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Complexity and Operations Performance: A Case Study

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Abstract

The purpose of this research is to analyze the relationship between production complexity and operational performance in a mass customization (MC) production system, typical in automobile industry of commercial vehicles, such as trucks and buses. A mixed quantitative-qualitative approach was used in this research. That is, two main research methods were combined: Case Study and Quantitative Modelling. Information Entropy was applied as an indicator of operations complexity. Production performance was measured with production downtimes and non-conformities. Logistics performance was measured with parts obsolescence, stock-outs and days of supply. Although the results show small positive correlations between pairs of operations complexity and operations performance and pairs of operations complexity and logistic performance indicators, the tests of significance performed on these corrections show that they are statistically insignificance. Although they are not statistically or theoretically significant, we believe that, practically, the positive values of correlations between pairs of operations complexity and operations performance indicators and pairs of operations complexity and logistic performance indicators show that complexity has some direct relationship with production and logistic efficiencies.

Keywords: *automobile industry, complexity, mass customization, operational performance.*

1. Introduction

One of the popular competitive strategies used by automakers is to increase their product portfolio. They must have seen that this strategy works well despite the fact that more variety of products causes escalating costs and complexity in the manufacturing systems (Alford, Sackett, & Nelder, 2000). Producing high variety products within greater production volumes is a strategy known as mass customization (MC). Managing MC environments involves managing many production or operational complexities and balancing of workforce (Zhu, Hu, Koren, & Marin, 2008), planning and managing logistics (Wilding, 1998), and developing

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and operationalizing product structure architecture (Vickery, Koufteros, Droge, & Calantone, 2016), to name a few.
Sometimes, there are cause-effect relations among product variety, production flexibility and operational complexity (Hu, et al., 2011). That is, product variety may require production flexibility, which results in operational complexity (Fisher & Ittner, 1999). With higher product variety, MC offers competitive advantages, if effectively managed. However, if not well-managed, MC may lead to many problems such as increase in production cost, decrease in product quality and delayed delivery (Gotzfried, 2012).

The purpose of this work is to analyze the relationship between production complexity and operational performance in an MC production environment, typical in automobile industry of commercial vehicles, such as trucks and buses. From the review of Operations Management (OM) literature, we identified some research opportunities. The relate to the definition of multiple strategies for assembly lines (Da Silva, Tubino, & Seibel, 2015); and designing assembly systems more efficient to shorten time-to-market (Rekiek, De Lit, & Delchambre, 2002).

Product variety may have impact on all the functions of a company, including operations, finance, marketing, design, and human resources functions and more. Nevertheless, this study will focus on operational performance in the areas of production and logistics. Specially, our focus is on the production of truck cabins by a Brazilian plant of a transnational company. This plant operates in an MC environment. Information Entropy (Frizelle & Suhov, 2008) is the main complexity measure in this study. In workstations with manual operations, combinations of assembly do influence operational performance, causing assembly errors and delivery delays.

Section 2 of the research presents literature review on mass customization and conceptualizes information entropy. Section 3 presents the research methodology. Section 4 presents the research case. Section 5 presents the information entropy calculation and analyses the relationship between operation complexity and operation performance. Summaries, conclusions and recommendations from the research are presented in Section 6.

2. Literature Review

2.1. Mass Customization

Product variety does stimulate sales and does satisfy some specific requirements from customers, and this creates the need for MC (Xia & Rajagopalan, 2009). By offering customized products, companies may reduce competitive pressures in that this make direct comparisons of their products with the products of their competitors impossible or difficult to make and thereby avoiding price wars (Lancaster, 1990). MC environment allows higher returns for suppliers because customers are usually willing to pay more for products that perfectly meet their requirements (Ulrich, 2011). The heterogeneity of products in MC also enhances operational performance. If demand for a product drops, the plant can continue operating by replacing the production of the product with the production of another product. In this way, MC production plants are much more capable of absorbing the negative effect of market fluctuations than plants with smaller mix of products (Fisher & Ittner, 1999).

Table 1. Top-seller models of compact automobile in Europe 2002

Model	Sales	Total number of variations
Peugeot 206	596,531	1,739
VW Golf	595,465	1,999,813,504
Ford Focus	523,356	366,901,933
Renault Clio	502,497	81,588
Peugeot 307	441,468	41,590
GM Astra	440,567	27,088,176
GM Corsa	420,296	36,690,436
FIAT Punto	416,843	39,364
VW Polo	357,539	52,612,300,800
BMW 3 Series	350,723	64,081,043,660,000,000
Ford Fiesta	294,360	1,190,784
Renault Megane	261,383	3,451,968
Mercedes-Benz C-Class	254,836	1,131,454,740,000,000,000,000
Toyota Yaris	194,256	34,320
FIAT Stilo	173,453	10,854,698,500
Mercedes-Benz E-Class	157,584	3,347,807,348,000,000,000,000,000
Toyota Corolla	139,837	162,752
Nissan Micra	106,428	676
BMW Mini	105,617	50,977,207,350,000,000
Nissan Almera	87,474	3,086

Source: (Pil & Holweg, 2004)

However, product variety may lead to cases of canceled orders or postponed orders by customers who are confused by availability of many different product options (Thompson, Hamilton, & Rust, 2005).

It has been found that for the automobile industry in Europe, product variety (measured in number of variations, which includes bodies, power trains, paint and factory-fitted options) and sales volume are not correlated. This is shown by the data in Table 1 below and by the correlation analyses done with the data.

For the data in Table 1, the correlation between sales and product variety is $r \approx -0.23$. This shows that there is a little negative linear correlation. A test of significance with the correlation index results in a *p-value* of 0.16. Thus, there is only 84% statistical significance in the affirmation of a negative correlation between sales and product variety.

Despite the disagreements on the costs and benefits of MC, truck assemblers continue to pay attention to this production strategy (Fujita, 2002). They aim to produce in the same assembly line a greater variety of customized products with the operational performance of mass production (Smith, Smith, Jiao, & Chu, 2013).

Complexity in the automotive industry relates to complex systems that have unpredictable results, full of uncertainty, and composed of many parts with difficult to characterize relations (Efthymiou, Pagoropoulos, Papakostas, Mourtzis, & Chryssolouris, 2012). Operational complexity does have effect on the high-content information required for correct manual assembly. A number of decisions are delegated to operators. An example of this is the relative direction of assembling (backward, forward, etc.) or the screw tightening intensity (El Maraghy, Kuzgunkayaa, & Urbanic, 2005).

2.2. Information Entropy

Information Entropy was firstly proposed as a measure ofthe uncertainty of outcomes in a random experiment on communication systems (Shannon, 1948). Operational complexity is the average uncertainty in a random process i of handling product variety (Hu, Zhu, Wang, & Koren, 2008), which can be described by Entropy H_i given by:

$$H_i = -C \, \Sigma \, [p_{ij} \log(p_{ij})] \tag{1}$$

Where p_{ij} is the occurrence probability of a state j in the random process i and C is a constant depending on the base of the logarithm function chosen. For instance, if $\log_2$ was chosen, then $C = 1$ and the unit of complexity is *bit*.

An assembly line is composed of more than one workstations. In some workstations, more than one operation may be necessary. The overall complexity C_k (Equation 2), for the workstation k is the sum of entropies for every process i.

$$C_k = \Sigma \, H_i \tag{2}$$

Line downtime (Trovinger & Bohn, 2005) and non-conformities in assemblies (El Maraghy & Al Geddawy, 2012) are indicators for production efficiency (or lack it) P_k of workstation k. Obsolescence, stock-out and days of supply (Blackstone, 2013) are indicators for logistics efficiency (or lack it) L_k. Stock-out and days of supply are trade-offs.

3. Research Methodology

This research intents to achieve its main objective of analyzing the relationship between production complexity and operational performance in an MC production system by analyzing the correlations between overall complexity C and production performance P, and between C and logistics performance L. The research hypothesis is that there is negative correlation between each of these pairs of variables.

Our major concern is with the relevance of the data and the results obtained when they were used as inputs into our analysis. To address this concern, a mixed quantitative-qualitative approach (Creswell, 2014) will be used. After all, qualitative research is an approach to understand the meaning individuals or groups ascribe to a human or social problem. Quantitative research, on the other hand, is an approach to test objectives theory, by exanimating relationship among variables. The combination of qualitative and quantitative approaches provides a more complete understanding of the problem than either approach alone. Case Study (Yin, 2014) is a research method for qualitative approach. An illustrative case study is presented in this paper (Jackson, 1991). Quantitative modeling (Bertrand & Fransoo, 2002), on the other hand, is a research method for quantitative approach. An empirical-descriptive modeling is conducted with correlation between variables that represent operational complexity and operational performance.

4. Research Case

The research case is from a plant of a multinational corporation based in Germany. In particular, we studied an assembly line of commercial automobiles. This assembly line is operated in a major plant located in Brazilian State of Rio de Janeiro. The plant competes in an MC environment. It assembles buses and trucks with 2.5×10^{13} possible variation of products. To strengthen and enhance this operation, eight partner companies operate inside the plant. These companies specialize in chassis, cockpit, power train, suspension, and wheels assembling, blanking and painting.

From various processes within the assembly line, the dashboard assembly was chosen for the study. Its choice is due its product variety and to its use of different assembling methods. That is, operational activities for dashboard assembly have different degrees of difficulty for the workers. This process is performed with 11 operations flowing through four workstations. Panel (Operation A) and cables (Operation B) are assembled in Workstation 1; supports (Operation C), command unit (Operation D), modules (Operation E), belt (Operation F) and cover (Operation G), are assembled in Workstation 2; keys (Operation H), relays (Operation I) and tachograph (Operation J) are assembled in Workstation 3; finally, the cluster (Operation K) is assembled in Workstation 4.

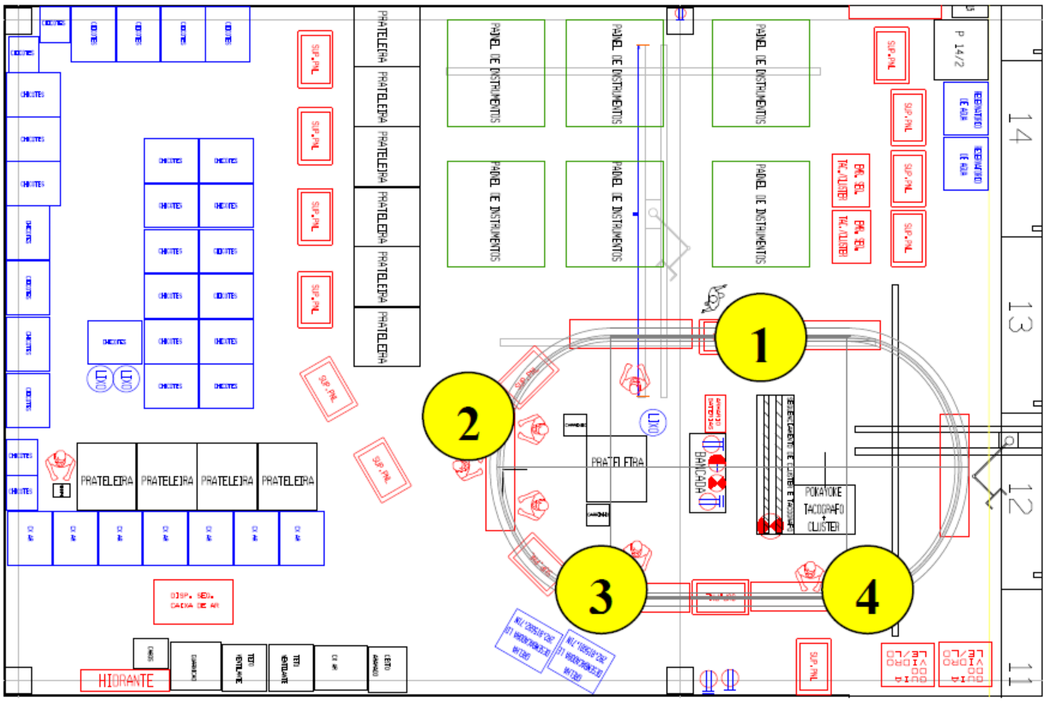

Figure 1. Workstations 1 to 4 for dashboard assembly

5. Analyses and Results

5.1. Entropy Calculation from the Case

The different options for every operation result in different complexity. As an example, if we assume the same probability for each option, the entropy for Operation A is H_A = 4.32 bits. This is obtained by substituting C =1, and $p_{A1} = p_{A2} = \ldots = p_{A20}$ = 1/20 and using logarithm to base 2 in Equation 1, just as indicated in Section 2.2. Entropy for each of the remaining operations in each of the workstations is similarly calculated by feeding the values of their associated parameter values into Equation 1.

Using Equation 2, the entropies for operations in each workstation are added together to obtain the workstation's entropy. As can be seen in Table 2, workstation 3 has the most complex set of operations.

Table 2. Complexity of Workstations 1 to 4

Workstation	Operation	Total options	Entropy for operation	Entropy for workstation
1	A	20	4.32	12.07
	B	216	7.75	
2	C	7	2.81	12.56
	D	8	3.00	
	E	9	3.17	
	F	6	2.58	
	G	2	1.00	
3	H	57	5.83	15.94
	I	41	5.36	
	J	27	4.75	
4	K	131	7.03	7.03

5.2. Relationship between Operation Complexity and Production Efficiency

Let us consider data from production operations for a typical month. That is, a month without collective vacations or stoppage for maintenance. As Table 3 shows, only Workstation 1 had downtime during the month. The table (Table 3) shows that Workstations 1 and 2 have the greatest numbers of non-conformities. These data represent the worst production performances for Workstations 1 and 2. One reason for the large numbers of their non-conformities is due to the fact that their operations require handling of plastic parts, which are sensitive to human touch.

Since there is only one non-zero value for Downtime, it appears that there are no correlation between operation complexity, measured by information entropy and production performance, measured by production downtime. Pearson's correlation index between entropy (Table 2) and non-conformities (Table 3) is $r \approx 0.2758$ with a *p-value* of 0.36. This shows that correlation between complexity and production efficiency, indicated by non-conformities, is very statistically insignificant.

Table 3. Downtime and non-conformities on Workstations 1 to 4

Workstation	Downtime [min]	Non-conformities
1	96	1,612
2	0	3,412
3	0	887
4	0	437

5.3. Relationship between Operation Complexity and Logistics Efficiency

Let us consider the logistics data for the same month (see Table 4 below) as the data analyzed in the case in Section 5.2 above. In our study, we discover that parts assembled in Workstation 3 are more expensive than others. Higher prices force the inventory levels down. This is the reason why Workstation 3 has the highest stock-out. In our study, we find out that Just-In-Time (JIT) system is used in the whole cell (Workstations 1 to 4). This is the reason for the lowest level of days of supply in Workstations 1 and 4. The days of supply for Workstations 2 and 3 shows that there is a great need to improve the logistic efficiencies in the two workstations.

Table 4. Obsolescence, stock-out and days of supply for Workstations 1 to 4

Workstation	Obsolescence	Stock-Out	Days of supply
1	122	0	1
2	2	1	26.6
3	23	32	13.9
4	0	11	0

Source: data collected from company's enterprise resources planning software

Pearson's correlation index *r* between entropy (see Table 2) and obsolescence, entropy and stock-out, and entropy and days of supply (see Table 4) are, respectively, 0.181, 0.466 and 0.535. However, their *p-values* are 0.82, 0.533 and 0.465. Thus, the correlation between operations complexity and logistics performance, as indicated by parts obsolescence, stock-outs and days of supply, is very statistically insignificant.

6. Conclusions and Recommendations

One of the major conclusions from this study is that there are some positive correlations between pairs of operational complexity and production performance indicators and between operational complexity and logistics performance indicators. Another major conclusion is that the tests of significance performed on these corrections show that they are each statistically insignificance. Although they are not statistically or theoretically significant, we believe that, practically, the positive values of correlations between pairs of operations complexity and operations performance indicators and between operations complexity and logistic performance indicators show that operations complexity has some direct relationship with production and logistic efficiencies. The more complex the production and logistic systems, the less efficient they will be.

The study also shows that the greater the operational complexity, the greater the number of non-conformities and the lower the production efficiency. Also, the more complex the operation, the longer the assembled parts will be in stocks.

It is important to note that, these findings resulted from a case study in a commercial automobile plant operating in mass customization environment. The plant is located in Southern Brazil. Since the plant belongs to multinational group with headquarters in Europe, this case may be extrapolated to model MC situations in other countries, particularly the countries in which the multinational group has operations or plants.

We would like to make the remark that if well and effectively managed, the adoption and practice of mass customization in the plant may lead to more and large variety of customers. One other remark that we would like to make is that the modular production in the plant is enabled by co-operations of eight different partner companies operating inside the plant, with different missions, but sharing values and visions.

We suggest that further studies be conducted in any other MC environments to compare findings or results from such studies with our research findings. New empirical studies may lead to definitive conclusions on the key focus of this research, which is examining the relationship between operational complexity and efficiency.

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