processes to ensure efficiency, reduce waste, and enhance overall performance. Value Stream Mapping (VSM) has emerged as a valuable tool for visualizing and analyzing the end-to-end processes within an organization (Lugert, Völker et al., 2018). VSM plays a crucial role in the lean production system by emphasizing activities that add value and pinpointing opportunities to eliminate waste (Lugert, Batz et al., 2018). This tool can be described as a graphical representation used to depict the current state of an organization, determine areas where waste can be reduced, and make decisions on necessary improvements to eliminate waste. It has become a widely adopted technique across various industries and domains and is considered a crucial aspect of lean production (Mudgal et al., 2020; Valencia et al., 2019).

VSM helps identify bottlenecks, inefficiencies, and opportunities for improvement. However, conventional static VSM may fall short of capturing the dynamic nature of processes and the inherent variability that occurs in real-time operations (Krishnan et al., 2018). Product variation due to increasing customer demand refers to the process of adapting or modifying a product to meet customers' changing needs and preferences (Womack et al., 1990). It can include introducing new features, changing the design, or offering different sizes, colors, or styles.

Product variation can be a good way for companies to stay competitive and meet the evolving needs of their customers (Abdulmalek & Rajgopal, 2017). While static VSM provides a snapshot of the process, it often fails to capture the variations that naturally occur due to changing demands, machine breakdowns, workforce availability and other unpredictable factors (Romero & Arce, 2017). These variations can lead to inefficiencies, lower productivity and increased operational costs. Therefore, there is a need to develop a methodology that integrates the concept of process variability into the existing framework of VSM (Venkataraman et al., 2014).

Variability significantly impacts the duration of each stage's cycle time and the work-in-process (WIP) between stages, causing extended wait periods, congestion, and a lack of predictability in terms of input and processing times (Woehrle & Abou-Shady, 2010). This difference arises from numerous factors, including product characteristics, workforce, equipment, and the environment in the value stream (Busert & Fay, 2019).

Thus, obtaining definite values when collecting data on time, inventory, and control parameters is challenging. The ambivalence and inherent variability of data contribute to waste and significant sources of noise in pull systems (Li & Wang, 2017). The failure to consider real variability in VSM is a significant drawback, and this article suggests a fuzzy VSM technique to overcome this weakness by incorporating uncertainty into value stream analysis and improvement (Azizi & Manoharan, 2015).

BACKGROUND STUDY

The primary objective of dynamic VSM is to enhance the conventional VSM approach by incorporating real-time data and variability analysis. The goal is to create a more accurate and holistic representation of the process that takes into account the dynamic nature of operations. It involves capturing the average state of the process and its fluctuations and how those impact the overall performance metrics. Thus, this research presents a comprehensive approach that considers the unique characteristics of the production environment, such as its dynamic impact on the value stream. It is achieved by employing dynamic VSM with triangular fuzzy numbers (TFN) to drive ongoing enhancements in the face of uncertainty. By addressing variability and uncertainty, they can achieve sustained operational excellence.

Value Stream Mapping (VSM)

Value stream mapping (VSM) is a lean tool that helps identify value-added and non-value-added activities in a production process with the goal of continuous improvement by eliminating waste. It is regarded as the most effective and widely used visual tool (Roessler et al., 2015; Tabanli & Ertay, 2013). VSM is used to map the current and future states of a production process and to control variability and uncertainty in the dynamic production process (McDonald et al., 2002). However, the uncertainty inherent in dynamic and complex products, such as the Order (MTO) manufacturing environment, limits the use of traditional VSM in this area (Rahani & Al-Ashraf, 2012; Tasdemir & Hiziroglu, 2019). A fuzzy VSM approach is proposed that considers the inherent vagueness and uncertainty of dynamic production and reflects this uncertainty using fuzzy set theory to address this issue. Fuzzy VSM can visualize uncertainty in a wide range of industrial applications, making it a suitable tool for this purpose. Table 1 shows the lean manufacturing applications and VSM in various industries.

Table 1
Lean manufacturing applications and VSM in various industries

Author/year	Objective	Case Sectors	Results	Contribution
Zahraee (2016)	Integrating the Lean tool of VSM with computer simulation to identify the underlying sources of waste and enhance production rates to meet customer demand	Small-scale heater industry	The production lead time (PLT) was shortened from 17.5 days to 11 days, accompanied by a reduction in value-added time from 3412 seconds to 2415 seconds. Additionally, the takt time experienced a decrease from 250 seconds to 192 seconds.	Future studies could focus on incorporating green manufacturing principles to minimize waste and pollution, fostering economic growth, and establishing mechanisms for recycling industrial waste generated during operational activities.

Table 1 *(Continue)*

Author/year	Objective	Case Sectors	Results	Contribution
Liu and Yang (2020)	This study employs commonality analysis to discern shared processes within a Make-to-Order (MTO) context, aiming to underscore unique characteristics inherent to the MTO environment.	Cast stone manufacturing company based in the UK	The approach presented in the paper, commonality analysis, introduces an additional step to the conventional methodology for creating future value streams. This extra step enhances data analysis for improved insights.	The effectiveness of commonality analysis has been demonstrated, and conducting a more comprehensive analysis could yield even more satisfactory results.
de Paula Ferreira et al. (2020)	To introduce an expansion of the VSM idea that involves calculating the costs linked to essential operations and the overall expenses of the complete production process	Production of ceramic capacitors	The suggested approach for evaluating the efficiency and flexibility of a production process relies on cost-based Value Stream Mapping (VSM), portfolio analysis, and simulating the impact of enhancements on the economic effectiveness of the production system.	Extending conventional VSM to capture time and cost analysis through a simulation program
Busert and Fay (2019)	The goal is to introduce an innovative method for creating a Lean Service System within the India Post service sector. This method involves using Simulation to simplify the system and reduce its complexity.	India Post service industry	The discovery reveals a 9.62 percent improvement in the delivery of items per individual.	This research marks the first instance of merging Value Stream Mapping with Simulation (VSM-Sim) to model and enhance the operational performance factors of mailing service operations.
Ghobakhloo and Fathi (2019)	To analyze the role of VSM in healthcare services by eliminating everything that adds no value to the organization	Healthcare services	VSM helps reduce patients' waiting time in healthcare lines by synchronizing different activities. Secondly, VSM helps to standardize symbols and make them easier to understand.	As the lean approach has been introduced in healthcare organizations, VSM and other tools related to process improvement have been incorporated into these organizations.

Table 1 *(Continue)*

Author/year	Objective	Case Sectors	Results	Contribution
Mudgal et al. (2020)	The objective is to expand the application of Value Stream Mapping into the context of Industry 4.0, focusing on supporting Industry 4.0 efforts in manufacturing firms, particularly in smaller and medium-sized enterprises (SMEs).	Small and mid-size enterprises (SMEs)	VSM combined with hybrid simulation can assist Industry 4.0 roadmap development and help companies understand changes in materials, equipment, processes, and information flows associated with Industry 4.0 application scenarios.	This study explores the integration of the Lean practice value stream mapping (VSM) with hybrid simulation (HS), which combines discrete event and agent-based modeling and simulation, contributing to reducing this research gap.

FUZZY VSM

Fuzzy VSM is used to convert ambivalence into fuzzy numbers to deal with the uncertainty of value stream parameters in a computational manner (Stadnicka & Litwin, 2019). A subset of the real number set is known as a fuzzy set that denotes unsure figures (Liu & Yang, 2020). Zadeh (1965) denotes a class of items with a variety of degrees of membership as what is meant by a fuzzy set. The degree draws attention to whether a piece of equipment is entirely inside the set, entirely outside, or halfway inside and halfway outside. This set's membership is promoted rather than connected to a probability distribution.

According to Liu and Yang (2020), inventories, periods, and other operating factors in a value stream, such as TFN and NFN, were acquired to represent inventories, periods, and other operating factors in a value stream. A commercial strategy demonstrates the applicability and efficacy of the suggested A production lot for incorporating variability in VSM analysis for both TFN and NFN forms. Based on the results, Liu and Yang (2020) conclude that Triangular fuzzy VSM chooses, in a complex manufacturing environment with complex operational procedures, to misinterpret the unpredictability of the process. The author suggests that to improve the accuracy of VSM analysis, fuzzy VSM should be analyzed through a simulative approach.

Integration of VSM with Fuzzy Algorithm

According to Braglia et al. (2009), the traditional VSM procedure is not able to provide an actual illustration of the production process ambiguity issues related to the analysis. Besides, variability is one of the main elements affecting the work-in-process (WIP) between side-by-side processes and the cycle time of each stage. The variability impacts the queueing time and leads to blocking and unreliability in inputs and time of the process (Chen et al., 2013). Uncertainty occurs in many aspects, including WIP, equipment, manpower, and the environment of the value stream (Faulkner & Badurdeen, 2014). Hence, it causes difficulty when collecting data related to time, inventories, and other operating variables (Zahraee, 2016). Additionally, one of the main causes of waste is the inaccuracy of data and the inherent fluctuation in such statistics (Stadnicka & Litwin, 2019), and it stands out when it comes to pulling system inputs, outputs, processes, unpredictable breakdowns, and random setup times (Dai et al., 2012).

Given the problems, one of the key drawbacks of VSM is the inadequate treatment of actual variability in the value stream (Liu & Yang, 2020). To overcome this weakness, Braglia et al. (2009) suggested a few substitute methods based on fuzzy algebra and statistics, respectively. Both approaches were created to ease the users' understanding and applied to company practices. Pacchini et al. (2019) mapped the value stream using fuzzy set theory and chose the optimum future-state VSM. Although they suggest a fuzzy VSM method to manage variability in value stream analysis and enhancement, these two studies solely utilize triangular fuzzy numbers to represent values in VSM. They do not explore the appropriateness of other fuzzy expressions in diverse production settings. (Deshkar et al., 2018).

Triangular Fuzzy Number (TFN)

A mathematical arithmetic framework is required to control the uncertainty of value stream specifications in a computation method. According to Zadeh (1965), a fuzzy distribution has been established based on the theory of fuzzy sets as a possible methodology for the mathematical control of variability and unreliability (Galan et al., 2007; Karim et al., 2012).

Due to varying membership degrees, Zadeh (1965) denotes a fuzzy set as a class of objects. This set is organized by the membership function $\mu(x)$, which maintains a membership degree for each object class between zero and one. It also implies that an object or element is probably "a little" included in the set, whether it exists inside the set or not. This set's membership changes frequently and is irrelevant to a probabilistic function (Guo et al., 2019; Gurumurthy & Kodali, 2011).

Triangular fuzzy numbers are used for further modeling. More complicated membership functions increase computational demands without enhancing any appreciable returns (Braglia et al., 2009). Triangular fuzzy numbers are likewise simple to use and reasonably depict the circumstances being examined (Ferreira et al., 2020). Fuzzy numbers express the uncertain aspects of value stream indicators such as cycle times, inventories, and lead times (Detty & Yingling, 2000). Since value stream analyses cannot produce probabilities due to their qualitative nature, utilizing theoretical variables is not considered in this scenario.

The purpose of applying fuzzy set theory is to translate the unpredictability of value stream features into fuzzy numbers for computational management. A fuzzy set is a subset of real numbers that represent uncertain values. It is defined by a membership function μ(x) that assigns a membership degree from zero to one to each object class. Based on this degree, an element can be fully inside, entirely outside, or partially within the set. The membership degree is graded and is not linked to a probability distribution. This research introduces a triangular fuzzy number (TFN) to illustrate the variability in value stream management (VSM).

Data collecting must be done properly to express the process and waiting times with the suitable TFNs. This study gives a parameter identical to the previous study and is used to calculate the values of a, b, and c, as suggested by Liu and Yang (2020).

MATERIALS AND METHODS

The integration of Fuzzy Triangular Numbers with Value Stream Mapping was introduced to build a dynamic VSM that can capture variability and uncertainty in a complex and more customized production operation such as an MTO manufacturing industry. It consists of a set of steps: (1) Collection of manufacturing process data, (2) analysis of process variability using Triangular Fuzzy Number, (3) Implementation of lean improvement tool, and (4) Design of future state VSM.

Case Study

A conveyor chain manufacturing company, referred to as CM, is studied to display the utilization of fuzzy value stream mapping to integrate variability/uncertainty in value stream analysis. CM is a make-to-order manufacturing company with an average production rate of 1,500 m of chain per week. The production process comprises a shop flow system that is segmented into six primary stages: (1) coining, (2) drilling, (3) chamfering, (4) welding, (5) heat treatment/coating/plating (sub-cont), (6) sub-assembly, (7) main assembly and (8) quality check and packaging. All these activities are carried out within the company except for heat treatment/ plating or ed-coating, which are outsourced to various subcontractors. The choice of a conveyor manufacturing company as a case study is attributed to its ability to operate in a wide variety of processes and low volume. The production process is made-to-order, and a wide range of goods have various process parameters. Its unchanging and rigid nature characterizes a VSM and is inefficient in capturing varying process parameters. Hence, this research demonstrates controlling variability using fuzzy algorithms and mapping the current value stream.

Designing Current Value Stream Map

In order to progress a current state map, it is relevant to collect information regarding shipment frequency and quantity, client orders, processes involved in product manufacturing processes, for instance, changeover times (COs), cycle times (CTs), variables such as the number of operators, the frequency and amount of materials received, the quantity and storage locations of inventory, and working time related to the manufacturing system data collection involved gathering and meticulously reviewing 100 data sets to create a sufficient sample for subsequent analysis. Additionally, data pertaining to the quantities of raw materials, work-in-progress (WIP), and finished products were collected according to the flow chart shown in Figure 1 to build the Current VSM.

The time was taken to measure the cycle time (C/T) when the worker had finished repeating a particular task. The measurements include the manual cycle time and machine cycle time. The machine cycle time indicated on value-added actions and the manual cycle time measured are non-value-added actions but necessary. Manual and machine cycle time are considered for the calculations in all the workstations. Although there was available cycle time stated in the production job sheet, the researcher conducted a time study using a stopwatch. Since it is not distinguished that the recorded cycle times were measured in the condition of the machine and the status of the workers, according to the Rother and Shook (2003) recommendation, cycle times were measured at the time of investigation to explore the real condition of the value stream.

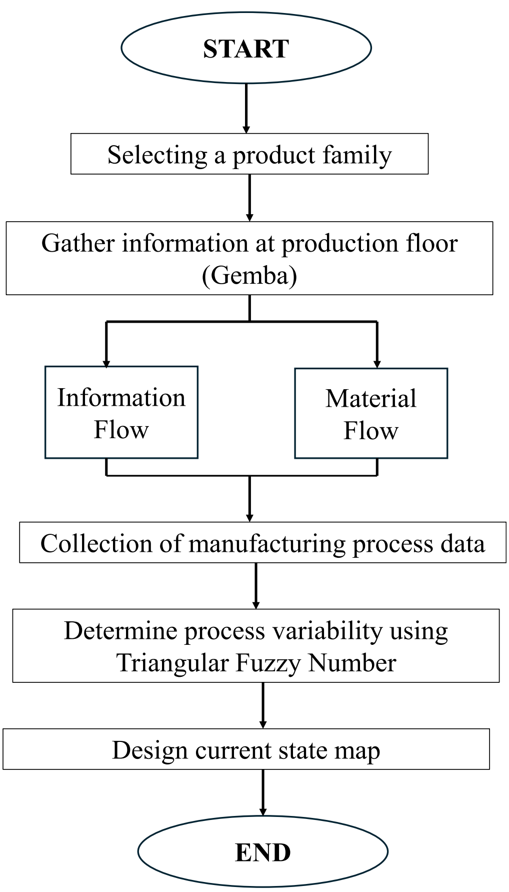

Figure 1. Flowchart to build Current VSM

Analyze Process Variability Using Triangular Fuzzy Number

The Conveyor Manufacturing (CM) facility is overseen by an ERP production control system, which transmits a daily schedule to individual workstations. The first method uses TFN to show how long an item spends at each stage of manufacture. While TFNs offer a compromise between computational cost and the accuracy of the final ranking, their use in the context of VSM seems reasonable. An ordered quartet = (a, b, c) defines a generic TFN, where a and c stand for the lower and upper bounds, respectively. The fuzzy degree is indicated by c-a, with larger values indicating a higher degree of fuzziness. TFNs provide a favorable trade-off between computation c. If a=b=c, TFN diverges into a real number. The interval [a, c] is represented as the support of Ã as shown in Equations 1 to 4.

The following relation details the bilinear relation that constitutes the membership function μÃ(x):

$$\mu\tilde{A}\,(x) = \begin{cases} 0, & x \leq a, \\ \dfrac{x-a}{b-a}, & a < x \leq b \\ \dfrac{c-x}{c-b}, & b < x \leq c, \\ 0, & x > c, \end{cases} \qquad [1]$$

(i) α = 1: μ(x) = 1 denotes the value x unequivocally falls within the range of potential values.
(ii) α = λ: μ(x) > λ means that the value λ has a possibility of μ(x)> λ falls within the range of potential values

Hence, the value of b is established as the average of the sample data for condition α-cut α**1** = 1. The sample's minimum and maximum values correlate to an α-cut α2 = 0.1 rather than to 0 to integrate other possible maximum values that are unable to be expressed by inspection to incorporate more potential maximum values that cannot be conveyed by inspection.

$$\mathrm{a} = \frac{(\min(sample) - 0.1b)}{0.9} \qquad [2]$$

$$\mathrm{b} = \mu\ (\mathrm{sample}), \qquad [3]$$

$$\mathrm{c} = \frac{(\max\,(sample) - 0.1b)}{0.9} \qquad [4]$$

Implement Lean Improvement Tools

After identifying waste by mapping the current state, actions need to be taken to reduce or eliminate the waste in the next stage. Waste can occur in two different stages: one at the managerial level and another at the worker level. The waste that occurs at the worker level is selected for further improvements using the Value Stream Mapping (VSM) tool. The causes of waste can be grouped into two classes: behavioral and information factors. The root of each waste is distinguished by using the number of questions and the trace of causes, including behavioral and information factors (Romero & Arce, 2017).

A future state map is then created by eliminating waste at the worker level. In the future state map, it is tried to make the flow continue through waste elimination. It can dramatically reduce throughput time and almost always reduces costs substantially. Achieving frequent, continuous flow requires brainstorming, but the straightforward road map for mapping the future state is answering several questions stated by Rother and Shook (2003).

Answering these questions gives us an idea of the future state's mapping needs. The step-by-step answering of these questions leads the researcher to map the optimized state map. Hence, to answer the questions, the appropriate data was collected to map the current state. The first five questions concern "basic” issues in constructing the future state map, as shown below.

1. What is the Takt time for the projected product family at the conveyor manufacturing company?
2. Should the products produced be directly shipped or sent to a finished goods supermarket?
3. Where will CM use a pull system supermarket inside the value stream?
4. Where can continuous flow be used?
5. What process improvement tools will be needed to achieve the future state design?

Design Future State Value Stream Map

The fuzzy set theory is performed to context preceding data sets at the beginning to determine the most appropriate future state, which is practical. It is carried out to convert the vectors to make the input data for the following decision-making process more comprehensible. Therefore, for every output C = {c1, c2,…cj} associated with each future state A = {a1,a2,..., ai}, a fuzzy number must be constructed from the n unique data sets (Xks = ck(as)) n. The values of m, α, and β must be determined, as shown in Equations 5 and 6, to express each column of simulation results as a fuzzy number.

The triangular form is used to depict data as the middle value (m), and the median (also known as the 50%-quantile or Q 0.5-value) from the set of n results is considered the best approximation. The median separates the set into two parts, one with larger numbers and the other with smaller numbers. Additionally, the median is considered the best choice for elaborating accumulations in sets (Zahraee, 2016). The lower and upper spreads are measured by incorporating the 5% and 95% quantiles to minimize the impact of outliers on the fuzzy sets' absolute spread. Figure 2 shows the holistic view of the methodology used in this study, and Figure 3 shows the representation of Triangular Fuzzy Distribution.

$$\text{m for all n} \qquad m = Q_{0.5}\ \{X_{id0},\ldots,X_{idn}\} \tag{5}$$

$$\text{a and b for all n} \qquad a = m - Q_{0.05}\{X_{id0},\ldots,X_{idn}\}$$

$$b = Q_{0.95}\ \{X_{id0},\ldots,X_{idn}\} - m \tag{6}$$

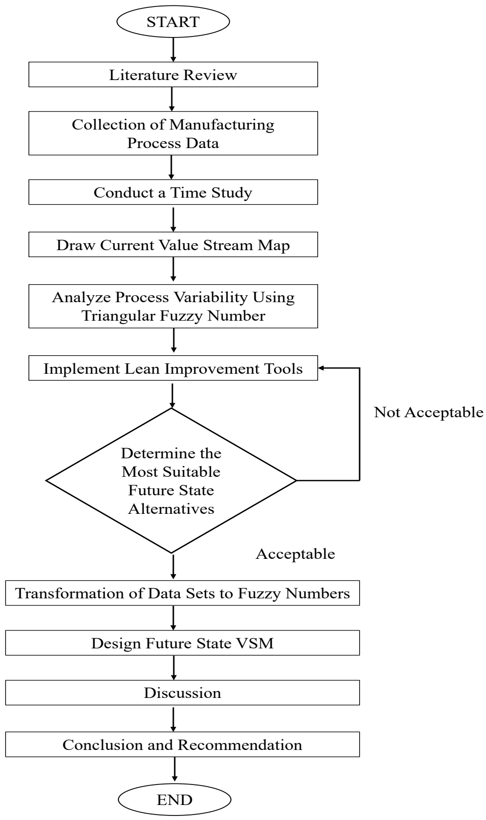

Figure 2. A holistic view of the methodology

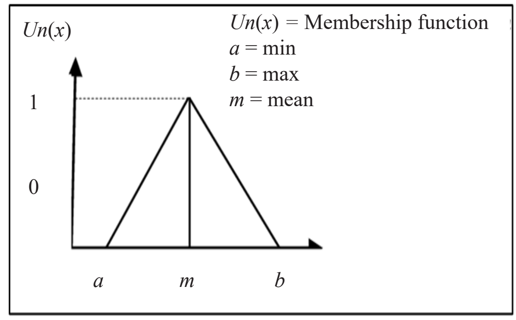

Figure 3. Representation of Triangular Fuzzy Distribution

RESULTS

The proposed methodology is implemented in a real case study for the dynamic value stream mapping conducted by integrating with fuzzy triangular distribution and providing manufacturing process data.

Current State Analysis

Current state analysis and their processes are explained in detail. The processes are grouped into two main categories: value-added activities (VA) and non-value-added activities (NVA).

i. A product family was selected to prevent complexity in mapping the value stream of CM. Three family products are identified in this conveyor manufacturing company: single former chain, double former chain, and condom chain. Among these three, only one product family is chosen based on their common process and high customer demand, as shown in Table 2.

Table 2
Product family selection

Product/ Workstation	STP 1	MAC	WEL	STP 2	Sub-Cont	ASY 1	ASY 2
Single former chain	X	X			X	X	X
Double former chain	X	X	X	X	X	X	X
Condom chain	X	X			X	X	X

ii. Information flows from upstream, which begins with receiving customer orders. Production Planning and Control (PPC) creates production orders and bills of materials based on the sales orders.

iii. Material flows from downstream to upstream, starting from receiving goods from suppliers. Figure 4 shows the sequence of material flow at CM.

iv. Manufacturing process data were collected by measuring the cycle time (C/T), including manual and machine cycle times.

v. Other than C/T, other process parameters include machine changeover time (C/O), every part every x (time) (EPEx), the number of operators, and the number of inventories between stations.

vi. Average daily output is calculated as Equation 7.

$$\text{Average daily output} = \frac{\text{Demand}}{\text{Working Days}} = \frac{84{,}240\text{ meter}}{156\text{ Days}} = 540\text{ meters/day} \qquad [7]$$

vii. Takt time is calculated based on the available production capacity over customer daily demand, which is 780 minutes, as shown in Equation 8.

$$\begin{aligned}\text{Takt Time} &= \frac{\textit{Net Available for Production}}{\textit{Customer's Daily Demand}} \\ &= \frac{780\ \textit{minutes}}{270\ \textit{coil}} \qquad [8] \\ &= 173\ \textit{seconds/coil}\end{aligned}$$

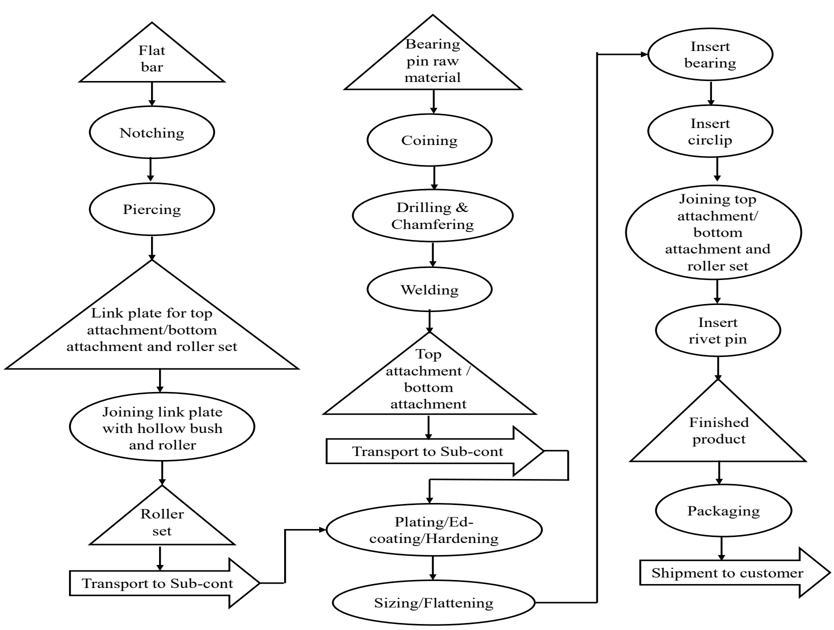

Figure 4. Sequence of material flow at CM

Triangular fuzzy numbers were used to distribute process data to (min, mean, and max) and standard variables using mean and variance based on the 100 groups of data sets. Table 3 shows the data distribution for five different processes.

Table 3
Triangular Distribution for measured cycle time and buffer/WIP for five workstations

	Standard Variable		Observed Value			TFN
	Mean	Std. Dev	Min	Mean	Max	
Raw material inventory (days)	6.03	2.37	1.1	6.03	12	(1.1, 6.03, 12.0)
Coining (s)	89.84	6.74	68.02	89.84	100.01	(68.02, 89.84, 100.01)
Buffer 1 (days)	3.42	1.72	1.2	3.42	7.01	(1.2, 3.42, 7.01)
*Drilling (s)	208.13	7.66	191.1	208.13	225.01	(191.10, 208.13, 225.01)
Buffer 2 (days)	5.78	2.09	1.2	5.78	9.10	(1.2, 5.78, 9.10)
Chamfering (s)	89.97	7.06	68.01	89.97	100.01	(68.01, 89.97, 100.01)
Buffer 3 (days)	4.02	1.85	1.11	4.02	8.20	(1.11, 4.02, 8.20)
Welding (s)	97.52	8.67	90.1	97.52	122	(90.1, 97.52, 122)
Buffer 4 (days)	2.42	1.72	1.11	2.01	4.2	(1.11, 2.01, 4.2)
*Assembly (s)	331.07	12.97	288.2	331.07	375	(288.2, 331.07, 375)
Buffer 5 (days)	3.42	1.68	1.01	3.42	7.03	(1.01, 3.42, 7.03)

viii. Table 3 depicts the current value stream of the conveyor manufacturing in Figure 5. The timelines for the standard and triangular fuzzy number (TFN) approaches are demonstrated in Figure 5.

ix. The present state map (Figure 5) illustrates that the overall production lead time (TPLT) is 28 days, while the total value-added time (TVAT) is only 13 minutes, which leaves a significant gap for improvement.

x. Using the triangular fuzzy timeline, TPLT (days) denoted as µA(x) ~ (11.01, 28.87, 54.24) and TVAT (min) denoted as µB(x)~ (11.73, 13.61, 15.37) with the following Equations 9 and 10, respectively.

$$\mu A(x) = \begin{cases} 0, x < 11.01 \\ \frac{x - 11.01}{17.86}, 11.01 \leq x \leq 28.87 \\ \frac{54.24 - x}{25.37}, 28.87 \leq x \leq 54.54, \\ 0, x < 54.24. \end{cases} \quad [9]$$

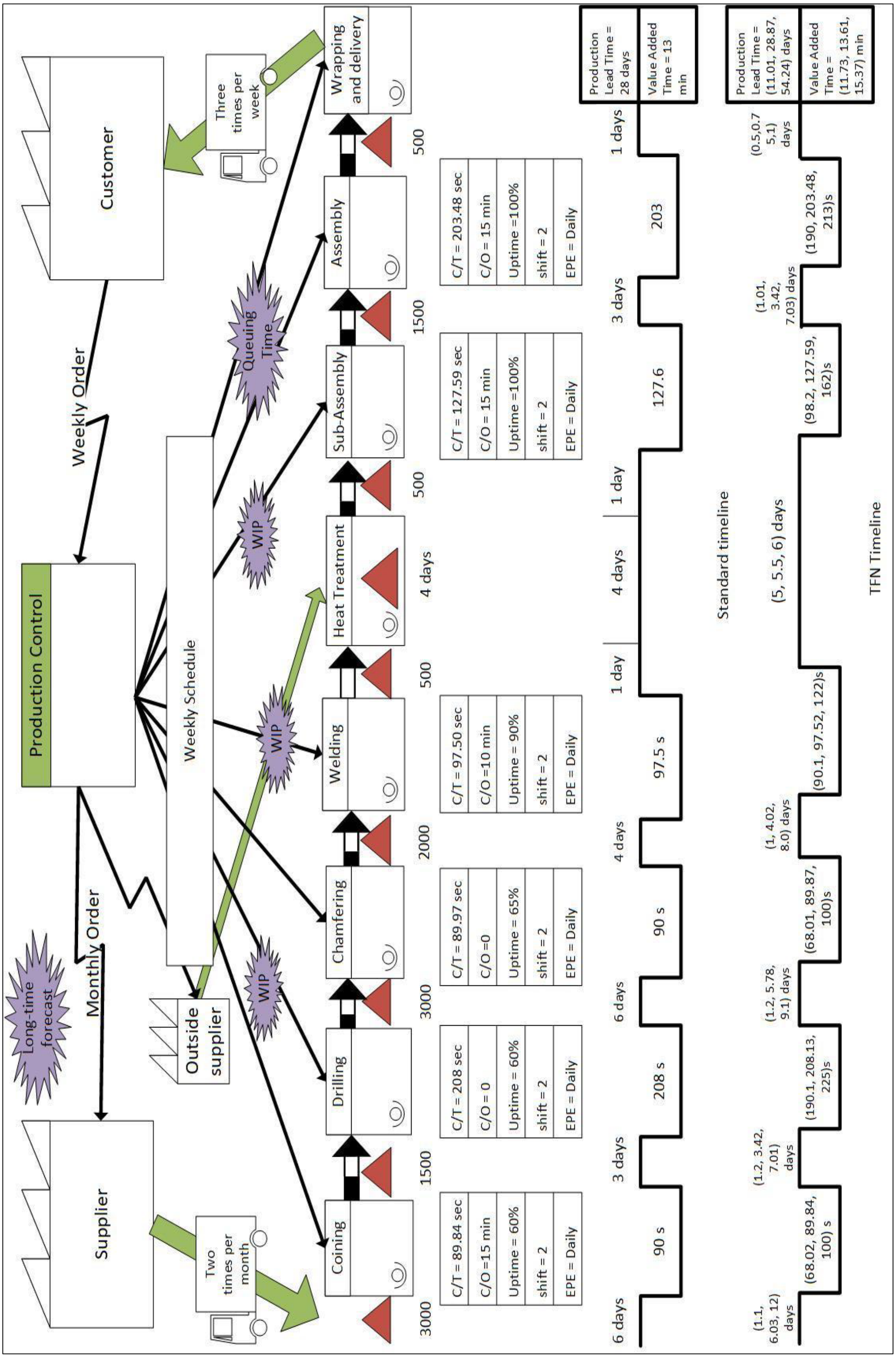

Figure 5. Current value stream map

$$\mu B(x) = \begin{cases} 0, x < 11.73 \\ \frac{x - 11.73}{1.88}, 11.73 \leq x \leq 13.61 \\ \frac{15.37 - x}{1.76}, 13.61 \leq x \leq 15.37, \\ 0, x < 15.37. \end{cases} \qquad [10]$$

Developing Future State Mapping

In order to create a future state map, the areas of improvement in the current state map must be determined. As listed below, several problems are identified on the production floor, mainly due to unsystematic process flow lines.

1. Large amounts of inventories and WIP are in each processing department.
2. There are big differences between the total production lead time (28 days) and value-added time (13 min)
3. High process variabilities, such as in cycle time and setup time due to different product models
4. Unbalanced utilization of workers
5. Complexity in production planning and a high amount of inventory
6. Delayed in the arrival of subparts from subcontractors after the heat-treatment/ plating/ Ed-coating process.

Lean manufacturing aims to improve production efficiency by producing quality output according to specifications and delivering it to customers on time. Although the purpose of this research is to focus on reducing total production lead time, the lead time and inventory are two equivalent factors.

Implement Lean Improvement Tools

Waste is identified by analyzing the material and information flow in the value stream based on the current state map. In order to redesign the current state map and develop an improved future state map, a set of questions needs to be answered. There are five questions in total related to the basics of the construction of a future state map. Below are descriptions of the answers to the questions from 1 to 5.

Question 1: What is the Takt time for the proposed product family of the CM?

i. Takt time is calculated based on Equation 8, which is 173 seconds/coil.

Question 2: Where will the supermarket system be used inside the value stream by the CM?

ii. A "supermarket" is similar to a storage area (a space allocated to keep finished goods) packed and ready to be shipped. Supermarkets aim to control the process, which cannot be linked to the continuous flow. The supermarkets enable CM to minimize the inventory. As a result, the lead time was reduced, and the turnover ratio increased. In similar orders, supermarkets can be dedicated with similar planning. So that once a coined bearing pin becomes full, the workstations are arranged to produce other orders.

Question 3: Where will CM use a pull system supermarket inside the value stream?
iii. The pull system works as a channel where the welding department is located at the beginning and the sub-contractor at the end of the value stream. Hence, any excess inventory or disturbance caused by the push system at this channel can be controlled easily.

Question 4: Where is the continuous flow technique applied?
iv. The balance chart, as shown in Figure 6, indicates the variabilities for cycle times at CM.

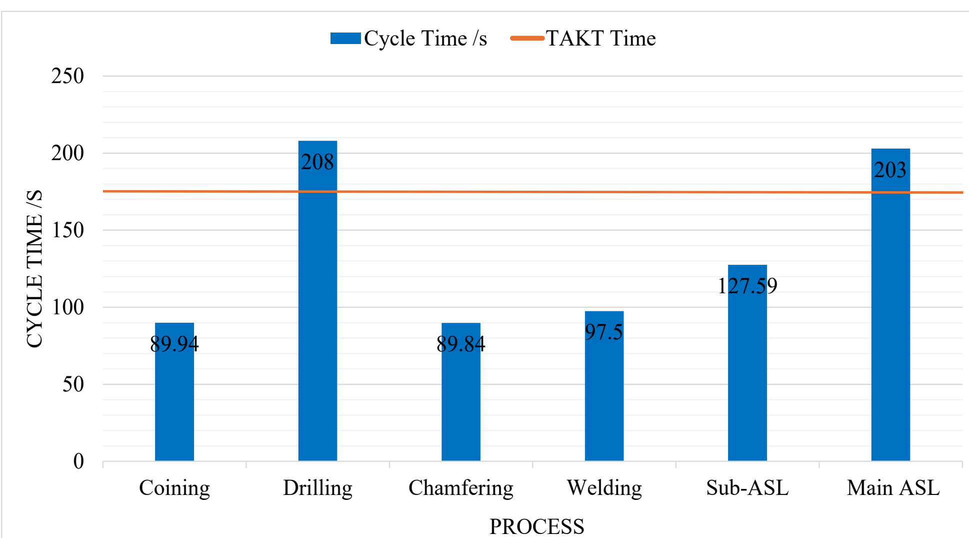

Figure 6. Balancing chart of current value stream

v. Figure 6 shows that the major obstacles to balancing the cycle times are the drilling and main assembly stations, which have higher cycle times than takt time.

a. Two different areas are drilled separately on the bearing pin at the drilling station, called the center drill and top drill. The setting time taken by the current operator to change the chuck is 3.26 minutes or 196 seconds on average, plus 7 seconds taken to clean the burr. If the current worker changes with an expert worker, it can help to reduce the manual setting time from 3.26 minutes to 2.5 minutes on average. Eventually, the cycle time at this station can be reduced to 157 seconds, and the output can be increased from 1125 units to 1400 units per day.

b. The main assembly department has particular production features and can be improved by balancing skilled and unskilled workers evenly between night and morning shifts. The cycle time in this department is 203 seconds, which is higher than the takt time. In order to increase the current output at the main assembly department, the unskilled workers must work alongside the skilled workers. As such, the workers are rebalanced by arranging three skilled and two unskilled workers in the morning shifts and two skilled and three unskilled workers in the night shift. Through these arrangements, the current output from 230 units per day to 280 units can reduce the cycle time to 167 seconds.

vi. Figure 7 shows the improved cycle times for the stations. The workloads for each station are balanced according to the following explanations.

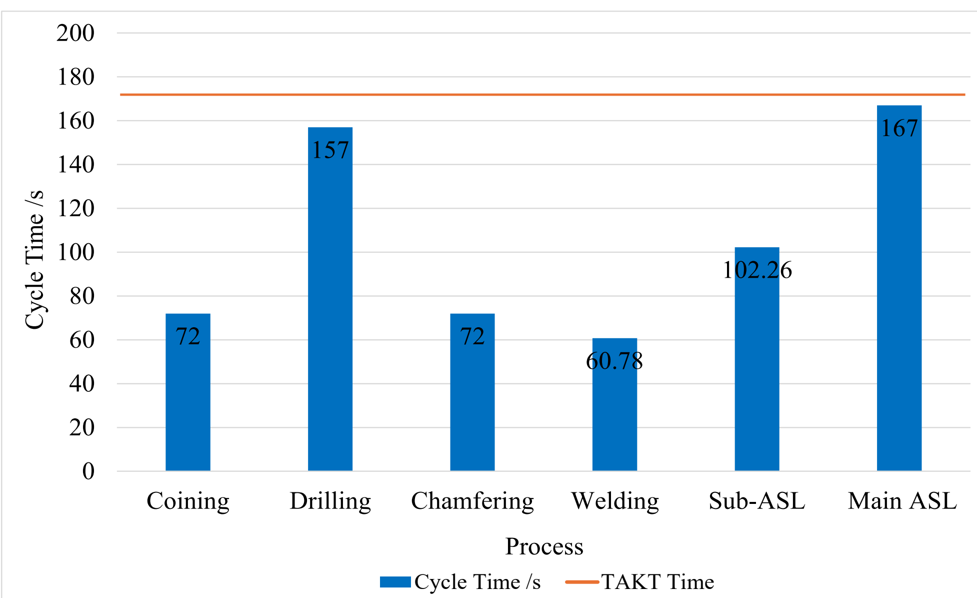

Figure 7. Balancing chart of future value stream

Question 5: What process improvement will be needed to achieve the future state design?

vii. Using the transfer of Kanban cards is the most effective tool for designing a smooth flow. The Heijunka box decides when the Kanban card should be released. FIFO and the one-piece-in-flow method manage the continuous flow before sending it to sub-contractors and welding workstations. So, the production Kanban cards should be sent to the coining workstation directly at every pitch. The pitch is calculated by multiplying the Takt time or coefficient by the quantity of finished goods transferred. At every pitch, one production Kanban was dispatched to the welding department. In each turn, the orders are released at a fast pace, and the finished products are stocked at the FIFO channel before delivery to the subcontractors. So, the pace of production is maintained a constant role.

The type improvements for the future state map are summarized in Table 4.

Table 4
Improvement for future state map

Improvement in	**Information Flow**	**Reduction of monthly order from 250k of raw materials to 150k based on actual monthly output**
		Controlling information flow using heijunka box instead of sending individual production orders from production control
		Use Kanban cards to send order schedules between stations to control the pull system at CM.
		Routinely check and fix the production order schedule on the CM shop floor.
	Material Flow	Minimizing raw material and parts delivery from a weekly to monthly.
		Standardize and control buffer inventory between each station using the supermarket.
		Overproduction is removed at each station, and buffer inventory is predefined based on the demand in the next station and Takt time.
		Reduction of cycle time in drilling machine using controllers and sensors (TPM technique) and use of expert operator
		Using the one-piece-in- flow technique in the sub-assembly department
		Using the First-In-First-Out (FIFO) technique before sending products to outside suppliers to prevent overproduction
		Fixing the lot size delivery to 20 pallets equivalent to 270 units of conveyor chain

Based on the lean improvement tools described in Table 4, a future state value stream was developed and depicted in Figure 8, which includes all information transfer, material movement, and recommended kaizen.

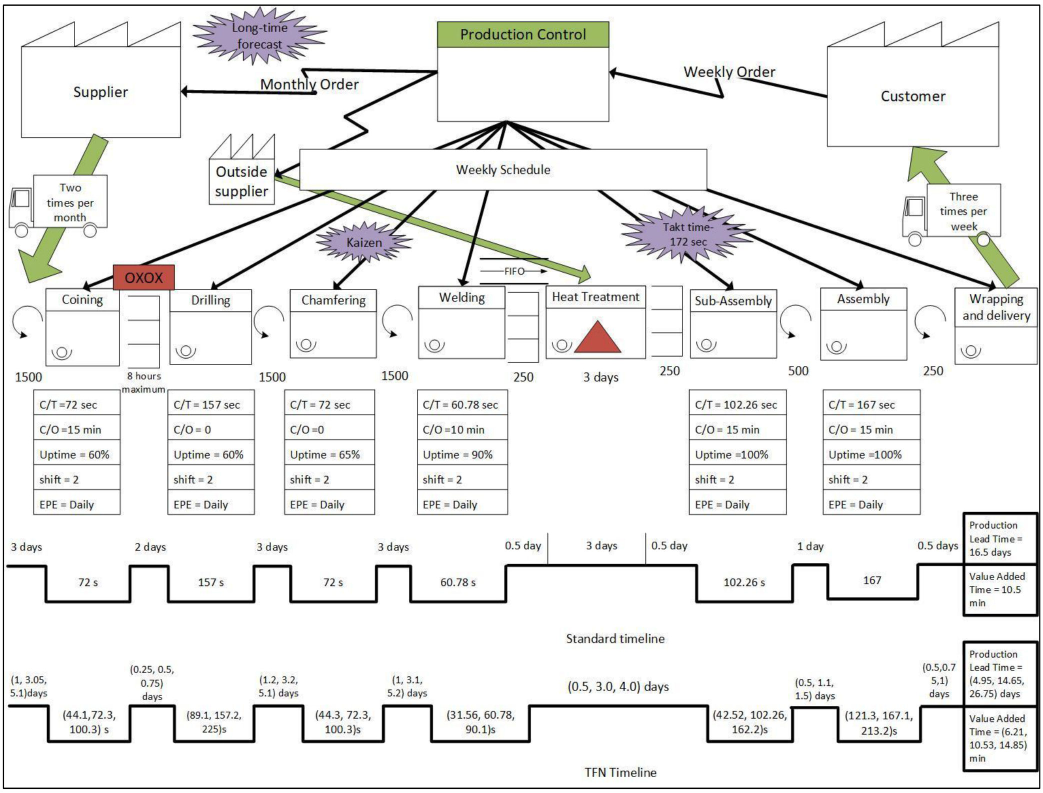

Figure 8. Future value stream mapping

Analysis of Future VSM using Triangular Fuzzy Number

Data representation in the triangular form as a middle value (m) uses the median (also referred to as the 50% quantile or Q- 0.5 value) from the set of n results as the most suitable approximation. The median splits the set into two number groups, one with larger values and one with smaller ones. Furthermore, the median is ideal for describing accumulations within sets (de Paula Ferreira et al., 2020). The information regarding the approximation of future state designs, FVSM, and their transformation into fuzzy numbers is detailed in Table 5 based on Equations 5 and 6. The visualization of triangular fuzzy numbers is denoted in Figure 9.

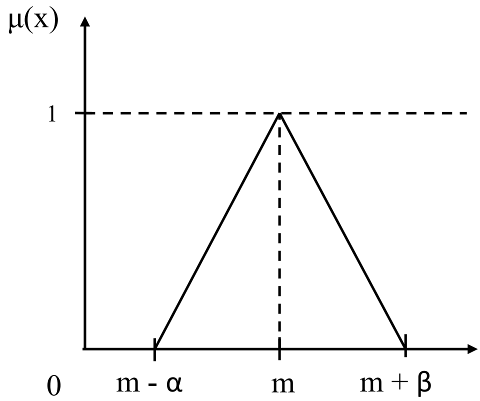

Figure 9. Visualization of triangular fuzzy numbers (TFN) (Liu & Yang, 2020)

DISCUSSION

Integration of Value Stream Mapping with Triangular Fuzzy Analysis aligns with the growing trend of incorporating uncertainty analysis into process improvement methodologies. Similar studies have utilized fuzzy logic, Monte Carlo simulations, and other probabilistic methods to capture the inherent variability present in operational processes. While different studies employ varied techniques, this study contributes by applying Triangular Fuzzy Analysis to Value Stream Mapping, enabling it to address uncertainties in process time, inventory, and resource availability.

Table 5
TFN for calculated cycle time and WIP for FVSM

Cycle Time and WIP	Stock at a defined minimum	Stock at physical maximum	Fuzzy stock (m;α;β)
Raw material inventory (days)	1	5	(3; 2; 2)
Coining (s)	44	100	(72; 28; 28)
Buffer 1 (days)	0.25	0.75	(0.5; 0.25; 0.25)
Drilling (s)	89	225	(157; 68; 68)
Buffer 2 (days)	1	5	(3; 2; 2)
Chamfering (s)	44	100	(72; 28; 28)
Buffer 3 (days)	1	5	(3; 2; 2)
Welding (s)	31.56	90	(60.78; 29.22; 29.22)
Sub-Assembly (s)	42.52	162	(102.26; 59.74; 59.74)
Buffer 5 (days)	0.5	1.5	(1; 0.5; 0.5)
Main-Assembly (s)	121	213	(167; 46; 46)

Incorporating Triangular Fuzzy Analysis enhances the accuracy of decision-making processes by explicitly considering uncertainties. It equips managers with more robust insights to develop adaptable strategies that perform well under various scenarios. For instance, they can allocate additional resources to critical process stages that exhibit high variability due to uncertain factors.

Consider a manufacturing company aiming to optimize its production line. Traditional VSM identifies a bottleneck in the assembly stage, suggesting increased machine capacity as a solution. However, fuzzy analysis reveals that machine breakdowns and variations in worker efficiency significantly impact assembly time. The managerial implication is investing in machine capacity, developing preventive maintenance schedules, and cross-training workers to mitigate uncertainties. This holistic approach ensures consistent production even when unexpected events occur.

CONCLUSION

The study's integration of Value Stream Mapping (VSM) with Triangular Fuzzy Numbers (TFN) has substantially contributed to process optimization and uncertainty management. Based on the identifications, appropriate lean improvement tools were applied to develop an optimized future VSM. As a result, the future state map shows a 71.74% and 19.45% improvement ratio in terms of production lead time and value-added time, respectively, compared to the current VSM.

While the study presents a novel approach, it is important to acknowledge its limitations. One potential limitation is the complexity associated with determining appropriate membership functions for TFN. The accuracy of results heavily depends on the selection of membership function parameters, which might be challenging to establish in some contexts.

Future studies can build upon the work to further refine and expand the application of VSM with TFN. Exploring alternative methods for membership function determination, such as data-driven or expert-driven approaches, could help mitigate uncertainties associated with TFN modeling. Furthermore, research could delve into integrating TFN with other process improvement methodologies, such as Six Sigma or Lean Thinking. Investigating how TFN can contribute to optimizing processes within the context of broader quality and efficiency improvement initiatives could open new avenues for research.

The principles of VSM are universally applicable and widely recognized as effective tools for identifying process inefficiencies. Similarly, TFN, as a representation of uncertainty, is a concept that transcends industry boundaries.

In summary, the study's integration of VSM with TFN offers a novel pathway for addressing uncertainty in process optimization. Its significant contribution lies in combining systematic process mapping with a quantitative representation of uncertainty, resulting in more informed decision-making. As the industrial landscape continues to evolve, this work is a foundation for fostering resilient and adaptable operations in diverse industries worldwide.

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