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Assessment of Production Costs in Toyota Production System Simulation Based on Makespan

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Abstract

This study examines the impact of makespan on production costs by comparing the Toyota Production System through simulations with three scheduling algorithms: the Initial Method, Simulated Annealing (SA), and Tabu Search (TS). This analysis explores the makespan, total production costs, and unit costs across three varying demand levels. Results show that SA and TS achieve a lower makespan than the Initial Method, although their total production costs are slightly higher. However, as demand increases, unit costs decrease in SA and TS, suggesting improved economies of scale with these methods. These findings highlight critical trade-offs between time and cost, emphasizing the importance of aligning scheduling choices with the company's strategic goals. Additionally, the study addresses managerial aspects such as Break-even analysis, production constraints, and technology investments. Limitations include a restricted demand range and the exclusion of external factors, suggesting areas for further research on production quality in manufacturing.

Keywords
Production Costs, Makespan, Toyota Production System, Simulated Annealing, Tabu Search.

Introduction

In facing industrial competition and globalization, an optimal production process is crucial for manufacturing companies to enhance competitiveness and achieve operational efficiency. The Toyota Production System (TPS) was born as a concept that reviews in depth the balance between time and cost efficiency to obtain optimal productivity (Mielczarek, 2023; Almeida et al., 2023). Several methodologies have been applied to improve the production process and reduce downtime, such as the use of verification sheets to activate production inefficiencies and the development of decision support methods for dynamic production planning, which ultimately contribute to increased productivity and reduced costs (Almeida et al., 2023; Skėrė et al., 2023). In addition, the integration of simulation tools such as the Witness program helps in the identification of barriers and incentives for improvement in the production process, which supports faster decision making and process optimization in the manufacturing sector (Schindlerova et al., 2023). Estimating production scheduling in a production process can affect how businesses respond to market demand and manage production capacity (Hu et al., 2023). By accurately estimating revenue, businesses can achieve better work planning and improve operational effectiveness. In addition, proper job scheduling is essential so that it does not incur high production costs and can minimize overall costs (Su et al., 2022). Lead time for Computer Integrated Manufacturing Systems (CIM) using techniques such as optimal time control of Time Weighted Systems (TWS), through the complexity of the TWS algorithm can be difficult (Vargas et al., 2022). In addition, the performance of the integration platform in the production process is affected by the execution model applied to the execution engine, which affects the execution process time and resource management (Neuckamp et all., 2022). The company is able to optimize production costs, increase profitability, and maintain price competitiveness by considering production costs and production scheduling.

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In the context of the Toyota Production System (TPS), which emphasizes principles such as just-in-time production and continuous improvement, a deep understanding of the relationship between production and production costs becomes increasingly important. TPS simulation is an ideal simulation for analyzing complex interactions in a controlled environment, in TPS simulation helps researchers in testing various scenarios and scheduling techniques without disrupting real operational activities. Three scheduling methods used in this study are the Initial Method, Simulated Annealing, and Tabu Search are used, this method aims to obtain the makespan value used to analyze production costs in TPS simulation. The first method used is the initial method of the traditional heuristic approach commonly used for production scheduling. then the makespan calculation is carried out using the Simulated Annealing and Tabu Search Methods which use metaheuristic optimization techniques that have been proven effective in solving complex problems with combinatorial optimization.

In Toyota Production System (TPS), principles such as timely completion of production processes and continuous improvement have been emphasized. Therefore, it is important to thoroughly understand the relationship between production and production costs. TPS simulation provides researchers with the opportunity to test various scheduling scenarios and techniques without disrupting real operations on the production floor. TPS is an ideal platform for analyzing complex interactions in a controlled environment. The makepan value in TPS simulation can be used to perform production cost analysis. In this study, there are three scheduling methods used, namely the Initial Method, Simulated Annealing, and Tabu Search. The Initial Method is a conventional or simple heuristic production scheduling approach, and Simulated Annealing and Tabu Search are metaheuristic optimization techniques that have proven effective in solving complex problems with combinatorial optimization. The results of this research can be the basis for developing an adaptive scheduling system that is able to adapt to dynamic changes in market demand and production conditions.

Literature review

Toyota Production System (TPS) has become the main basis for developing efficient and effective production systems in the manufacturing industry globally. The system applied to TPS is known as lean manufacturing, which aims to eliminate waste and increase productivity on the production floor through various principles and techniques that can be used (Liker, 2004). One of the critical aspects in TPS is the analysis of production costs which are closely related to the makespan value, namely the total time needed to complete all work in a production process.

The concept of makespan is essential to optimize the production process. Production processes that require shorter time usually show higher efficiency and allow for reduced production costs (Pinedo 2022). This theory is in line with the just-in-time (JIT) principle which aims to reduce inventory during the production process and waiting time in the Toyota production system (Ohno, 1998).

Computer simulation has become a very effective tool in analyzing and optimizing complex production systems such as TPS. Using simulation, researchers and practitioners can display various scenarios and parameters without disturbing the actual production operation (Banks et al., 2010). Simulation can provide useful information about the relationship between system configuration, production time, and associated costs when performing a production cost analysis based on makespan values.

In the context of lean manufacturing, studies have investigated the relationship between production and production costs. Zahraee et al. (2014) used simulation to ensure that lean production lines perform better. They used makespan as one of the key performance indicators and found that optimizing resource allocation and layout can reduce makespan by up to 23%, which benefits overall production costs. Research conducted by Kumar et al. (2018) showed that increasing output and reducing work in progress (WIP) on the production floor can result in a 15% decrease in revenue and a 10% decrease in costs. This study used simulation to identify the impact of performance on production costs in the automotive industry. In the case of TPS, a comprehensive cost analysis – including costs related to quality, inventory, and setup – is essential (Monden, 2011). This method is referred to as "cost management in the Toyota Production System" and incorporates time elements, such as makespan, into the total cost calculation.

Research conducted by Li et al. (2018) uses agent-based simulation to analyze the impact of process variability on makespan and production costs in a lean manufacturing environment. They found that reducing variability can significantly reduce makespan and production costs, especially in systems with high levels of complexity.

Production cost analysis based on makespan value is also closely related to the concept of value stream mapping (VSM) in TPS. Rother et al. (2003) explains how VSM can be used to identify areas that have potential for time and cost reductions. Integration of VSM with simulation has proven to be an effective approach to optimize production flows and reduce costs.

A comparative assessment of the effects of different lean approaches on operational performance metrics, such as costs and makespan, was carried out in the automotive sector, which is where TPS first appeared Belekoukias et al. (2014). They found that the implementation of JIT and autonomation (jidoka) had the most significant impact in reducing makespan and production costs.

The use of simulation in production cost analysis based on makespan values also enables the evaluation of complex "what-if" scenarios. Negahban et al. (2014) used simulation to evaluate the impact of various scheduling policies on makespan and production costs in a job shop environment. They show that choosing the right scheduling policy can reduce makespan by up to 18% and production costs by up to 12%.

The integration of makespan-based cost analysis with other TPS concepts such as kaizen (continuous improvement) and heijunka (levelized production) has also been the focus of several studies. Omogbai et al. (2016) developed a simulation framework that combines these principles to optimize production system performance. In comparison to conventional methods, they showed that this integrated approach can lead to production cost savings of up to 25% and makespan reductions of up to 30%. In the Industry 4.0 era, the integration of information and communication technology (ICT) with TPS opens up new opportunities for more accurate and real-time production cost analysis. Kolberg & Zuhlke (2015) explored how the concept of "lean automation" can increase the flexibility and efficiency of production systems, which in turn has a positive impact on makespan and costs. They highlight the importance of cyber-physical systems in optimizing production flows and reducing costs.

In conclusion, production cost analysis based on makespan values in Toyota Production System simulations is a critical and dynamic research area. The integration of lean manufacturing principles with modern simulation techniques and Industry 4.0 technology opens up new opportunities for more effective optimization of production systems. Further research is needed to explore the long-term implications of this approach for the competitiveness and sustainability of the global manufacturing industry. Even though there has been a lot of research related to the Toyota Production System (TPS), production cost analysis, and makespan optimization, there are still several gaps that need to be explored further. The following is a more detailed explanation of the identified research gaps. Comprehensive Integration of TPS and Makespan-Based Cost Analysis (Liker, 2004) has provided an in-depth understanding of TPS principles, but does not specifically discuss how these principles can be integrated with makespan-based production cost analysis. Monden (2011) developed a cost management framework in the context of TPS, but focused less on the use of simulation for cost analysis. There is a need for research that comprehensively integrates TPS principles with makespan-based production cost analysis using a simulation approach. TPS Parameter Variations in Simulation, (Kumar et al., 2018) demonstrated the effectiveness of the Lean–Kaizen approach in reducing makespan and costs, but their research was limited to specific industries and did not explore variations in TPS parameters widely. Further research is needed to evaluate how various TPS parameters (such as takt time, kanban, and jidoka) affect makespan and production costs in various industrial scenarios. Li et al. (2018) used agent-based simulation to analyze the impact of process variability on makespan and costs, but did not consider all aspects of TPS in their analysis. A more thorough sensitivity analysis that addresses the relationships between different TPS components and their effects on production costs and makespan is possible. The potential of Industry 4.0 technologies in production optimisation has been investigated by Kolberg & Zuhlke (2015), while integration with conventional TPS principles has received less attention. Further research is needed to analyze how TPS can be optimized with Industry 4.0 technology to increase cost efficiency and makespan. Although Negahban et al. (2014) and Omogbai et al. (2016) have shown the potential for reducing makespan and costs through simulation, there is still a need for more detailed and granular cost analysis based on makespan values. Further research could focus on developing a more comprehensive cost model that includes the various cost components in TPS and how they correlate with changes in makespan. The majority of existing research focuses on optimizing one or two parameters (such as makespan and cost). There is an opportunity to develop multi-objective optimization models that consider makespan, production costs, product quality, system flexibility and other factors relevant in the TPS context.

Short- or medium-term optimisation is the main focus of the majority of current research. Research that examines the long-term effects of cost-cutting and makespan tactics in the TPS setting, including their implications for environmental and operational sustainability, is required. The majority of existing research focuses on traditional manufacturing or automotive industries. There is an opportunity to explore the application of makespan-based production cost analysis in TPS in various industrial sectors, including process industries, services, and high-mix low-volume manufacturing. Although many studies use simulation, no specific simulation tools have been developed for makespan-based production cost analysis in the TPS context. The development of simulation tools tailored to the unique characteristics of TPS can facilitate more accurate and efficient analysis. This study can significantly advance our knowledge of cost control and production system optimisation in the context of lean manufacturing by addressing this research gap.

Materials & Methods

This research adopts a quantitative approach with a simulation experimental design to analyze the relationship between makespan and production costs in the context of the Toyota Production System (TPS). The main focus of the research is to compare three scheduling methods: Initial Method, Simulated Annealing, and Tabu Search, and evaluate their impact on makespan, Total Production Cost, and Unit Cost at three different demand levels.

The research object is a vehicle production system which includes six types of vehicles: Pick Up, MPV, Double Cabin, Concrete Mixer, Excavator, and Roller Cylinder Truck. Data was collected through TPS simulations with three demand scenarios: Demand 1 (186 units), Demand 2 (216 units), and Demand 3 (246 units). The Initial Method is used as a baseline, representing the traditional approach to production scheduling. To increase scheduling efficiency, two options are used: Tabu Search, a local search strategy that employs memory to avoid local optima, and Simulated Annealing, a metaheuristic optimisation methodology inspired by annealing processes in metallurgy.

Calculation of production costs uses the formula $\mathrm{TC} = (\mathrm{CL} + \mathrm{CM} + \mathrm{CE} + \mathrm{CO}) \times \mathrm{M}$ where TC is Total Cost, CL is Labor Cost, CM is Machine Cost, CE is Energy Cost, CO is Other Costs, and M is Makespan (Pinedo 2022). In the context of TPS, the cost components calculated include Fixed Costs, Labor Costs, and Production Costs per Workstation for the four existing workstations.

Simulation and data analysis were carried out using Microsoft Excel to calculate total production costs and unit costs based on three scheduling methods and three demand levels. Analysis includes comparison of makespan between methods, evaluation of Total Production Cost and Unit Cost, as well as identification of the relationship between makespan and costs. Model validation is carried out by comparing simulation results with historical data or industry benchmarks, as well as checking the internal consistency of the model to ensure the reliability of the results.

The interpretation of the results considers several key aspects: the inverse relationship between makespan and production costs, the efficiency trade-off between time and costs, linear scalability in the analyzed demand range, and the influence of job sequence on costs and makespan. Managerial implications analysis is carried out to provide practical insight for decision makers, including strategic priorities in selecting scheduling methods, break-even analysis, production flexibility, technology investment, and capacity management.

This research method is designed to provide a comprehensive understanding of the complexity of the relationship between makespan and production costs in the TPS context. This study intends to lay a strong foundation for managerial decision-making in production process optimisation by employing a simulation technique and comparison analysis, while also opening the door for additional research in this field. The outcomes should assist manufacturing firms in striking a balance between cost and time efficiency, allowing them to sustain operational sustainability and competitiveness in a business climate that is becoming more complicated and dynamic by the day.

Results

Increasing business efficiency and competitiveness in the manufacturing sector requires optimising the production process. Production time (makespan) and production expenses are the two primary elements that are frequently the subject of optimisation. Three scheduling techniques – Initial Method, Simulated Annealing, and Tabu Search – are used in this study to examine the relationship between makespan and production costs in the context of car manufacturing. The amount of time needed to finish every task in a production process is known as makespan (Pinedo, 2022). Meanwhile, production costs include all expenses related to the manufacturing process, including raw material costs, labor and overhead (Horngren, et al., 2012).

The literature on operations management has extensively examined the connection between production costs and makespan. Numerous studies demonstrate that by increasing productivity and decreasing idle time, lowering makespan can save money. But according to other research, attempts to reduce makespan can occasionally result in higher production costs since they call for more resources or more costly production techniques (Shi et al., 2011) (Tab. 1 and Tab. 2).

In production scheduling, the term "Initial Method" often refers to a conventional or straightforward heuristic technique. Inspired by the metallurgical annealing process, Simulated Annealing employs metaheuristic optimization approaches. Complex combinatorial optimization issues can be effectively solved with this approach. To prevent becoming trapped in local optima, Tabu Search is a local search technique that makes use of memory. The following is the standard method for figuring out production costs depending on the makespan value:

$$\mathrm{TC} = (\mathrm{CL} + \mathrm{CM} + \mathrm{CE} + \mathrm{CO}) \times \mathrm{M} \tag{1}$$

TC = Total Cost, CL = Labor Cost per unit time, CM = Machine Cost per unit time, CE = Energy Cost per unit time per unit time), CO = Other Costs per unit time (Other Costs per unit time), M = Makespan (in the same time unit as the costs above). Calculation of production costs based on makespan involves the components of labor, machine, energy and other costs multiplied by the makespan value (Pinedo, 2022). This formula is a basic form and needs to be adapted to the specific context and additional factors that may be relevant in a particular production situation.

In the context of the Toyota Production System Simulation, the cost components taken into account are Fixed Costs (A), Labor Costs (F), Perworkstation Production Costs in units of time per hour. Perworkstation Production Costs are divided into four because they consist of four workstations, namely Workstation Production Costs 1 (1), Workstation Production Costs 2 (2), Workstation Production Costs 3 (3), and Workstation Production Costs 4 (C). Production costs for Workstations 1 to 3 are accumulated to become Total costs WS 1-3 (B) (Toyota, 2018). The image below shows the simulation results of calculating total production costs and unit costs based on the initial method, Simulated Annealing, and Tabu Search using Ms. Excel.

Makespan

Based on the image above, the data shows that Simulated Annealing and Tabu Search produce identical and shorter makespan compared to the Initial Method for all levels of demand showing results Demand 1: 569.67 minutes vs 588.54 minutes (3.2% reduction), Demand 2: 663.27 minutes vs 681.38 minutes (2.7% reduction), and Demand 3: 756.91 minutes vs 774.22 minutes (2.2% reduction). his makespan reduction is in line with the findings of (Li et all., 2013) which shows that metaheuristic methods such as Simulated Annealing and Tabu Search often produce better solutions in terms of production time than traditional methods.

Table 1
Demand and job

Job	**Type**	**Demand 1 (Unit)**	**Demand 2 (Unit)**	**Demand 3 (Unit)**
J1	*PICK UP*	35	40	45
J2	*MPV*	31	36	41
J3	*DOUBLE CABIN*	27	32	37
J4	*MIXER BETON*	35	40	45
J5	*EXCAVATOR*	31	36	41
J6	*TRUCK SILINDER ROLLER*	27	32	37
	Total Demand	186	216	246

Table 2
Makespan value

Method	**Demand 1 (minutes)**	**Demand 2 (minutes)**	**Demand 3 (minutes)**	**Job Sequence**
Initial Method	569.68	663.29	756.90	Same for every demand
Simulated Annealing	588.54	681.38	774.22	Not the same for every demand
Tabu Search	588.54	681.38	774.22	Same for every demand

Total Demand					186		--->	G
The cost of depreciation is fixed:						$ 200	--->	A
Labour			No. of Labour :		12	$ 15		
Cost of Labour /hours						$ 180	--->	F
WS	**Area**	**Status**	**Quantity (Q)**		**Cost © / hours**	**Total Cost (Q x C)**		
#1	In Process product	Good Product	246	Pcs	$ 10	$ 2.460		
		No Good Product	0	Pcs	$ 10	$ -		
	In Warehouse	Good Product	0	Pcs	$ 10	$ -		
			Sub Total 1			$ 2.460	--->	1
#2	In Process product	Good Product	246	Pcs	$ 20	$ 4.920		
		No Good Product	0	Pcs	$ 20	$ -		
	In Warehouse	Good Product	0	Pcs	$ 20	$ -		
			Sub Total 2			$ 4.920	--->	2
#3	In Process product	Good Product	246	Pcs	$ 30	$ 7.380		
		No Good Product	0	Pcs	$ 30	$ -		
	In Warehouse	Good Product	0	Pcs	$ 30	$ -		
			Sub Total 3			$ 7.380	--->	3
			Total 1 + 2 + 3			$ 14.760	--->	B
#4	Final Inspection	Good Product	246	Pcs	$ 40	$ 9.840		
		No Good Product	0	Pcs	$ 40	$ -		
			Total			$ 9.840	----->	C
			Total Production Costs / hours =		**F+B+C**	**$ 24.980**		
			Makespan =			**569,68 minutes**		
						9,49 hours	----->	D
			Total Production Costs =		**A + ((F+B+C) x D)**	**$ 237.377**	----->	E
			Unit Cost =		**E/ G**	**$ 1.276**		

Fig. 1. Results for Demand 1 Initial Method

Total Demand					216		--->	G
The cost of depreciation is fixed:						$ 200	--->	A
Labour			No. of Labour :		12	$ 15		
Cost of Labour /hours						$ 180	--->	F
WS	**Area**	**Status**	**Quantity (Q)**		**Cost © / hours**	**Total Cost (Q x C)**		
#1	In Process product	Good Product	246	Pcs	$ 10	$ 2.460		
		No Good Product	0	Pcs	$ 10	$ -		
	In Warehouse	Good Product	0	Pcs	$ 10	$ -		
			Sub Total 1			$ 2.460	--->	1
#2	In Process product	Good Product	246	Pcs	$ 20	$ 4.920		
		No Good Product	0	Pcs	$ 20	$ -		
	In Warehouse	Good Product	0	Pcs	$ 20	$ -		
			Sub Total 2			$ 4.920	--->	2
#3	In Process product	Good Product	246	Pcs	$ 30	$ 7.380		
		No Good Product	0	Pcs	$ 30	$ -		
	In Warehouse	Good Product	0	Pcs	$ 30	$ -		
			Sub Total 3			$ 7.380	--->	3
			Total 1 + 2 + 3			$ 14.760	--->	B
#4	Final Inspection	Good Product	246	Pcs	$ 40	$ 9.840		
		No Good Product	0	Pcs	$ 40	$ -		
			Total			$ 9.840	----->	C
			Total Production Costs / hours =		**F+B+C**	**$ 24.980**		
			Makespan =			**663,29 minutes**		
						11,05 hours	----->	D
			Total Production Costs =		**A + ((F+B+C) x D)**	**$ 276.350**	----->	E
			Unit Cost =		**E/ G**	**$ 1.279**		

Fig. 2. Results for Demand 2 Initial Method

Total Demand					246		---->	G
The cost of depreciation is fixed:						$ 200	---->	A
Labour				No. of Labour :	12	$ 15		
Cost of Labour /hours						$ 180	---->	F
WS	**Area**	**Status**	**Quantity (Q)**		**Cost © / hours**	**Total Cost (Q x C)**		
#1	In Process product	Good Product	246	Pcs	$ 10	$ 2.460		
		No Good Product	0	Pcs	$ 10	$ -		
	In Warehouse	Good Product	0	Pcs	$ 10	$ -		
			Sub Total 1			$ 2.460	---->	1
#2	In Process product	Good Product	246	Pcs	$ 20	$ 4.920		
		No Good Product	0	Pcs	$ 20	$ -		
	In Warehouse	Good Product	0	Pcs	$ 20	$ -		
			Sub Total 2			$ 4.920	---->	2
#3	In Process product	Good Product	246	Pcs	$ 30	$ 7.380		
		No Good Product	0	Pcs	$ 30	$ -		
	In Warehouse	Good Product	0	Pcs	$ 30	$ -		
			Sub Total 3			$ 7.380	---->	3
			Total 1 + 2 + 3			$ 14.760	---->	B
#4	Final Inspection	Good Product	246	Pcs	$ 40	$ 9.840		
		No Good Product	0	Pcs	$ 40	$ -		
			Total			$ 9.840	----->	C
			Total Production Costs / hours =		**F+B+C**	**$ 24.980**		
			Makespan =			**756,9 minutes**		
						12,62 hours	----->	D
			Total Production Costs =		**A + ((F+B+C) x D)**	**$ 315.323**	----->	E
			Unit Cost =		**E/ G**	**$ 1.282**		

Fig. 3. Results for Demand 3 Initial Method

Total Demand					186		---->	G
The cost of depreciation is fixed:						$ 200	---->	A
Labour				No. of Labour :	12	$ 15		
Cost of Labour /hours						$ 180	---->	F
WS	**Area**	**Status**	**Quantity (Q)**		**Cost © / hours**	**Total Cost (Q x C)**		
#1	In Process product	Good Product	246	Pcs	$ 10	$ 2.460		
		No Good Product	0	Pcs	$ 10	$ -		
	In Warehouse	Good Product	0	Pcs	$ 10	$ -		
			Sub Total 1			$ 2.460	---->	1
#2	In Process product	Good Product	246	Pcs	$ 20	$ 4.920		
		No Good Product	0	Pcs	$ 20	$ -		
	In Warehouse	Good Product	0	Pcs	$ 20	$ -		
			Sub Total 2			$ 4.920	---->	2
#3	In Process product	Good Product	246	Pcs	$ 30	$ 7.380		
		No Good Product	0	Pcs	$ 30	$ -		
	In Warehouse	Good Product	0	Pcs	$ 30	$ -		
			Sub Total 3			$ 7.380	---->	3
			Total 1 + 2 + 3			$ 14.760	---->	B
#4	Final Inspection	Good Product	246	Pcs	$ 40	$ 9.840		
		No Good Product	0	Pcs	$ 40	$ -		
			Total			$ 9.840	----->	C
			Total Production Costs / hours =		**F+B+C**	**$ 24.980**		
			Makespan =			**569,68 minutes**		
						9,49 hours	----->	D
			Total Production Costs =		**A + ((F+B+C) x D)**	**$ 237.377**	----->	E
			Unit Cost =		**E/ G**	**$ 1.276**		

Fig. 4. Results for Demand 1 Simulated Annealing and Tabu Search

Total Demand				216			---->	G
The cost of depreciation is fixed:						$ 200	---->	A
Labour			No. of Labour :	12		$ 15		
Cost of Labour /hours						$ 180	---->	F
WS	Area	Status	Quantity (Q)		Cost © / hours	Total Cost (Q x C)		
#1	In Process product	Good Product	246	Pcs	$ 10	$ 2.460		
		No Good Product	0	Pcs	$ 10	$ -		
	In Warehouse	Good Product	0	Pcs	$ 10	$ -		
			Sub Total 1			$ 2.460	---->	1
#2	In Process product	Good Product	246	Pcs	$ 20	$ 4.920		
		No Good Product	0	Pcs	$ 20	$ -		
	In Warehouse	Good Product	0	Pcs	$ 20	$ -		
			Sub Total 2			$ 4.920	---->	2
#3	In Process product	Good Product	246	Pcs	$ 30	$ 7.380		
		No Good Product	0	Pcs	$ 30	$ -		
	In Warehouse	Good Product	0	Pcs	$ 30	$ -		
			Sub Total 3			$ 7.380	---->	3
			Total 1 + 2 + 3			$ 14.760	---->	B
#4	Final Inspection	Good Product	246	Pcs	$ 40	$ 9.840		
		No Good Product	0	Pcs	$ 40	$ -		
			Total			$ 9.840	----->	C
			Total Production Costs / hours =		F+B+C	$ 24.980		
			Makespan =			663,29 minutes		
						11,05 hours	----->	D
			Total Production Costs =		A + ((F+B+C) x D)	$ 276.350	----->	E
			Unit Cost =		E/ G	$ 1.279		

Fig. 5. Results for Demand 2 Simulated Annealing and Tabu Search

Total Demand				246			---->	G
The cost of depreciation is fixed:						$ 200	---->	A
Labour			No. of Labour :	12		$ 15		
Cost of Labour /hours						$ 180	---->	F
WS	Area	Status	Quantity (Q)		Cost © / hours	Total Cost (Q x C)		
#1	In Process product	Good Product	246	Pcs	$ 10	$ 2.460		
		No Good Product	0	Pcs	$ 10	$ -		
	In Warehouse	Good Product	0	Pcs	$ 10	$ -		
			Sub Total 1			$ 2.460	---->	1
#2	In Process product	Good Product	246	Pcs	$ 20	$ 4.920		
		No Good Product	0	Pcs	$ 20	$ -		
	In Warehouse	Good Product	0	Pcs	$ 20	$ -		
			Sub Total 2			$ 4.920	---->	2
#3	In Process product	Good Product	246	Pcs	$ 30	$ 7.380		
		No Good Product	0	Pcs	$ 30	$ -		
	In Warehouse	Good Product	0	Pcs	$ 30	$ -		
			Sub Total 3			$ 7.380	---->	3
			Total 1 + 2 + 3			$ 14.760	---->	B
#4	Final Inspection	Good Product	246	Pcs	$ 40	$ 9.840		
		No Good Product	0	Pcs	$ 40	$ -		
			Total			$ 9.840	----->	C
			Total Production Costs / hours =		F+B+C	$ 24.980		
			Makespan =			756,9 minutes		
						12,62 hours	----->	D
			Total Production Costs =		A + ((F+B+C) x D)	$ 315.323	----->	E
			Unit Cost =		E/ G	$ 1.282		

Fig. 6. Results for Demand 3 Simulated Annealing and Tabu Search

Production Cost

Interestingly, despite producing shorter makespan, Simulated Annealing and Tabu Search actually produce higher Total Production Cost as shown in Table 3 from Demand 1: $245,229 vs $237,377 (3.3% increase), Demand 2: $283,881 vs $276,350 (2.7% increase), and Demand 3: $322,534 vs $315,323 (2.3% increase). This phenomenon indicates a trade-off between time and cost efficiency, as discussed by Shi, Zhang, & Sha (2011), they state that efforts to minimize makespan sometimes require more expensive or intensive use of resources, which in turn increases production costs.

Unit Cost

The Unit Cost Analysis provides additional insight that Initial Method: Unit Cost increased slightly from $1,276 (Request 1) to $1,282 (Request 3) and Simulated Annealing/Tabu Search: Unit Cost decreased from $1,318 (Request 1) to $1,311 (Request 3). The Unit Cost results of these three methods are shown in Table 4. This trend shows that although Simulated Annealing and Tabu Search result in higher Total Production Costs, these methods have the potential to achieve better economies of scale at higher production volumes. This is in line with production economic theory which states that increasing production volume can reduce unit costs through a wider distribution of fixed costs (Pindyck & Rubinfeld, 2020).

Discussion

Makespan and Cost Relationship

The data shows that there is an inverse relationship between makespan and production costs. The Initial Method with the longest makespan produces the lowest costs, while Simulated Annealing and Tabu Search with shorter makespans produce higher costs. This finding contrasts with several previous studies that showed a positive correlation between makespan reduction and cost savings. Based on the Efficiency Trade-off, a makespan reduction of approximately 3.2% by Simulated Annealing and Tabu Search results in a cost increase of between 2.3% to 3.3%. This illustrates the complexity of optimization in manufacturing, where increasing efficiency in one aspect (time) can come at the expense of efficiency in another (cost). These findings support the argument Moreira et al. (2012) that optimization in manufacturing often involves multidimensional trade-offs.

The increase in makespan and costs from Demand 1 to Demand 2 and Demand 3 is relatively consistent for all methods. This shows a relationship that tends to be linear between makespan, costs, and production volume in the analyzed demand range. However, it should be noted that this linearity may not apply to a much wider range of production due to factors such as capacity constraints or diseconomies of scale (Heizer, et al., 2023). The effect of Job Sequence shows that even though

Table 3
Total Production Cost

Method	Total Production Cost Demand 1 ($)	Total Production Cost Demand 2 ($)	Total Production Cost Demand 3 ($)
Initial Method	237,377	276,350	315,323
Simulated Annealing	245,229	283,881	322,534
Tabu Search	245,229	283,881	322,534

Table 4
Unit Cost

Method	Unit Cost Demand 1 ($)	Unit Cost Demand 2 ($)	Unit Cost Demand 3 ($)
Initial Method	1,276	1,279	1,282
Simulated Annealing	1,318	1,314	1,311
Tabu Search	1,318	1,314	1,311

Simulated Annealing produces a different job sequence for each demand, the resulting costs and makespan are identical to Tabu Search. This indicates that in this case, job order may not significantly affect costs or makespan as long as the optimization method used is effective. This finding is in line with research (Öztop et al., 2019) which shows that in some cases, multiple optimal solutions can exist with equivalent performance.

Based on Strategic Priorities, the selection of scheduling methods must be aligned with the company's strategic priorities. If production speed and responsiveness to market demand are top priorities, Simulated Annealing or Tabu Search is more appropriate despite the higher costs. On the other hand, if the emphasis is on cost efficiency, the Initial Method may be a better choice. This decision must consider factors such as the company's competitive position, market segments served, and product differentiation strategy (Porter, 2008).

Break-even analysis shows that companies need to carry out break-even analysis to determine at which production level the method with a shorter makespan (Simulated Annealing/Tabu Search) becomes more profitable than the Initial Method. This analysis should consider factors such as inventory costs, the opportunity cost of faster production times, and the potential for increased market share (Drury, 2018). Meanwhile, Production Flexibility shows that all methods have good scalability in dealing with increasing demand. However, Simulated Annealing and Tabu Search offer greater flexibility in terms of speed of response to changing requests. In a dynamic business environment, this flexibility can be a significant competitive advantage (Slack, et al., 2013).

In terms of Technology Investment, considering that Simulated Annealing and Tabu Search produce shorter makespan but at higher costs, companies may need to consider investing in technology or processes that can reduce production costs while maintaining time efficiency. This could involve automation, use of Industry 4.0 technologies, or re-engineering of production processes (Xu et al., 2018). Based on Capacity Management, the difference in makespan between these methods has implications for production capacity management. The method with a shorter makespan allows increasing production capacity without adding physical facilities. However, this must be balanced with a comprehensive cost-benefit analysis (Chase & Jacobs, 2021).

In this study, factors such as production quality, downtime, and failure rate were not included in the cost model. This was done to guide the analysis and focus the study on the relationship between production time and costs. However, the exclusion of these factors may result in results that do not reflect real-world conditions, as in practice, production quality and disruptions significantly influence total operational costs. Therefore, future research is recommended to develop a more comprehensive model incorporating these variables so that production cost analysis can more accurately and thoroughly reflect field conditions.

Furthermore, the results from Simulated Annealing and Tabu Search show identical makespan and cost values across all scenarios. Although the two algorithms use different approaches, this similarity in results warrants further examination. This could be due to the narrow solution space, or the parameter settings that cause them to explore similar solution paths. Future studies could further examine how algorithm variations affect results to gain a more comprehensive understanding.

Conclusions

This research analyzes the relationship between makespan and production costs in the context of a Toyota Production System simulation using three scheduling methods: Initial Method, Simulated Annealing, and Tabu Search. The results show that Simulated Annealing and Tabu Search produce shorter makespan compared to the Initial Method, with a reduction of around 2.2–3.2% for various demand levels. Interestingly, even though it produces a shorter makespan, Simulated Annealing and Tabu Search actually produce a higher Total Production Cost, with an increase of 2.3–3.3%. This shows that there is a trade-off between time and cost efficiency in the production process.

Unit Cost analysis reveals that Simulated Annealing and Tabu Search have the potential to achieve better economies of scale at high production volumes, indicated by a decrease in Unit Cost as demand increases. This research reveals the complexity of optimization in manufacturing, where increasing efficiency in one aspect can come at the expense of efficiency in another. Managerial implications include the importance of aligning scheduling method selection with the company's strategic priorities, conducting break-even analysis, and considering technology investments to reduce costs while maintaining time efficiency. In conclusion, production process optimization requires a holistic approach that considers the trade-off between makespan and costs, as well as other strategic factors to maintain competitiveness in a dynamic business environment.

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