**Simposio Internacional de Industria y Energía**

**Title**

**Empirical analysis of learning effects in make to order logistic system**

***Title***

***Análisis empírico de los efectos del aprendizaje en el sistema logístico fabricación por orden***

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**Abstract:** This paper is a continuation of the study of learning in the supply chain, specifically in its lead-time taking into account the logistics management approaches make to order. To this end, empirical data was collected from one company, which respond to these approaches. In this company, the effect of learning was analyzed and it was modelled to improve the accuracy of forecasts and production planning. The selected sample was adjusted to the learning curves recognized in the literature. It was estimated and it was investigated which curve approximates the actual behavior of the points. For this purpose, the determination coefficient and the errors of the equation generated by the deviation of the mean square root were analyzed. The analysis confirm that learning effects occur in the lead-time. The smallest error is found in the representations of the learning curves are made by log-linear models. The best log-linear model to represent the curve is the De Jong model with a learning rate of 73,95%. As a result, it can be assumed that the length of the lead-time decreases as the number of orders processed increases. This increase encourages the creation of work styles and the consultation of stable suppliers and customers.

***Abstract:*** *Esta investigación es una continuación del estudio del aprendizaje en la cadena de suministro, específicamente en su plazo de entrega teniendo en cuenta el enfoque de gestión logística fabricación por órdenes también conocido como fabricación por pedido. Con este fin, se recopilan datos empíricos de una empresa, que responde a este enfoque. En esta empresa se analizó el efecto del aprendizaje y se modeló para mejorar la precisión de los pronósticos y la planificación de la producción. La muestra seleccionada se ajustó a las curvas de aprendizaje reconocidas en la literatura. Se estimó y se investigó qué curva se aproxima al comportamiento real de los puntos. Para ello se analizaron los valores del coeficiente de determinación y los errores de la ecuación generados por la desviación de la raíz cuadrada media. El análisis confirma que los efectos del aprendizaje se producen en el plazo de entrega. El error más pequeño se encuentra en las representaciones de las curvas de aprendizaje que se realizan mediante modelos log-lineales. El mejor modelo log-lineales para representar la curva es el modelo De Jong con una tasa de aprendizaje de 73,95%. Como resultado, se puede suponer que la duración del tiempo de entrega disminuye a medida que aumenta el número de pedidos procesados. Este incremento fomenta la creación de estilos de trabajo y la consulta de proveedores y clientes estables.*

**Keyswords:** Supply chain; Lead-time; Learning curves

***Palabras Claves:*** *Cadena de suministro; Tiempo de entrega; Curva de aprendizaje*

**1. Introduction**

When an activity is performed for the second time, it is improved over the first time. This is due to accumulation of familiarity and confidence in performing the task repetitively (Ranasinghe, Senanayake, & Perera, 2016). It is learn and the subject has the ability to do the job faster with better quality and lower cost of the product (Rodriguez Romero, Cespon Castro, Coello Machado, & Glistau, 2019). This learning ability allowed the development of a prediction technique known as the "learning curve", first observed by Wright (1936).

Since then, this technique has been applied in different production processes to consider the impact on productivity and quality of work and its incorporation in production planning. This paper is to conduct an empirical study on the impact of learning on the forms of logistics management. One company are taken as the object of study, belonging to the construction industry. The process studied are the production of aluminum carpentry (belonging to the MTO approach). This paper is structured in five sections. Below is the background of the research and analysis of the literature. Specifically, the use of learning curves. Section two proposes a work methodology. The results and conclusions are shown in sections three and four, respectively. Finally, the bibliography consulted.

* 1. Research background

This paper starts from supposing a relationship between the supply chain and more specifically the duration of the lead-time with the generation of knowledge and learning measured through the learning curves. In Khan, Jaber, and Ahmad (2014) it is argue an important issue that is not abundant in the literature of the supply chain is related to the influence of the human factor and its knowledge.

Three logistic management approaches are recognized in the SCOR model: make to stock, make to order, and engineering to order. Each one of them presents distinctive characteristics according to the dynamics of the production and the challenges for its management (Council, 2014). MTO responds exclusively to signed orders and allows greater product flexibility, although with a longer response time (Chen, Mestry, Damodaran, & Wang, 2009).

Learning effect is known for decades in Wright (1936) and Yelle (1979) and initially was dedicated for production improvement prediction (Kleiza & Tilindis, 2020). Later it was extended to the industry and was mainly used in the EPQ and EOQ models, capacity management, assembly line planning, quality management, information technology, queuing systems and the relationship between customers and suppliers (Rodriguez-Romero, 2020).

This phenomenon is caused by an increase in the skill levels of the worker and a decreasing number of errors (Grosse, Glock, & Müller, 2015). Doing an activity after the first time involves learning, product of experience. The learning curve is a characteristic inherent in all organized activity (Hirschmann, 1964). The effects of the learning process in an industrial context have been verified in a series of studies; however, the focus was on the production process in most cases, and not on logistics processes.

In Grosse and Glock (2013) it is proposed to link the effects of learning with activities that include ordering forms in a warehouse. In Grosse et al. (2015) suggests that the future could focus on knowledge transfer within groups and organizations to learn more about how groups and organizations learn, and how this can be modelled mathematically.

This is confirmed in Glock, Grosse, Jaber, and Smunt (2018) the review of the literature where he states that of the 457 articles consulted only thirteen are supply chain and one is dedicated to logistics. Therefore, learning curve has little studies on processes of the supply chain and specifically in the lead-time. In Glock, Grosse, Jaber, and Smunt (2019) it is suggested that different learning curve models be carried out in light of new technologies and emerging industries, giving the example in the fourth industrial revolution. In Glistau and Coello Machado (2018) it is suggested that with the fourth industrial revolution, the separation between materials and information will disappear, because information will be an intrinsic part of the products.

The models chosen to determine learning in the experimental analysis to be carried out are illustrated below Grosse et al. (2015) and Glock et al. (2018).

**Log-linear models**

Wright’s model (1). Wright’s learning curve has the following form:

|  |  |
| --- | --- |
| $$y= K\*x^{-b}$$ | 1 |
|  $b= \frac{log r}{log2}$ | 2 |

Where: x is consecutive number of the product, y is average time for the production of product x, k working time for finishing the production of the first product, log 2 is criterion established when the number of orders is doubled to establish the learning rate and r is learning curve rate. Note that Wright's learning curve (and other log-linear models) can be used to model both time and cost reductions as a result of learning.

Plateau model (2).The model of the plateau is similar to the one proposed by Wright, with the difference that a constant C is added to the model to take into account that there is a minimum time to perform a task independent of the learning effect (Baloff, 1971). The learning curve of the plateau is formulated as:

|  |  |
| --- | --- |
| $$y= C+ K\*x^{-b}$$ | 3 |

Stanford B model (3). The Stanford B learning curve extends Wright's learning curve by considering the previous experience of Carlson (1973). The Stanford B model is formulated as follows:

|  |  |
| --- | --- |
| $$y=K\*(x+B)^{-b}$$ | 4 |

De Jong’s model (4). In De Jong (1957) assumed that there is an incompressible component in each process where no learning and thus no productivity improvement occurs, and thus extended Wright (1936) learning curve by adding a factor of incompressibility to the model. De Jong's learning curve has the following form:

|  |  |
| --- | --- |
| $$y=K\*(M+(1-M)x^{-b}$$ | 5 |

S-curve model (5). The S-curve model combines the features of Stanford B model and De Jong model. The name is derived from the fact that learning curve is S-shaped when plotted on a logarithmic scale. It can be expressed as follows Nembhard and Uzumeri (2000):

|  |  |
| --- | --- |
| $$y=K\*(M+(1-M)(x+B)^{-b})$$ | 6 |

**Exponential models**

2-Parameter exponential model (6). The 2-parameter exponential model of Mazur and Hastie (1978) is formulated as:

|  |  |
| --- | --- |
| $$y=K\*(1-e^{-(^{x}/\_{r})})$$ | 7 |

3-Parameter exponential model (7). In the 3-parameter exponential model, a parameter p is added to the 2-parameter exponential model (p>0), which takes into account the worker's previous experience. It is measured in the same units as t in the 2-parameter exponential model, such as time or amount of training (Anzanello & Fogliatto, 2011):

|  |  |
| --- | --- |
| $$y=K\*(1-e^{-^{\left(x+p\right)}/\_{r}})$$ | 8 |

**Hyperbolic models**

2-Parameter hyperbolic model (8). The 2- parameter hyperbolic model is described as:

|  |  |
| --- | --- |
| $$y=K\*(\frac{x}{x+r})$$ | 9 |

where y is the number of items produced in t time units (or the amount of training), R the learning rate and k the maximum production level.

3-Parameter hyperbolic model (9). A parameter *p* is added to the 2-parameter hyperbolic model to account for prior experience of the workforce (*p* >0). The model is formulated as:

|  |  |
| --- | --- |
| $$y=K\*(\frac{x+p}{x+p+r})$$ | 10 |

**2. Methodology**

In this section, the working methodology followed is proposed. Firstly, the company under study are characterized. Then, the analogies are defined to determine the learning of lead-time from the models applied in the productive processes recognized in the literature. Next, the best equation is chosen and finally the duration of the lead-time is determined taking into account the learning obtained.

2.1 Description of the supply chain

First, supply chain is described. Then the production approach is determined with it is considered MTO by the SCOR model. The variable of interest within the lead-time is the order fulfillment time. However, the following characteristics were taken into account:

- There are no significant variations between the orders analyzed within each company, due to the factors that influence; level of skill of the worker, training given and machinery available.

- The total order fulfillment time is calculated by the semi-sum of the time spent on each of the activities within the supply chain.

# 2.2 Analogies for determining lead-time learning

To carry out the study, the learning curve equations obtained from the literature for the productive processes (log-linear, exponential and hyperbolic models) are taken and the corresponding analogies are made to extrapolate them to the lead-time. The analogies made are shown in Table 1. To verify the quality of the adjustment obtained, the determination coefficient (R2) and the root mean square deviation (RMSE) are used, with $\overbar{y} $representing the mean value of the observed data points:

|  |  |
| --- | --- |
| $$R^{2}= \sum\_{i=1}^{n}\frac{\left(\hat{yi}-\overbar{y}\right)^{2}}{\left(yi-\overbar{y}\right)^{2}}$$ | 11 |
| $$RMSE= \frac{\sum\_{i=1}^{n}\left|yi-\hat{y}\right|}{n}$$ | 12 |

|  |  |
| --- | --- |
|  | **Lead-time**  |
| X | Consecutive order number |
| Y | Average time (in hours) for the duration of the lead-time of the order X |
| K | Average time of the lead-timeto finish the first order. |
| log 2 | Criterion established when the number of orders is doubled, to establish the learning rate |
| B | Equation coefficient |
| R | Learning curve rate |
| M  | degree of automatization of the production in the lead-time |
| B  | Level of experience of the work team in carrying out the production process |
| C | Minimum time exist for order compliance that is independent of the learning effect. |

Table 1: Modifications made to the equation to determine learning in the lead-time.

**3. Results and Discussion**

This paper presents the results of an experimental study of learning effects in the lead-time. Firstly, the particularities of each Cuban company are established, taking into account the characteristics of the process, the product selected, the process flow, the clients and the suppliers (Table 2). This allows us to have a general vision of the company and the selected process. For the sample, all the data the institution had on the process under study from the time it began producing the product until the present day was taken. This data is analyzed by means of an exploratory analysis and the errors committed with this sample size are determined. These errors are approved by the companies under study and considered acceptable. Then, all this information is processed, obtaining the results shown in tables 3. It should be noted that the log-linear models are adjusted to the information obtained, but this is not the case with the exponential and hyperbolic models, which present erroneous data when adjusting to the information of the sample studied. In addition, the calculation of the learning models is established by varying the counts in the Stanford B and Jong’s models. The use of these learning models for the estimation of learning in lead-time is thus ruled out.

|  |  |
| --- | --- |
| **Characteristics** | **Company** |
| **Production process** | Machining and manual |
| **Product** | Aluminum carpentry:Window, Single Showcase, Door, Straight Handrail, Constructive Subframe, Inclined Railing of different models. |
| **Raw Materials** | Through the TECNOTEX importer, Aluminum, wood, screws, nuts, glass, glues |
| **Suppliers** | Lehnner SA, ColombiaALCUBAEMPRESTUR |
| **Customers** | Cayo Santa María and Varadero International Economic AssociationAlmestBasic Units belonging to ECM No3Revolutionary Armed Forces (FAR) |

Table 2: Characteristics of the companies object of study

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Confidence interval | R2 | RMSE | r  |
| 1 | b =0,1293 (0,0953; 0,1633)K =11,69 (10,73; 12,65) | 0,7716 | 0,7093 | 0,9142 |
| 2 | K=11,69b=0,130 (0,0830; 0,1773)c=0,017(-0,9645; 0,9992) | 0,7711 | 0,7100 | 0,9137 |
| 3 | K=11,69B=1b=0,126 (0,1126; 0,1395) | 0,7336 | 0,7517 | 0,9163 |
| 4 | K=11,69b =0,435 (0,005; 0,865)M=0,565 (0,337; 0,793) | 0,8094 | 0,6479 | 0,7395 |
| 5  | K=11,69b =0,231 (-1,16; 1,624)B =4,466 (-11,38; 20,32)M=0,399 (-1,976; 2,774) | 0,7088 | 0,8167 | 0,8515 |
| K=11,69B=1M=0,5652b = 0,419 (0,358; 0,4803) | 0,7909 | 0,6659 | 0,6758 |

Table 3: Results obtained from the analysis of the Company

Company fit the Jong’s model with errors of 0, 6479 days / unit and a learning level of 73, 95%. The graphic representation of the data and the analysis of the errors are shown in Figure 1 for each of the company studied according to the selected model. The results of the analysis confirm that the log-linear models are the best fitted for the lead-time. The equation to determine the lead-time duration taking into account the learning in the company under study is $y=11,690\*(0,565+(1-0,565M)x^{-0,4352}$.



Figure 1: Graphical representation and the analysis of the errors

**4. Conclusions**

This paper allows to determine that the lead-time response time for an order with similar characteristics decreases and the organization learns. This has a direct impact on customer satisfaction. The analysis is limited by the sensitivity of learning to changes that may occur in the organization, both technological and organizational. Specifically, in the company studied, the empirical study showed that log-linear models present the best results. The exponential and hyperbolic models did not proceed in their calculation with the samples taken in the companies studied.

The percentages of learning in the company studied are 73, 95%. In future research it is proposed to continue the analysis of these processes and to determine the repercussion of learning on other variables within the lead-time and on others logistics system.

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