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A simulation-based approach to decision support for lean practitioners

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Abstract: In today's global competition, having a lean production system is a must for companies to remain competitive. By identifying and eliminating waste throughout a product's entire value stream by means of a set of LM tools, companies are able to produce and assemble any product range in any order or quantity. In order to do these, personnel needs to have the expertise in deciding which LM tool to implement at the right time and on the right place. However, this expertise is not always available. Therefore, this paper proposes a simulation-based decision support (SDS) tool to assist the decision making in LM tool implementation. The SDS tool provides five functions through an interactive use of process simulation. The functions are layout, zoom-in/zoom-out, task status, Key Performance Indicators (KPI) status and R.A.G (Red, Amber and Green) status (quantifying waste). These functions are incorporated into a process model of coolant hose manufacturing (CHM) factory which was developed in this study. Layout function provides a bird's eye view of the whole process model and shows how the manufacturing process runs with the flow of materials and products. Zoom-in/zoom-out function provides a detail view of manufacturing processes of the factory. For KPI and RAG status functions, examples of LM tool implementations are used to show how different parameters affect the outcome of manufacturing process. Bar charts of KPIs are also available during simulation. Feasibility study showed how SDS tool enhance the visual perception and analysis capabilities of lean practitioners through availability of specific functions in the simulation model. Hence, decisions in LM implementation could be made correctly and with increased confidence by lean practitioners.

Keywords: Simulation, Lean Manufacturing, Decision support

Introduction and Research Background

To date, the lean manufacturing (LM) philosophy has been applied to many manufacturing processes and its feasibility has been reported so far [1]. By identifying and eliminating waste throughout a product's entire value stream by means of a set of

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LM tools, companies are able to produce and assemble any product range in any order or quantity. In order to do these, personnel needs to have the expertise in deciding which LM tool to implement at the right time and on the right place. However, this expertise is not always available [2, 3]. The decision making in manufacturing systems is becoming more difficult nowadays due to increasing amount of data and complex interrelations between manufacturing processes [4].

Simulation has been asserted as a tool to quantify the effectiveness of LM tool implementation and assist lean practitioners with the decision to implement LM [1, 5-6]. Simulation is an effective method of supporting and evaluating LM tools, assessing current and future state of manufacturing process, performing "what-if" analysis and measuring impact of improvement after LM implementation. Most importantly, simulation could represent a large number of interdependent input parameters and manage the complexity of interactions effectively [7].Using simulation to analyse real data enables lean practitioners to forecast the output of manufacturing processes base on the input values. This provides the lean practitioners time to react to emerging problems, evaluate potential solutions and decide on LM implementation.

However, most studies use simulation to design, test and improve lean system. Yet, studies on usage of simulation to support decision-making in replacing an existing manufacturing process with a lean system are still lacking [1]. Lean practitioners (decision-makers) understanding on how to implement LM and the impact of LM on performance measures is also still lacking [8]. Thus, the decisions to adopt LM are often made based on their own intuitions, faith in LM philosophy, consulting the experts, utilizing handbooks, experiences of other management teams who have implemented LM and using their own calculation methods [4, 9].

There are research attempts which present the application of simulation-based approaches to decision making issues in LM implementation. A research conducted by [10], uses simulation to support decision-makers in production design and operations while the study of [4] deployed simulation in operational scheduling system and concluded that simulation-based approaches could alleviate the works required to plan day-to-day scheduling, ensure conformance of customer order due date, synchronize flow through the plant, reduce changeover time and forecast potential problems.

Nevertheless, there are minor drawbacks associated with these simulation-based approaches to decision making in LM implementation. As far as the limitation of these approaches are concerned, the biggest obstacle is to develop a system capable of supporting operational (real-time) decision making as opposed to strategic manufacturing decision making [11]. Another obstacle is the "gap" which exists between lean practitioners and simulation-based approaches in terms of expertise in utilising the simulation software tools. The simulation software tools are generally more suitable for simulation engineers who know how to design/build/analyse a simulation model, and how to integrate it to LM tool software [12]. Basically, simulation studies in lean projects are managed by simulation engineers and real time updating of simulation model is also performed by them [13]. Therefore, these approaches are not suitable for lean practitioners who are familiar with neither simulation software, nor LM tool software. Misunderstanding between simulation engineers and other lean practitioners may lead to development of a biased simulation model [14]. Therefore, a structured approach of using simulation software tools is required to support decision-making process in manufacturing and increase the understanding of decision-makers in the company because it will determine the future of the company [15].

Motivated to address this gap, [16] developed a decision support system targeted for users who are not experts in simulation. The decision support system was developed using Visual Basic Application and designed to work with Witness package and Superscape VRT software to enable non-expert users to develop simulation and virtual models. Users are also able to interact with the simulation models in real time using voice commands and observe the virtual model using head mounted display. With this decision support system, the targeted users could develop simulation models of manufacturing systems and addresses their behavior.

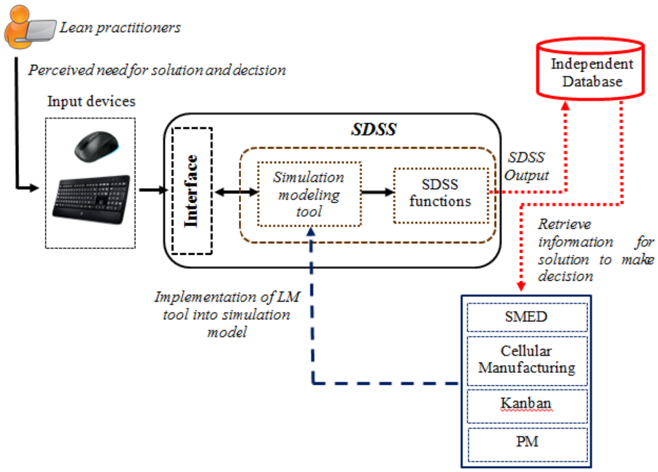


Figure 1. The simulation-based decision support system (SDSS) architecture

In this study, a simulation-based decision support system (SDSS) is proposed to address the gap between lean practitioners and simulation-based approaches in terms of expertise in utilising simulation software tools. SDSS is a system capable of supporting operational (real-time) decision making by providing five functions through interactive use of process simulation to assist lean practitioners (who are not experts in simulation) in their decision to implement LM tools.

The functions are layout, zoom-in/zoom-out, task status, Key Performance Indicators (KPI) status and RAG (Red, Amber and Green) status. Following simulation runs, results (SDSS output) will be saved in an independent database. These results could be retrieved during or at the end of simulation runs in the form of total production output, total production time, changeover time, bar chart, Work in Progress (WIP) and Inbound/Outbound buffer values. From the results, lean practitioners could detect problems in the simulated production line and select the most suitable LM tool to be applied to solve the problems. For example, if the result shows high changeover time, lean practitioners could choose Single Minute Exchange of Die (SMED), implement it into the simulation model and conduct simulation run again to observe the improvement brought by the chosen LM tool (Figure 1). The process could be repeated countlessly until the desired results are achieved. By using this process simulation approach, lean practitioners are able to forecast the output of manufacturing processes and the effectiveness of LM tools base on the input values. This provides the lean practitioners time to react to emerging problems, evaluate potential solutions and decide on LM implementation. Feasibility of SDSS is studied using a manufacturing process model of Coolant Hose Manufacturing (CHM) factory which was developed in this study. The details of SDSS will be elaborated in the next section.

1. Overview of SDSS

As mentioned earlier, this research proposes SDSS to address the gap between lean practitioners and simulation-based approaches in terms of expertise in utilising simulation software tools. SDSS plays a critical role to support lean practitioners in real-time decision making and selection of LM tools. SDSS provides five functions through an interactive use of process simulation to assist lean practitioners (who are not experts in simulation) in their decision to implement LM tools.

The layout function of SDSS provides a bird's-eye view of the simulated factory floor. By using this function, lean practitioners could observe how the manufacturing process runs with the flow of materials and products throughout the manufacturing process. They could identify workstations that cause bottleneck, movement of operators, movement of material transportations and other problems.

On the other hand, zoom-in/zoom-out function is designed for obtaining a detail view of each section of manufacturing processes. For example, if the lean practioners noted a section with product congestion during simulation run, they could click on the zoom-in button to get a better view of that particular section and find out the cause of product congestion. To find the cause of product congestion, they are provided with the third function of SDSS which is the task status function. The task status functions of SDSS provides three status illustrations i.e. busy, idle, and fail to represent operator status in every workstation in the factory. The three task statuses of operator are differentiated by means of colours and location of the operator from the machine. By observing these status illustrations, lean practitioners would be able to understand the changing task status in real time during the simulation runs. Once they have understood the problem at the workstation, they could resume viewing the layout view by clicking on the zoom-out button. Following that, they could proceed to the next function of SDSS which is KPI status function to acquire more information on the existing problems.

The KPI status function which includes total production output and total production time and changeover (C/O) task time, are presented by means of KPI tables. KPI values in this simulation model are generated and updated in real time during simulation. By conducting what-if analysis and observing the KPI, the lean practitioners could see the performance of the existing production line and compare it with the performance post LM tool implementation. For visual understanding of KPI, bar charts of KPI tables are also generated and updated in real time during simulation. These bar charts also provide information on WIP and Inbound/Outbound buffer which assist lean practitioners in their decision to implement LM tools.

Apart from providing KPI status function, SDSS also provides RAG status function which is capable of quantifying waste in manufacturing process. RAG status function continuously monitors the status of waste quantitatively during simulation runs. RAG status is developed in the following three steps. Step 1 is collection of observation data. Step 2 is performance level (PL) calculation of workstation (WS) in manufacturing line using mathematical calculation. Step 3 is determination of waste level by quartile calculation method. To determine waste level, distribution pattern of PL was assessed by using quartile calculation to attain Q1, Q2 and Q3 of each WS in the simulation study. The method of quartile calculation is described below:-

A set of data from each WS is arranged in ascending order of magnitude $X_{(1)}, X_{(2)}, \ldots, X_{(n)}$ .The median (middle value of the data set) is determined followed by calculation of each quartile. Quartile calculation is executed for even and odd sample size (n) accordingly.

i. For even sample size (n),

$$\text{Q2 (Second quartile)} = [x_{(n/2)} + x_{\left(\frac{n}{2}+1\right)}]/2 \quad (1)$$

$$\text{Q1 (First quartile)} = \text{median of } x_{(1)},\ldots\ldots,x_{(n/2)} \quad (2)$$

$$\text{Q3 (Third quartile)} = \text{median of } x_{\left(\frac{n}{2}+1\right)},\ldots\ldots,x_{(n)} \quad (3)$$

ii. For odd sample size (n),

$$\text{Q2 (Second quartile)} = \mathrm{x}_{((\mathrm{n}+1)/2))} \quad (4)$$

$$\text{Q1 (First quartile)} = \text{median of } \mathrm{x}_{(1)},\ldots\ldots,\mathrm{x}_{\left(\frac{(\mathrm{n}+1)}{2}-1\right)} \quad (5)$$

$$\text{Q3 (Third quartile)} = \text{median of } \mathrm{x}_{\left(\frac{\mathrm{n}+1}{2}+1\right)},\ldots\ldots,\mathrm{x}_{\mathrm{n}} \quad (6)$$

Table 1. Waste level for different condition of manufacturing line

Waste Level	R (Red)	A(Amber)	G(Green)
Condition A	PL ≤ Q1	Q1 < PL < Q3	PL ≥ Q3
Condition B	PL ≥ Q3	Q1 < PL < Q3	PL ≤ Q1

After determining Q1, Q2 and Q3, waste level is set depending on the condition of the manufacturing line (Table 1). During simulation runs, the RAG status function continuously monitors the waste level and display it in the form of graphical image. A green status indicates that waste is not present. Amber status indicates that waste exists but still within acceptable limits and warrants attention. Red status indicates that waste is beyond the acceptable limits.

2. CHM factory simulation model

The CHM factory simulation model is developed in this study using Arena simulation software [17]. This factory produces four types of coolant hose products, which are called CH4, CH6, CH8 and CH10.

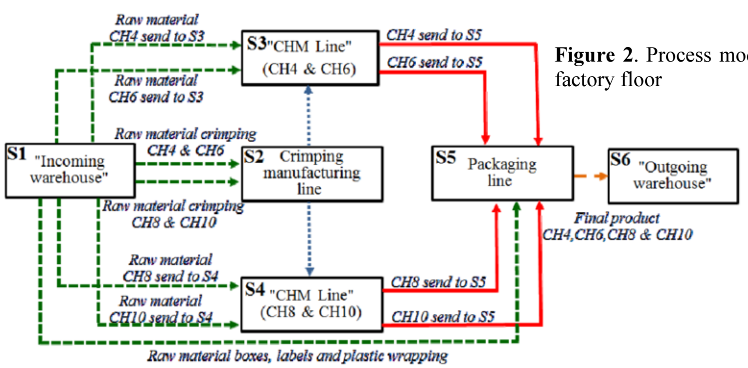


Figure 2. Process model of CHM factory floor

The factory floor is divided into six sections from Section 1(S1) to Section 6(S6). S1 (supplier section) supplies raw materials to S2, S3, S4, and S5. Then, S2, S3, S4 and S5 supply their processed parts to S3/S4, S4, S5 and S6, respectively as shown in the process model of CHM factory (Figure 2). Material handling of these parts is performed by either forklift or trolley. Production capacity for each product is 150units/day in nine hours operation.

Following the process model, layouts and model logic of CHM factory were then created. Figure 3 shows the layout of CHM factory using S4 as an example. The simulation model for CHM factory was designed based on a certain assumptions; all workstations operate at full capacity; all workstations have triangular distribution process time; product arrival time is based on a deterministic arrival pattern; and all results are reported at a confidence interval level of 95%.

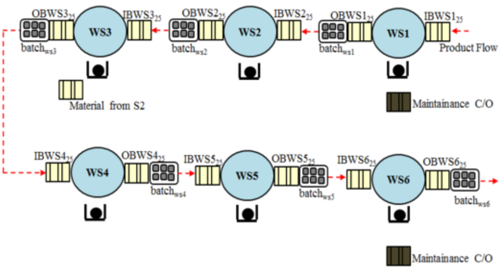


Figure 3. Layout of S4 of CHM Factory

Verification of the model was proved by tracing all the products from the point of their creation (S1: Incoming warehouse) to the point of their disposal from the system (S6: Outgoing warehouse) to ensure that the simulation model closely approximate the real system. Validation of the model was also proved by comparing the output of simulation (total production time) with its mathematical calculation results by applying Little's Law equation [18]. Total production time is obtained from WS with the longest φ_{tot} (total mean flow time) in the production line. φ_{tot} is calculated by considering the buffer, batch size, process time and route time for each WS.

$$\varphi_{tot} = \varphi_B + \varphi_{Bq} + \varphi_{Bk} + t_0 + t_{route} \tag{7}$$

where,

t_{route} : route time between workstation (in time unit)

t_0 : process time for workstation (in time unit)

φ_B : mean flow time for waiting in buffer (in time unit)

φ_{Bq} : mean flow time for queuing on the inter-arrival of a batch (in time unit)

φ_{Bk} : mean flow time for wait-to-batch time (in time unit)

To calculate total production time, this formula is used:

$$Total\ production\ time = \varphi_{tot}\ .\ total\ demand/no\ of\ batch \tag{8}$$

Table 2. Validation of CHM factory model

Section	Simulation result (minute)	Mathematical calculation result (minute)	Similarity (%)	Confidence interval range (95%)	Status
S2	385.59	380.02	98.56	342.13-519.58	Valid
S3	834.61	853.60	97.77	639.43-1001.3	Valid
S4	887.14	853.60	96.22	572.08-989.3	Valid
S5	118.89	111.40	96.70	91.36-203.70	Valid

The similarity of simulation results and mathematical results for total production time for each section in CHM factory model were above 93%, which is within the range of 95% confidence interval level (Table 2). Therefore the CHM factory model was validated.

3. Feasibility of SDSS in CHM factory simulation model

Feasibility study of SDSS was done using S4 of CHM factory as an example. By using layout, zoom in/zoom out function and bar charts (Figure 4 & 5), bottleneck is observed at WS1 of S4. The reason for this bottleneck situation is acquired from the KPI status function which showed high changeover time (51 minutes). This has caused a low total production output (100 units/day) and high total production time (531.33minutes) as can be seen in Figure 6.

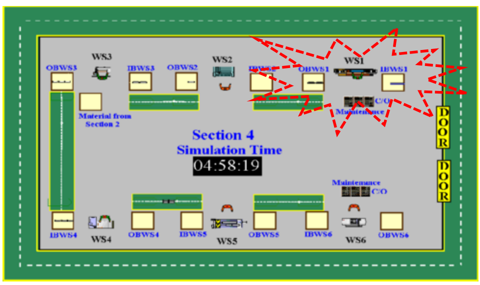


Figure 4. Snapshots of S4by zoom-in function

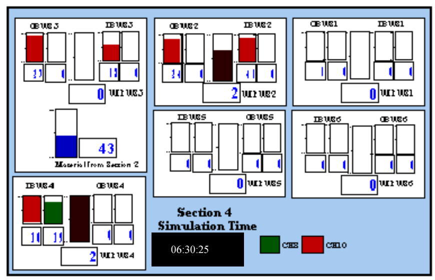


Figure 5. Snapshots of bar charts for S4

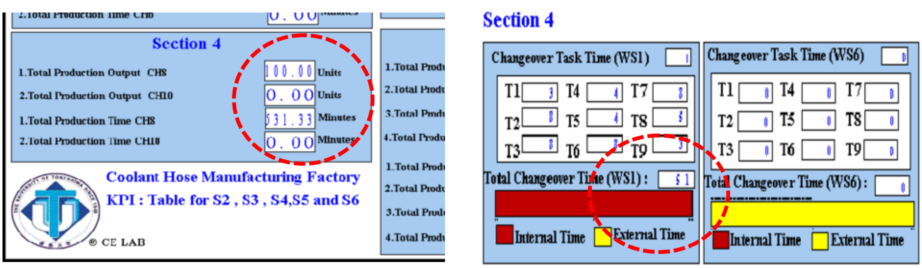


Figure 6. Snapshots of KPI table for S4

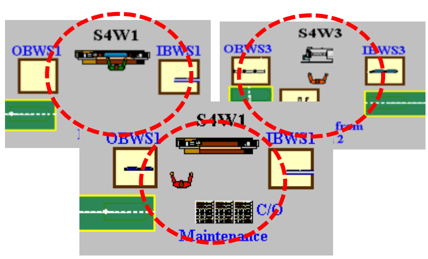


Figure 7. Task status illustration

To react to this problem, one of the potential solutions is implementing SMED at WS1 and WS6 of S4 to reduce changeover time. Following SMED implementation, the total production output is increased by 9% while the total production time is reduced by 4%. For further improvement of S4, the functions of SDSS are observed continuously during simulation runs. Another problem detected in S4 is prolonged idle status of operators in WS4, WS5 and WS6. A potential solution for this problem is to implement cellular manufacturing (CM) in S4. By implementing CM, the total production output is increased by 1% while total production time is reduced by 1.14%. Despite the minor improvements, the number of operator has been reduced by 33.33% (from six to four people).

This feasibility study is also used to show RAG status function in CHM factory simulation model using WS1 of S4 and one of the seven wastes of manufacturing (waiting) as an example. In this study, 'waiting' is defined as an idle status of operator due to starvation of parts/materials and high changeover task time in WSs. As mentioned earlier, S4 consists of six WSs, produces two types of products (CH8 and CH10) and has a scheduled changeover process at WS1 and WS6.

Table 3. PL for WS1 of S4 within Time Range t_{30} to t_{540}

Time Range	t_{30}	t_{60}	t_{90}	t_{120}	t_{150}	t_{180}	t_{210}	t_{240}	t_{270}
PL	0.0207	0.0103	0.0069	0.0348	0.1279	0.1899	0.2199	0.1015	0.0757
Time Range	t_{300}	t_{330}	t_{360}	t_{390}	t_{420}	t_{450}	t_{480}	t_{510}	t_{540}
PL	0.0681	0.0619	0.0568	0.0524	0.0487	0.0426	0.0502	0.0500	0.0370

No	PL (WS1)	
X_1	0.0069	
X_2	0.0103	
X_3	0.0207	
X_4	0.0348	
X_5	0.0370	*Q1 (First quartile)*
X_6	0.0426	
X_7	0.0487	
X_8	0.0500	
X_9	0.0502	*Q2 (Second quartile)*
X_{10}	0.0524	
X_{11}	0.0568	
X_{12}	0.0619	
X_{13}	0.0681	
X_{14}	0.0757	*Q3 (Third quartile)*
X_{15}	0.1015	
X_{16}	0.1279	
X_{17}	0.1899	
X_{18}	0.2199	

Table 4. PL for WS1

Waste level	Range for waste level
Red	$PL \geq 0.0757$
Amber	$0.0370 < PL < 0.0757$
Green	$PL \leq 0.0370$

Table 5. Waste level of WS1

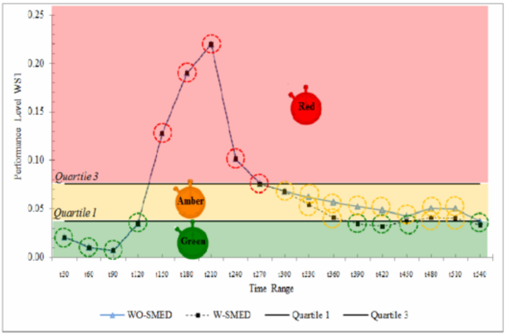
After conducting a series of simulation runs with different time range between t_{30} to t_{540}, PL values were calculated as shown in Table 3. Then, Q1, Q2 and Q3 for WS1 with sample size ($n=18$) were calculated using quartile calculation. The results are 0.0370, 0.0513, and 0.0750, respectively (Table 4). Base on Q1, Q2 and Q3 values, waste level is determined (Table 5) using condition B (please refer to Table 1). These waste levels were presented in real-time in the form of RAG status.

The customized RAG status was then incorporated into WS1 simulation model followed by implementation of SMED LM tool. The PL of WS1 with and without SMED implementation was updated in real-time during simulation from t_{30} to t_{540} as shown in Table 6 and Figure 8. Figure 8 shows that the RAG status remains the same from t_{30} to t_{300} because no C/O process took place in WS1 within this time range. However, the RAG status changes from amber to green at t_{390} when SMED was implemented and the green colour continued until t_{450}. This behaviour of RAG status detected the process improvement by SMED LM tool and proved that the process improvement was successfully achieved. This behaviour of RAG status coupled with quantitative information on the percentage of PL improvement (Table6) were designed to provide pro-active assistance to LM practitioner so that decision making and selection of LM tool could be made appropriately.

Time Range			t_{30}	t_{60}	t_{90}	t_{120}	t_{150}	t_{180}	t_{210}	t_{240}	t_{270}
WS1	PL	WO-SMED	0.0207	0.0103	0.0069	0.0348	0.1279	0.1899	0.2199	0.1015	0.0757
		W-SMED	0.0207	0.0103	0.0069	0.0348	0.1279	0.1899	0.2199	0.1015	0.0757
	Improvement	(%)	0%	0%	0%	0%	0%	0%	0%	0%	0%
Time Range			t_{300}	t_{330}	t_{360}	t_{390}	t_{420}	t_{450}	t_{480}	t_{510}	t_{540}
WS1	PL	WO-SMED	0.0681	0.0619	0.0568	0.0524	0.0487	0.0426	0.0502	0.0500	0.0370
		W-SMED	0.0681	0.0543	0.0410	0.0349	0.0322	0.0370	0.0412	0.0401	0.0334
	Improvement	(%)	0%	12%	28%	33%	34%	13%	18%	20%	10%

 # W-SMED (with SMED); WO-SMED (without SMED)

Table 6. PL improvement of WS1 W-SMED and WO-SMED



 # W-SMED (with SMED); WO-SMED (without SMED)

Figure 8. Performance level of WS1 W-SMED and WO-SMED

4. Conclusion

This research proposed a simulation-based decision support system (SDSS) for the implementation of LM. SDSS plays a critical role to support lean practitioners for their decision making and selection of LM tools through an interactive use of process simulation. SSDS provides five functions, namely layout, zoom-in/zoom-out, task status, Key Performance Indicators (KPI) status and RAG (Red, Amber and Green) status. Using a process model of CHM factory, feasibility of SDSS was studied. The feasibility study showed that SDSS play an indispensable role in enabling lean practitioners to detect problems and quantify the effectiveness of LM tools on manufacturing process. However, the results can be further validated if they are reproduced experimentally in a real case study.

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