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A HEIJUNKA STUDY FOR AUTOMOTIVE ASSEMBLY USING DISCRETE-EVENT SIMULATION: A CASE STUDY

Ivan Arturo Renteria-Marquez
Carmen Noemi Almeraz
Tzu-Liang (Bill) Tseng

Dept. of Ind., Manufacturing and Systems Eng.
University of Texas at El Paso
500 West University Avenue
El Paso, TX 79968, USA

Anabel Renteria

Department of Mechanical Engineering
University of Texas at El Paso
500 West University Avenue
El Paso, TX 79968, USA

ABSTRACT

The automotive manufacturing industry is constantly challenged with an unpredictable costumer demand with considerable fluctuation. In addition, the number of products and the complexity is constantly growing. These characteristics make it very difficult to implement lean manufacturing tools such as production leveling (Heijunka), because it is extremely difficult to find the optimal production leveling batch size of complex systems. This paper presents a methodology to model with a high degree of accuracy the production floor, warehouse and material handling system of an automotive assembly facility through discrete-event simulation software; allowing one to determine the optimal batch size of complex manufacturing assembly system through "what-if" analysis.

1 INTRODUCTION

As manufacturing continues to develop, the use of Simulation of Queuing Systems (SQS) techniques has become essential in order to have a flexible pull system to satisfy product demand. Two lean manufacturing tools to have a successful system are Kanban and Heijunka. By applying these lean pull principles when manufacturing, planning future work becomes much easier to predict since data of the task cycle times and workflow will be more practical to collect. The purpose of implementing a pull system is to produce based only on customer demand, meaning stock levels of raw materials, work in progress (WIP), and finished products can be kept at a minimum; improving flow efficiency and increasing productivity.

Discrete-Event Simulation (DES) allows for the behavior of events, processes, and objects to make predictions in short and long-term relationships. The implementation of DES helps companies determine how many resources are needed in production and identify where the bottleneck is occurring. As explained by Michalos et al. (2010), manufacturing research is still based mostly in experimentation, but the prognostics for the future includes the use of simulated models during the early phase of manufacturing plants. Due to limited simulation implementation by modern automotive manufacturing companies, experimentation and evaluation of a complex system becomes more difficult to perform. With customer demand constantly changing, planning and scheduling production decisions facilitate the reduction of overhead and optimize storage costs when manufacturing.

The main objective of this manuscript is to report the methodology followed, and the main findings when implementing a production leveling (Heijunka) strategy in a flexible automotive manufacturing assembly line.

The paper is organized as it follows: In section 2 a literature review of simulations related with the automotive industry, Heijunka, Kanban, and planning and scheduling is presented. Section 3 presents a description of the automotive manufacturing assembly plant modeled in this manuscript. In section 4, the simulation approach of the automotive manufacturing assembly plant, Kanban-based material handling system and the warehouse of raw material is presented. Section 5 presents the numerical results. Finally, section 6 contains the conclusions and a summary of the findings.

2 LITERATURE REVIEW

Over the years, the automotive manufacturing industry has been moving from a mass production basis of vehicles to a customization basis in order to satisfy customer requirements. At the very beginning, Henry Ford started with a narrow number of models and colors, but nowadays most brands offer a wide variety of options. Due to the complexity involved when manufacturing a vehicle, customization in the automotive industry represents a big challenge for manufacturers and the supply chain.

In addition, globalization and the unpredictable customer demand make the market very competitive. Thus, the automotive manufacturing industry must have a flexible production system with a quick response capable to react to the continuously variable market.

Simulations are used to imitate how a process or system runs over a certain period of time. In manufacturing, simulations provide an inexpensive, risk-free way to test changes in the system production line, predict system behavior, learn and understand how multiple components interact with each other in the system, and measure system performance over time (Smith et al. 2018).

2.1 General automotive simulations

This subsection presents a summary of simulation implementations for the automotive industry. Wang et al. (2011) proposed a data-driven simulation of an automotive manufacturing plant. The goal of this work was to automatically generate a simulation of the manufacturing plant, including a feedback of the current state of the real system. Another example of a data-driven simulation for automotive assembly plants can be found in Kibira and McLean (2007). In this reference, an extensive description of the basic processes involved in an automotive manufacturing assembly plant is presented.

Patel et al. (2002) describe a discrete event simulation of the final process system of an automotive plant. The impact of the throughput (i.e. vehicles) as a function of the number of operators, mechanical repair stations and paint repair stations was analyzed with the proposed simulation.

Yu et al. (2006) shows an interesting application of an automotive assembly workstation simulation that involves a lift assists machine. The goal of this approach was to protect operators, predicting ergonomic risks in a new manufacturing area. Andrade et al. (2015) presents an implementation of value stream mapping and simulation of an assembly line of clutch discs. The authors reported that a combination of value stream mapping with simulation was a useful tool for the decision-making team of the automotive company.

2.2 Heijunka

Production leveling, also known as Heijunka is a lean manufacturing tool that overtime, evenly distributes volume and product type mix production. Heijunka is an important tool that helps to eliminate uneven customer pull and transforms it into a predictable manufacturing process. Production leveling stabilizes the manufacturing process by eliminating the overburden of individuals and/or equipment as well as excessive lead and idle times. The tool allows the manufacturer to detect variability in processing job sequences, such that scheduled production produces an equal amount of products between the most demanded and less demanded products. In other words, Heijunka is the action of leveling the production of a manufacturing system by reducing the ups and downs of work in process (WIP) caused by the fluctuation demand (Lippolt and Furmans 2008).

Proper planning with Heijunka allows for the improvement of WIP and the minimization of throughput time, which allows a system to be stabilized with more ease when manufacturing products. Korytkowski et al. (2013) presents a simulation of manufacturing systems with the Heijunka approach, where cyclic scheduling along with other statistical analysis are used to determine how assembly line performance is affected.

2.3 Kanban

Kanban is a lean manufacturing tool that works as a “visual card” system in which supply process production is controlled and improved by managing work flow. This visual system allows to improve flow, reduce lead time, and identify bottlenecks and/or potential bottlenecks in order to deliver value to customers. Kanban systems are usually called pull systems because material is manufactured only when requested by the customer, which helps the production process in reduction of WIP, delays, and time to market.

The simplest Kanban form is a board divided into three sections to visualize the workflow, labeled “To-Do”, “In Progress”, and “Done”. However, over the years a Kanban developed into more modern tools like an email, electronic dashboards, sensors, etc...; all leading to continuous improvement (Kaizen). Establishing a Kanban system results very useful in the workplace since it brings flexibility and improves overall workflow efficiency. Sternatz (2015) implements simulations with Kanban systems and presents an analysis of the relationship between the line balancing and the material handling system and how the planning strategy needs to consider this interdependency. Lolli et al. (2016) presents an interesting methodology used to simulate an assembly line in a Kanban system supplied by operators that transport raw materials from the supermarket to the point of use. In this reference, a probability density function was derived to simulate the stochastic demand.

2.4 Planning and scheduling

Planning and scheduling can sometimes be confused as being the same thing. However, in a manufacturing setting, planning is defining the work that is to be done, while scheduling is defining a sequence of start and end times for a given process with limited resources to complete the planned work. Planning refers to the action of identifying the products that need to be manufactured and the required raw materials; this process is typically determined without a model of the company. On the other hand, scheduling refers to the action of doing a detailed timetable with the products that need to be manufactured, where critical variables such as the required raw materials, on time delivery, required work force and machines are considered in the generation of the schedule. This process needs to be determined with a detailed model of the company (Pegden 2017).

The number of references focused in the area of planning and scheduling for the automotive manufacturing assembly industry are limited because of the complexity of applying them in simulations. However, in recent years, simulation planning and scheduling has grown to be a highly used resource in manufacturing since it helps conduct analyses of multiple scenarios without compromising the actual system; saving time and costs to the company. Emde et al. (2015) reports a just in time (JIT) scheduling approach focused on the delivery of raw material for an automotive assembly line. It was found that simulation can help organizations to consider different lean production techniques while measuring possible benefits in the planning and evaluation stages.

3 DESCRIPTION OF THE AUTOMOTIVE MANUFACTURING ASSEMBLY PLANT

In these paragraphs, the automotive manufacturing plant considered for this study is described. The production floor of this plant is formed by nine sections: three sections of trim, three sections of chassis, one line that assembles the doors, and one final assembly section. Where these sections are composed by 18, 16, 16, 11, 10, 12, 9 and 4 workstations, respectively. This is a flexible manufacturing line that produces two different vehicle models. A total number of 96 workstations forms these nine sections where workers perform the different operations. The WIP is moved by conveyors through the whole system.

The warehouse of raw materials has twenty vehicles with operators that deliver the material at the point of use. A total number of 202 parts (raw material) is considered into this system. The operators located at the workstations are in charge of generating the Kanban signal. The operators receive the production order electronically, and then calculate the amounts of material and sends an electronic signal to the warehouse. According to the vehicle model being produced at a specific moment in time and the batch size, they need to specify the quantity and the delivery location of the required raw materials. Figure 1 shows a diagram of the presented automotive manufacturing assembly plant.

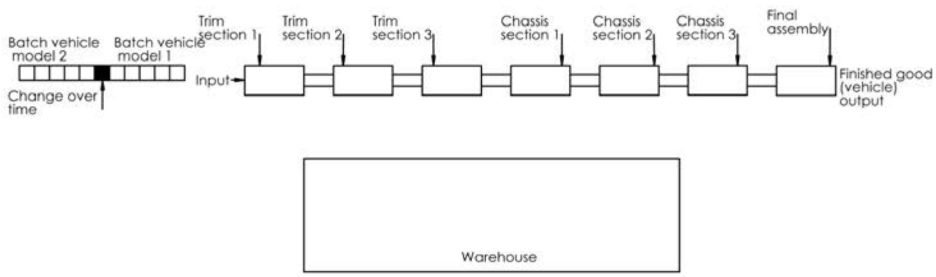

Figure 1: Automotive manufacturing assembly plant.

4 THE SOLUTION APPROACH. SIMULATION OF THE AUTOMOTIVE MANUFACTURING ASSEMBLY PLANT

Simio simulation software was chosen for this simulation scenario because it offers the four discrete modeling paradigms developed for SQS with a focus on intelligent objects (Smith et al. 2018; Renteria 2017). The paradigms encompassed by this software have been successfully implemented in systems like airports, hospitals, ports, mining, call centers, supply chains and manufacturing.

The logical model being simulated is composed of 96 workstations that form trim sections 1, 2, and 3, chassis sections 1, 2 and 3, door assembly and final assembly sections.

The WIP is moved through the assembly process using conveyor belts. Inside the sections, the buffer capacity is defined as zero, which means that the workstations will be blocked if the workstation doing the next operation is still processing WIP. A buffer is defined after each station.

The operators are in charge of monitoring the amount of raw material, calculating and sending the Kanban signal requesting the raw materials to the warehouse. This is a flexible manufacturing line that produces two different vehicle models, where a changeover time is required after each vehicle model change.

4.1 Kanban-based material handling system and warehouse of raw material

As explained in section 3, operators are in charge of generating the Kanban signal that request the raw materials to the warehouse. In order to simulate the action of the operators generating the Kanban signal, an algorithm was developed and embedded into the simulation using the Processes tool offered by Simio. Smith et al. (2018) defines Processes as a flowchart that uses steps to change the states of the simulation elements.

One can summarize the actions that were modeled with the algorithm as follows:

1) Check for the number of orders of the current batch waiting to start the production process.
2) Decide if the number of orders of the current batch is smaller than the specified threshold value.
3) Decide which vehicle model needs to be produced next, and generate the Kanban signal that asks for the frames of these vehicles.
4) Calculate the quantity of material required to assembly the next batch of vehicles and send the signal to the warehouse. The calculation of the Kanban signal is a function of the replenishment time,

production rate and the container size. The equation used to calculate the amount of raw material is presented below.

The Kanban equation embedded into the algorithm is:

$$kanban = \frac{(Replenishment\ Time\ x\ Production\ Rate)\ (1+Alpha)}{(Container\ Size)} \quad (1)$$

where $Alpha$ is the safety factor (Sternatz 2015). In the warehouse, the operators of the twenty vehicles pick up the raw materials and distribute them at the points of use. Additionally, the presented algorithm is used to simulate the changeovers suffered after each change of vehicle model.

After the logic of the automotive manufacturing assembly plant was completely built in Simio, 3D animation was added into the model. Animation is a tool that helps designers to troubleshoot the logic of the model. Also, 3D animation is becoming an excellent method to communicate the simulation results to the stakeholders. A picture of the 3D animation built for the automotive assembly plant is shown in Figure 2.

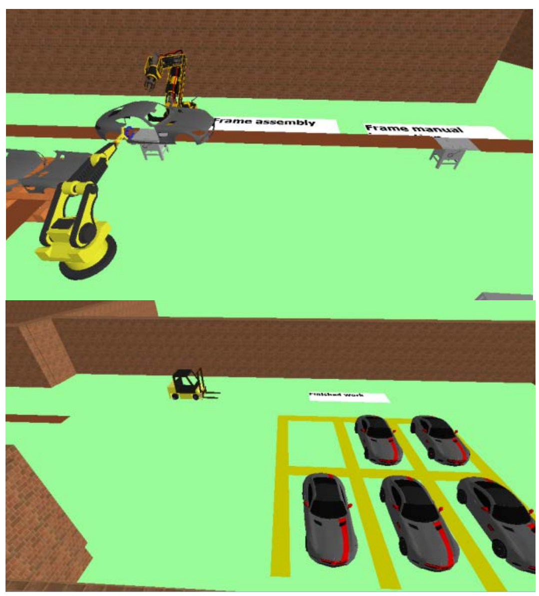

Figure 2: 3D view of the generated automotive manufacturing plant.

5 NUMERICAL RESULTS

In this section, the proposed model is used to simulate the entire assembly manufacturing plant with the goal of analyzing and leveling the production of two different vehicle models. It will be shown how the proposed model enables "what-if" analyses for improved planning that will bring down the WIP and lead time. Therefore, the probability of production delays will be reduced.

The processing times for both vehicle models are considered to be the same for common workstations, except for the first workstation located at trim section one and the first workstation located at chassis section one. The processing times for vehicle model two at those two workstations are eight times longer than the processing times for vehicle model one. In order to approach the variability of the different processes, triangular distributions were employed.

In order to determine the proper warm-up period, an arbitrary mix of 30 vehicles (i.e. 30 vehicles for model one followed by a changeover delay, then 30 vehicles for model two) was run during 30 days. It was observed that steady state is reached after 1.55 hours. Hence, a warm-up period of 2 hours was defined. The warm-up period allows the statistical accumulators of the software to be cleared during the specified time (Kelton et al 2015). Figure 3 shows a graph of the first 50 hours of the simulation time versus the WIP, which was used to determine the transient and steady state periods of the system.

After the warm-up period was defined, an experiment was run to determine the proper number of replications. Table 1 shows the average WIP, average lead time, and percentage of utilization of stations 1, 18, 34, 50, 61, 71, and 83. Since convergence is achieved between scenarios 5 and 6, a number of ten replications was selected for this analysis.

Subsequently, the model was verified and validated. In one hand the verification process can be defined as the action that determines that model behaves as the developer wants. In the other hand, the validation process is the action that determines how well the model approach the real system (Smith et al. 2018). The validation technique used for this project consist of running a known scenario in the model, and subsequently comparing it with the real system. In order to keep the confidentiality of the manufacturing plant, the results of the validation process cannot be shown.

5.1 Heijunka analysis

The historical monthly demand for each model during four months is 8000, 6000, 7500 and 7300 units, respectively. The average of these monthly demands will help determine the amount of vehicles to be produced each month (i.e. 7200 units for each model).

In order to see how much the WIP could increase, the capacity of the buffers in the model is defined as infinity for this study; the simulation is run for 30 days (720 hours). During the first study, a batch size of 7200 units was scheduled for both vehicle models considering a changeover time of 20 minutes between the models. Graphs of the WIP and the lead time are shown in Figures 4 and 5.

One can see in Figure 4 a linear growth of the WIP from time zero until 76 hours with a maximum value of 4761 units being processed. After that, the WIP linearly drops until reaching a steady WIP of 17 units. On the other hand, one can observe in Figure 5 a linear growth of the lead time which never stops, reaching a maximum value of 582 hours. Two different slopes of the lead time are shown, which belong to the two different vehicle models. One can see from both graphs that the system is unstable for this batch size.

Due to the fact that leveling production by volume is not enough to achieve the expected demand, the production needs to be also leveled by product type mix. The goal is to stabilize the unstable system obtained with the previous run. The system was run with batch sizes 20, 30, 40, 50, 80, 90, 100, 150 and 200 units. For example, a batch size of 20 units means that 20 units of vehicle model one are manufactured followed by a changeover time and a batch of 20 units of vehicle model two, until the maximum time or the maximum number of units is reached (i.e. 720 hours or 14400 units). The obtained results are shown in Figures 6 and 7.

One can see in Figures 6 and 7 that the uncontrolled linear growth disappears for both, the WIP and the lead time. It was observed that the lower the batch size, the lower the WIP in the system. Similarly, the lower the batch size, the lower the lead time.

In table 2 a summary with the results obtained with the different batch sizes is presented. One can see that the system is no able to produce the expected demand with batch sizes of 20, 30, 40, 50, 60, and 80 units. The system is able to produce the expected demand with batch sizes of 90, 100, 150, 200 and 7200 units. Nevertheless, the higher the batch size, the higher the WIP. Thus, for this particular case a batch size of 90 units is proposed. With this batch size, the average lead time and maximum WIP for vehicle model one and two are 3.33 hours, 90 units, 5.54 hours and 35 units, respectively.

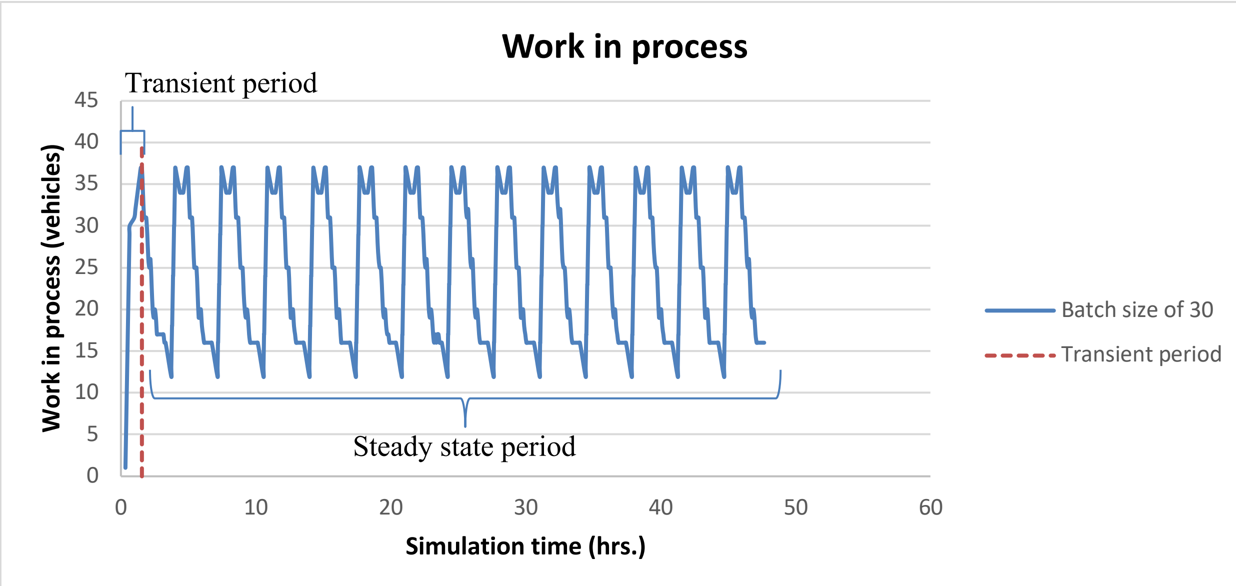

Figure 3: Transient and steady state period of the average WIP.

Table 1: Results of the experiment.

Number of replica-tions	**WIP average (vehicles)**	**Lead time average (hours)**	**Utiliza-tion Station 1 (per-centage)**	**Utiliza-tion Station 18 (per-centage)**	**Utiliza-tion Station 34 (per-centage)**	**Utiliza-tion Station 50 (per-centage)**	**Utiliza-tion Station 61 (per-centage)**	**Utiliza-tion Station 71 (per-centage)**	**Utiliza-tion Station 83 (perc-entage)**
1	24.4827	2.61297	1.70928	8.79277	11.7205	8.7934	5.86428	2.93473	5.85879
2	24.4783	2.6131	1.70867	8.78732	11.7214	8.79161	5.86321	2.93	5.85309
3	24.4755	2.61322	1.70907	8.78902	11.7192	8.79085	5.86147	2.931	5.85182
4	24.4791	2.61332	1.70968	8.79184	11.72	8.79158	8.86216	2.93157	5.85594
5	24.4792	2.61324	1.70942	8.79185	11.7198	8.79155	5.86265	2.93185	5.85772
6	24.4774	2.61334	1.70919	8.78929	11.7206	8.79088	5.86265	2.932	5.85818
7	24.4779	2.61328	1.70893	8.78743	11.721	8.79058	5.86306	2.93176	5.8573
8	24.4785	2.6132	1.70863	8.78797	11.7223	8.79018	5.86312	2.93188	5.8579
9	24.4789	2.61319	1.70837	8.78829	11.7228	8.79046	5.86309	2.9316	5.85769
10	24.4787	2.61314	1.70837	8.78877	11.7222	8.79036	5.86295	2.9314	5.85739

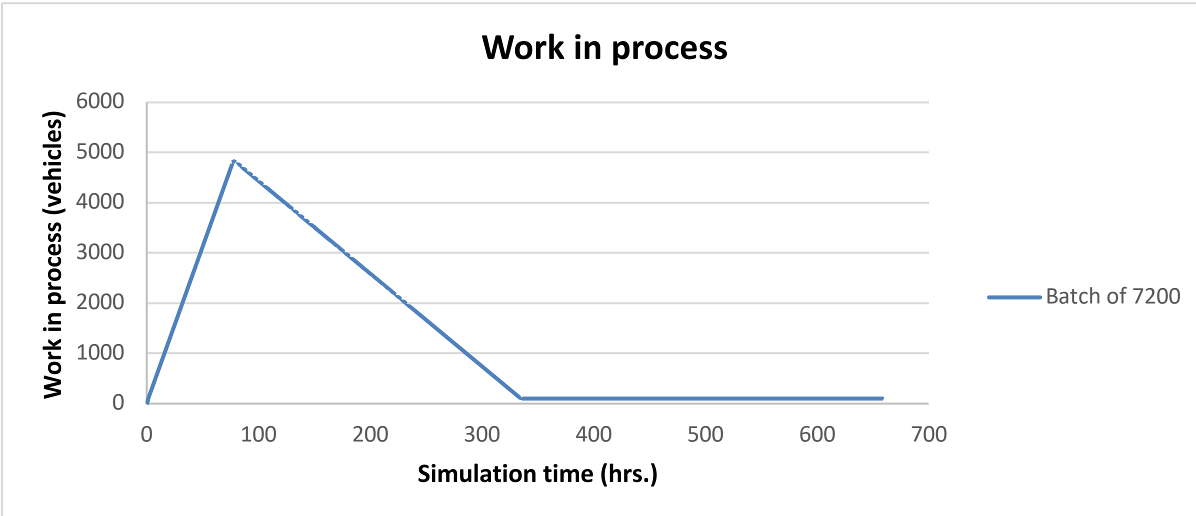

Figure 4: WIP for a batch size of 7200 vehicles.

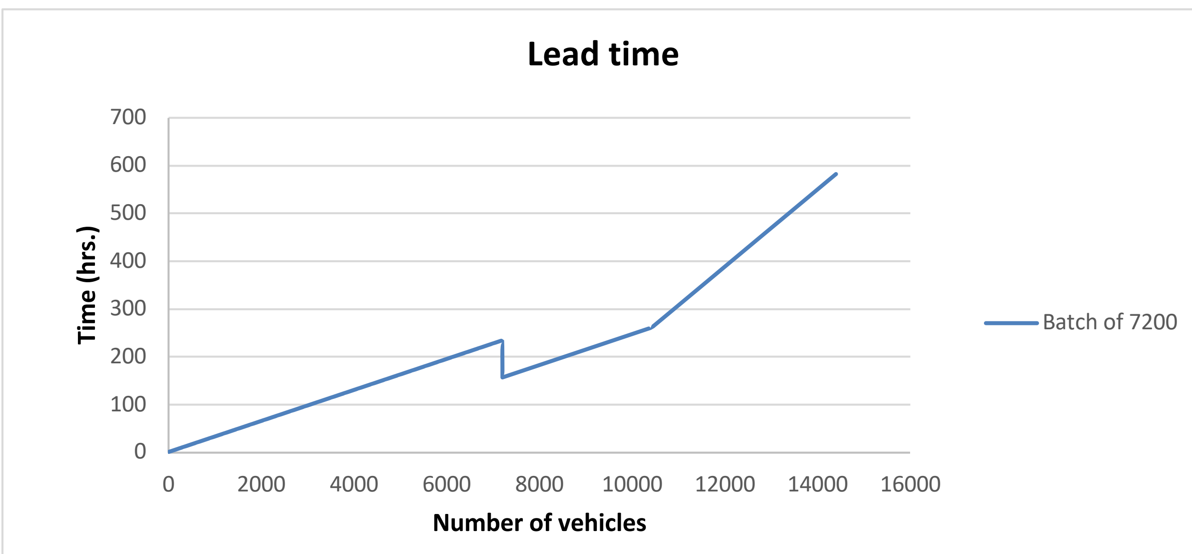

Figure 5: Lead time for a batch size of 7200 vehicles.

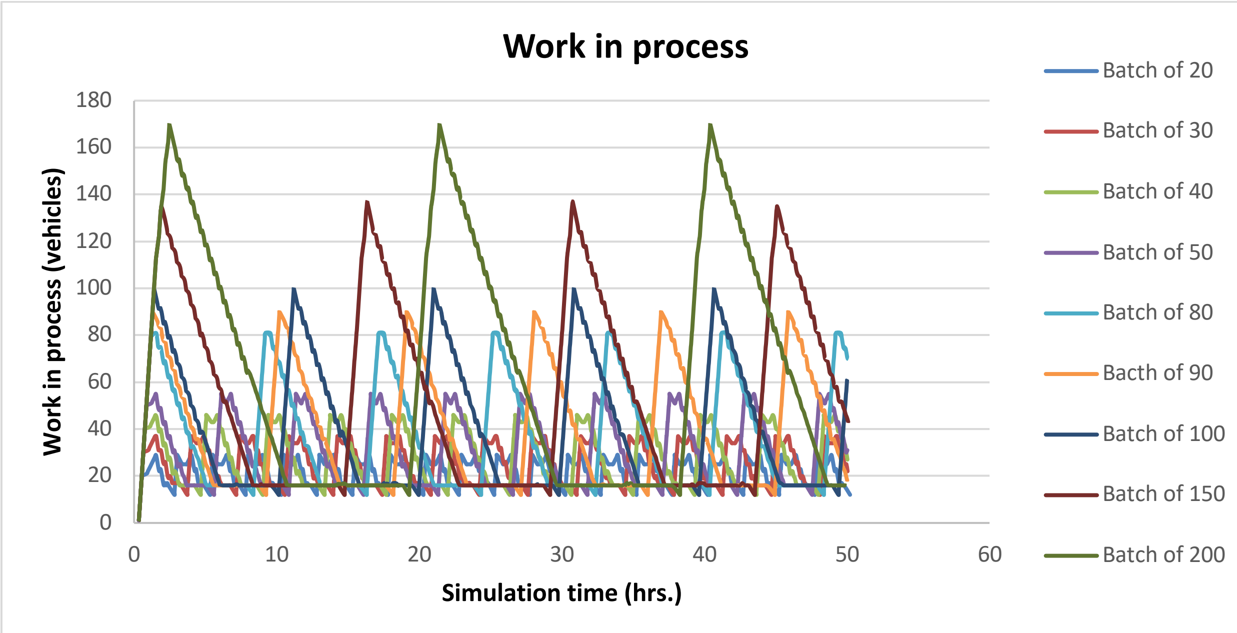

Figure 6: WIP for batch sizes of 20, 30, 40, 50, 80, 90, 100, 150 and 200 vehicles.

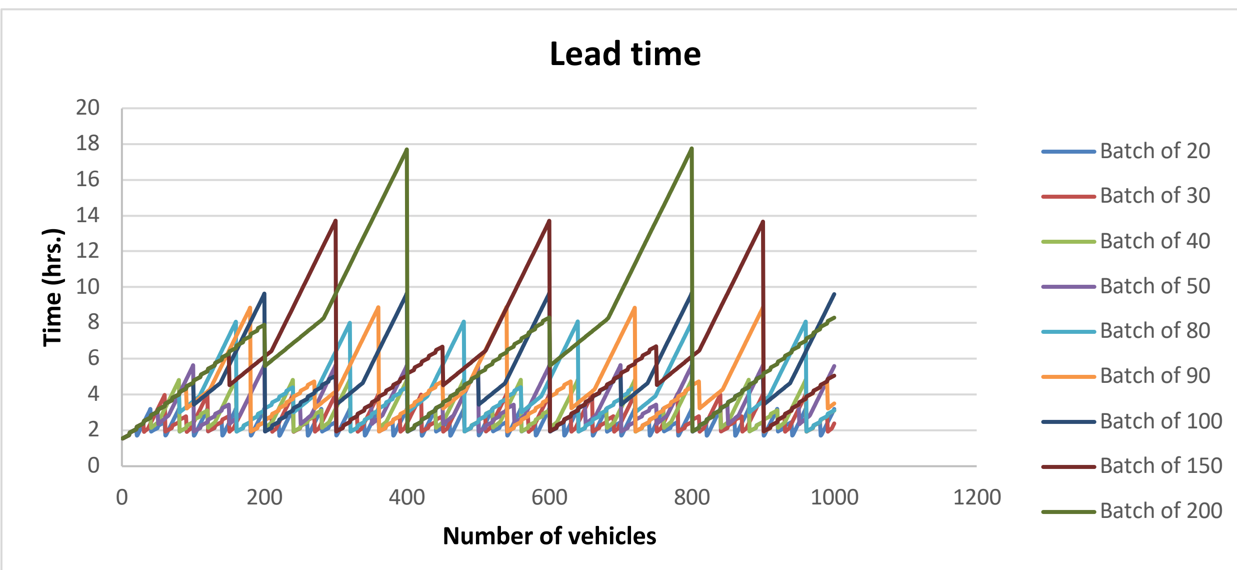

Figure 7: Lead times for batch sizes of 20, 30, 40, 50, 80, 90, 100, 150 and 200 vehicles.

Table 2: Lead time, units manufactured and WIP for both vehicle models.

	Batch size	**Lead time (average hrs.)**	**Lead time (maximum hrs.)**	**Units (vehicles) manufactured**	**WIP (max)**
Model 1	20	2.20	2.48	5760	20
	30	2.36	2.80	6330	30
	40	2.52	3.12	6644	40
	50	2.68	3.44	6859	50
	60	2.84	3.76	7020	60
	80	3.17	4.42	7200	80
	90	3.33	4.75	7200	90
	100	3.49	5.06	7200	100
	150	4.30	6.68	7200	136
	200	5.10	8.30	7200	170
	7200	118.17	234.80	7200	4848
Model 2	20	2.43	3.21	5756	16
	30	2.86	4.03	6317	19
	40	3.30	4.84	6640	22
	50	3.74	5.64	6850	24
	60	4.19	6.45	6999	27
	80	5.09	8.09	7198	32
	90	5.54	8.89	7200	35
	100	5.99	9.72	7200	38
	150	8.25	13.75	7200	51
	200	10.51	17.78	7200	65
	7200	327.05	582.85	7200	1942

6 CONCLUSIONS

This manuscript successfully demonstrates the importance of a proper Heijunka implementation for the automotive manufacturing assembly industry. The model simulation results show that for this particular case the WIP and the lead time grow up as a function of the batch size. Which leads to the conclusion that the analyzed system becomes unstable if the batch size is not properly chosen. After testing several simulation runs with different batch sizes, one can conclude that a batch size of 90 vehicles is the option that allows the current system to produce the required demand on time with the minimum amount of WIP on production floor and the shortest lead time.

The methodology proposed here, consists of combining in a unique model production floor, warehouse and the material handling system. This method allows a convenient interaction of these three sections of the factory into a unique model, resulting in a model that combines all the critical variables of the system. The proposed methodology allows one to perform valuable "what-if" analyses, such as the Heijunka implementation presented here. This strategy can help practitioners and researchers to analyze this kind of automotive manufacturing systems.

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AUTHOR BIOGRAPHIES

IVAN A. RENTERIA-MARQUEZ is a Research Professor within the Industrial, Manufacturing and Systems Engineering Department at UTEP. He earned a Bachelor of Technology in Mechatronic Engineering from Technologico de Monterrey, Mexico. He earned two Masters of Science, the first one on Electrical Engineering and the second one in Manufacturing Engineering at UTEP. He holds a PhD in Electrical and Computer Engineering from UTEP with conentration in modeling and simulation of piezoelectric traveling wave rotary ultrasonic motors. His research interest include modeling and simulation of actuators, application of digital twins for manufacturing systems, and Industry 4.0 technologies. His email address is iarenteria@utep.edu.

ANABEL RENTERIA received a Master of Science in Industrial Engineering at The University of Texas at El Paso. She is currently a PhD student in Mechanical Engineering in the same institution. Her research interest is in modeling and simulation of supply chain and manufacturing systems using discrete events, and Industry 4.0 technologies. Her email adress is arenteriamarquez@miners.utep.edu.

CARMEN N. ALMERAZ is an Undergraduate Research Assistant for the Department of Industrial, Manufacturing, and Systems Engineering at The University of Texas at El Paso where she is currently a student in that same field. Her research interest is in simulation-based scheduling and model-based systems. Her email address is calmeraz@miners.utep.edu.

TZU-LIANG (BILL) TSENG received a PhD in Industrial Engineering at the University of Iowa. He is a Professor and chair in Industrial, Manufacturing and Systems Engineering at The University of Texas at El Paso. His current research focuses on data analytics, discrete event simulations, and autonomous systems. His email adress is btseng@utep.edu.