Proceedings of the 2015 Winter Simulation Conference
L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, eds.

A SIMULATION ANALYSIS OF THE VEHICLE AXLE AND SPRING ASSEMBLY LINES

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ABSTRACT

A discrete event simulation model was developed to represent the current vehicle axle and spring assembly lines and understand their dynamics for an automotive company in need of production increase to accommodate expected demand growth. The aim of this study is to provide viable manufacturing plans to improve productivity, and we propose several alternative system component changes to reach the desired throughput level as well as determine the corresponding optimal system configurations. Sensitivity analyses were conducted to measure the effects of various factors such as arrival rate, batch size, and operator resource on throughput, and consequently to find the best scenario. The results of the proposed simulation model demonstrated potential impacts on production capacity increase by considering multiple operational factors while applying feasible improvement strategies.

1 INTRODUCTION

1.1 Background

Simulation has been widely used and applied to modeling manufacturing systems in part due to its capability to analyze complex automated systems and to capture the effect of local changes on the performance of the overall system. It is an effective analytical tool in solving problems that arise in manufacturing design and operation such as allocating resources, determining operational procedures, and evaluating performance measures. In the competitive automotive industry today, simulation plays an important role from design to development, manufacturing, and pricing of motor vehicles.

A simulation model can be implemented for many situations in a vehicle assembly line, for example, as a tool for predicting manufacturing system performance or comparing different scenarios (Dalvi and Guay 2009). In our paper, the simulation study is focused on the axle and spring assembly lines operated by one of the largest automotive manufacturers in the Middle East, which has been producing auto parts such as gear boxes, transmissions, and axles for various types of vehicles.

Axles are an integral component of building wheeled vehicles. In an axle-suspension vehicle system, axles serve to transmit driving torque to wheels as well as to maintain the position of the wheels relative to each other and to the vehicle body. The axles in this system must also bear the weight of the vehicle in addition to any additional cargo.

Simulating an axle assembly line and developing an accurate model of each individual process enable us to analyze the assembly line system, identify bottlenecks, and explore the opportunities for improvement. The assembly line simulation is also used for facility planning, applying proposed assembly line changes to the model, and analyzing their effects on production.

1.2 Literature

Researchers have reported the benefits of simulation modeling of complex automotive manufacturing systems. Gujarathi et al. (2004) used computer simulation to improve the capacity of shock absorber assembly lines of a motorcycle production system. They modified the original layout via simulation and demonstrated that the system output was improved without increasing the number of laborers. Nguyen and Takakuwa (2008) studied using simulation for designing the manufacturing line of an auto company and proposed a framework for rapid model development in comparison with the conventional method based upon engineering experience.

In the complex systems such as automotive assembly lines requiring a lot of resources and times, it is important to balance the lines for efficiency while preventing critical resource stations from being blocked or starved (Saberi et al. 2008). Duanmu and Taaffe (2007) investigated increasing the throughput of a manufacturing system where several parallel assembly lines share common resources. They also considered adding buffers, compared the MRP (Material Requirements Planning) and the pull system models, and reported the benefit of combining simulation analysis and takt time tools.

Tahar and Adham (2010) developed a simulation model of auto manufacturing system design, operation, and maintenance by considering two different levels; the supply chain and the assembly plant. They used the amount of products and the time savings as the main performance measures, and analyzed the trade-off between the two. Wang et al. (2011) used a data-driven simulation methodology to model a production system and to make changes to the model in response to dynamic requirements and real time information from the demand side. Their approach was applied to an automotive general assembly plant integrated with an online material handling system in order to improve production flexibility as well as demand responsiveness.

Based on a case of an assembly line in the automotive industry, Steinemann et al. (2012) proposed an approach for running production environments that can benefit from simulation experiments. The goal was to extend and simplify the current discrete event simulation tool to be readily applicable right at the production lines on site, and to support simulation experiments within the improvement process. Lastly, Feng et al. (2013) addressed the issues of worker heterogeneity, stochastic processes, and different learning levels among workers in a manufacturing plant of automobile engine parts. Using discrete event simulation, they explored different schedule policies with regard to running a production line and applied Markov decision process to find the policy that maximized productivity.

2 PROBLEM STATEMENT

The manufacturing facility in our study produces two automotive parts, i.e., axle system and spring system, each requiring distinctive and dedicated subassembly lines. Some parts such as tubers, linchpins, hubs, shock absorbers, and coil springs are provided by outsourcing from vendors whereas raw materials including bolts, washers, and brake pads are directly purchased.

The current production level has been reduced to around 700 for both axle and spring systems due to low demand. In response to recent rising demand, however, the production level for each item needs to increase to close to 1,000 per day. The aim of this study is to provide the company with feasible manufacturing plans to achieve this nominal capacity level. More specifically, we propose several alternative system component changes to reach the desired throughput level as well as determine the optimal resource allocation.

The main operation of the manufacturing line is comprised of the axle production line and the spring production line. The axle operation has two subassembly lines and the spring operation has one as depicted in Figure 1. In the following subsections, we further explain in detail each of the main operations as well as the corresponding operational constraints to the model.

2.1 Axle and Spring System Operations

Two subassembly lines of the axle operation are named Subline 1 and Subline 2. In Subline 1, tuber and linchpin units arrive to Station 1-1 where they are assembled and tested. Subsequently, an assembled unit (or tork) is sent to Station 1-2 where ball bearing units are available. Two ball bearing units and two tuber-and-linchpin subcomponent units are joined and move to the tinfoil sink Station 1-3 and the sensor assembly Station 1-4 in sequence. In Subline 2, both hubs and brake disks are washed in Station 2-1 and then only brake disks proceed to Station 2-2 for the carving process. Two pairs of hub and brake disk units are assembled at Station 2-3.

Station 3 receives one subcomponent type of two ball bearing units and two tuber-and-linchpin units from Subline 1, and another subcomponent type of two hub units and two brake disk units from Subline 2. The subcomponent of either type is stored in buffer until both types are available for the next operation, alternating to the assembling and packing left or right caliper station.

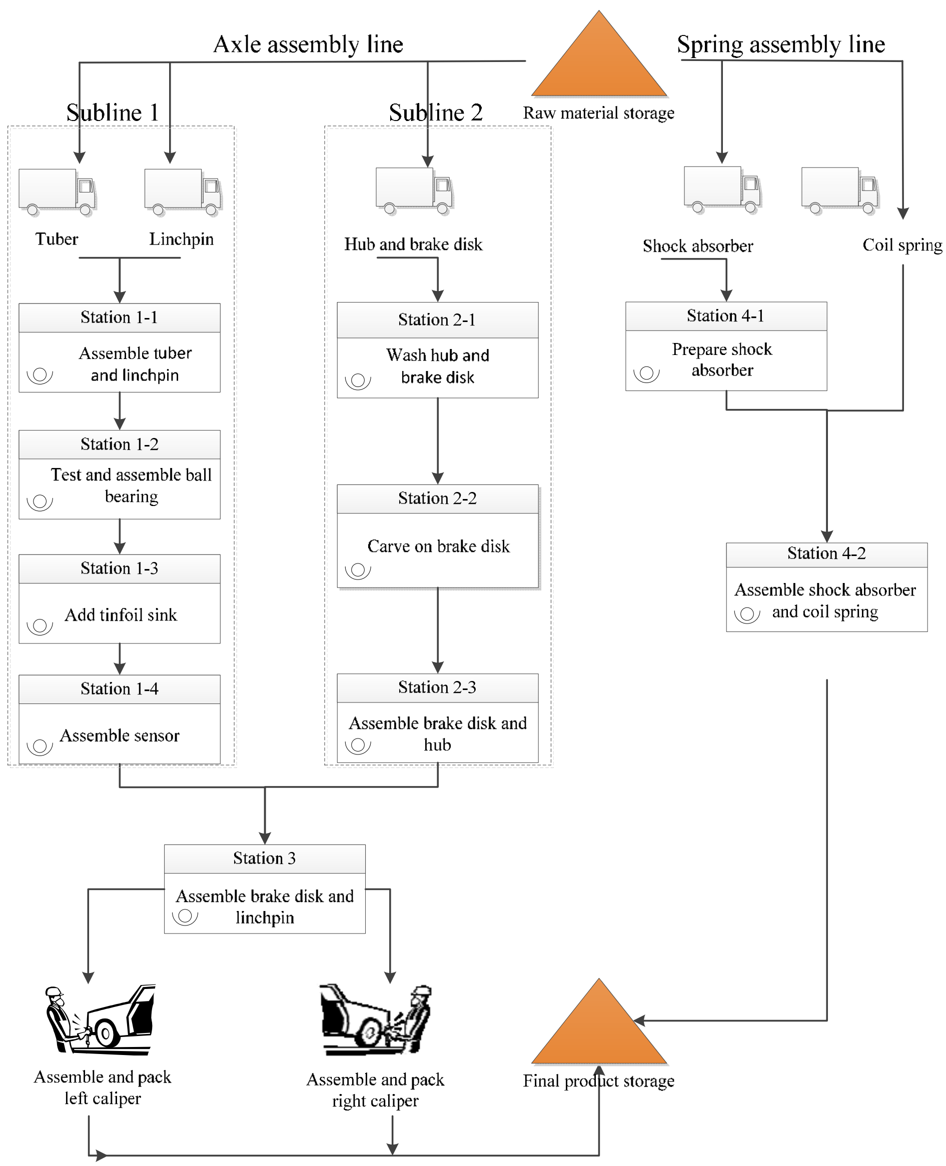

Figure 1: Production line of the axle and spring system.

Shock absorber spring systems are processed in a separate manufacturing assembly line. First, shock absorber parts are prepared at Station 4-1 and moved to the next station to be joined with coil springs, which are available at that station as procured outsourcing parts. Two shock absorber units and two coil spring units are assembled in Station 4-2.

2.2 Operational Constraints

The manufacturing line runs in three 8-hour shifts, and one operator assigned to each station works for a single shift with one hour of break time. For instance, during the shift of 0:00 to 8:00, an operator would work from 0:00 to 4:00 and from 5:00 to 8:00 with a break between 4:00 and 5:00. In addition, when the final assembly axle and spring systems are ready, they are transported in a batch of 32 and 30 units, respectively, per each trip to the warehouse where they are in turn separated and stored individually. All final assemblies are picked up and transported to the warehouse by a forklift truck, which moves at an average speed of 13.7 feet per second (15 km/h). A forklift responds to job requests for transporting between stations and the warehouse based on the rule of shortest distance first.

3 SIMULATION MODEL

3.1 Input Data

We analyzed real data obtained from the facility to determine the appropriate probability distribution for each source of system randomness. Processing times at 13 stations and interarrival times from 6 entity arrival streams were generated after fitting them to the input data. For example, the best fit of the processing time at Station 2-3 (brake disk and hub assembly) follows the beta distribution of 14*beta(1.81, 1.58) + 4.

3.2 Assembly Line Flows

Using Arena simulation software (Kelton et al. 2010), we developed a simulation model which includes the main logic along with two sublevel modules. The following figures provide description of each flow process in greater detail. Figure 2 and Figure 3 show the flowchart of the model logic for the axle assembly line and the spring system assembly line, respectively, at top level.

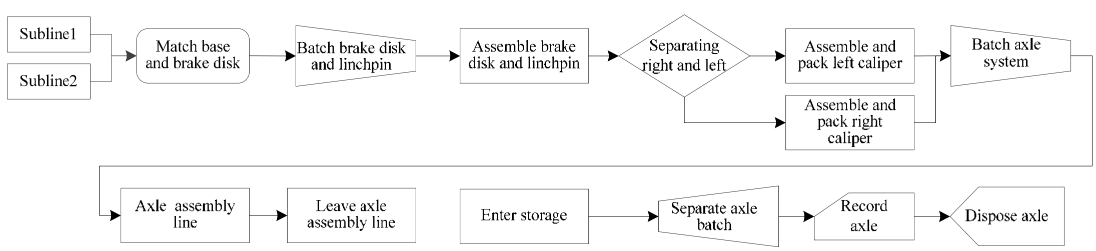

Figure 2: Model logic for the axle assembly line.

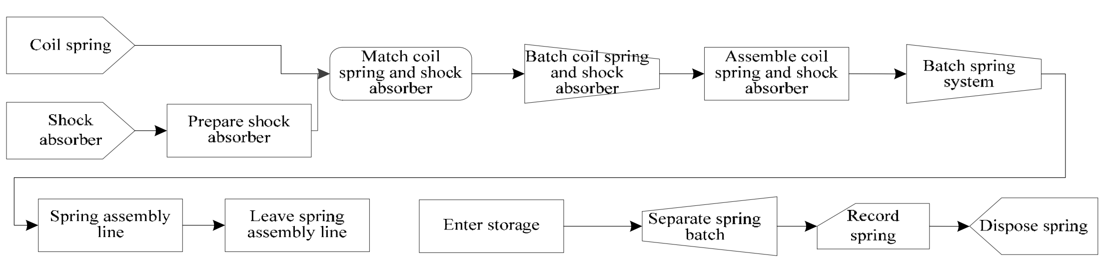

Figure 3: Model logic for the spring assembly line.

The flowcharts of Subline 1 and Subline 2 as sub-models are also shown in Figure 4 and Figure 5, respectively, and they serve as the first two modules of the axle assembly line as described in Section 2.1.

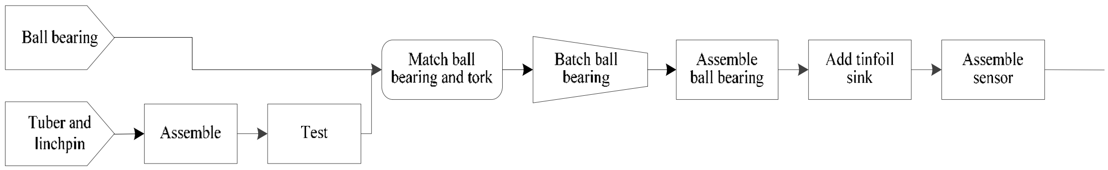

Figure 4: Subline 1 model logic.

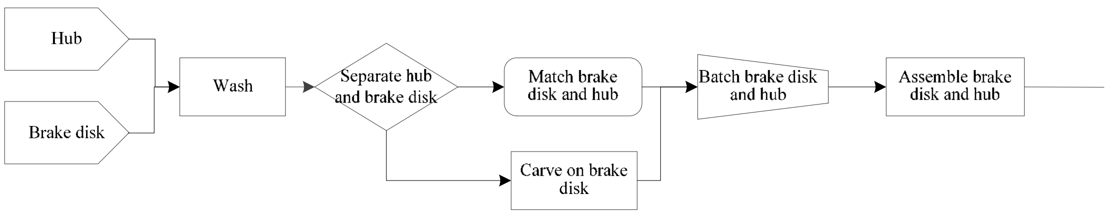

Figure 5: Subline 2 model logic.

4 SIMULATION EXPERIMENTS

All simulation runs were made on a DELL OptiPlex 780 computer having an Intel Core2 Duo 3.00 GHz processor, with 4.00 GB of RAM, and running Window 7. For the baseline case, in terms of computational effort, a single replication consumed 9.57 seconds and one complete run of five replications required 43.6 seconds. In addition, a terminating approach was used in running our simulation model since the company manufactures only the amount of its products (axle and spring) it can ship out to another vehicle assembly line nearby on a daily basis, and the current system starts in an empty-and-idle state and runs on all three eight-hour shifts in practice.

In order to determine the number of replications required to limit an estimate relative error γ while obtaining a desired confidence level for performance measures, we used the following approximation for number of replications, $n_r(\gamma)$, in Equation (1) from Law (2013).

$$n_r(\gamma) = \min\left\{ i \geq n_0 : \delta = \frac{t_{i-1,1-\alpha/2} \sqrt{S^2(n_0)/i}}{\left|\bar{X}(n_0)\right|} \leq \gamma' \right\}, \tag{1}$$

where $\gamma' = \gamma/(1+\gamma)$ is the adjusted relative error threshold. More specifically, n_0 is the initial fixed number of replications and i is the number of replications to decide subject to γ. $\bar{X}(n)$ and $S^2(n)$ are the sample mean and the sample variance, respectively, over a given replication n. The numerator term multiplied by t distribution approximates the half-length of the $100(1-\alpha)$ percent confidence interval, and the term δ, divided by $|\bar{X}|$, effectively estimates the actual relative error. With $\gamma = 0.05$ (or $\gamma' \approx 0.048$) and a confidence interval of 95%, we assessed that five initial replications ($i = 5$) sufficed to have the values of δ for the number of axle and spring outputs less than γ'. Table 1 provides the relevant statistics.

Table 1: Sample means and variances with five replications.

Output Measure	$\bar{X}$	$S^2(n)$	δ
Axle	665.6	14.3	0.027
Spring	768	34.2	0.045

Regarding the validation of the model, we compared the output statistics of axle and spring from the simulation model in Table 1 and those from the actual system. Based on the information obtained from the on-site manufacturing assembly lines, the average outputs in Table 1 closely approximate the actual daily production volumes by less than five percent, which indicates that the simulation model represents the actual system reasonably.

4.1 Bottlenecks

To improve the throughput level for both spring and axle systems, we identified bottlenecks in each assembly line after running the baseline model. Table 2 presents the relevant output statistics including average waiting time and average number waiting in each station at assembly level, and compares the five stations having longest average waiting times.

Overall, the most congested station was the match base and brake disk station in the axle assembly line with average waiting time of 6.74 hours. On the other hand, the match station joining a shock absorber and a coil spring was identified as the bottleneck within the spring assembly line. A large number of waiting parts from Subline 2 in contrast with Subline 1 indicates that the incoming flows need to be balanced at this match base and brake disk station. This leads to further investigation of the number of part waiting and the waiting time of each station at subline level. Similar to assembly level, the bottleneck occurred at one of the match station in Subline 1. Table 3 shows that, at match ball bearing and tork station, a ball bearing waited for 4.72 hours on average to be joined with a tuber-linchpin subcomponent.

Table 2: Average number waiting and waiting time at assembly level.

Line	Station	Average number waiting	Average waiting time
Axle assembly	Match base and brake disk (Subline 2)	390.79	6.74
	Batch axle system	15.86	0.56
Spring assembly	Match shock absorber with coil spring	18.10	0.53
	Batch spring system	14.34	0.43
	Match coil spring with shock absorber	6.15	0.18

Table 3: Average number waiting and waiting time at subline level.

Line	Station	Average number waiting	Average waiting time
Subline 1	Match ball bearing with tork	209.65	4.72
	Assemble tuber and linchpin	26.69	0.89
Subline 2	Match hub with brake disk	16.86	0.28
	Match brake disk with hub	17.26	0.28

4.2 Sensitivity Analysis

In this section, we conducted different sensitivity analyses to study the effects of various factors such as arrival rate, batch size, and operator resource on the system performance. For each experiment in the following subsections, we first designed one-way sensitivity analysis experiments by varying one parameter at a time. Based on the top performance values for each parameter, we considered multiple parameter changes simultaneously and provided the best cases in terms of throughput.

4.2.1 Arrival Rate

Six raw materials including ball bearing (T_1), tuber linchpin (T_2), hub (T_3), brake disk (T_4), coil spring (T_5), and shock absorber (T_6) were considered to understand their effects on the proposed model. For different arrival rates, we varied the mean values for exponentially distributed interarrival times. More specifically, one-way sensitivity analysis was used by changing the mean interarrival time between 60 and 120 seconds with increment of ten seconds for one particular arrival stream while keeping the others unchanged.

Figure 6 shows how the throughput level varies as we change the arrival rate for each entity stream at the first stage. Then the best three interarrival times for each part entity were selected and used to design experiments in order to find the combination of arrival rate settings across all entity types that can yield the maximum throughput.

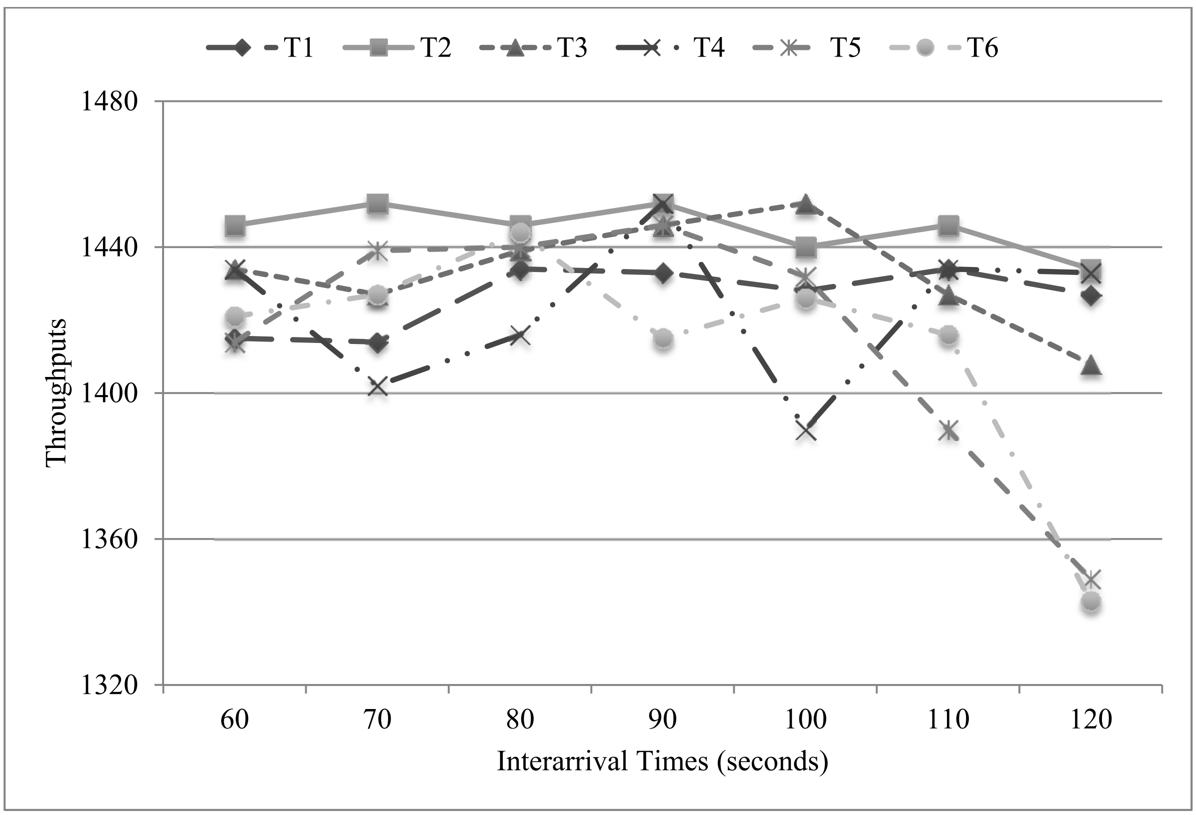

Figure 6: Effect of varying interarrival times for each part entity on throughput.

Among the total of 18 experiments conducted, Table 4 presents the most effective four arrival rate configurations, among which Case I achieved the most improvement. On the basis of the results from Cases I-IV, increasing interarrival times (decreasing arrival rates) for T_3 and T_4 and decreasing interarrival times (increasing arrival rates) for T_2, T_5, and T_6 resulted in more throughput, which implies the baseline case was not balanced for both assembly lines. Note that the increased throughput amounts in spring systems are significantly larger than in axle systems.

Table 4: Experiments of varying interarrival times for multiple part entities.

Case	Mean interarrival time in axle line				Mean interarrival time in spring line		Throughput		
	T_1 (ball bearing)	T_2 (tuber linchpin)	T_3 (hub)	T_4 (brake disk)	T_5 (coil spring)	T_6 (shock absorber)	Axle	Spring	Total
Base line	80	120	60	60	105	105	665	768	1433
I	80	70	90	90	80	70	678	1038	1716
II	80	70	90	90	80	80	678	1026	1704
III	80	70	90	90	90	80	672	918	1590
IV	80	90	100	90	90	80	672	912	1584

4.2.2 Batch Size

Next we considered having different batch size to parts along the assembly lines and measured their effects on axle, spring, and total throughputs. Two types of batch were taken into account: (i) *process* batch occurs at the brake disk-linchpin station (B_1) and the brake disk-hub station (B_3); and (ii) *move* batch occurs at the batch axle system stations (B_2) and the batch spring system (B_4). For this simulation experiment, the process batch size for B_1 and B_3 ranges from one to four, and the move batch size for B_2 and B_4 ranges from 26 to 34 with increment of two, resulting in the total of 400 combinations.

In Table 5, we selected the four best cases in terms of total throughput number, and each one of them has the batch size to B_1 as one and the batch size to B_3 as four. The process batch type (B_1 and B_3) has significant impact on throughput in comparison with the move batch type (B_2 and B_4) having little or no impact. This asserts that operating with the current batch size of two at both the brake disk-linchpin station and the brake disk-hub station is ineffective, thereby reducing the axle throughput level. Furthermore, intermittent arrivals to the brake disk-linchpin station limits the batch size of no more than one (B_1), whereas more frequent arrivals to the brake disk-hub station demonstrates the advantage of larger batch size of four (B_3).

Table 5: Effect of batch size change on throughput.

Case	Size of batch in Axle			Size of batch in Spring	Throughput		
	B_1	B_2	B_3	B_4	Axle	Spring	Total
Baseline	2	32	2	30	665	768	1433
I	1	28	4	34	991	775	1766
II	1	28	4	32	991	775	1766
III	1	32	4	32	985	780	1765
IV	1	32	4	34	985	775	1760

4.2.3 Operator Resource

We also experimented with different operator resource policies to assess the sensitivity of operator allocation decisions to the throughput level. First, one more operator was added to each of the bottleneck stations in Subline 1 that have two largest average waiting times from the baseline case (Case I). Second, as an alternative, we considered cross-training current operators, in particular those working at non-bottleneck stations, to be allowed to operate machines in other stations (Case II). Third, we included both additional operators from Case I and flexible operators from Case II to assess their combined effects on throughput (Case III). The result from Table 6 shows that, compared to the baseline, Case I increased the throughput for axles by 5.9% whereas Case II increased both axles and springs by 4% and 1.6%, respectively, indicating better improvement on the more congested line. On the other hand, 4.8% of increase in total throughput (7.7% for axle and 2.3% for spring) was obtained by Case III, achieving the most throughput of 1502.

Table 6: Impact of operator resource decision on throughput.

Case	Description	Axle	Spring	Total
Baseline		665	768	1433
I	One additional operator to each of assembly and test stations (Subline 1)	704	768	1472
II	Cross-training operators	691	780	1471
III	Case I and Case II	716	786	1502

5 SCENARIO DEVELOPMENT AND ANALYSIS

Based on the parameter values experimented regarding three factors (Factor 1: arrival rate, Factor 2: batch size, and Factor 3: operator resource) in Section 4, we composed different scenarios where each factor was allowed to vary at the same time in order to find the configuration setting of best performance.

Out of 48 scenarios developed for this experiment, Table 7 shows ten best scenarios sorted by the descending order of throughput. The output of 912 axle systems and 1024 spring systems was achieved with the configuration of arrival rate (I), batch size (II), and operator resource (III). This concerted improvement effort increased throughput more than when only considering a single factor alone.

Table 7: Throughputs of ten best scenarios.

Scenario No.	Factor 1 (arrival)	Factor 2 (batch)	Factor 3 (operator)	Axle	Spring	Total
1	I	II	III	912	1024	1936
2	I	IV	III	915	1020	1935
3	I	I	III	918	1013	1931
4	I	III	III	908	1017	1925
5	II	II	II	890	1024	1914
6	I	I	II	879	1026	1905
7	II	I	II	884	1020	1904
8	II	III	III	902	998	1900
9	II	IV	III	902	992	1894
10	I	II	II	868	1024	1892

Furthermore, we measured the improvements for the respective axle and spring system among the five best scenarios as in Figure 7. Verifying the effectiveness of employing the proposed changes from the sensitivity analysis described in Section 4, the combining effect was more evident for axle systems with an estimated increase of more than 35 percent in Scenarios 1-4, compared to spring systems with less than 35 percent increase in all Scenarios 1-5.

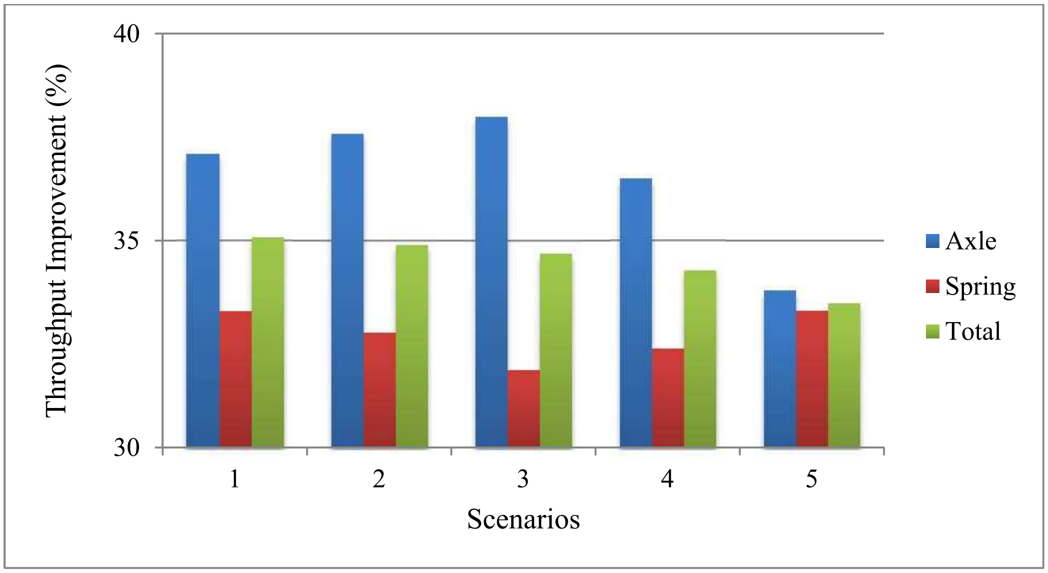

Figure 7: Throughput improvements by Scenarios 1-5.

6 CONCLUSION AND FUTURE WORK

In this study based on an automotive manufacturing system, a discrete event simulation model was developed to investigate the current level of output and to measure the effectiveness of improvement decisions on it. Axle, spring, and combined throughput levels were considered as the main performance measures, which were used to determine the parameter values of the factors such as arrival rate, batch size, and operator resource. First, we assessed that the axle assembly line had lower throughputs relative to the spring assembly line and that the root cause was that the bottleneck occurred at the match base and brake disk station in the axle assembly line. Next, by sensitivity analyses of one-way experimental design, we measured the impact each factor has on system throughputs and estimated up to 19.7%, 23.2%, and 4.8% increases when separately controlling arrival rate, batch size, and operator resource, respectively. Finally, we report that the best composite scenario resulted from the sensitivity analyses achieved more substantial amount of throughput with 35.1% increase.

Overall, the results of the proposed simulation model and experiment discussed in this paper have demonstrated potential impacts on production capacity for the auto company by jointly considering multiple operational factors while applying feasible improvement strategies. Moreover, it is in our interest to further incorporate cost aspects associated with arrival of raw materials, transportation of batch parts, and use of flexible and additional operators in the current model.

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