Acta logistica - International Scientific Journal about Logistics
Volume: 12 2025 Issue: 1 Pages: 91-102 ISSN 1339-5629

https://doi.org/10.22306/al.v12i1.592 *Received: 07 July 2024; Revised: 19 Sep. 2024; Accepted: 13 Nov. 2024*

Performance analysis of production scheduling in Toyota simulation

Saiful Mangngenre
Hasanuddin University, Faculty of Engineering, Department of Industrial Engineering, Jl. Malino No.8 F, 90 245 Gowa, South Sulawesi, Indonesia, saiful.ti@unhas.ac.id (corresponding author)
A. Besse Riyani Indah
Hasanuddin University, Faculty of Engineering, Department of Industrial Engineering, Jl. Malino No.8 F, 90 245 Gowa, Sulawesi Selatan, Indonesia, a.besseriyani@unhas.ac.id
Diniary Ikasari Syamsul
Hasanuddin University, Faculty of Engineering, Department of Industrial Engineering, Jl. Malino No.8 F, 90 245 Gowa, Sulawesi Selatan, Indonesia, diniaryi@gmail.com
Azran Budi Arief
Hasanuddin University, Faculty of Engineering, Departement of Electrical Engineering, Jl. Malino No.8 F, 90 245 Gowa, Sulawesi Selatan, Indonesia, azran@unhas.ac.id
Olyvia Novawanda
University of Surabaya, Department of Industrial Engineering, Jl. Raya Kalirungkut, Kali Rungkut, Kec. Rungkut, Surabaya, 60 293 Jawa Timur, Indonesia, olyvianovawanda@staff.ubaya.ac.id

Keywords: production scheduling, simulated annealing, tabu search, Toyota production system, makespan optimization.
Abstract: This research analyzes production scheduling performance in the context of sustainable manufacturing using Toyota Production System (TPS) simulation. The primary focus of this study is to study scheduling performance based on the makespan value and job order for each method. To reduce makespan, two metaheuristic techniques are employed: the tabu search (TS) method and the simulated annealing (SA) method. This research fills the literature gap by exploring makespan optimization methods, combining computer simulation with metaheuristics, and considering TPS scheduling constraints. Data obtained from a miniature car simulation based on the Toyota Production System concept. The research method includes SA and TS implementation using Python and Visual Basic 6.0. The results show that SA and TS produce makespan 2.2-3.2% lower than the Initial Method. SA shows flexibility with different job sequences for each level of demand, while TS produces consistent sequences. The increase in makespan as demand increases is consistent across all methods (14.1-16.4%). In conclusion, SA and TS are effective optimization methods for production scheduling, with the selection depending on the preference for flexibility or consistency.

1 Introduction

Sustainable manufacturing has indeed emerged as a critical focus for many companies, driven by the need to reduce environmental impact and enhance cost efficiency. While Toyota Production Systems (TPS) have demonstrated effectiveness in boosting productivity and supporting eco-friendly practices, there remains a need for further enhancements in optimal production scheduling and cost reduction. Efficient production scheduling is paramount for sustainable manufacturing success, enabling companies to streamline operations, minimize lead times, and cut operational costs by optimizing resource allocation, setup time, and operation sequences [1]. Despite the lean manufacturing principles offered by TPS, challenges persist in implementing optimal scheduling in intricate and dynamic production settings, particularly within the realm of sustainable manufacturing [2].

Scheduling is a process for arranging existing resources to carry out production within a certain time period. This is because proper production scheduling can increase production efficiency, reduce production costs, and reduce idle time, as well as minimize work in process. The goal of production scheduling is to reduce the makespan, or the amount of time needed to finish every step of production. Makespan can be an indicator to assess production speed, the smaller the makespan value, the more effective the production activities carried out.

Various scheduling methods, such as the Simulated Annealing Algorithm and Tabu Search, play a crucial role in optimizing production systems [3]. The Simulated Annealing Algorithm, a statistical and probabilistic optimization method, generates diverse solutions with varying probabilities to find the expected solution, potentially leading to different makespan times in production scheduling [3]. Computer simulations, utilizing accurate models, are essential for analyzing and optimizing production systems, enabling companies to assess scheduling scenarios, identify bottlenecks, and test alternative strategies before implementation in real production settings, ultimately reducing costs and aiding in making informed decisions for sustainable production [3,4]. The Simulated Annealing algorithm produces random results to find the expected solution, so that if used in production scheduling this method will produce many solutions with several probabilities of course with different makespan time results.

Computer simulation has become an invaluable asset for analyzing and optimizing production systems, allowing companies to assess different scheduling scenarios, pinpoint bottlenecks, and experiment with alternative scheduling strategies in a virtual environment before implementation in real production settings [5-7]. By utilizing accurate simulation models, organizations can significantly reduce the costs associated with physical experimentation and make more informed decisions regarding sustainable production scheduling. This approach not only enhances operational efficiency but also aids in streamlining processes, increasing production throughput, and ultimately improving overall business competitiveness.

In the realm of production scheduling, simulated annealing and tabu search methods have been selected for calculating the makespan value, showcasing their effectiveness in tackling complex and NP-hard optimization problems [8]. These meta-heuristic techniques are excellent at solving problems with large solution spaces in a reasonable amount of computational time. Particularly in the context of Toyota Production Systems (TPS), where scheduling involves diverse constraints like setup time, resource availability, and operation sequences, simulated annealing and tabu search prove invaluable [8]. Simulated annealing employs a controlled cooling mechanism to evade local optima, while tabu search leverages tabu lists to prevent redundant searches, offering distinct perspectives for exploring solution spaces [8]. These techniques are essential for handling the complexities of production scheduling in TPS, guaranteeing effective and practical scheduling results.

By integrating simulated annealing and tabu search methods in scheduling optimization, this study leverages the strengths of each to enhance the chances of finding superior scheduling solutions, ultimately contributing to sustainable manufacturing efforts by minimizing makespan, which reduces energy and resource consumption while enhancing production efficiency [9]. The widespread use of simulated annealing and tabu search in prior research on production scheduling and optimization in manufacturing systems, including within the context of TPS, establishes a robust foundation for their application in this study [10]. This approach aligns with the broader trend in manufacturing towards energy efficiency and sustainability, highlighting the potential for these methods to provide more optimal scheduling solutions and support sustainable production practices [9,10].

This research aims to analyze scheduling performance in the context of sustainable manufacturing using Toyota Production System simulations. By optimizing production scheduling based on makespan value. It is hoped that this research will provide valuable insights for manufacturing companies in their efforts to achieve greater operational efficiency and reduce environmental impact, as well as support sustainable manufacturing practices.

2 Literature review

2.1 Scheduling

Production scheduling plays a crucial role in manufacturing operations, aiding in achieving efficiencies, cost reduction, and supporting sustainable manufacturing practices. Various studies highlight the significance of optimal production scheduling in different industries. Hubert and Bleidorn emphasize the benefits of deep reinforcement learning (DRL) for optimized scheduling in the chemical industry [11], Lan and Chen [4] concentrate on the use of AI technology in intelligent manufacturing cells for unitary production scheduling. Additionally, Udayakumar et al. stress the importance of green technology efforts in reducing carbon emissions and setup costs through optimal production scheduling[12]. Torres underscores the complexity of decision-making processes in aquaculture and the need for decision support methods to enhance operational efficiency through production scheduling [13]. These studies collectively demonstrate the critical role of optimal production scheduling in enhancing production flow, reducing waste, and increasing productivity, aligning with the principles of Toyota Production Systems (TPS).

In industrial operations, production scheduling is critical, especially in lean systems like the Toyota Production Systems (TPS), where it is necessary to achieve efficiency, cut costs, and promote sustainability [14,15]. Previous research emphasizes the significance of effective production scheduling in lean sustainability, highlighting its role in waste reduction and resource efficiency [14,8]. Integrating environmental and economic aspects in optimization processes is key to sustainable production scheduling, as seen in multi-objective models considering energy consumption, production cost, and cycle time within TPS contexts [13,12]. Metaheuristic methods like genetic algorithms and local search have been employed to enhance scheduling performance and minimize energy consumption and costs in lean production systems [8,15]. Additionally, computer simulations have proven valuable in analyzing and optimizing production systems, providing insights into the environmental and economic impacts of continuous production scheduling in TPS environments [8,13,15].

2.2 Toyota Production System (TPS)

Toyota Motor Corporation created the well-known lean manufacturing approach known as the Toyota Production System (TPS), incorporating principles such as just-in-time (JIT) and jidoka, focusing on timely production and intelligent automation to prevent defects [16]. TPS also includes continuous improvement (kaizen), process standardization, and waste elimination, leading to increased productivity, cost reduction, and enhanced product quality [16]. Recent research by Nahmens and Ikuma highlights TPS's role in lean sustainability by reducing waste and enhancing resource efficiency. Chiarini and Vagnoni emphasize the significance of TPS in supporting sustainable manufacturing practices, showcasing its effectiveness in achieving operational excellence and sustainable manufacturing goals.

Several studies have indeed integrated sustainability aspects into production scheduling optimization within the context of the Toyota Production System (TPS). A multi-objective optimization model considering energy consumption, production costs, and production cycle time in Toyota's production system . [17] analyzed the impact of sustainable production scheduling on environmental and economic performance in TPS, focusing on carbon emissions and resource consumption. Hybrid optimization method for continuous production scheduling is conducted through agent-based simulation on Toyota production system. Additionally, [1] provided a comprehensive review of simulation usage in sustainable manufacturing, including TPS applications. These studies collectively highlight the importance of incorporating sustainability considerations into production scheduling optimization within the TPS framework, emphasizing the need for environmentally and economically efficient practices.

2.3 Simulated annealing and tabu search

Simulated annealing is a metaheuristic method widely applied in solving complex production scheduling optimization problems, inspired by metallurgical annealing processes [18]. This technique efficiently explores solution spaces to identify optimal or near-optimal schedules by iteratively modifying solutions and accepting new ones based on goal function improvement or with a probability to avoid local optima. Additionally, simulated annealing with adaptive cooling schedules has been proposed to enhance convergence speed and performance in optimization problems, offering a theoretically sound approach with variational approximations of Boltzmann distributions. Furthermore, it has been demonstrated that simulated annealing, when combined with suitable cooling schedules, can compute precise constant-factor approximations for the minimal spanning tree issue in polynomial time, demonstrating its adaptability and efficiency in a range of optimization applications[19].

In the realm of sustainable production scheduling, simulated annealing has been extensively utilized to enhance scheduling efficiency by considering factors like energy consumption, carbon emissions, and production costs. In a multi-objective optimization model for continuous production scheduling in lean production systems, [12] used simulated annealing. [4] focused on energy and carbon emissions inside Toyota Production Systems and used simulated annealing to optimize production scheduling. Additionally, [8] suggested a hybrid optimization strategy for continuous production schedule optimization in Toyota Production Systems that combines genetic algorithms and simulated annealing. Despite its effectiveness, simulated annealing can suffer from drawbacks such as prolonged computational time and parameter selection challenges, leading researchers to explore variations and hybrids with other methods to enhance its performance [20].

Tabu Search is a powerful metaheuristic approach extensively utilized for tackling complex and NP-hard production scheduling optimization problems. Inspired by human search behavior, it employs adaptive memory to prevent revisiting previously explored solutions, enhancing efficiency [21,22]. The search process in Tabu Search begins from an initial solution and iterates through neighboring solutions by making adjustments; if a neighboring solution proves superior, it replaces the current one, facilitating continuous improvement [21]. To circumvent local optima traps, Tabu Search employs a tabu list that records visited solutions, ensuring that the algorithm explores diverse solution spaces and avoids stagnation [21,23]. This strategic use of memory and solution tracking enables Tabu Search to navigate complex problem landscapes effectively, making it a valuable tool for optimization tasks in various domains [22].

In the realm of sustainable production scheduling, Tabu Search has been a valuable tool for optimizing scheduling performance while considering critical factors such as energy consumption, carbon emissions, and production costs. Research studies like [8] focus on utilizing Tabu Search within a multi-objective optimization framework to enhance sustainable production scheduling in lean manufacturing systems, emphasizing the reduction of carbon emissions and energy consumption. Additionally, works such as [2] demonstrate the effectiveness of Tabu Search in hybrid optimization methods, combining it with genetic algorithms for continuous production scheduling optimization in systems like Toyota Production Systems. These studies underscore the versatility and efficiency of Tabu Search in addressing the complexities of sustainable production scheduling across various manufacturing environments

By investigating sustainable production scheduling optimization within the framework of the Toyota Production System (TPS), this study seeks to close a gap in the literature. The research's position is shown in Table 1.

Table 1 Research gap

No.	Research Gap	References
1	Integration of sustainability aspects in TPS production scheduling optimization, specifically focusing on simultaneous minimization of production costs, energy consumption, and greenhouse gas emissions.	[2,12,23]
2	Exploration of scheduling optimization methods to minimize production costs in TPS simulation, considering the influence of employee and tool selection on the scheduling process.	[15,24]
3	Integration of computer simulation with metaheuristic methods (such as simulated annealing and tabu search) to optimize continuous production scheduling in Total Productive Systems (TPS).	[25,26]
4	Integration between classical scheduling theory and practical scheduling applications in	[27,28]

	TPS, considering constraints such as setup time, resource availability, and operation sequence.	
5	Practical validation and implementation of optimized production scheduling solutions in real TPS environments, including verification using discrete event simulation (DES).	[29,30]

3 Methodology

3.1 *Data collection*

The goal of this research is to create a production process simulation at lean manufacturing laboratory, which is part of the department of industrial engineering, Hasanuddin University. The research data used in this research is divided into 2 data, namely primary data, which is data obtained directly while in the field. The data collected is in the form of cycle time for each work station, obtained from time measurements, rating factors obtained directly while working, allowances obtained directly when workers do work, number of processes and the number of machines and equipment used. , Sequence of vehicle assembly work. Secondary data is data obtained without making direct measurements or observations. Secondary data for this research is product type and specifications, data on the number of consumer requests, and a simulation master plan.

The population and sample in research are important aspects taken to draw general conclusions. The population and sample in this study are as follows. A population is an approximation made up of items with specific attributes chosen by researchers for analysis and inference. Based on the population definition, the population of this study is the observation time of the production process of the 6 specimens tested. The sample is part of the number and characteristics of the population. The sample used in this research was random sampling. Random sampling was used to reduce data bias in this research.

3.2 *Test materials and instruments*

The test materials used in this research were 5 miniature cars, namely, miniature P/U cars, D-Cab, MPV, Excavator and Truck Mixer. Figure 1 displays the types of materials used in the research.

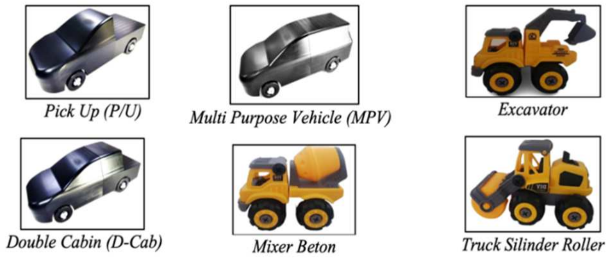

Figure 1 Test materials

A number of data gathering techniques were employed in this study, including a review of the literature, direct data collection from the Lean Manufacturing Laboratory during the simulation process, and observation, and carrying out simulation tests related to the vehicle assembly process in the Lean Manufacturing Laboratory.

The research method used in this research includes statistical analysis to assist researchers in processing initial data. Researchers also use the Simulated Annealing and Tabu Search algorithms as methods for determining new scheduling solutions. The Simulated Annealing algorithm itself uses Python as a tool to complete the algorithm. Meanwhile, the Tabu Search algorithm uses Visual Basic 6.0 (VB6) software.

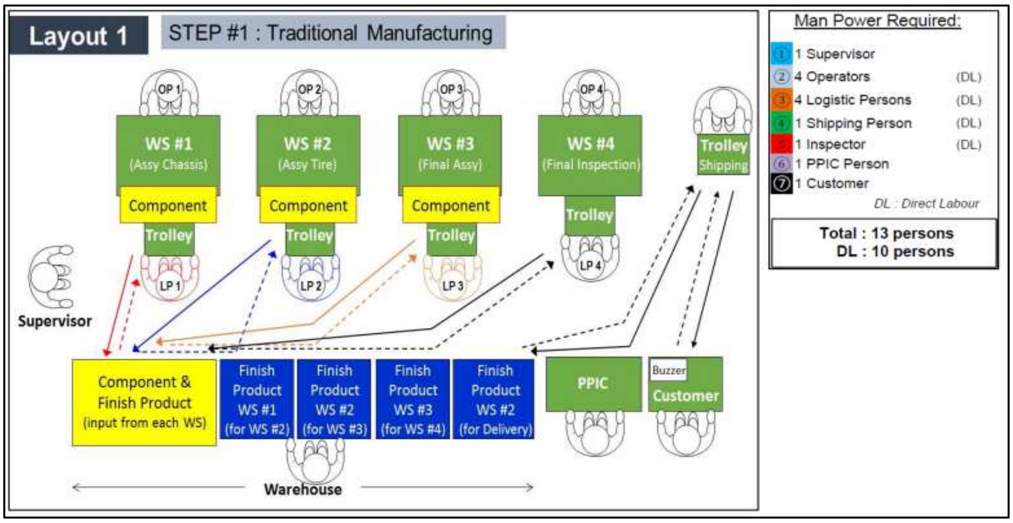

Figure 2 TPS simulation scenario [31]

The simulation, depicted in Figure 2, will take place in the setting of a business that employs a conventional production system and still needs a warehouse to store raw materials, semi-finished products, and finished goods that are prepared for shipment to customers. The following is the simulation scenario that will be carried out:

Acta logistica - International Scientific Journal about Logistics
Volume: 12 2025 Issue: 1 Pages: 91-102 ISSN 1339-5629

- The alarm will sound every 1.5 minutes.
- The customer gives the order to the PPIC (Production Planning and Inventory Control) after the first alarm sounds.
- The PPIC gives the production order sheet to the production supervisor.
- The supervisor gives production instructions to each Work Station and monitors during the simulation.
- The Work Station Operator works according to the instructions after the second alarm sounds, requests an empty box for finished goods, and asks the supply operator if the goods are finished. The operator can process goods out of sequence.
- The supply operator goes around to the designated Work Station to provide empty boxes and send finished goods to the warehouse, as well as supply components from the warehouse.
- The shipping operator prepares the shipment of goods by picking goods from the warehouse according to the PPIC process if the goods are available. The first shipment is made after the sixth alarm sounds, and the preparation for the second shipment is made when the seventh alarm sounds, with the shipment after the eleventh alarm sounds.
- The Work Station #4 operator (inspector) checks the quality of the goods and records the results on the quality check sheet. If NG (Not Good) goods are found, place them in the NG goods area.
- The warehouse operator prepares materials to fill the reduced or out of stock, provides empty boxes for finished goods, and places finished goods from each Work Station according to their addresses.
- Customers check the items that have been delivered using the delivery confirmation sheet.
- The simulation stops when the twelfth alarm sounds, and PPIC records the stock on the evaluation sheet.
- Have a discussion about the simulation based on the evaluation sheet and observation points.

The point that will be seen during the simulation is the makespan value based on demand variations consisting of three demand variations with a job sequence consisting of six jobs.

4 Results and discussion

In this research, a comparison of three production scheduling methods was carried out: Initial Method, Simulated Annealing and Tabu Search in the context of optimizing production schedules for six types of vehicles at four workstations with three different demand scenarios. Table 2 shows demand data for six different vehicle types in three different demand scenarios. Vehicle Types in Table 2 includes six different vehicle types, each coded J1 to J6. J1: Pick Up J2: MPV (Multi-Purpose Vehicle) J3: Double Cabin J4: Concrete Mixer J5: Excavator J6: Roller Cylinder Truck. The Demand Scenario consists of three different demand scenarios, namely Demand 1, Demand 2, and Demand 3. Each scenario shows an increase in demand from the previous one. Demand for each type of vehicle consistently increases by five units for each demand. This increase pattern was consistent for all types of vehicles, indicating uniform demand growth. Vehicles with the highest demand: Pick Up (J1) and Concrete Mixer (J4), ranging from 35 units in Demand 1 to 45 units in Demand 3. Vehicles with the lowest demand: Double Cabin (J3) and Roller Cylinder Trucks (J6), starting from 27 units in Demand 1 to 37 units in Demand 3. This consistent increase in demand indicates the need to increase production capacity gradually. The difference in demand between vehicle types indicates the need for different resource allocation for each production line.

Table 2 Demand data

Job	Type	Demand 1	Demand 2	Demand 3
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

4.1 Initial method

Table 3 displays information about variations in makespan and job sequence for three different demand scenarios using the initial method.

Table 3 Makespan and job sequence initial method

Demand Variations	Makespan (minute)	Job Sequence
Demand 1	588.54	J1 - J2 - J3 - J4 - J5 - J6
Demand 2	681.38	J1 - J2 - J3 - J4 - J5 - J6
Demand 3	774.22	J1 - J2 - J3 - J4 - J5 - J6

Table 3 provides an illustration of how total completion time (makespan) changes as demand increases, while job order remains constant. There was a significant and consistent increase in makespan along with increasing demand. From Demand 1 to Demand 2, makespan increases by 92.84 time units (15.8% increase). From Demand 2 to Demand 3, makespan also increases by 92.84 time units (13.6% increase). This linear increase in makespan shows a proportional relationship between increasing demand and total production time. For all three demand levels, the job order displayed is the same: J1- J2- J3- J4- J5- J6. The consistency of this job sequence shows that the initial method uses a static or fixed approach, not considering changes in demand levels. This order may be based on fixed priorities or simple scheduling rules such as First Come First Served (FCFS). This static scheduling approach may be simple to implement, but may not be optimal for all levels of demand. A significant increase in makespan indicates that production capacity needs to be increased proportionally to the increase in demand. Maintaining the same job sequence despite increasing demand may not optimize resource usage or minimize completion time. This method does not consider the possibility of different bottlenecks at different demand levels, which could be a reason for job sequence changes.

4.2 Simulated Annealing (SA) method

In this research, the Simulated Annealing Algorithm is used as a reliable computational solution to overcome production scheduling problems. The implementation of this algorithm is carried out using the Python programming language as a calculation tool. The developed code divides the Simulated Annealing Algorithm into two variants: Classic and Modified. The Classic variant refers to a more traditional and simple approach, using insertion operations in the job sequence as a mutation method. Meanwhile, the Modification variant makes several adjustments, including changes to the temperature function, use of different iterations, and modification of the probability function. In the final analysis, the makespan value resulting from the modified algorithm code is chosen as the best makespan value. This shows that the modified variant is considered more effective in optimizing production schedules. Figures 3, 4, and 5 show the output results from applying the Simulated Annealing Algorithm in Python as a tangible illustration of how well this technique works to solve challenging production scheduling issues.

```
Number of tasks:  6
Number of machines:  4
Tasks:
 [[129.88  56.58  68.17  50.74]
 [106.46  52.22  58.75  27.54]
 [ 81.38  41.39  41.13  23.7 ]
 [ 59.38  44.99  54.66  27.27]
 [ 55.62  31.19  57.36  20.45]
 [ 38.77  26.16  41.1   13.33]]
Classical
Best sequence:  [1, 0, 3, 5, 4, 2]
Best Cmax:  579.0400000000001
Midificated
Best sequence:  [0, 4, 3, 1, 2, 5]
Best Cmax:  569.6700000000001
<ipython-input-9-f0da30e480c0>:43: RuntimeWarning: overflow encountered in scalar divide
  prob = math.exp((Cold-Cnew)/Temp)
```

Figure 3 Demand 1 simulated annealing

```
Number of tasks:  6
Number of machines:  4
Tasks:
 [[148.43  64.66  77.91  57.99]
 [123.63  60.64  68.22  31.98]
 [ 96.46  49.05  48.75  28.09]
 [ 67.86  51.41  62.47  31.16]
 [ 64.59  36.22  66.61  23.75]
 [ 45.95  31.    48.71  15.79]]
Classical
Best sequence:  [4, 3, 5, 0, 1, 2]
Best Cmax:  672.81
Midificated
Best sequence:  [1, 4, 0, 3, 2, 5]
Best Cmax:  663.27
<ipython-input-12-f0da30e480c0>:43: RuntimeWarning: overflow encountered in scalar divide
  prob = math.exp((Cold-Cnew)/Temp)
```

Figure 4 Demand 2 simulated annealing

```
Number of tasks:  6
Number of machines:  4
Tasks:
 [[166.98  72.74  87.65  65.24]
 [140.8   69.06  77.7   36.43]
 [111.53  56.72  56.37  32.47]
 [ 76.35  57.84  70.28  35.06]
 [ 73.57  41.25  75.86  27.05]
 [ 53.13  35.84  56.33  18.26]]
Classical
Best sequence:  [5, 1, 0, 3, 2, 4]
Best Cmax:  766.5199999999999
Midificated
Best sequence:  [0, 1, 4, 3, 2, 5]
Best Cmax:  756.91
<ipython-input-15-f0da30e480c0>:43: RuntimeWarning: overflow encountered in scalar divide
  prob = math.exp((Cold-Cnew)/Temp)
```

Figure 5 Demand 3 simulated annealing

Table 4 shows the results of scheduling calculations using the Simulated Annealing method for three different demand scenarios. There has been a significant increase in line with increasing demand. From Demand 1 to Demand 2, the increase was 93.6 minutes (16.4% increase). From Demand 2 to Demand 3, the increase was 93.64 minutes (14.1% increase). This relatively consistent increase in makespan indicates a nearly linear relationship between increased demand and total production time. The job sequence varies for each request level, indicating that Simulated Annealing dynamically adjusts the sequence to optimize Makespan. Job 6 is always in last position, which may indicate the special characteristics of this job. Positions Job 1, Job 2, and Job 5 tend to be in the starting order, although the specific positions vary.

Table 4 Makespan and job sequence for simulated annealing method

Demand Variations	Makespan (minute)	Job Sequence
Demand 1	569.67	J1 - J5 - J4 - J2 - J3 - J6
Demand 2	663.27	J2 - J5 - J1 - J4 - J3 - J6
Demand 3	756.91	J1 - J2 - J5 - J4 - J3 - J6

The Simulated annealing method shows flexibility in adjusting job sequences for various levels of demand, which can result in better production efficiency. Changing the job sequence shows that this method considers the specific characteristics of each job and the level of demand in optimizing the schedule. Despite the order change, the increase in makespan remains significant, indicating that production capacity may need to be increased to accommodate higher demand. When compared with the initial method, Simulated Annealing is likely to produce a lower makespan and a more optimal job sequence.

4.3 Tabu Search (TS) method

The Tabu Search (TS) in calculating makespan and determining job sequences is an optimization method that searches for the optimal job sequence to minimize the total completion time (makespan), uses a tabu list to avoid newly explored solutions, generates and evaluates neighboring solutions by swapping job positions, accept better or less tabu solutions, and iterate the process to find the best solution. The results of makespan calculations made using Visual Basic 6.0 and the TS technique are displayed in Figure 6, Figure 7, and Figure 8. The results of the work sequence and makespan for three demand variations are derived from the Visual Basic 6.0 results.

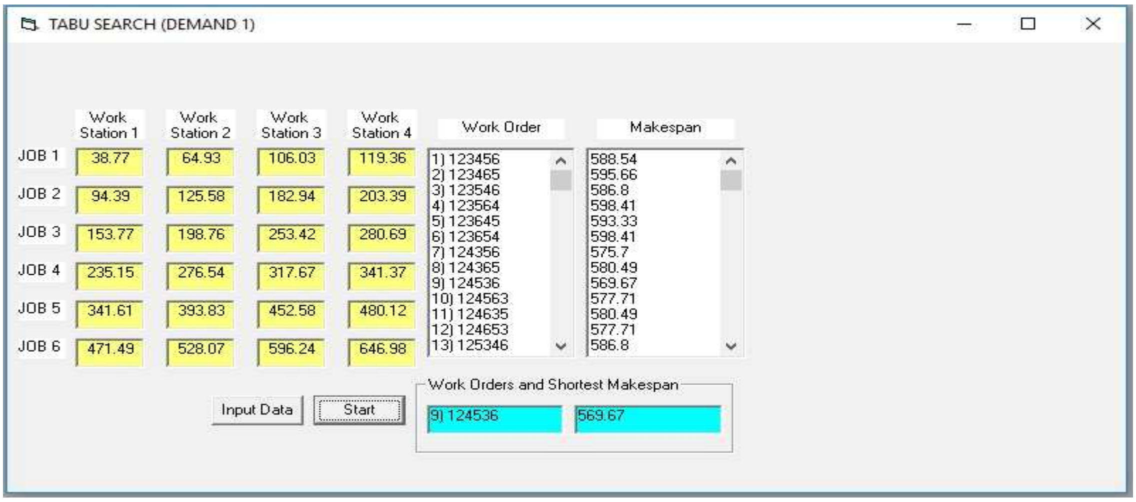

Figure 6 Demand 1 tabu search

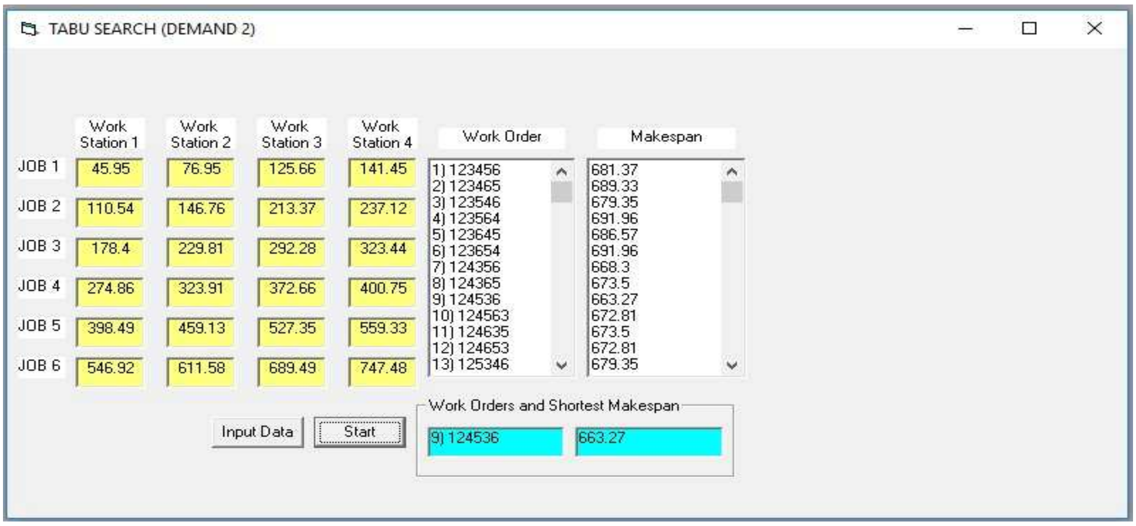

Figure 7 Demand 2 tabu search

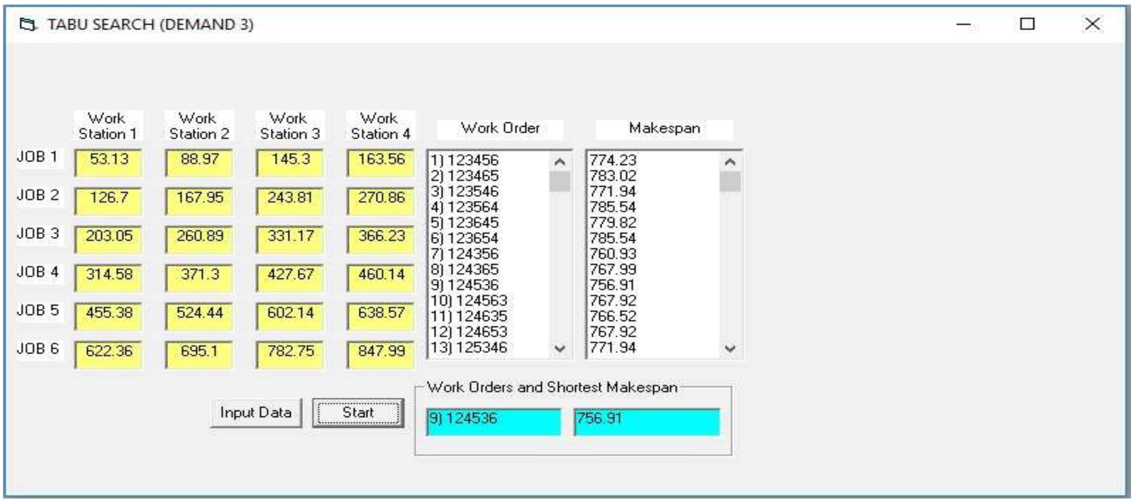

Figure 8 Demand 3 tabu search

Table 5 shows the results of applying the Tabu Search method for job scheduling with three different demand scenarios. For the three demand variations, the Tabu Search method produces the same job sequence. This indicates that this sequence tends to be optimal or near optimal for various levels of demand. It can be seen that makespan increases as demand increases. This is logical because higher demand usually requires longer production times. Sequence consistency indicates a consistent job sequence indicating that this sequence may have a structural advantage in minimizing idle time between workstations. The rise in makespan from Demand 1 to Demand 2 (16.4%) and from Demand 2 to Demand 3 (14.1%) demonstrates that the relationship between the rise in production time and the rise in demand is not necessarily linear.

Table 5 Makespan and job sequence tabu search method

Demand Variations	Makespan (minute)	Job Sequence
Demand 1	569.67	J 1 - J 2 - J 4 - J 5 - J 3 - J 6
Demand 2	663.27	J 1 - J 2 - J 4 - J 5 - J 3 - J 6
Demand 3	756.91	J 1 - J 2 - J 4 - J 5 - J 3 - J 6

The efficiency improvement at higher demand levels despite the disproportionate increase in makespan, indicating a robust solution applicable across various demand scenarios. The TS method showcased in the research demonstrates its capability to manage demand variations without altering the job sequence, offering significant utility in production planning [32]. This approach not only optimizes makespan but also ensures adaptability to fluctuating demand levels, enhancing operational flexibility and efficiency in production scheduling. The consistent job sequence for different demand levels underscores the method's resilience and effectiveness in addressing dynamic production requirements, making it a valuable tool for optimizing scheduling processes in diverse manufacturing environments [33].

4.4 Comparison of makespan values

Table 6 shows makespan data which shows a comparison between three scheduling methods, namely the Initial Method, Simulated Annealing, and Tabu Search, for three different demand scenarios.

Table 6 Comparison of makespan values

Method	Demand 1 (minute)	Demand 2 (minute)	Demand 3 (minute)	Job Sequence
Initial Method	588.54	681.38	774.22	Same for every demand
Simulated Annealing	569.67	663.27	756.91	Not the same for every demand
Tabu Search	569.67	663.27	756.91	Same for every demand

The Initial method produces the highest makespan for all scenarios, while Simulated Annealing and Tabu Search show identical and better performance. These two methods succeeded in reducing makespan by 3.2% for Demand 1, 2.7% for Demand 2, and 2.2% for Demand 3 compared to the Initial Method. Although these improvements may seem small, in the context of large-scale production, even small reductions in makespan can result in significant savings. The increase in makespan as demand increases is seen consistently across all methods, with an increase of around 16.4% from Demand 1 to Demand 2, and 14.1% from Demand 2 to Demand 3. This shows that all methods respond proportionally to the increase in workload. Additional information about the job sequence provided is obtained based on the three methods used:

- The Initial Method produces the same job sequence for each demand.
- Simulated Annealing produces a different job sequence for each demand.
- Tabu Search produces the same job sequence for each demand.

This shows that Simulated Annealing is more flexible in responding to changes in demand, while Tabu Search finds a more consistent solution. Nevertheless, both methods produce identical makespan, indicating that both are able to achieve optimal or near-optimal results through different approaches. Based on these results, both Simulated Annealing and Tabu Search can be recommended as effective optimization methods for this problem. Both outperform the Initial Method in terms of makespan minimization. The choice between these two methods may depend on user preference:

- If flexibility in responding to changes in demand is considered important, Simulated Annealing may be preferred.
- If job sequence consistency is considered important for long-term planning, Tabu Search may be a better choice.

For practical implementation, it is recommended to:

- Adopt Simulated Annealing or Tabu Search as a replacement for the Initial Method.
- Carry out further analysis to understand the implications of the differences in job sequences produced by Simulated Annealing.
- Consider factors such as solution stability, computing time, and ease of implementation in final method selection.

In conclusion, although both metaheuristic methods show similar performance in terms of makespan, the difference in the sequence of generated jobs can be an important factor in the choice of method depending on the specific needs of the production system. Simulation and digital technologies have significant potential in facilitating comprehensive product life cycle management. Its capabilities cover various stages, starting from the initial stage of product development, continuing to the innovative production system design stage, to the process of perfecting the production system that is already running [34]. With an emphasis on cutting overall production time and raising throughput, optimizing the makespan value in the Toyota Production System is essential to enhancing the effectiveness of logistics and production systems [35]. The approach used in this research focuses not only on reducing production time, but also on better synchronization between various processes in the supply chain, which in turn optimizes the flow of materials and information, and reduces waste in a lean production system

5 Conclusions

In order to optimize production schedules for six different types of vehicles at four workstations with three distinct demand situations, this study examines three production scheduling methods: the Initial Method, the Simulated Annealing (SA) method and Tabu Search (TS) method. The findings demonstrate that, on average, the TS and SA methods yield shorter makespan times than the Initial Method, with a reduction of around 3.2% for Demand 1, 2.7% for Demand 2, and 2.2% for Demand 3. Although the SA method and TS method produce lower makespan identical, they differ in approach, namely the SA method produces a different job sequence for each level of demand, showing flexibility in responding to changes in demand. Meanwhile, the TS method produces consistent job sequences for all demand levels, indicating the stability of the solution. The increase in makespan as demand increases is consistent across all methods (approximately 16.4% from Demand 1 to 2, and 14.1% from Demand 2 to 3), indicating a proportional response to increasing workload. In conclusion, both the SA method and the TS method are recommended as effective optimization methods, outperforming the Initial Method. The choice between the two depends on the preference between the flexibility of the SA method or the consistency of the TS method in scheduling. Practical implementations must consider factors such as solution stability, computing time, and ease of implementation. The next potential research is an in-depth analysis of the trade-off between the flexibility of the SA method and the consistency of the TS method in the context of long-term scheduling. The SA method offers flexibility with a varying work sequence according to demand, while the TS method provides consistency with a fixed sequence. Explore the combination of the SA method and the TS method to utilize the advantages of each method. Apply this method to more complex production scenarios, for example with more types of products or workstations.

Acknowledgement
The research team conveyed their sincere gratitude for all of the support and contributions from various sources. The research was financed under number of contract "00309/UN4.22/PT.01.03/2024" by "Lembaga Penilitian dan Pengabdian Kepada Masyarakat (LPPM) Universitas Hasanuddin", which provided excellent support. In addition, PT Toyota Motor Manufacturing Indonesia has supplied the facilities needed to conduct this research, and the Lean Manufacturing Laboratory, which is run by Department of Industrial Engineering Hasanuddin University, also offers significant assistance.

References

[1] BERTOLINI, M., LEALI, F., MEZZOGORI, D., RENZI, C.: A Keyword, Taxonomy and Cartographic Research Review of Sustainability Concepts for Production Scheduling in Manufacturing Systems, *Sustainability*, Vol. 15, No. 8, pp. 1-21, 2023. https://doi.org/10.3390/su15086884
[2] MOKHTARI-MOGHADAM, A., POURHEJAZY, P., GUPTA, D.: Integrating sustainability into production scheduling in hybrid flow-shop environments, *Environmental Science and Pollution Research*, pp. 1-19, 2023. https://doi.org/10.1007/s11356-023-26986-3
[3] LI, X., ZHANG, C.: Some new trends of intelligent simulation optimization and scheduling in intelligent manufacturing, *Service Oriented Computing and Applications*, Vol. 14, No. 3, pp. 149-151, 2020. https://doi.org/10.1007/s11761-020-00299-6
[4] LAN, X., HUA, C.: Simulation analysis of production scheduling algorithm for intelligent manufacturing cell based on articial intelligence technology, *Research Square*, Preprint, pp. 1-16, 2023. https://doi.org/10.21203/rs.3.rs-2551439/v1
[5] QUADRAS, D., FRAZZON, E.M., MENDES, L.G., PIRES, M.C., RODRIGUEZ, C.M.T.: Adaptive simulation-based optimization for production scheduling: A comparative study, *IFAC-PapersOnLine*, Vol. 55, No. 10, pp. 424-429, 2022. https://doi.org/10.1016/j.ifacol.2022.09.430
[6] KORMIN, T.G., OVCHINNIKOVA, V.A., TSUMBU, J.D.B.: *Simulation modeling of manufacturing* IOP Conf. Series: Materials Science and Engineering, 17th International Symposium on Solid Oxide Fuel Cells (SOFC-XVII), Vol. 1047, pp. 1-7, 2021. https://doi.org/10.1088/1757-899X/1047/1/012090
[7] ZDENKA, V., ZOLTAN, B., PETER, A.: Simulation as a tool for process optimization in a manufacturing company, *SHS Web of Conference*, Vol. 92, 8023, pp. 1-10, 2021. https://doi.org/10.1051/shsconf/20219208023

[8] DAI, L.: A Novel Production Scheduling Approach Based on Improved Hybrid Genetic Algorithm, *Sustainability*, Vol. 14, No. 18, pp. 1-15, 2022. https://doi.org/10.3390/su141811747

[9] PARASCHOS, P.D., KOULINAS, G.K., KOULOURIOTIS, D.E.: A reinforcement learning/ad-hoc planning and scheduling mechanism for flexible and sustainable manufacturing systems, *Flexible Services and Manufacturing Journal*, Vol. 36, pp. 714-736, 2024. https://doi.org/10.1007/s10696-023-09496-9

[10] TIAN, Y., GAO, Z., ZHANG, L., CHEN, Y., WANG, T.: A multi-objective optimization method for flexible job shop scheduling considering cutting-tool degradation with energy-saving measures, *Mathematics*, Vol. 11, No. 2, pp. 1-31, 2023. https://doi.org/10.3390/math11020324

[11] HUBERT, S., MEINTSCHEL, J., BLEIDORN, D., ORTMANNS, Y. WALLARTH, R.: Production scheduling using deep reinforcement learning and discrete event simulation, *Chemie Ingenieur Technik*, Vol. 95, No. 7, pp. 1003-1011, 2023. https://doi.org/10.1002/cite.202200242

[12] UDAYAKUMAR, R., PRIYAN, S., MITTAL, M., JIRAWATTANAPANIT, A., RAJCHAKIT, G., KAEWMESRI, P.: A Sustainable production scheduling with backorders under different forms of rework process and green investment, *Sustainability*, Vol. 14, No. 24, pp. 1-38, 2022. https://doi.org/10.3390/su142416999

[13] LUNA, M., DE LA FUENTE, D., PARRENO, J., LEON, O.: *Production scheduling in the aquaculture industry based on bio-economic simulation and genetic algorithms*, In: García Márquez, F.P., Segovia Ramírez, I., Bernalte Sánchez, P.J., Muñoz del Río, A. (eds) IoT and Data Science in Engineering Management. CIO 2022, Lecture Notes on Data Engineering and Communications Technologies, Vol. 160, Springer, Cham., pp. 130-135, 2023. https://doi.org/10.1007/978-3-031-27915-7_25

[14] AZEVEDO, B.F., MONTANNO-VEGA, R., VARELA, M.L.R., PAREIRA, A.I.: Bio-inspired multi-objective algorithms applied on production scheduling problems, *International Journal of Industrial Engineering Computations*, Vol. 14, No. 2, pp. 415-436, 2023. https://doi.org/10.5267/j.ijiec.2022.12.001

[15] CIEPLINSKI, P., GOLAK, S., BLACHNIK, M., GAWRYS, K., KACHEL, A.: Production scheduling methodology, taking into account the influence of the selection of production resources, *Applied Sciences*, Vol. 12, No. 11, pp. 1-20, 2022. https://doi.org/10.3390/app12115367

[16] HELMOLD, M.: *Lean Production as Part of QM*, In: Virtual and Innovative Quality Management Across the Value Chain. Management for Professionals, Springer, Cham., pp. 127-137, 2023. https://doi.org/10.1007/978-3-031-30089-9_11

[17] TRIKI, H., BENAMMAR, H., TCHAICHA, Y.: *A multi-objective model case study for the sustainable flow-shop scheduling issue*, In: Akrout, A., Abdennadher, M., Feki, N., Abbes, M.S., Chaari, F., Haddar, M. (eds) Advances in Acoustics and Vibration IV, ICAV 2022, Applied Condition Monitoring, Vol. 22, Springer, Cham., pp. 398-406, 2023. https://doi.org/10.1007/978-3-031-34190-8_42

[18] SANTOS, J.I., PEREDA, M., AHEDO, V., GALAN, J.M.: *NetLogo teaching tool to illustrate the cooling process in simulated annealing using the metropolis model*, In: Izquierdo, L.R., Santos, J.I., Lavios, J.J., Ahedo, V. (eds) Industry 4.0: The Power of Data, Lecture Notes in Management and Industrial Engineering, Springer, Cham., pp. 19-27, 2023. https://doi.org/10.1007/978-3-031-29382-5_3

[19] DOERR, B., RAJABI, A., WITT, C.: Simulated annealing is a polynomial-time approximation scheme for the minimum spanning tree problem, *Algorithmica*, Vol. 86, No. 1, pp. 64-89, 2023. https://doi.org/10.1007/s00453-023-01135-x

[20] DANISH, A.A.K., KHAN, A., MUHAMMAD, K.: A simulated annealing based stochastic long-term production scheduling of open-pit mines with stockpiling under grade uncertainty, *International Journal of Mining, Reclamation and Environment*, Vol. 37, No. 1, pp. 43-65, 2023. https://doi.org/10.1080/17480930.2022.2140543

[21] SUBASH, N., RAMACHANDRAN, M., VIMALA, S., VIDHYA, P.: An investigation on tabu search algorithms optimization, *Electrical and Automation Engineering*, Vol. 1, No. 1, pp. 13-20, 2022. https://doi.org/10.46632/eae/1/1/3

[22] VENKATESWARLU, C.: *A metaheuristic tabu search optimization algorithm: applications to chemical and environmental processes*, In: Tsuzuki, M.S.G., Takimoto, R.Y., Sato, A.K., Saka, T., Barari, A., Rahman, R.O.A., Hung, Y.T. (ed.), Engineering Problems - Uncertainties, Constraints and Optimization Technique, Rijeka, IntechOpen, 2021. https://doi.org/10.5772/intechopen.98240

[23] AMARAL, P., MENDES, A., ESPINOSA, J.M.: *A tabu search with a double neighborhood strategy*, In: Gervasi, O., Murgante, B., Misra, S., Rocha, A.M.A.C., Garau, C. (eds) Computational Science and Its Applications – ICCSA 2022 Workshops, ICCSA 2022, Lecture Notes in Computer Science, Vol. 13378, Springer, Cham., pp. 219-230, 2022. https://doi.org/10.1007/978-3-031-10562-3_16

[24] ISTOKOVIC, D., PERINIC, M., VLATKOVIC, M., BREZOCNIK, M.: Minimizing total production cost in a hybrid flow shop: A simulation-optimization approach, *International Journal of Simulation Modelling*, Vol. 19, No. 4, pp. 559-570, 2020. https://doi.org/10.2507/IJSIMM19-4-525

[25] DANESHDOOST, F., HAJIAGHAEI-KESHTELI, M., SAHIN, R., NIROOMAND, S.: Tabu search based hybrid meta-heuristic approaches for schedule-based production cost minimization problem for the case of cable manufacturing systems, *Informatica*, Vol. 33, pp. 499-522, 2022. https://doi.org/10.15388/21-INFOR471

[26] HE, Y., HE, Z., WANG, N.: Tabu search and simulated annealing for resource-constrained multi-project scheduling to minimize maximal cash flow gap, *Journal of Industrial and Management Optimization*, Vol. 17, No. 5, pp. 2451-2474, 2022. https://doi.org/10.3934/jimo.2020077

[27] RUAN, M., XU, F.: Improved eightoprocess model of precast component production scheduling considering resource constraints, *Journal of Civil Engineering and Management*, Vol. 28, No. 3, pp. 208-222, 2022. https://doi.org/10.3846/jcem.2022.16454

[28] MACCARTHY, B.L., LIU, J.: Addressing the gap in scheduling research: a review of optimization and heuristic methods in production scheduling, *International Journal of Production Research*, Vol. 31, No. 1, pp. 59-79, 1993. https://doi.org/10.1080/00207549308956713

[29] YANG, S.L., WANG, J.Y., XIN, L.M., XU, Z.G.: Verification of intelligent scheduling based on deep reinforcement learning for distributed workshops via discrete event simulation, *Advances in Production Engineering & Management*, Vol. 17, No. 4, pp. 401-412, 2022. https://doi.org/10.14743/apem2022.4.444

[30] MICIETA, B.: Innovative system for scheduling production using a combination of parametric simulation models, *Sustainability*, Vol. 13, No. 17, pp. 1-20, 2021. https://doi.org/10.3390/su13179518

[31] PT TOYOTA MOTOR MANUFACTURING: *Toyota Indonesia: Modul Sistem Produksi Toyota Production*, Indonesia, PT Toyota Motor Manufacturing (TMMIN), 2018. (Original in Indonesian)

[32] RAJU, Y.H.P., DEVARAKONDA, N.: *Makespan Efficient Task Scheduling in Cloud Computing*, In: Abraham, A., Dutta, P., Mandal, J., Bhattacharya, A., Dutta, S. (eds) Emerging Technologies in Data Mining and Information Security, Advances in Intelligent Systems and Computing, Vol. 755, Springer, Singapore, pp. 283-298, 2019.

[33] SOMASHEKHARA, S.C.H., SETTY, A.K.Y., SRIDHARMURTHY, S.M., ADIGA, P. MAHABALESHWAR, U.S., LORENZINI, G.: Makespan reduction using dynamic job sequencing combined with buffer optimization applying genetic algorithm in a manufacturing system, *Mathematical Modelling of Engineering Problems*, Vol. 6, No. 1, pp. 29-37, 2019. https://doi.org/10.18280/mmep.060104

[34] PEKARCIKOVA, M., TREBUNA, P., KLIMENT, M.: Digitalization effects on the usability of lean tools, *Acta logistica*, Vol. 6, No. 1, pp. 9-13, 2019. https://doi.org/10.22306/al.v6i1.112

[35] ZAHRAEE, S.M., ROHANI, J.M., FIROUZI, A., SHAPANAH, A.: Efficiency improvement of blood supply chain system using taguchi method and dynamic simulation, *Procedia Manufacturing*, Vol. 2, pp. 1-5, 2015. https://doi.org/10.1016/j.promfg.2015.07.001

Review process
Single-blind peer review process.