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APPLYING DISCRETE-EVENT SIMULATION AND VALUE STREAM MAPPING TO REDUCE WASTE IN AN AUTOMOTIVE ENGINE MANUFACTURING PLANT

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ABSTRACT

This paper aims to apply a combination of Value Stream Mapping (VSM) and Discrete-Event Simulation (DES) in an automotive engine manufacturing plant. First, a current state VSM was created and the sources of waste were identified. The leak-test area and engine impregnation process were identified as major sources of waste. Based on that, two potential improvement scenarios were developed and analyzed using DES. The simulation was used to compare key measures of performance in the current state and the proposed scenarios, using different setting for adjustable system parameters. Results showed improvements of up to 29% in annual engine impregnation cost for one scenario, without detriment to other measures. The study's major takeaway is demonstrating that VSM in conjunction with DES is a powerful alternative in studying changes in production processes, which leverages the advantages of both methodologies.

1 INTRODUCTION

Value Stream Mapping (VSM) is a lean manufacturing tool that has been used by automotive manufactures to identify and eliminate waste in the systems. The analysis of a VSM leads to a process improvement through the reduction of non-value added steps. A Discrete-Event Simulation (DES) is often used to verify and analyze potential improvement scenarios before the actual implementation in the factory. It allows companies to make predictions about the behavior of processes, objects, and events in the short and long-term. The conjunction of VSM and DES can help automotive organizations to analyze and test solutions without interfering with the real system, enabling decision makers to understand how changes in the process will be reflected throughout the system. This paper aims to combine VSM and DES in the engine block machining line of an automotive engine manufacturing plant and report the main findings. This paper will outline the use of simulation to analyze multiple improvement configurations prior to selection of the best alternative to reduce waste without compromising other measures of performance.

The current state VSM of the engine block machining line was constructed to identify existing sources of waste within the system. The main source of waste was found to be in the leak-test area of this line, which causes delays, creates off-line WIP, uses manpower, causes waste in transportation, and generates extra processing in the form of block impregnation to repair suspected leaky engine blocks. We created a DES model that represented the real system and we proposed two potential scenarios that would re-organize the process. We chose to use DES for this study because it can incorporate variability into the system that is difficult to capture in real life. The simulation software used was Simio because it provides an expansive environment for performing validation and executing complex systems.

In addition to comparing the two potential improvement scenarios, we were interested in testing the sensitivity of each scenario with respect to three adjustable systems parameters. We performed single-parameter and two-parameter experiments with each of these three parameters for each scenario. The goal was to determine the effect of the variation of these parameters on the measures of performance.

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The results from the single-parameter and two-parameter experiments showed that the line throughput was not significantly impacted by the varying the systems parameters. Comparative results show that the improvement scenarios save 2.5% and 29% in annual impregnation cost, by scraping no-good blocks earlier in the process and avoiding unnecessary impregnation, without any expected negative impacts.

This paper is organized as it follows: In section 2, a literature review of simulation related to the automotive industry and VSM is presented. Section 3 presents a description of the automotive engine manufacturing plant modeled in this manuscript. In section 4, the simulation of the current state and two improvement scenarios of the engine block machining line is presented. Section 5 presents the findings of this study. Finally, section 6 contains the conclusions and a summary of the findings.

2 LITERATURE REVIEW

Automotive manufacturers are increasing the implementation of lean manufacturing principles and tools, such as continuous flow and value stream mapping, to identify, eliminate or reduce waste and improve the system (Habidin and Yusof 2013). VSM is a lean manufacturing tool that helps to identify and eliminate sources of waste in a manufacturing process in order to serve customers with higher quality and promptness (Rother and Shook 2003). The main purpose of applying this tool is to reduce time between the customer placing an order and the time of delivering the final product.

At the same time, the automotive industry involves complex supply chain and manufacturing settings that may be difficult to fully capture with lean tools, such as VSM. Applications of DES have been useful in this field because they can incorporate several sources of variability, complex constrains, and interactions that are difficult to measure and understand directly from the real system (Williams 2012). DES models represent the production system in a virtual environment, enabling the decision makers to understand and optimize their operations (Kuhn 2006). DES can be used in conjunction with VSM to help automotive organizations to further analyze data, quantify gains, identify needs for resources, and generate performance statistics (Donatelli and Harris 2001). Both techniques, DES and VSM, have a long history of application in automotive manufacturing. However, they are usually applied separately.

Manufacturing research is experimentally oriented and simulation models, such as the one we use here, have long been applied to analyze different experiments and optimize a system through "what-if" analysis (Michalos et al. 2010). For example, Renteria-Marquez et al. (2020) presented a simulation methodology to model the production floor, warehouse and material handling system of an automotive assembly facility. Emde and Gendreau (2017) applied simulation in an automotive assembly line to approach a Just in Time (JIT) delivery of raw material. Alsakka et. al (2020) demonstrated the importance of using simulation to test what-if scenarios in a manufacturing process. Kibira and McLean (2007) presented a description of the basic process using data-driven simulation in an automotive manufacturing assembly plant. Wang et al. (2011) proposed a simulation of an automotive manufacturing plant that can be automatically generated.

Furthermore, a few publications have also highlighted the application of VSM with DES in manufacturing. For instance, Andrade et al. (2015) combines VSM and DES as a decision making tool of an assembly line of clutch discs in an automotive company. Lian and Landeghem (2002) proposed a method for using simulation to extend the analysis of a VSM, evaluating two scenarios of push and pull manufacturing systems. Mahfouz and Arisha (2013) presented a lean assessment framework that integrates VSM with simulation in a tire distribution company. Similarly, Rajenthirakuma et al. (2012) used VSM and simulation as mutually complementary. Going further, Narasimhan et al. (2007) introduced a new approach known as "Simulation-aided VSM" and applied it in a global engine manufacturer's test environment. Antonelli and Stadnicka (2018) discussed the combination of VSM with simulation and concluded it is beneficial not only for verification but also for seeing different pictures of the investigated manufacturing system. Donatelli and Harris (2001) stated that combining VSM with simulation provides an accurate analysis of system's current and future states and it is an efficient quantitative assessment for the lean practices and policies. In this work, we use VSM to identify the existing sources of waste within the engine block machining line of an automotive engine manufacturing plant and develop a DES model to conduct analyses of multiple improvement scenarios and find the best alternative to reduce waste without compromising other metrics of performance. To the best of our knowledge, this is the first use of "Simulation-aided VSM" applied to engine block machining to be reported in the literature.

The strategy of combining VSM and DES presented in this paper can help automotive manufacturers to avoid costs related to physical experimentations. The integration of lean tools, such as VSM, with a simulation-based technique helps companies to visualize different implications and have different insights into the process of interest. Before using a DES model for decision-making, model verification and validation must be performed (Smith, et. al 2018). In this study, we used Parameter Variability-Sensitivity Analysis (Sargent 2013) for model verification, and Event Validity for model validation.

3 THE MACHINING LINE IN THE AUTOMOTIVE ENGINE MANUFACTURING PLANT

The automotive engine block manufacturing plant that we studied for this research is divided into three sections: die-casting, machining and engine assembly. The scope of this study is limited to the machining line, in particular, the engine block machining line. Figure 1 shows a high-level VSM of the engine block machining line, which comprises 20 stations, represented in grey boxes, that perform different machining operations on engine blocks. Consecutive stations are connected by conveyors, which are represented in orange boxes. The current state VSM was developed by following a block's production path backwards from customer (Engine Assembly) to supplier (Block Die-Casting) and drawing a visual representation of every process in the product flow. This engine block machining line includes a few parallel and sequential sub-processes. These processes were taken into consideration while building the VSM, but are not depicted in detail in Figure 1 to protect our industry partner. The simulated section does not have that feature.

The current state VSM is based on the current practices at the facility and its information and data were gathered from two streams. First, we conducted a time study to collect the cycle time and lead time of each station on the engine block machining line. Second, data such as down time was acquired from interviewing workers. Production requirements, cycle time, lead time, change over time, number of operators, available time, and inventory numbers were some of the main data collected to build the current state VSM. Detailed information from the original VSM, including specific steps and duration for each process, as well as value-added and non-value-added time, has been redacted to protect the automotive company's trade secrets. The current state VSM was constructed to identify existing sources of waste within the system. After creating and analyzing the current state VSM, the main source of waste was found to be in the Leak Test area, which is represented inside the red rectangle in Figure 1.

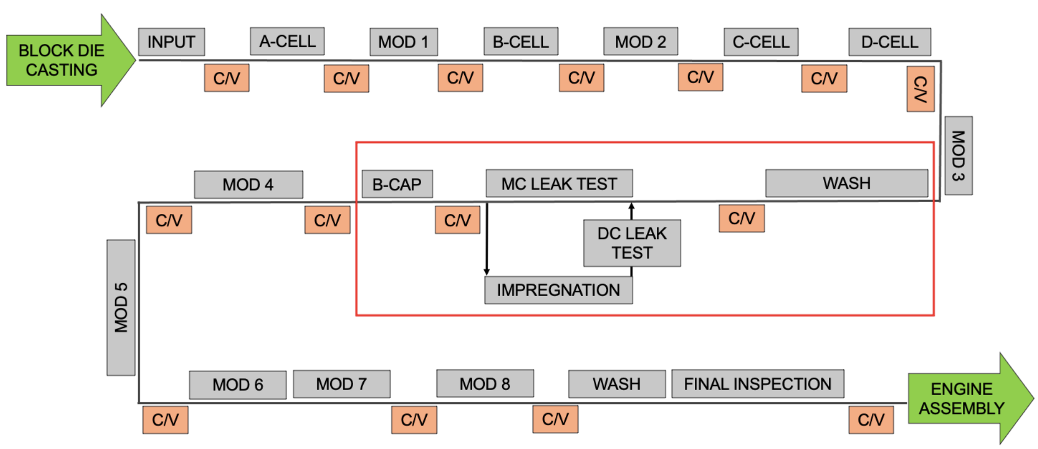

Figure 1: Current state value stream map.

3.1 Machining Leak Test

There are two leak test machines in this area: Machining Leak Test (MC Leak Test) and Die Cast Leak Test (DC Leak Test). Machining Leak Test is considered the Master Leak Test and it is an automated process where the machine makes the decision on the condition of the block. Die Cast Leak Test is operated manually, here the operator gets the results from the machine and makes a decision on the condition of the block. Both machines test leaks and follow standards to determine the condition of the block. The majority of the blocks that go through MC Leak Test pass the test, so they stay in the conveyor and go to the next process, which is called B-CAP. The blocks that fail MC Leak Test can be classified as large leaker, pull-off or straight to impregnation. A large leaker block is identified when MC Leak Test determines that the leak is too large, so this block is kicked out of the conveyor and put in a skid to be retested in DC Leak Test. A pull-off block is a block that is pulled-off the line because the conveyor that goes to impregnation is full or in danger of blocking (and hence shutting down) MC Leak Test. The decision to test all pull-off blocks in DC Leak Test instead of inputting them back into the conveyor that leads to impregnation was made because this conveyor is small and is always at almost full capacity; it also allows identifying potential false positives. Lastly, a straight to impregnation block is a block that needs to go through the impregnation process to be repaired. All blocks that fail MC Leak Test are eventually tested in DC Leak Test, whether they are pull-offs, impregnation, or large leaker. DC Leak Test determines if the block is scrapped, if it needs another round of impregnation, or if it passes the test. A block that passes DC Leak Test is routed to be tested again in MC Leak Test, as that is considered the Master Leak Test. The current state of this area was modeled as “Base-Line Model” (BL) and it is represented in Figure 2.

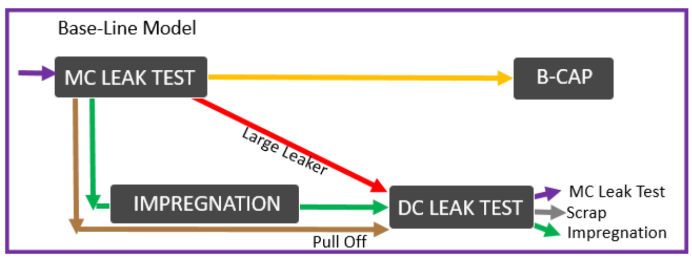

Figure 2: Leak test area in base-line model.

The VSM revealed that the Leak Test area is the source of the waste in the system, causing delays, off-line Work In Process (WIP), extra processing in the form of impregnation and re-testing, and waste in transportation. Additionally, because the Leak Test area has a complex and stochastic routing structure, we were unable to calculate a lead time for it when building the VSM. For these two reasons, we decided to develop a DES model of the current state of this area, to estimate the average lead time that a block spends in this area and also to study different scenarios/approaches that could reduce the waste generated here.

We chose to use DES for this study because it can incorporates interaction between sources of variability in the system that is difficult to capture in other methods. Moreover, it is a very useful tool to assess different strategies and explore its impacts upon automotive manufacturing operations, without requiring actual physical changes. The simulation model is explained in the next section.

4 SIMULATION AND ANALYSIS

In this section, we give an overview of the simulation model and explain the assumptions that were made and the scenarios that we considered. The first step in building the simulation model was getting it to represent the current state of the system as accurately as possible. Once the model was validated and it reflected the real processes, we were able to test new potential scenarios. The simulation model created to represent the current state VSM of the Leak Test area is titled “Base-Line Model” (BL). We incorporated downtime, processing time, availability, shifts, flows, and reliability logic gathered from the VSM data into this model. Building the VSM, not only identified the critical process to simulate, but also allowed the modeler to become familiar with the system and facilitated the data collection, such as downtime, processing time, availability, flows, and reliability logic, which were readily available from the VSM. It allows us to track the engine blocks and capture many measures of performance. The study's major takeaway is that building a VSM before embarking on building a DES model facilitated the data collection, familiarized the modeler with the details of the system, and allowed better verification and validation.

4.1 Model Construction and Assumptions

Several assumptions were made to develop the simulation model. First, those stations that were outside the scope of the model were assumed to always be functioning, thus never blocking or starving the stations that were modeled. Therefore, the suggested improvements would be fully effective for the overall factory's production process only if the assumption holds true. Second, lunch breaks, scheduled quality checks, and any other scheduled breaks were embedded in different work schedules for each station. There are two operators in the Leak Test area that are in charge of off-loading blocks from the line (and into a WIP staging area) if the conveyors are full and putting WIP blocks back into the line if the conveyors are empty.

Probability distributions were fitted to the data for each machine and fed into the model elements. These distributions were used to define the arrival time of engine blocks in the model and to define the processing time and reliability logic of each machine. The simulation software used to build the models was Simio, which we chose due to its object oriented architecture, which we prefer.

4.2 Verification and Validation

The Base-Line model was verified and validated. A warm-up period of a month was defined in order to allow the system to reach the steady state of operation. The model was run for three months after the warm up and we performed 30 replications. Replications are necessary since this system contains stochastic parameters with random probability distributions. We increased the number of replications until the outputs achieved a satisfactory confidence interval half-width for measures of performance.

In this study, verification was performed by applying Parameter Variability-Sensitivity Analysis (Sargent 2013). We used the Status-Label from Simio to track the engine blocks in the system and evaluate the output variation based on changes on the input. Status-Label displays values of specific expressions as the model runs allowing us to track numbers at any given time We observed several outputs, such as the number of engine blocks tested in MC Leak Test, number of engine blocks and how many times they went through impregnation, and number of blocks considered as scrap. We compared the results shown in the Status-Label to what we expected from the changes on the inputs, and the model discrepancies were adjusted until a convergence of the model to the expected results was obtained.

In order to validate the Base-Line model, we performed Event Validity Analysis (see e.g. Smith et al. 2018), in which we compared three-months of historical data from the real system to the 30 replication's results obtained from the simulation. The total number of engine blocks tested in MC Leak Test, from the Base-Line Model is within 5% of the real system. The impregnation results were also within a range of 5% of the real system. The total number of blocks considered as scrap from the model were almost exactly the same as the real system, which confirms that the Base-Line model is close enough to accurately represent the real system. In order to keep the confidentiality of the manufacturing plant, detailed numerical results of the verification and validation process cannot be shown.

Once the model was verified and validated, we were able to test ideas and what-if scenarios. After several brainstorming sessions with the stakeholders, including managers, engineers and associates, we settled down on two improvement scenarios that were realistic and applicable, which we named Scenario 1 (S1) and Scenario 2 (S2). We define and describe each of these in detail in the following section.

4.3 Scenarios

Base-Line Model: The Base-Line model (BL) represents the current state of the Leak Test area. In this model, engine blocks arrive at the MC Leak Test machine and depart going through the B-CAP process. Since MC Leak Test is the Master Leak Test, every block that goes through DC Leak Test needs to go through MC Leak Test again. A visual representation of the Base-Line Model can be found in Figure 2.

Scenario 1: The first what-if scenario considered in this study is titled Scenario 1 (S1). The only difference, when comparing to the Base-Line Model, is that we no longer have MC Leak Test as the only Master Leak Test; instead, we also consider DC Leak Test as a Master Leak Test. In other words, this scenario trusts DC Leak Test results and does not perform retesting in MC Leak Test. When a block passes DC Leak Test, it goes straight to the next process, B-CAP, instead of going through MC Leak Test again. The initial decision to have MC Leak test as the only master leak tester was managerial, not technical; experts in this area believe that DC Leak Test results are at least as accurate as MC Leak test results and hence this change would have no impact on test quality. For that reason, we decided to consider DC Leak Test as a Master Leak Test and test this scenario. This scenario prevents (what management believes to be) unnecessary retests to occur in MC Leak Test. A visual representation of Scenario 1 can be found in Figure 3.

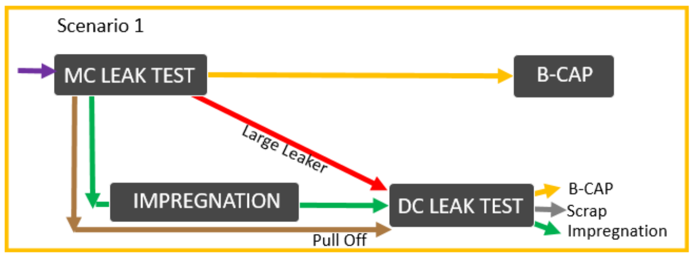

Figure 3: Scenario 1 model.

Scenario 2: The second improvement scenario considered in this study is titled Scenario 2 (S2). This scenario considers that all blocks that fail MC Leak Test should be tested in DC Leak Test, before deciding their destination, which is either they need impregnation, or they should go back to MC Leak Test, or if they are scrapped. This scenario allows DC Leak Test to catch false leakers from MC Leak Test, preventing unnecessary impregnation. It also limits spending unnecessary time in lineside WIP but it still uses MC Leak Test as the Master Leak tester of the system, so the number of false negatives that move on to B-CAP is no worse than in the Base Line model. A visual representation of Scenario 2 can be found in Figure 4.

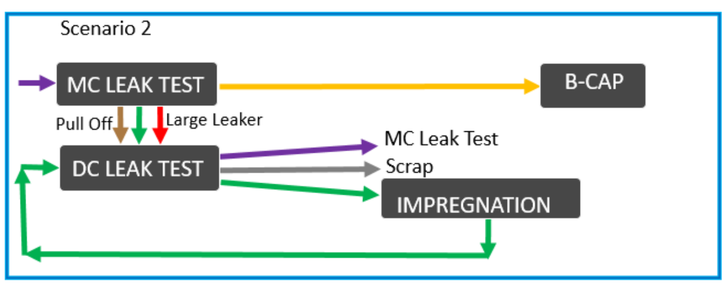

Figure 4: Scenario 2 model.

4.4 Measures of Performance of Interest

The Base-Line model tracks five measures of performance that were used to compare the Base-Line with Scenario 1 and Scenario 2. These measures of performance are:

1. WIP ready for B-CAP (WIP B-CAP): Off-line WIP waiting to go through the B-CAP process
2. WIP ready for MC Leak Test (WIP MCLT): Off-line WIP waiting to go through MC Leak Test Machine
3. Line Throughput: The total number of blocks that go through B-CAP and leave the system
4. Impregnation rates: Number of blocks that go through impregnation and how many times it occurs
5. Scrap rates: How many blocks are discarded as scrap

In addition to comparing the three models, we were interested in testing the system under different combinations of system parameters (for each scenario). The system parameters, as well as their test levels were chosen in conjunction with the stakeholders to reflect current and potential realistic operating conditions. Specifically, we tested the sensitivity of each scenario with respect to three main parameters:

WIP Trigger: In practice, there is no clear-cut rule for when off-line WIP blocks should be put back into the line, rather, the worker does it whenever he has availability. In order to model this behavior more formally, we defined a threshold of WIP that would trigger this activity, which we call WIP Trigger. We determined that current practices are equivalent to a WIP Trigger of 3 skids worth of engine blocks. Then, we were interested in whether variation of the WIP Trigger (0 and 10 skids) would influence the results.

Worker Availability: The worker that is responsible for the MC Leak Test cell manages the WIP in that area, loading and unloading blocks from and to that conveyor. This same worker also works in other machines and performs other tasks during the shift. The current time that the worker is assigned to performing WIP tasks is 2 hours/shift. Managers were interested in whether this worker could perform the same tasks in less time. We decided to make the worker available for either 2 hours or just 1 hour.

MC Leak Test Processing Time: In the current state system, the MC Leak Test Processing Time is fixed to slightly below the cycle time of the line (current). We were interested in whether a delay in MC Leak Test processing time would impact the results, because management believes that if its processing time is increased, it could improve the fidelity of the leak test. We decided to use MC Leak Test Processing Time with a delay of 33%, and MC Leak Test processing time with a delay of 44%. We did not however, consider a change to the test's fidelity as that amount (if any) is unknown.

These system's parameters were used to compare performance across scenarios and between levels of the parameters within each scenario. Specifically, we performed single-parameter experiments with each of these three parameters (WIP Trigger, Worker Availability, and MC Leak Test Processing Time) for the Base-Line Model, Scenario 1, and Scenario 2. The goal was to determine the effect of the variation of these parameters on the first three measures of performances listed above. The other two measures of performance, that is Impregnation and Scrap rates, are not affected significantly by these parameters. Instead, those measures were used to compare Scenarios 1 and 2 with the Base-line model, using the current and best-case system parameter settings for each model.

Once we analyzed the impact of these single-parameter experiments, we created a Design of Experiments, which helps identify important interactions that may be missed when experimenting with one parameter at a time. The two-parameter experiments performed were: Worker Availability x WIP Trigger, MC Leak Test Processing Time x WIP Trigger, and Worker Availability x MC Leak Test Processing Time. The results gathered from the several experiments are presented in the following section. Preliminary tests were conducted and based on those, we selected levels for each parameter (Table 1).

Table 1: System parameters.

WIP Trigger (Skids)	MC Leak Test Processing Time (Seconds)	Worker Availability (Hours)
0	Current	1
3	+33%	2
10	+44%	-

5 RESULTS AND DISCUSSION

In this section, we will present and discuss the results from the single-parameter and two-parameter experiments. Here we present comparisons within scenarios, as well as across scenarios, relative to the current state of the system. For these experiments, the measures of performance that we will focus on are WIP B-CAP, WIP MCLT, and Line Throughput.

First, we obtained simulation results for the measures of performance using the Base-Line Model, with system parameters that represent the current state of the system, these are a WIP Trigger of 3 skids, MC Leak Test Processing Time of slightly below the cycle time of the line (current), and Worker Availability of 2 hours/shift. We then calculated a 95% Confidence Interval of the measures of performance from the 30 replications and performed the single-parameter experiments. We compare the results from Scenario 1 and 2 to the Base-Line model current results and classified them based on whether they had positive, negative or no impact. Table 2 shows the results for each of the measures of performance that were impacted by the variation in levels of the system parameters. For WIP MCLT and WIP B-CAP, positive impact means that the experiment resulted in fewer WIP blocks and negative impact means that it resulted in more WIP blocks. For the Line Throughput, positive impact means that the experiment resulted in more blocks produced and negative impact means fewer blocks. Positive impacts are represented in green and negative impacts are represented in red in Table 2. No impacts means that the results were within the confidence interval of the current state and thus were not significantly impacted from the change in parameters.

From the results in Table 2, the parameter WIP Trigger of 10 skids had a significant negative impact on the WIP MCLT and WIP B-CAP, when compared to the current values from the Base-Line model. Also, the parameter MC Leak Test +44% seconds had a very high negative impact WIP MCLT. Since these results were significantly negative, we decided to eliminate these two levels when performing the two-parameter experiments. The Line Throughput was not impacted by varying these parameters, except for a very small impact when using MCLT Processing time of +44% seconds.

Table 2: Single-parameter results.

	WIP MCLT			**WIP B-CAP**			**Line Throughput**		
Parameters	BL	S1	S2	BL	S1	S2	BL	S1	S2
WIP Trigger 0	-80%	-92%	-87%	-74%	-55%	-72%	0%	0%	0%
WIP Trigger 3	Current	0%	0%	0%	0%	0%	0%	0%	0%
WIP Trigger 10	+198%	+188%	+194%	+177%	+197%	+172%	0%	0%	0%
MCLT Current	Current	0%	0%	0%	0%	0%	0%	0%	0%
MCLT +33%	+54%	0%	+43%	0%	0%	0%	0%	0%	0%
MCLT +44%	+1205%	0%	+1003%	0%	0%	0%	-1.3%	0%	-1.2%
1 hour	0%	0%	0%	0%	+174%	0%	0%	0%	0%
2 hours	Current	0%	0%	0%	0%	0%	0%	0%	0%

Similarly to the single-parameter results, for the two-parameter experiments we performed 30 replications of four months of production, dropping the first month as a warm-up period. We calculated the 95% confidence interval of the results of the Base-Line Model under the current operating conditions, and presented the results relative to the Base-Line model results, where falling within the original confidence interval was considered "no impact".

Table 3 shows the results from the experiment varying WIP Trigger and Worker Availability. In Scenario 1, the Worker Availability of 1 hour in combination with the WIP Trigger 0 and 3 generated a negative impact in the WIP B-CAP, which implies that only 1 hour is not enough to manage WIP around the B-CAP machine area, in this Scenario. In both Scenario 1 and 2, the worker availability of 2 hours in combination with WIP Trigger 0 skids had a positive impact in the WIP MCLT and WIP B-CAP; however, WIP Trigger of 0 skids is not realistic because the worker is not actually going to manage WIP for just a couple of engine blocks, when they have other more pressing responsibilities.

Table 4 shows the results from the experiment varying MC Leak Test Processing Time and Worker Availability. The results show negative impact when MC Leak Test processing time is +33% seconds and the worker is only available 1 hour/shift, indicating that this combination is detrimental to the process. Table 5 shows the results from the experiment combining WIP Trigger and MC Leak Test Processing Time. As expected, the WIP Trigger 0 results in fewer blocks in WIP around MC Leak Test and B-CAP.

Considering these specific measures of performance: WIP MCLT, WIP B-CAP and Line Throughput, we were able to identify some system parameter combinations that would lead to significantly negative impacts. Next, we shift to comparing the results of last two measures of performance (Impregnation and

Scrap rates) from Scenarios 1 and 2 with the results obtained from the Base-Line Model, using the base line parameters, which are WIP Trigger of 3 skids, MC Leak Test Processing Time of slightly below the cycle time of the line (current), and Worker Availability of 2 hours/shift. We had not discussed these measures of performance previously, as they are not significantly affected by changes in parameters, but vary considerably when comparing across scenarios.

Table 3: WIP trigger X worker availability.

	WIP MCLT			**WIP B-CAP**			**Line Throughput**	
	1 hour	2 hours		1 hour	2 hours		1 hour	2 hours
	Base-Line Model			**Base-Line Model**			**Base-Line Model**	
WIP Trigger 0	-64%	-86%		-55%	-75%		0%	0%
WIP Trigger 3	0%	Current		0%	Current		0%	Current
	Scenario 1			**Scenario 1**			**Scenario 1**	
WIP Trigger 0	-89%	-92%		+97%	-57%		0%	0%
WIP Trigger 3	0%	0%		+157%	0%		0%	0%
	Scenario 2			**Scenario 2**			**Scenario 2**	
WIP Trigger 0	-70%	-87%		-50%	-68%		0%	0%
WIP Trigger 3	0%	0%		0%	0%		0%	0%

Table 4: MC leak test processing time X worker availability.

	WIP MCLT			**WIP B-CAP**			**Line Throughput**	
	1 hour	2 hours		1 hour	2 hours		1 hour	2 hours
	Base-Line Model			**Base-Line Model**			**Base-Line Model**	
MCLT Current	0%	Current		0%	Current		0%	Current
MCLT +33%	+1171%	+84%		0%	0%		-1.9%	0%
	Scenario 1			**Scenario 1**			**Scenario 1**	
MCLT Current	0%	0%		+200%	0%		0%	0%
MCLT +33%	0%	0%		+211%	0%		0%	0%
	Scenario 2			**Scenario 2**			**Scenario 2**	
MCLT Current	0%	0%		0%	0%		0%	0%
MCLT +33%	+1157%	+41%		0%	0%		-1.7%	0%

Table 5: WIP trigger X MC leak test processing time.

	WIP MCLT			**WIP B-CAP**			**Line Throughput**	
	MCLT Current	MCLT +33%		MCLT Current	MCLT +33%		MCLT Current	MCLT +33%
	Base-Line Model			**Base-Line Model**			**Base-Line Model**	
WIP Trigger 0	-88%	0		-76%	-73%		0%	0%
WIP Trigger 3	Current	0%		Current	-72%		Current	0%
	Scenario 1			**Scenario 1**			**Scenario 1**	
WIP Trigger 0	-94%	-87%		-58%	-51%		0%	0%
WIP Trigger 3	0%	0%		0%	0%		0%	0%
	Scenario 2			**Scenario 2**			**Scenario 2**	
WIP Trigger 0	-89%	0%		-72%	-72%		0%	0%
WIP Trigger 3	0%	+38%		0%	-63%		0%	0%

Under the current process, blocks can go through impregnation zero times (0x impregnation), one time (1x impregnation) and two times (2x impregnation). Block are not supposed to go through impregnation for a third time (3x impregnation). However, since the blocks are not tracked, there is no way to know if that actually happens or not. The simulation results revealed that it can happen and probably does, which implies that the current routing rules are having unexpected consequences. The results from the Base-Line model (see Table 6) indicate that there are an average of 0.2% of blocks that go through impregnation for a third time. While it is possible to impregnate a block for the third time in the Base-Line model, Scenarios 1 and 2 do not allow it to happen, as the results show zero 3x impregnation blocks.

Table 6: Impregnation results.

Simulation Data	Base-Line Model	Scenario 1	Scenario 2
1x Impregnation Blocks	82.7%	-3%	-50%
2x Impregnation Blocks	17.1%	-12%	-53%
3x Impregnation Blocks	0.2%	-100%	-100%
Total Impregnation Blocks	**100%**	**-4%**	**-51%**

In order to identify financial improvement in the proposed scenarios, we used the cost of impregnation. This cost includes the impregnation, conditioner and catalyst fluids. The impregnation throughput in Scenario 1 was lower that the results from the Base-Line Model, which generated impregnation savings of 2.5% in a year. When performing the same analysis for Scenario 2, we noticed a significant decrease in number of impregnated blocks, providing better savings than both the Base-Line Model and Scenario 1. By implementing the proposed improvements from Scenario 2, a 29% reduction of the annual impregnation cost would be achieved. A graph summarizing the cost of impregnation is shown in Figure 5.

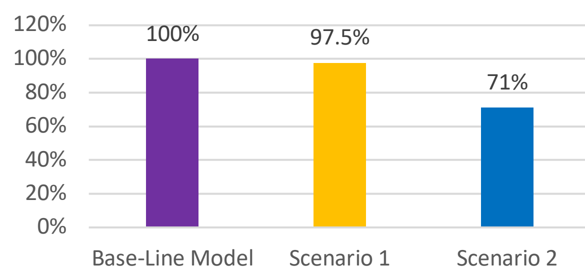

Figure 5: Cost of impregnation.

A scrap block is classified by how many times it went through impregnation, which could be 0 times (0x impregnation scrap), one time (1x impregnation scrap), and two times (2x impregnation scrap). When looking at the scrap results (see Table 7) of Scenario 1, it did not vary much from the Base-Line model; however, Scenario 2 had a more significant change. When analyzing the scrap results for Scenario 2, there is a significant increase in 0x impregnation scrap and fewer 1x impregnation and 2x impregnation blocks being scrapped when compared to the Base-Line model, which means that the blocks were getting scrapped earlier in the process. This would reduce the cost of unnecessary impregnation.

It is important to emphasize that the reduction in impregnation cost obtained from Scenario 2 does not affect the quality of impregnation. The impregnation cost that is being eliminated refers to being more selective about what goes through impregnation and scraping blocks earlier in the process. Although Scenario 2 shows better improvements on the 1x and 2x impregnation scrap blocks, the total leak scrap resulted to be higher by 5% when compared to the Base-Line Model. However, the additional cost generated by this increase in number of blocks being scrapped is only a fraction (less than 5%) of the total impregnation savings that Scenario 2 provides.

Table 7: Impregnation scrap results.

Simulation Data	Base-Line Model	Scenario 1	Scenario 2
0x Impregnation Scrap Blocks	55%	-2%	+155%
1x Impregnation Scrap Blocks	10%	-4%	-50%
2x Impregnation Scrap Blocks	35%	-14%	-82%
Total Leak Impregnation Scrap	**100%**	**-7%**	**+5%**

The three simulation models allowed us to capture the time a block spends in the Leak Test area. We, then, input these times back into the VSM to have a measure of the total delay caused by the Leak Test area in each scenario and suggest the best scenario based on the analysis of the VSM and DES together. The current state model (BL) provides that the Leak Test area accounts for 6.2% of the total lead time of the system. Once we know the total lead time of the current state of the line, we are able to compare with the results from Scenario 1 and Scenario 2. In Scenario 1 the total lead time in the machining area increases by 2%. On the other hand, in the Scenario 2 the total lead time decreases by 5%. The value of using the combination of VSM and DES simulation is that it helped identify the problem area and calculate lead times of the Leak Test area, and the machining line as a whole. We would have not arrived to this conclusion by only analyzing the VSM or the DES on their own. In this case, the two tools complement each other.

6 CONCLUSIONS

In this study, we have showcased the use of simulation combined with VSM in an automotive manufacturing engine plant. We created a DES model that represented the real system (Base-Line Model) and we proposed two potential sets of changes in the process (Scenario 1 and Scenario 2). A detailed simulation analysis allowed us to test these different "what-if" scenarios and determine the impact of the proposed changes. The strategy proposed from this study consists of combining VSM and simulation and using this combination as a decision-making tool. This strategy is useful because it combines the high-level results of VSM with a detailed DES analysis of several sets of potential scenarios to find an better solution without requiring actual physical test changes. The study's major takeaway is that building a VSM before embarking on building a DES model facilitated the data collection, familiarized the modeler with the details of the system, and allowed better verification and validation. This process also contributed to intangible benefits, such as building trust between the modeling team and the local team, so that the results of the DES model were taken seriously by the management. The results showed that DES in conjunction with VSM is a good alternative in studying changes in production processes.

The Base-Line Model revealed that it is possible to have 3x impregnation in the process, which is something that is not supposed to happen. It also showed that the WIP around MC Leak Test is higher than WIP in B-CAP. Finally, it showed that under the current configuration it is possible to moderately increase the time of MC Leak test, but changing the WIP trigger, Worker Availability, or a major increase to MC Leak Test time could have very negative consequences. Results from Scenario 1 show that 3x impregnation does not happen and it saves 2.5% in annual impregnation cost. Also, under this scenario, 1 hour worker availability per shift is not enough to input WIP from B-CAP back into line. Scenario 2 also eliminates 3x impregnation, but more importantly it saves 29% in annual impregnation cost, by scraping no-good blocks earlier in the process and avoiding unnecessary impregnation. This scenario increases the total scrap, but this cost is far lower than the savings from impregnation.

Overall, both scenarios showed improvements related to impregnation compared to the Base-Line Model; however, Scenario 2 showed to have a lower impregnation cost and lower impregnated blocks in scrap when compared to Scenario 1. These results indicates that implementing the changes made in Scenario 2 would lead to significant improvements in some areas, without any expected negative impacts. Therefore, we recommended to our industry partners to implement Scenario 2, keeping the current system parameters. As of this writing, they were in the process of implementing some of the recommended changes.

REFERENCES

Alsakka, F., Khalife, S., Darwish, M., Al-Hussein, M., and Mohamed, Y. 2020. "Deploying Discrete-Event Simulation and Continuous Improvement to Increase Production Rate in a Modular Construction Facility". In *Proceedings of the 2020 Winter Simulation Conference*, edited by Bae, K.; Feng, B.; Kim, S.; Lazarova-Molnar, S.; Zheng, Z.; Roeder, T.; and Thiesing, R, editor(s), pages 1676-1687. Piscataway New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Antonelli, D., and Stadnicka. D. 2018. "Combining Factory Simulation with Value Stream Mapping: A Critical Discussion". *Procedia CIRP* 67:30-35.

Andrade, P., Pereira, V., and Del Conte, E. 2015. "Value Stream Mapping and Lean Simulation: A Case Study in the Automotive Industry". *International Journal of Advanced Manufacturing Technology 85(1-4):547-555*.

Donatelli. A. and Harris, G. 2001. "Combining Value Stream Mapping and Discrete Event Simulation". In *Proceedings of the 2001 Huntsville Simulation Conference*, Huntsville, AL, October 3rd - 4th

Emde, S. and Gendreau, M. 2017. "Scheduling in-house Transport Vehicles of Feed Parts to Automotive Assembly Lines". *European Journal of operational research* 260(1): 255-267.

Habidin, N. F. and Yusof, S. M. 2013. "Critical Success Factor of Lean Six Sigma for the Malaysian Automotive Industry", *International Journal of Lean Six Sigma* 4(1): 60-82.

Kibira, D. and McLean, C. 2007. "Generic Simulation of Automotive Assembly for Interoperability Testing". In *Proceedings of the 2007 Winter Simulation Conference*, edited by S. G. Henderson, B. Biller, M.H. Hsieh, J. Shortle, J. D. Tew, and R. R. Barton, editor(s), pages 1035-1043. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Kuhn, W. 2006. "Digital Factory - Simulation Enhancing the Product and Production Engineering". In *Proceedings of the 2006 Winter Simulation Conference*, edited by L.F. Perrone, F.P. Wieland, J. Liu, B.G. Lawson, D.M. Nicol, and R.M. Fujimoto, editor(s), pages 1899-1906. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Lian, Y. H. and Landeghem, H. V. 2002. "An Application of Simulation and Value Stream Mapping in Lean Manufacturing". In *Proceedings 14th European Simulation Symposium*, SCS Europe BVBA, 1-8.

Mahfouz, A. and Arisha, A. 2013. "Lean Distribution Assessment Using an Integrated Framework of Value Stream Mapping and Simulation." In *Proceedings of 2013 Winter Simulations Conference*, edited by R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, and M. E. Kuhl, editor(s), pages 3440-3449. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Michalos, G., Makris, S., Papakostas, N., Mourtzis, D., and Chryssolouris. G. 2010. "Automotive Assembly Technologies Review: Challenges and Outlook for a Flexible and Adaptive Approach". *CIRP Journal of Manufacturing Science and Technology* 2(2): 81-91.

Narasimhan, J., Parthasarathy, L., and Narayan, P. S. 2007. "Increasing the Effectiveness of Value Stream Mapping Using Simulation Tools in Engine Test Operations". In *Proceedings of the 18th IASTED International Conference*, Montreal, Canada, 30 May-1 June, 260-264.

Rajenthirakuma, D., Sridhar, R., Savio, A. D., Prakash, S. J. C., and Srinath, N. 2012. "Lean Manufacturing: A Study of Application in a Customary Atmosphere. *International Journal of Lean Thinking*. 20–35.

Renteria-Marquez, I., Renteria, A., Almeraz, C., and Tseng, T. 2020. "A Heijunka Study for Automotive Assembly Using Discrete-event Simulation: A Case Study". In *Proceedings of the 2020 Winter Simulation Conference*, edited by Bae, K.; Feng, B.; Kim, S.; Lazarova-Molnar, S.; Zheng, Z.; Roeder, T.; and Thiesing, R, editor(s), pages 1641- 1651. Piscataway New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Rother, M. and Shook, J. 2003. *Learning to See: Value Stream Mapping to Add Value and Eliminate Muda*. Lean Enterprise Institute.

Sargent, R. G. 2013. "Verification and Validation of Simulation Models". *Journal of Simulation* 7(1):12–24.

Smith, J., Sturrock, D., and Kelton, W. 2018. *Simio and Simulation: Modeling, Analysis, Applications*. 5th ed. Pittsburgh, Pennsylvania: Simio.

Wang, J., Chang, Q., Xiao, G., Wang, N., and Li, S. 2011. "Data driven production modeling and simulation of complex automobile general assembly plant". *Computers in Industry* 62(7): 765-775.

Williams, E. J., Ülgen, O. M. 2012. "Simulation Applications in the Automotive Industry". *Use Cases of Discrete Event Simulation*. Springer, Berlin, Heidelberg, 45-58.

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