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Optimization Model for Production Scheduling Requirements Applied on Heavy Truck Assembly Lines

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Abstract. The sequencing of production issue is one of the most complex problems that arise in the automotive industry when producing various assembly line products. The objective of this article is to propose a production sequencing model for automotive components. The aim is to define the process variables that affect the number of units produced, process time (from entering the first station until exiting the assembly lines), and the utilization rate of the workstations. Currently, computer simulation is one of the most used tools to analyze, design, and evaluate complex production processes. It is able to make decisions about the real system without affecting it. The experimental design in this research was principal when generating the combinations of the inputs and how they affect the response variables. For this study, multivariable predictive regression models were used in order to verify the hypotheses described below and to identify which variables' main effects and interactions positively or negatively impact the assembly process.

Keywords. Simulation, automotive industry, predictive models, promodel.

1 Introduction

In recent years, the Mexican automotive industry has been characterized as one of the most productive sectors of the Mexican economy with 3% of Gross Domestic Product (GDP) and 18% manufacturing GDP. According to the National Institute of Statistics and Geography (INEGI).

For this reason, it has been the biggest attraction for foreign investors. Investments in this industry generate approximately 870,000 direct jobs per year [1]. Mexico has positioned itself as the 7th producer of vehicles in the world and the 1st in Latin America, surpassing countries such as Spain, Brazil, and Canada.

The Mexican automotive industry must comply with quality standards as the country has also contributed 3.8% to the world production of automobiles; this compliance is due to the demands of international markets, where the variety of products are presented.

At the international level, the automotive industry is made up of two sectors: terminal and auto parts. The terminal industry is divided into two segments: light vehicles and heavy vehicles according to the definitions presented by the International Organization of Motor Vehicle Manufacturers [2].

The light vehicles are used to transport passengers containing less than eight seats (including the conductor), whereas the heavy vehicles are those used for the transport of merchandise. The latter's weight is greater than 7 tons. For this investigation, this last definition will be used for heavy vehicles.

2 Literature Review

When producing in line, one of the most common problems of the automotive industry is the sequencing of production orders to workstations.

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Graham first described the overall problem of sequencing production, which was defined as an optimization problem of computer science and operations research. Where n jobs J_1, J_2, J_n with different processing times must be programmed in "m" machines minimizing the total of all workstations [3]. Parello et. al first outlined the production sequencing of the automotive industry The objective was to program vehicles along an assembly line where the number of infractions towards workstation restrictions could be minimized, i.e., capacity limitations and sequence changes according to the original production plan [4].

The literature discusses two types of approaches to solve the problem of sequencing in the automotive industry. The first is by means of exact approximations (restriction programming, whole programming, Ad-Hoc, and Simulation). The second is by means of heuristic approaches (local search, genetic algorithm, and optimization of the ant colony) [5].

The simulation technique is used in this study. In fact, today, this technique is one of the most used tools for quantitative analysis. Immediate results can be seen without manipulating the real system [6].

Computer simulation is a numerical technique for conducting experiments. It requires certain types of logical and mathematical models, describing the performance of a business or a system over extended periods of real time [7].

In this study, ten variables will be used to verify how they affect the sequencing of production in the automotive industry, defined as follows:

1. Installed Capacity: is the production potential or maximum production volume that a particular company, unit, department or section; can achieve over a period of time, taking into account all the resources available to them, be it the production teams, facilities, human resources, technology, experience / knowledge, etc. [8].

2. Inventory in Process: it is any article or elements that are used in a production process and its main characteristic is that with each process its value increases until it becomes a finished product. In other words, they are partially finished products [9].

3. Lot Size: is the quantity of raw material that enters into a production process as a whole [10].

4. Takt Time: is the available work time divided by the number of completed units required in that period of time. [11].

5. Product Mix: also known as the product variety, it refers to the total number of product lines that a company can offer its customers [12].

6. Cycle Time: it is the maximum time allowed to work in the elaboration of a unit in each station [13].

7. Operation Times: it is the time interval necessary to complete a work order, with certain work stations [14].

8. Bottlenecks: it is defined as any resource whose capacity is less than its required demand. In other words, it is a resource that limits the finished pieces. At the point in the production process where the flow tends to be slower, which can be a machine, poorly trained operators, specialized tools, etc. [15].

9. Downtimes: it is defined as the amount of time that can elapse between the start of an A1 activity and the initial one in an A2 activity, as long as A1 precedes A2 [16].

10. Waste Generation: Former Toyota President Fujio Cho defines waste as "anything other than the minimum amount of equipment, materials, parts, hours of work, absolutely essential to production." Any amount that exceeds the minimum required is considered a waste, because effort and material are invested in something that is not necessary at the time [17].

3 Methodology

The research design will be experimental, analyzing through intentional manipulation if one or more independent variables affect the dependent variable. According to the classification by Campbell et al., experimental designs are divided into three categories: pre-experiments, "pure" experiments, and quasi-experiments.

This research will be a "pure" experiment based on the presented definition. The following requirements are met to achieve control and internal validity: comparison groups (manipulation of the independent variable) and equivalence of the groups [18].

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Table 1. Input factors and their levels

Independent Variables	Factor Description	High Level	Low Level
X_1	Inv. In Process	1500 pcs.	1200 pcs.
X_2	Batch Size	3000 pcs.	2400 pcs.
X_3	Product Mix	20 pcs.	14 pcs.
X_4	Processing Time Station1	U(154.45, 90.60) min	U(46.20, 24.10) min
X_5	Processing Time Station3	U(238, 124) min	U(100.10, 70.83)min
X_6	Assembly of radiator (Downtime)	90 min	30 min
X_7	Assembly of porteria, (Downtime)	95 min	25 min
X_8	Assembly waste (rework)	5%	1%
X_9	Installed Capacity	3 Shifts x 8 hrs	1 Shift x 8 hrs

Table 2. Coefficients for determining the SPSS result model

Dependent Variables	F	Sig.	R^2	Number of models	Condition Index
Y_1	24445.8	0.00%	85%	6	9.1
Y_2	829.9	0.00%	62%	5	6.6
Y_3	234.6	0.00%	27%	4	5.4

Table 3. Coefficients of β SPSS for the dependent variable Y1

Independent Variables	Non-standardized coefficients		Classified Coefficients	t	Sig.	Collinearity statistics	
	B	Error típ	Beta			Tolerance	FIV
(Constant)	14.68	0.3		47.8	0.00		
Capacity	17.29	0.19	0.76	91.08	0.00	0.83	1.2
Product Mix	8.67	0.20	0.38	41.56	0.00	0.68	1.45
Takt Time	-0.09	0.00	-0.2	-19.94	0.00	0.55	1.79
Cycle Time	-0.003	0.00	-0.13	-15.58	0.00	0.76	1.3
Inv. In Proce	0.017	0.00	0.03	3.83	0.00	0.81	1.22
Batch size	0.406	0.18	0.01	2.21	0.02	0.88	1.12

Significance level α = 0.05

Due to the nature of this research, and in order not to affect the real system through experimentation, a productive process of heavy truck assembly will be simulated in order to explain

Table 4. Coefficients of β SPSS for the dependent variable Y2

Independent Variables	Non-standardized coeficcients		Classified Coefficients	t	Sig.	Collinearity statistics	
	B	Error típ.	Beta			Tolerance	FIV
(Constant)	253.14	15.73		16.09	0.00		
Downtime	0.10	0.00	0.51	40.80	0.00	0.92	1.08
Bottleneck	0.43	0.02	0.34	22.44	0.00	0.63	1.58
Takt Time	3.16	0.30	0.15	10.4	0.00	0.68	1.47
Capacity	-109.68	14.20	-0.10	-7.72	0.00	0.74	1.34
Batch size	56.81	12.31	0.05	4.61	0.00	0.99	1.00

Significance level α = 0.05

how the independent variables affect the dependent one.

The scope of this investigation involves the assembly process of heavy coaches for a manufacturing company located in Garcia N.L.

A computer simulation model was first developed for the assembly process of urban and extra-urban coaches where 18 workstations and their eight sub-assembly stations were simulated. The computer simulation model was developed by using the software Promodel.

Once the model was developed in the simulator, an experimental analysis was carried out with the basic 2^k design that establishes two levels for each set of factors k, leaving the design 2^6, e.g. 2 levels with 9 factors. Table 1.

For the operation times, probability distributions were generated. In this case, uniform distribution represented as U (A ± B) was used, where A represents the upper limit of the uniform distribution and B the lower limit. Of note is that these data were generated from the historical data of the company and with a daily production.

4 Analysis

Considering this was an experimental study, it was necessary to define the number of replicas (experimental samples) based on the factorial design 2^6, i.e., 2 levels with 9 factors and 5 replicas.

By multiplying these elements, it gives us a total of 2560 replicas used in the simulation to study the behavior of the dependent variables defined as: units completed (Y_1), Process Time (the time it takes to enter the chassis: from the first assembly station to the last) (Y_2), and utilization rate of stations (Y_3).

For each dependent variable, the following model was defined as:

$$\mathrm{Y} = \beta i + \beta i\, Xi + \cdots + \beta nXn + \beta ijXi * Xj + \varepsilon\,, \tag{1}$$

where:

Y = Dependent variable,

β_i = Regression coefficient,

X_i = Independent variables,

X_i*X_j = Interaction effects,

ε = Error.

Once the models were generated, the multicollinearity of the data was validated (statistical test to verify that the variables were uncorrelated to each other). Since more than one model was generated for each dependent variable, the best model based on the highest R^2 has a condition index of less than 15. Table 2.

Subsequently, the Beta coefficients (β) were generated for each of the models presented in Table 3, 4, and 5 for Y_1, Y_2, Y_3, respectively.

The standardized coefficients in these tables, ordered from highest to lowest, show that if a value of beta is positive in the independent variable, then there is an increase in the dependent variable. If beta is negative in the independent variable, then there is a decrease over the dependent variable.

Table 5. Coefficients of β SPSS for the dependent variable Y3

Independent Variables	Non-standardized coeficcients		Classified Coefficients	t	Sig.	Collinearity statistics	
	B	Error típ.	Beta			Tolerance	FIV
(Constant)	-61.11	4.62		-13.22	0.00		
Bottleneck	-0.15	0.005	-0.56	-29.54	0.00	0.78	1.27
Capacity	66.5	3.88	0.30	17.1	0.00	0.89	1.11
Downtime	-0.001	0.00	-0.17	-9.77	0.00	0.91	1.08
Product Mix	29.82	3.81	0.13	7.82	0.00	0.92	1.07

Significance level α = 0.05

Table 6. Solver Vs. Promodel

		VARIABLES	SCALE	SOLVER	PROMODEL	
	X1	Installed Capacity	1	8	8	
	X2	Product Mix	1	20	20	
	X3	Takt Time	1	205	205	
	X4	Cycle time	1	300	300	
	X5	Inventory in Process	1	1,500	1,500	
	X6	Batch Size	1	3,000	3,000	
	X7	Stop Time	1	4	4	
	X8	Bottleneck	1	450	450	**% Promodel Vs Solver**
Max	**Y1**	**Finished Pieces**	**1**	**1,551**	**1,551**	**100%**
Min	**Y2**	**Process minutes**	**1**	**170,676**	**170,676**	**100%**
Max	**Y3**	**Utilization %**	**10000**	**998**	**998**	**100%**
		Integration		**173,225**	**173,225**	**100%**

Model for Finished Parts (Y_1):

$$14.68 + 17.29 capacity + 8.67 product\ mix - 0.09 takt - 0.003 cycle\ time + 0.01 invproc + 0.40 batchsize$$

Model for Process Time (Y_2):

$$253.14 + 0.10 downtime + 0.43 bottleneck + 3.16 takt - 109.68 capacity + 56.81 batchsize \quad (2)$$

Model for the utilization rate of stations (Y_3):

$$-61.11 - 0.15 bottleneck + 66.50 capacity - 0.001 downtime + 29.82 product\ mix \quad (3)$$

For the model of the dependent variable finished pieces (Y_1), it is observed that the variables with greater explanatory weight (taking into account absolute values, highest to lowest) are: Installed Capacity, Product Mix. Those that

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Table 7. Current situation vs Optimal Value

Variables	Current Situation	Optimal Value
Takt Time (min)	45	25
Cycle Time (min)	540	300
Maximum units	84	151

Table 8. Current situation Vs Optimal Value

Variables	Current Situation	Optimal Value
Inventory in Process (units)	2,600	2,000
Batch Size (units)	5,000	4,000

had the least impact were: Inventory in Process, Cycle Time. All these variables had a P-value of less than 5%, indicating that they are sufficiently explanatory for the model.

For the model of the dependent variable termination time (Y2), it is observed that the variables that have a greater explanatory weight for the model (taking into account absolute values, highest to lowest) are: Installed Capacity, BatchSize, Takt Time. Those that had less impact were: Bottleneck, Downtime. All of these variables had a lower P-value of 5%, indicating that they are sufficiently explanatory for the model.

For the model of the dependent variable percentage of use (Y_3), it is observed that the variables with a greater explanatory weight (taking into account absolute values, highest to lowest) are: Installed Capacity, Product Mix.

Those that had the least impact were; Bottleneck, Downtime. All these variables had a P-value of less than 5%, indicating that they are sufficiently explanatory for the model.

5 Optimization of the Variables

Based on the multivariable linear regression equations obtained in the previous step, the mathematical model was designed to optimize our case study. The following objective functions were defined: maximize finished parts, minimize process time, and maximize percent utilization of workstations.

It was decided to use the meta heuristic techniques of the Excel Solver and Promodel Simmrunner tools.

As can be seen in table 6 the results of the Solver and Promodel were congruent and optimal, so that the maximum number of pieces that can be produced is 1,551 units, the minimum time that can be for the completion of the process is 170,676 minutes and the maximum utilization percentage of 0.0998, this with the conditions of the independent variables obtained.

6 How to Analyse Data and Make Decisions

Below is a comparative analysis of the current situation of the company vs. our proposed solutions with optimal values.

In table 7 with an 8-hour shift in both scenarios, the company in its current working conditions, can produce a maximum of 126 units, while in our proposed model it can produce 151 maximum units, which represents an increase in 20 % of production, generating in turn an income of $ 740,031 USD.

The heavy truck assembly line currently has nine sub-assembly stations, which are in charge of supplying the kit of semi-assembled products to the line, one of the problems that the company shows is that it does not know what the optimal quantities are.

You must have of those kits, nor what is the adequate capacity for the subassembly stations, which generates having a high cost of inventory in annual process having a current average inventory cost of $ 4 Million USD. Considering the current interest rate as a cost of capital at 5%, a profit of $ 208,000 USD was obtained and with a reduction of 25% it gave a total of $ 52,000 USD. Table 8 shows how the current situation and the proposal are found.

Another of the improvement proposals is the payment of overtime, due to the bottlenecks that occur in the production line due to the lack of resources to operate in the assembly stations and due to the high turnover of personnel; as well as

Table 9. Current situation Vs Optimal Value

Variables	Curren Situation	Optimal Value
Cap. Installed (hrs)	8	8
Takt Time (min)	45	25
Batch Size (units)	5,000	2,400
Downtimes (hrs)	5	1
Bottleneck (min)	500	25
Finished Time (min)	280,712	135,829

Table 10. Summary of hypothesis results

Variables	Finished Pieces (Y1)	Process minutes (Y2)	% Utilization (Y3)
Inventory in Process	✓		
Batch Size	✓	✓	
Takt Time	✓	✓	
Product Mix	✓		✓
Bottleneck		✓	✓
Re-work			
Downtime		✓	✓
Installed Capacity	✓	✓	✓
Cycle time	✓		
Operation Time			

unexpected stoppages on the line due to a lack of supplies from the sub-assembly station kits.

Under current conditions, the company can have a minimum production completion time of 280,712 minutes, while our model could have 135,829 minutes, representing a decrease of 144,883 minutes (2,415 hours), which would represent a saving of $ 56,161 USD, annually, in the payment of overtime, see Table 9.

7 Conclusions

Our experimental design were completed using 3 relevant response variables (Y_1, Y_2, Y_3) we find very frequent around heavy manufacturing sector. As for the set of independent variables ($X_1...X_9$) we modeled in our experiment applying some pre-analytics on the historical data provided by the business. Specific custom distributions were constructed using 2 years of data; some were based on normal and uniform distributions.

As a result, different combinations of factors tested have been found significant for each response variable.

Experiment was a factorial design using a simple dichotomy approach (i.e. low and high) to measure factors ($X_1...X_9$). For each combination of factors, we applied 5 replicas ending up with a sample of 2560 measures.

The regression analysis was useful to identify how these variables are interacting each other. A very large number of models were constructed using well know “step-wise” approach.

Significance and collinearity validation was done for each model looking to increase variance explained (R^2). We have already discussed regression coefficients results in terms on magnitude and sign. This is true for main principal effects.

Here we include table 9 with the summary of our initial hypothesis. Further analysis for utilization % variable (Y_3) is suggested as we end up with a high significant model but with a low explanation variance when compared with (Y_1 & Y_2); surely other factors are impacting (Y_3) requiring to be included on a new experiment.

In table 10, you can see which were the variables that affected each of the resulting models. One of the variables that affected the three models is the installed capacity, which was one of those that had the greatest impact in our experiment.

For the finished parts model (Y1), the bottleneck was expected to have an impact; surprisingly we found that this did not happen; and that it had a relationship with the variable Product Mix (X4), due to the complexity of the mixtures.

In the case of process minutes (Y2), it is expected that the variable inventory in process (X1), had some impact on it, but it was not resulting; What was found was that bottlenecks do have an effect on this variable, but it was not found to be related to the Product Mix (X4).

In the case of the variables Downtime (X7) and Operation time (X10), they were variables that did not really affect any of the models, this may be due to the little rework that exists in the lines and in the time of Operation of each of the stations was maintained at a constant rate. Most of the standardized regression coefficients results are sorted out and validated from our initial hypothesis in terms of importance and impact. On “results” section we have included an interesting discussion particularly when coefficients magnitude and signs are getting out of the range of what would be expected in terms of direct or inverse impacts over the response variables.

We have already discussed that not all factors are relevant for each response variable; furthermore any given factor may have the most of the impact in one response variable and have no significance at all when compared with other response variable.

This is interesting and explained as we find out a low correlation among response variables (Y1, Y2, Y3). Further analysis can be done here to develop sophisticated surface response techniques.

Moving forward, unstandardized coefficients could be used to predict results on the real world operation pursuing different settings as for scheduling strategy on manufacturing. Moreover, if unstandardized coefficients are useful and accurate for prediction then we can ingest these as valid inequalities on more advanced optimization frameworks. This is a relevant endeavor in order to deal and optimize complex interrelated independent factors impacting a set of response variables; more importantly when these response variables (i.e. Y1, Y2, Y3) are related too and/or are in a “trade-off” decision making structure. A multi-objective optimization model framework would be expected. We particularly suggest this approach as for the next steps on our research work.

As we present in our research, the use of simulation tools, multivariate regression analysis and multiobjective optimization allow the organization to make decisions in the short, medium and long term, in order to make its operations profitable and highly productive. , this without affecting the operations of the organization directly and seeing the results immediately.

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