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Article

Integrating Simulation-Based Optimization for Lean Logistics: A Case Study

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Featured Application: The application of stochastic and optimization tools through simulation and Response Surface Methodology (RSM) is useful defining the optimal distribution cost in a logistic process.

Abstract: The present work aims at the comprehensive application of stochastic and optimization tools with the support of Information and Communication Technologies (ICT) through a case study in a logistics process for electronic goods; simulation and Response Surface Methodology (RSM) are applied for this purpose. The problem to be evaluated is to define an optimal distribution cost for products shipped to wholesale customers located in different cities in Mexico from a manufacturing plant in Tijuana, Mexico. The factors under study are the product allocation for each distribution center, finished good inventory level and on time deliveries, which are supposed to be significant to get the objective. The methodology applied for this problem considers the design of a discrete event simulation model to represent virtually the real life of logistics process, which is considered a complex system due to different activities are interrelated to carry it out. This model is used to execute the different experiments proposed by the RSM. The results obtained from simulation model were analyzed with the RSM to define the mathematical model that allows identifying the parameters of the factors in order to optimize the process. The findings prove how the ICT facilitate the application of stochastic tools with the purpose of process optimization.

Keywords: Lean-logistics; optimization; simulation, Response Surface Methodology

1. Introduction

Besides high product quality, total cost and response time seem to be the key success factors to be optimized in Logistics Process (LP) in order to be more competitive in the global markets [1]. Therefore, in today environment the organizations cannot afford to keep the LP within traditional frameworks, which consider a high Finished Good (FG) inventory level and slow response times [2]. Consequently, organizations should consider and incorporate strategies to improve organizational performance by reducing costs and achieving excellence in the LP [3]. Lean manufacturing tools and

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techniques used to reduce waste in the processes, such as just-in-time and inventory management [4].

Logistics cost has an important role in the organizations, being that worldwide cost of LP represents between 9% and 20% of Gross Domestic Product; the variation depends on the region where the process is carried out [5]. As shown by research conducted by [6], the average cost to carry out LP in Latin America is 18.6% of the total cost of sales. However, some Latin America countries are above average, as is the case of Mexico, where the average cost constitutes a 21%. Therefore, it can be concluded that there is a great opportunity to optimize LP in the Mexican enterprises, because on average, almost a quarter of the selling price to the consumer is used in this activity [6].

The inventory management and transportation are two of the main logistical costs in the electronics industry [7]. In logistics, optimization is used for different purposes, such as minimizing Total Logistics Cost (TLC). For the case study presented in this paper, which was implemented in the electronic industrial cluster, the purpose is to improve TLC. In the other hand, constraints to achieve this objective are Inventory Carrying Cost (ICC), Response Time Cost (RTC) and Lost Sales Cost (LSC) [1], which is represented by the mathematical equation (1)

$$\text{Min TLC} = \text{ICC} + \text{RTC} + \text{LSC} \tag{1}$$

Optimization of TLC can be achieved with the application of analytical models and simulation. However, LP is categorized as a complex system and it is difficult to study it via analytical models. On the other hand, simulation is considered a powerful tool for comparing alternatives for decision-making; and due to the stochastic nature of this technique, an efficient comparison needs to consider the application of statistical techniques for a better analysis [8]. Those concepts are presented in a friendly manner in this study with the application of commercial software to design the simulation model that represents virtually the real life of LP and to run the statistical analysis with the RSM technique.

The present case study, considers LP is performed under traditional framework; where, the majority of FG inventory is concentrated in a Distribution Center (DC) in Mexico City, which is 1750 miles from the manufacturing plant, in order to supply product to wholesale customers located in different cities of Mexico. Therefore, this study aims to test the following hypothesis: "stochastics tools can be used to define strategies that help to improve TLC without affecting customer service".

1.1. Logistics and the TV manufacturing industry in the Northern Border of México

Despite the logistics hurdles, the Mexican TV manufacturing role has been in constant evolution since the first Asian-owned factories began operations. About 1.7 million TV sets for the U.S. market were produced in Mexico in 1987 [9]. By 1998, the output was 19.1 million, about 25. Six million in 2003 and peaked at nearly 40 million sets in 2012, with most of the production coming from the regions around Tijuana and Mexicali in Mexico [10].

Although the state of Baja California has a strategic location in the Northern Border of Mexico for the TV manufacturing industry, there are weaknesses in the logistics process to supply finished good products to the local market. The Mexican TV sales in 2013 were 6.3 million, which represents around 15% of total local production so the remaining 85% is for exporting [11]. However, the logistics process for the local market is performed with the traditional framework, while for the exporting market the best practices are applied.

1.2. Lean Logistics

In the process of supply chain planning, logistics is a fundamental part; due to the activities involved: implementing and controlling the flow and storage of goods, services and information in an efficient way to meet customer requirements. Lean logistics applies lean manufacturing thinking to control logistics activities. The implementation of lean manufacturing strategies, tools and techniques into logistic operations has brought advantajes such as costs and product waste reduction, while improving productivity, efficiency, quality and delivery, as well as satisfying customers and employees [4, 12, 13, 14, 15].

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The goal of Lean Manufacturing is to control, reduce and even eliminate waste, at the right time, in the right place, providing the right amount of product. The logistics waste consist of inventory, wating, overproduction, overprocessing, defect, motion and transportation, respectively considered from greater to lesser impact on costs [16]. Lean logistics highlights customers first; timely, accurate and overall optimization; continuous improvement, and innovative ideas. Lean logistics system planning and design can be divided into two submodules: material flow and information flow. To analyze the material flow and information flow cross the company, Value Stream Map (VSM) is used [17]. The improvements in the system can be achieved through optimization strategies related to logistics process, logistics organization structure, logistic operation, standardization and logistic management, logistic profesional personnel´s, logistics cost management, and logistics performance evolution.

In a study conducted with companies registered in the Singapure Logistitcs Association, it was found that 37.5 percent has implemented lean tools in the development of its operations [18]. Within the case studies applying lean manufacturing in the logistic processes, an approach that integrates the Unified Modeling Language (UML), VSM tool and a mathematical formulation of the Genba Shikumi philosophy is highlighted as a precedent of how it is possible to optimize process with these methods. This integration allowed to improve the warehouse management, increasing profitability and quality as well as reducing errors [19]. In China, lean logistics was a tool applied in engine manufacturing to assist engineers in planning, where the Plan for Every Part (PFEP) methodology was used, and packaging specifications were analized, as well as storage logistics and production logistics [20]. Finally, there are other optimization techniques that are discussed in the next section.

1.3. Techniques for optimization in logistics

Traditional framework to perform the logistics process, it is to maintain FG high inventories to ensure customer satisfaction and avoid lost sales costs. However, maintaining high inventories hides many inefficiencies in the activities for this process, which are directly reflected in the logistics cost. By this reason, leading companies apply best practices, such as direct store deliveries, which dramatically reduce inventory levels and cycle times in product distribution [21].

In today's manufacturing environment, there is a wide range of methods, techniques and tools for optimization purposes; but although these have become universal application in many areas [22]. However, those have been few applied for optimization purposes in logistics processes [23]. It has been identified with the literature review that simulation in combination with other methods is a very powerful method for optimization purposes; by this reason, simulation and response surface methodology were considered to be applied for this research.

Simulation refers to a broad collection of methods and applications to mimic the behavior of real systems, where a system is defined as a facility or process, either actual or planned. This method has been effectively applied by several researchers for process optimization [24]. Other studies utilized a process simulator developed in MATLAB for optimization of Generalized Predictive Control (GPC) tuning parameters [25]. Izadi & Kimiagari were able to specify the optimal number and location of distribution centers to determine the allocation of customer demand to DC with a model based on Monte Carlo Simulation [26]. Chackelson use a discrete event simulation model to evaluate order picking performance in a warehouse operation and propose a new picking design process to improve performance [27].

Carson and Maria state that RSM is a method that can interact with simulation models for optimization purposes [28]. RSM can be defined as an experimental and modeling strategy to find the optimal operation conditions of a process [29]; the first-degree model (equation 2) and the second-degree model (equation 3) are commonly used in RSM [30].

$$Y = \beta o + \sum_{n=1}^{k} \beta i \, Xi + \epsilon \tag{2}$$

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$$Y = \beta o + \sum_{n=1}^{k} \beta i\, Xi + \sum\sum_{i<j} \beta ij\, XiXj + \sum_{n=1}^{k} Xi^2 + \epsilon \tag{3}$$

RSM uses different techniques for optimization purposes, such as the contour plots, which allows to visually identifying an area of compromise among the response variables. In Figure 1, it shows as an example for this technique a simultaneous optimization; the green region in the plot is the feasible region that satisfies the criteria for Strength value between 24 and 28, and VarStrength value between 0 and 1.

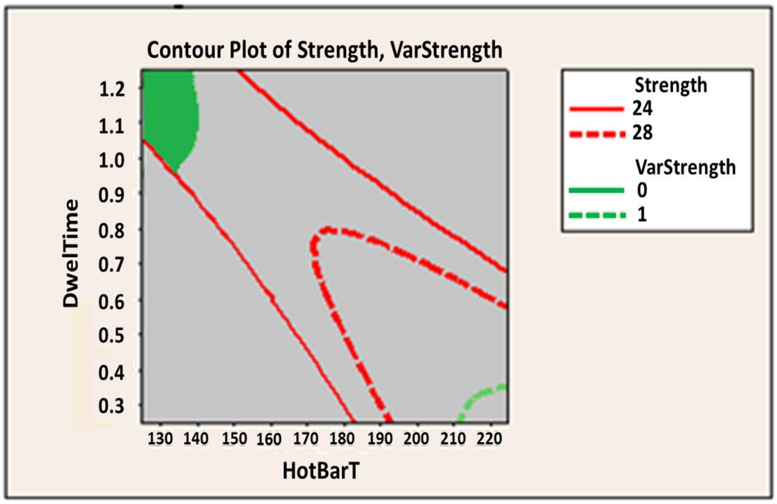

Figure 1. Two responses variables contour plot

Other technique is the desirability function analysis popularized by Derring and Suich [28], where response variables in simultaneous optimization can be maximize, minimize or set to a particular target. Therefore, the first step is to determine the individual desirability index (d_i) based on the expected characteristics of the response variable. There are three ways to calculate di; equation 4 is applied when a particular target is required. Then, the composite desirability (d_G) must be determined through the combination of all individual desirability indexes to form a single value; as seen in equation 5, this is applied for this purpose. The highest d_G value is the one that determines the optimal parameters, and its level combination for response variable optimization. The Minitab software supports both techniques and facilitates the statistical analysis.

$$d_i = \begin{cases} \left(\dfrac{\hat{Y} - Y_{min}}{T - Y_{min}}\right)^s, & Y_{min} \le \hat{Y} \le T, \quad s \ge 0 \\ \left(\dfrac{\hat{Y} - Y_{max}}{T - Y_{max}}\right)^s, & T \le \hat{Y} \le Y_{max}, \quad t \ge 0 \\ 0, & \end{cases} \tag{4}$$

Where:

d_i = Desirability index

$\hat{Y}$ = Value for a particular target

Y_{min} = Lower tolerance limit

Y_{max} = Upper tolerance limit

s and t = weights to define the shape of the desirability function

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$$d_G = \left(\prod_{i=1}^{n} di^{Wi}\right)^{\frac{1}{W}} \tag{5}$$

Where:

d_i = Individual desirability of each Y_i

W_i = weight of each Y_i

W = sum of individual weights $\sum_{i=1}^{n} W_i$

This research is organized as follow section 2 describes how the case study methodology was applied in three phases: collect information, build a discrete event simulation model and statistical method for optimization. Section 3 focuses on presents the application of the case study for the logistic process optimization of a television manufacturing company that supply finished good from two distribution centers to their customers. Section 4, as a result of this research the empirical mathematical model that allows making estimation is defined, and it's tested with different targets. Section 6 conclusions are commented remarking the importance that Stochastics methods have for optimization purpose.

2. Materials and Methods

This research was performed with a case study approach in a manufacturing company dedicated to the electronic sector in Tijuana, México. Groat and Wang defined that case study as a methodology that applied different strategies that could help to confirm, challenge or extend a theory [25, 31, and 32]. Base on this, it's considered this method will help to prove the hypothesis described previously.

Three phases are developed for this purpose; first a field research was performed to collect all the information required to build the simulation model. Then, it was considering the steps proposed by [22] to build a discrete event simulation model to represent virtually the real life of logistics process, as the Figure 2 illustrates. Finally, the RSM was utilized as statistical method for optimization purposes. Arena and Minitab software were applied as supporting ICT; trough Arena software the virtual model was represented and Minitab software to perform the RSM.

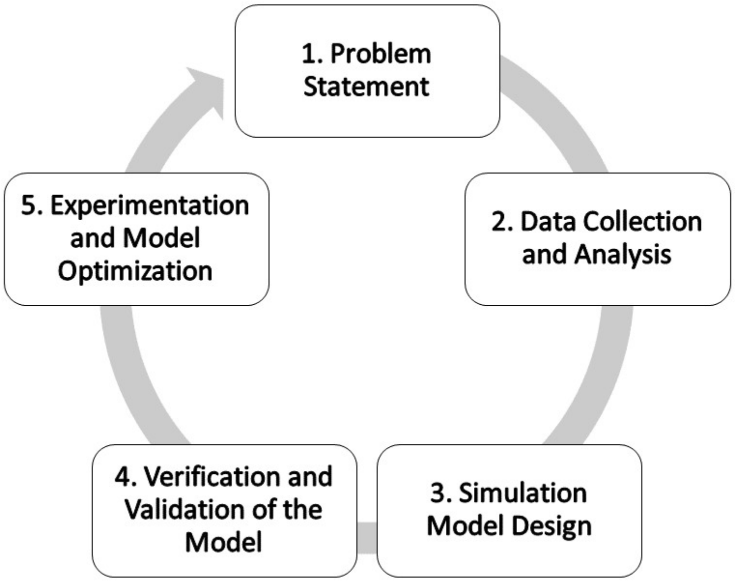

Figure 2. Methodology applied in the case study

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3. Case Study

This section focuses on presents the application of the case study for the logistic process optimization of a television manufacturing company that supply finished good from two distribution centers to their customers.

3.1. Problem Statement

For this case study, a manufacturing company was chosen. The company relies on two service providers to execute the logistics process in Mexico. The company's strategy is to allocate up to 30% of production to the logistics provider located in Tijuana for the distribution of FG to the retail customer located in Culiacan, Mexico; so, the remaining 70% is shipped to a distribution center located in the city of Mexico to perform the FG distribution from that point to their other customers located in Guadalajara, Monterrey, Mexico City and Veracruz. Therefore, the aim of this case study is to identify if increasing the volume assigned to the logistics service provider located in Tijuana and doing the distribution of FG from this point, the logistics process cost is improved, using stochastics tools for this purpose.

3.2 Data Collection and Analysis

The first step is to determine the products (FG) to be evaluated, for this purpose the two highest runner products were selected, which are two models of 40" TV's. Then the operations involved to perform the logistics process were identified, among which are the storage, transportation and inventory level; that according to studies conducted represent between 85% and 90% of the logistics cost [1]. Finally, we collect the FG inventory target in days that are defined by the manufacturer and the transportation transit time committed by the carriers, and the information necessary to develop the simulation model. The second step is to identify the different elements that should be considered in the simulation model, which are:

1. Entities. Finished Goods (Containers / TVs), as well as customers located in Mexico City, Culiacan, Monterrey, Guadalajara y Veracruz.
2. Variables. Two types of variables are considered. Cost to perform the logistics process, which is considered the output variable to be analyzed. Also, the input variables that are: FG allocation by supplier, Inventory level and on time delivery performance.
3. Resources. In order to perform the logistics process, the resources considered are shown in Table 1.
4. Statistics. This activity is considered to accumulate the statistics of the response variable, which is the cost of logistics process.

Table 1. Resources Considered in the Logistics Process

Resource	Cost (US Dollar)
Local Transportation	\$45 / shipment
Storage (include Handle in / out and storage)	\$60 In / \$60) Out and Storage \$2 Sq/Ft / Month
OTR Transportation	Variable (Base on Final Destination)
Inventory Carrying	3% of the inventory Value (Month)
Late Delivery Time	5% of the inventory value

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3.3 Simulation Model Design

Once step 3.2 is completed, the simulation model design needs to be performed based on the operations defined for the logistics process, as well as the interactions of entities, variables and resources. The representation of simulation model is shown in Figure 3; the model assumes a constant output of a TV's every minute from the production line. Also, that product is shipped from manufacturing plant by truck to two distribution centers, located in Tijuana and Mexico City to be storage before it is shipped to the wholesale customer; allocation for each customers is 30% for the Tijuana logistics service supplier and 70% to the logistics service supplier located in Mexico City. Finally, the model considers some failure such as the on time deliveries to customers, which has an economic penalty.

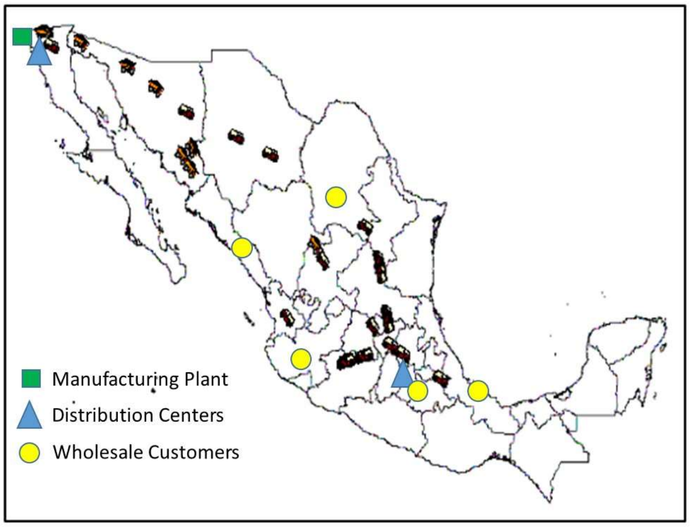

Figure 3. Simulation Model Representation

3.4 Verification and Validation of the Model

At this phase, verification is done by running the model to confirm that the different operations are executed without any problem; after that validation, a comparison of the results is issued by the model and it is made in terms of the cost of the logistics process. Hence, the result was a cost of $ 11,735,575 per 150 shipments evaluated.

3.5 Experimentation and Model Optimization

Three factors were considered and tested in two levels each one in the simulation model as follow: product allocation (PA), considering 30% low level and 70% as high level for Tijuana Distribution Center (TDC); inventory level (IL), tested at 1 week in low level and 2 weeks in high level and on time delivery (OTD), 80% low level and 95% high level. The central composite technique (CCD) of RSM is going to be applied with face centered, four central points, and .05 significance level (α). This activity is performed with Minitab Software and the design considers 18 experimental runs with different combinations of each level.

Each of the 18 experimental runs were executed in the simulation model designed in section 4.3 to find out the cost of logistics process under the different scenarios, all the information is collected

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in order to execute the statistical analysis. Table 2 shows the 18 experimental runs and results obtained with the DCC.

Table 2. Central Composite Design and Results

Std Order	Run Order	Pt Type	Blocks	PA	IL	OTD	Logistics Cost (thousand $)
16	1	0	1	0	0	0	$9,318.70
7	2	1	1	-1	1	1	$9,750.10
11	3	-1	1	0	-1	0	$8,796.20
18	4	0	1	0	0	0	$9,351.20
9	5	-1	1	-1	0	0	$9,675.70
4	6	1	1	1	1	-1	$9,282.70
10	7	-1	1	1	0	0	$8,634.80
5	8	1	1	-1	-1	1	$8,635.60
1	9	1	1	-1	-1	-1	$9,534.90
8	10	1	1	1	1	1	$8,430.20
12	11	-1	1	0	1	0	$9,910.70
2	12	1	1	1	-1	-1	$8,163.30
6	13	1	1	1	-1	1	$7,315.70
13	14	-1	1	0	0	1	$9,470.5
17	15	0	1	0	0	0	$9,245.20
3	16	1	1	-1	1	-1	$10,149.40
15	17	0	1	0	0	0	$9,245.20
14	18	-1	1	0	0	1-	$8396.30

After the model is executed with the support of software Minitab ®, an empirical mathematical model represented by the equation 6 is defined, this needs to be validating to determine if it's a good estimator for the response variable. This model is represented by a regression model with a second order equation. The following concepts are analyzed (where X_1 =PA, X_2=IL, X_3=OTD):

$$Y = 9283.70 - 591.80 (X_1) + 497.70 (X_2) – 397.30 (X_3) – 122.10 (X_1)^2 + 76.00 (X_2)^2 – 343.90 (X_3)^2 – 75.60 X_1X_2 -62.70 X_1X_3 + 74.30 X_2X_3 \quad (6)$$

1. Coefficient of determination analysis (R2adj). This indicator shows as a result 96.89%. Which indicates that the factors are statistically significant to the result (output variable), because those factors explain the 96.89% of the variability by the fitted model. Base on this information, the empirical mathematical model represented by the equation 2 needs to be validated to determine if it's a good estimator for the response variable.
2. Analysis of variance (ANOVA) is applied to ensure the significance of the regression model at 5% significance level (α). Based on the ANOVA results shown in the Table 3, it can be concluded that the regression is statistically significant at a F-value of 59.89 and p-values of 0.00; principal effects (PA, IL and OTD) and quadratic effects also are significant for the response variable (logistics cost) since p-value is less than α-value. As well as, model fit the data since the p- value for lack of fit is greater than α-value.

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Table 3. Analysis of Variance for Logistics Cost

Source	DF	Seq SS	Adj SS	F	P
Regression	9	8213433	8213433	59.89	0.000
Linear	3	7441983	7441983	162,79	0.000
Square	3	649993	649993	14.22	0.001
Interaction	3	121457	121457	2.66	0.120
Residual Error	8	121907	121907		
Lack of Fit	5	113323	113323	7.92	0.059
Pure Error	3	8583	8583		
Total	17	8335340			

F = Degree of Freedom, Seq SS = Square Sum, Adj SS = Adjusted Squared Sum,

Adj MS = Adjusted Mean Squared, F =F distribution and P = p-value

3. Residuals analysis is performed to determine how good the fitted model is. This analysis helps to determine if the ordinary least square assumptions are met to produce unbiased coefficient estimates with minimum variance. The residual Normal Probability Plot is in Figure 4, the points on the plot form a straight line, therefore it can be confirmed residuals are normally distributed. In Figure 5 shows residuals are distributed randomly and with similar distance on both sides of zero, therefore there are no outlier points, as well as, the plot confirms the equal variance assumption on the model. Therefore, it can be concluded that data transformation is not required.

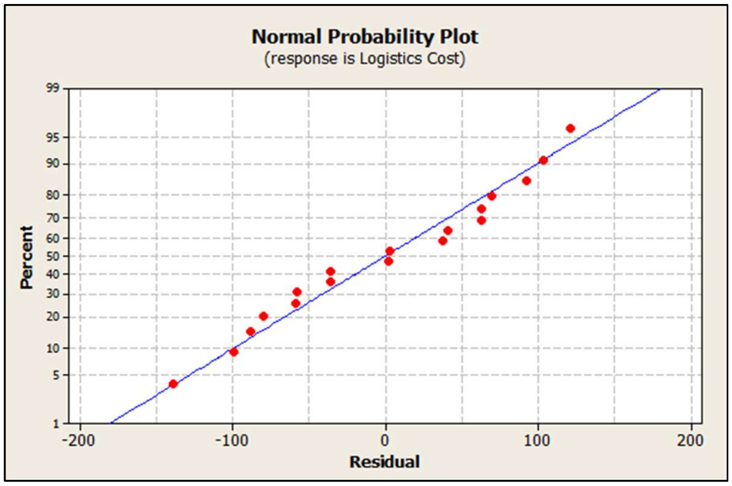

Figure 4. Residuals Normal Probability Plot for Logistic Cost

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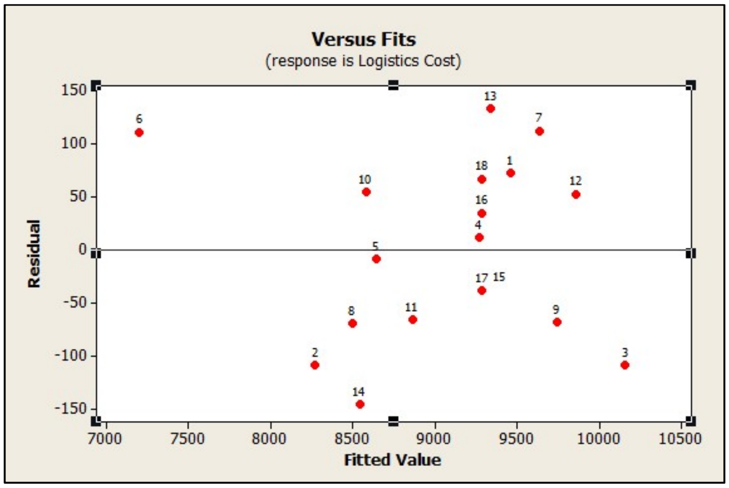

Figure 5. Residuals versus Fits Plot for Logistic Cost

4. The empirical mathematical model can be evaluated through the Response Surface and Contour Plots; which are visual tools for interpreting the result of the CCD. The Surface Plot in Figure 6 indicates the CCD model reaches a maximum logistics cost when PA is at low level as well as OTD, keeping blocked the IL at high level . In Figure 7 countour plot is reflecting that stationary point (Maximum) for the model is out of the experimental region, therefore a canonical analisis can be performed in order to determine the optimal point of the model. In this step, it can be validated that current logistics operations are according to the results of the model.

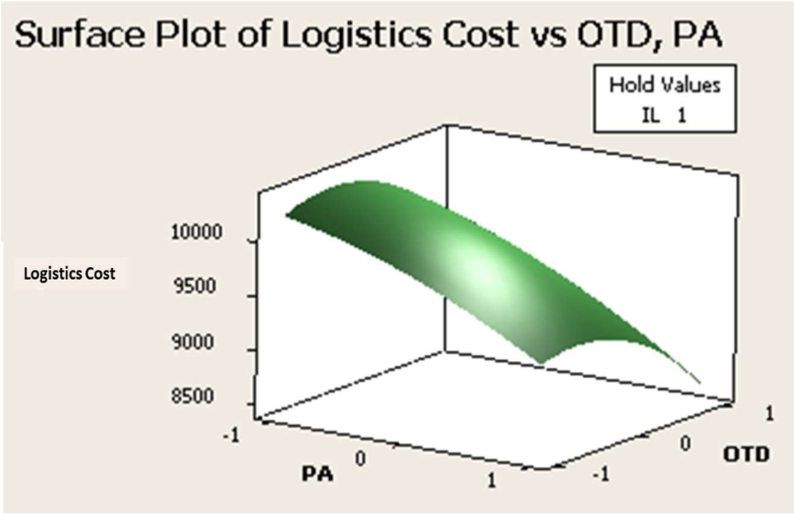

Figure 6. Surface Plot for Logistic Cost

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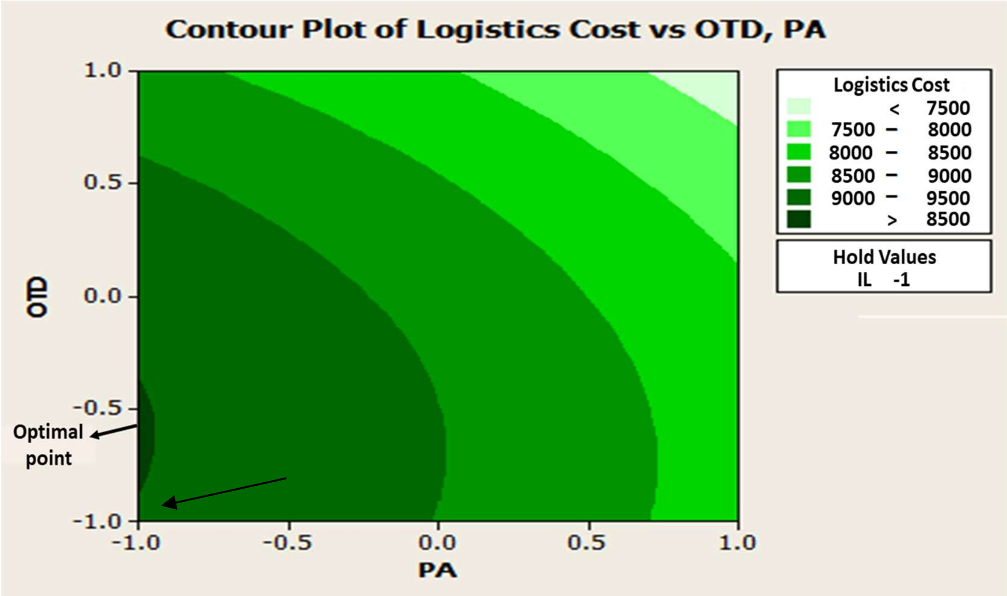

Figure 7. Surface Plot for Logistic Cost

5. Once the second order empirical mathematical model has been evaluated and confirmed, it is appropriate to define optimal points. Canonical analysis is performed applying the equation 7, in order to define the stationary points.

$$\hat{Y} = \beta_0 + x'b + \beta x_s \tag{7}$$

Where:

$$x_s = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad b = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} \quad B` = \begin{bmatrix} \beta_{11} & \frac{\beta_{12}}{2} & \frac{\beta_{13}}{2} \\ \frac{\beta_{12}}{2} & \beta_{12} & \frac{\beta_{23}}{2} \\ \frac{\beta_{12}}{2} & \frac{\beta_{23}}{2} & \beta_{33} \end{bmatrix}$$

Where x_s is any point in the region of process operability in coded units; vector b includes the coefficients of the linear part of the model and the matrix B includes the coefficients of quadratic terms and interactions pure. Then stationary points are the solution of equation 8.

$$x_s = \frac{B^{-1}b}{2} \tag{8}$$

The x_s, b and B matrices in Equation (8) were arranged by Equation (6) to get Equation (9) as follows:

$$x_s = \frac{\begin{bmatrix} -122.10 & 37.60 & -31.30 \\ 37.00 & 76.00 & 37.10 \\ -31.30 & 37.10 & -349.90 \end{bmatrix} \begin{bmatrix} -581.80 \\ 497.70 \\ -397.30 \end{bmatrix}}{2} = \begin{bmatrix} -2.70 \\ -1.60 \\ -0.50 \end{bmatrix} \tag{9}$$

The solution for equation 9 defines the optimum values for the model in coded units, such values are -2.7, -1.6 and 0.5 for PA, IL and OTD respectively. This result shows clearly that stationary point is out of the experimental region. Applying the equation 10, where Z_H Y Z_L are the high and low levels values for independent variables in original units, as well as X_i is the value in coded units defined in equation 5, the optimum values can be decoded in order to get original units, getting the

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value for PA equal to 0%, which means logistics operations needs to be managed by the logistics service supplier located at Mexico City, IL is going to keep at 0.67 and OTD at 84%.

$$Z_i = \frac{x_i(Z_H - Z_L) + (Z_H + Z_L)}{2} \tag{10}$$

Based on the information obtained in this step, it can be concluded that parameters determined with the mathematical model reflect the traditional operation in which the logistics process is performed by a supplier closer to the customers, in this case in Mexico City, at the highest operational cost. Since the goal of this research project is to find alternatives that optimize the logistics cost, we will proceed to evaluate the empirical mathematical model to determine if there is a better regression equation to estimate the parameters of optimizing the logistics costs.

6. A subsets regression technique was applied to evaluate the empirical mathematical model; this technique attempts to identify groups of predictors for further analysis. Ideally, the smallest subset that fulfills certain statistical criteria such as highest coefficient of determination adjusted ($R^2_{adj.}$), lowest Mallow's Cp and Mean Square Error (S) should be selected. Because, this subset of predictors may estimate the regression coefficients and predict future responses with smaller variance than the full model using all predictors.

This process was performed with the support of Minitab software, Figure 8 shows that a seven predictors subset is the one that fulfill the statistical criteria mentioned previously; however, there is a smaller subset with four predictors with similar statistical criteria, therefore a further analysis was done with both subgroups. Finding that four predictors subgroup is a better estimator since Predicted Residual Square Sum value is the smaller (671,820).

Best Subsets Regression:
Logistics Cost versus PA, IL, OTD, PA^2, IL^2, OTD^2, PA*IL, PA*OTD and IL*OTD

Vars	R-Sq	R-Sq(adj)	Mallows Cp	S	PA_1	IL_1	OTD_1	PA*PA	IL*IL	OTD*OTD	PA*IL	PA*OTD	IL*OTD
1	40.6	36.9	310.8	556.18	X								
1	29.7	25.3	370.4	605.07		X							
2	70.3	66.4	150.2	405.94	X	X							
2	59.6	54.2	209.2	474.05	X		X						
3	89.3	87.0	48.6	252.61	X	X	X						
3	77.6	72.8	112.4	365.04	X	X				X			
4	**96.6**	**95.5**	**10.8**	**148.61**	**X**	**X**	**X**			**X**			
4	93.2	91.0	29.4	209.50	X	X	X	X					
5	97.1	95.9	9.8	141.82	X	X	X			X	X		
5	97.1	95.9	9.9	142.26	X	X	X			X			X
6	97.6	96.3	8.9	133.86	X	X	X			X	X		X
6	97.5	96.1	9.8	138.14	X	X	X			X	X	X	
7	**98.0**	**96.6**	**8.9**	**128.70**	**X**	**X**	**X**			**X**	**X**	**X**	**X**
7	98.0	96.6	9.1	130.01	X	X	X	X		X	X		X
8	98.3	96.9	9.0	123.64	X	X	X	X		X	X	X	X
8	98.2	96.5	10.1	130.54	X	X	X	X	X	X	X		X
9	98.5	96.9	10.0	123.44	X	X	X	X	X	X	X	X	X

Figure 8. Subsets Regression

Therefore, the coefficient of determination to predict values will be the highest (91.94%) of the all subgroup. As a conclusion equation 11 is the best regression equation to predicted values.

$$Y = 9272.20 - 501.80\,X_1 + 497.70\,X_2 - 307.30\,X_3 - 369.30\,X_3^2 \tag{11}$$

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Once the validation of the model is completed, the model can be optimized. This process is going to define the parameters of the independent variables (PA, IL and OTD) which provide an optimal operation condition to achieve a particular objective for the logistics process cost. As Assumption for the model is to improve the logistics cost by 15% ± 2%. Therefore, the cost must be between \$8,525 and \$8,875 and a target of \$8,700 (thousands of USD). Based on this information we utilized the Minitab response optimizer module to define the optimal operation condition.

The optimum parameters in coded units for independent variables are showed in Figure 9 highlighted in red. Indicating that PA needs to be set up at 0.6212, which represents increasing the business with the logistics supplier located in Tijuana from 30% to 60%, the IL level parameter is -0.4798 which represent in decoded units 1.2 weeks and OTD is –- 0.0757, which is 87% in decode units.

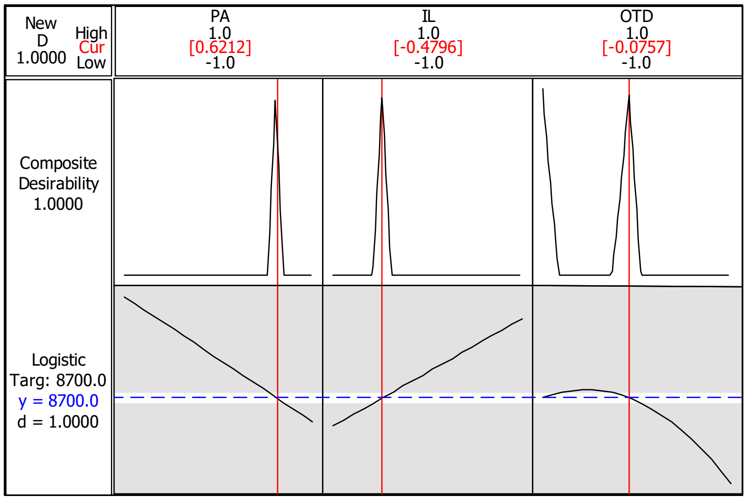

Figure 9. Logistics Cost Optimization Chart

3.5.1 Results

The purpose in this research project was achieved, since a strategy for TLC improvement was defined with the application of stochastics tools. As a result of this research, different alternatives were evaluated to define a mathematical model for optimization purpose; therefore, this project included:

Design a simulation model to represent in a virtual way, the real life of a complex process, as described in section 3.3 and 3.4. As well as, it's defined in section 3.5, the application of a statistical technique was performed to evaluate 18 different alternatives indicating how process can be developed, the results for this activity defined the logistics cost for each alternative Lastly, it was performed a statistical analysis to define an empirical mathematical model represented for regression Equation 10, that helps us to make estimations for a particular objective of the logistics process cost.

The application of the empirical model is described on the Table 4; where, the parameters for PA, IL and OTD were defined in order to achieve a cost improvement of 5%, 10% and 15%. As an outcome, the model describes that as much as the product allocation is increased for the DC located in Tijuana, the logistic cost is improved proportionally. Also, distribution activity can be managed with fewer inventories without affecting customer delivery performance, since this indicator is increased based on the simulation model evaluated.

Table 4. Logistic Cost Optimization Parameters Design

	Factor Parameters Coded Units			Factor Parameters Uncoded Units			
TLC	PA	IL	OTD	PA (TDC)	IL (Weeks)	OTD (%)	Logistic Cost Improvement
$10,149.40	-1	1	-1	30%	2	80	Current operation
$9,550.00	-0.1994	0.2687	-0.0757	46%	1.65	87%	5%
$9,150.00	0.1749	-0.0972	-0.0757	53.5%	1.45	87%	10%
$8,700.00	0.6212	-0.4798	-0.0757	62.5%	1.26	87%	15%

4. Conclusions

Based on the hypothesis statement posed in section 1, it can be concluded that stochastics tools can be used to define strategies to improve logistic cost without affecting customer service. For this purpose, this research was validated with a case study in a logistics process where the variables Product Allocation PA, Inventory Level IL and On Time Delivery OTD were evaluated. The results states that strategy needs to consider increase PA and reduce IL to improve cost, at this same time this changes are going to help to improve the OTD.

As it was stated in the introduction, two of the main contributor to the logistics cost are the transportation and inventory management; both elements were considered, showing in the results that PA needs to be increased to the DC located in Tijuana, which automatically reduces the transportation activity since the product will travel less distance to be delivered to the customer; in the other hand, shipping directly from Tijuana DC allows to has a leaner logistics process having as a result the FG inventory reduction. Both activities help to increase the on time delivery, which is one of the main key performance indicator related to the customer service.

Last but not least, the development of this research can corroborate the importance of stochastic tools application for the optimization purpose. The optimization steps have shown that the applied model helps to represent in a virtual way a complex process that hardly can execute the experiments activity in real time. Therefore, this is a well-founded tool for middle and/or top management decision making; as consequence, better business strategies decisions related to the logistics process are taken; as well as, this research could be a good practice to disclose in academia environment.

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