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Research Article

Keywords: Complexity, Manufacturing systems, Flow shop and Hybrid, Modeling, Statistical analysis

Posted Date: July 6th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-647913/v1

Version of Record: A version of this preprint was published at The International Journal of Advanced Manufacturing Technology on October 8th, 2021. See the published version at https://doi.org/10.1007/s00170-021-08028-9.

Modeling and Statistical Analysis of Complexity in Manufacturing Systems under Flow Shop and Hybrid Environments

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Abstract. In manufacturing systems, there are environments where the elaboration of a product requires a series of sequential operations, involving the configuration of machines by stages, intermediate buffer capacities, definition of assembly lines and routing of parts. The objective of this research is to develop a modeling and statistical analysis of complexity in manufacturing systems under flow shop and hybrid environments. The methodological approach starts with the structural modeling, then the measurement of the complexity in the systems is developed, the hypotheses are proposed and finally an experimental and factorial statistical analysis is developed. The results obtained corroborate the hypotheses proposed, where statistically the structural design factors and the variation of production time per stage have a significant influence on the response variable associated to the total complexity. Similarly, there is evidence of correlation between the performance indicators and the variable studied, in which the incidence with production costs stands out.

Keywords: Complexity, Manufacturing systems, Flow shop and Hybrid, Modeling, Statistical analysis.

1 Introduction

Manufacturing is the process of adding value to a material to build a product [1]. This art involves a repetitive sequence of operations that result in the production of goods and services, which requires resources such as facilities, people, material, capital, energy and information [2], allowing the emergence of the complexity component. Since a manufacturing system the intervention of these factors generate variations in quantity and variety of processes, products and services making the systems unstable and complex. These are reflected in (i) with materials when they do not meet time, quantity and quality specifications, (ii) with labor when there are changes in work rhythm, absenteeism and accidents, (iii) with machines when they fail, lack of spare parts and tools.

According to [3] complexity in manufacturing systems can be static or dynamic. Static complexity refers to a characteristic associated to the systems, and also to the production processes, aligned with the structure of the facilities or the plant structure and considers the degree of difficulty for its management and control, and dynamic complexity refers to the analysis of the systems over time, it studies the trend of the actual states that the process assumes within the time considered. The measurement of complexity is a metric is a useful and valid measure in the support of decision making. According to [4] the measurement of complexity in manufacturing systems serves as a parameter to establish improvement plans, determining that systems with high complexity present more problems than systems with low complexity.

Given the above, the purpose of this research is the development of modeling and statistical analysis of the complexity in manufacturing system, considering Flow shop (FS) and Hybrid (H) environments, which are characterized because all activities must be performed in the same order for the manufacture of the product, in this type of processes the volume to be manufactured is high, has few references and are continuous.

The scope of the paper covers the modeling of different structures considering the layout of the facilities in a production plant [5], such as serial lines and parallel stations. Allowing the obtaining of key performance indicators by means of simulation techniques, which lead to the development of a statistical study, with an analysis of variance (Anova) and multivariate. The work is divided into three sections, first the literature review is developed, then the method is established, then the results are presented and finally the conclusions.

2 Related Work

Several research works on the problem of complexity of manufacturing systems have been identified in the literature. According to [6], complexity in a system is linked to the high number of variables and uncertainty, where [7] establish that

uncertainty is everything whose behavior is not known with precision, and define it as the deviation of the system with respect to what was planned. According to [8] it is derived from the structural properties of the system, being determined by the number and variety of elements that integrate it and the relationships involved in the installations.

Similarly, [9] states that increased flexibility in manufacturing processes and product variety lead to greater complexity in the system. A complex system is understood as one that is composed of a large number of parts that interact in a non-simple way [10]. According to [11] it is also necessary to take into account the number of parts, the types of processes, the type of operation and the stability of production scheduling.

According to [12], they state that complexity has begun to be considered as a new form of evaluation of industrial companies, being also one of the useful tools for the analysis of improvements and business restructuring. This makes its management relevant since it has a direct impact on the system performance indicators [6]. According to [13][14] there are determining factors in manufacturing complexity such as: (i) the product structure, (ii) the plant structure, (iii) the planning and scheduling functions, (iv) the flow of information during the decision-making process, (v) the dynamism, variability and uncertainty of the environment and (vi) other functions within the organization such as training, information and policies.

Given the above, it is of vital importance to measure complexity when in an administrative environment it is desired to improve the operational indicators of the system and make efficient decisions. According to [15] the measurement of complexity in manufacturing systems is a metric that serves as a parameter to establish improvement plans, and it is determined that systems with high complexity present more problems than systems with low complexity. This measurement depends on the different types of complexity being addressed, one of them is the static complexity that refers to the structures of the system and production, another is the dynamic complexity that focuses on the behavior of the system in a time horizon. According to [15], when measuring complexity, it is necessary to consider on the one hand the system structure and on the other hand the uncertainty of the system. According to [7] static complexity is related to the system structure, such as the number of products, number of processes, number of machines, among others. And the dynamic complexity is a measure of the uncertainty in the behavior of the system during a time horizon, as for example the corrective maintenance of the machine. This research work will focus on a measurement approach of static, dynamic and total complexity, based on Shannon's entropy method, in different structures of manufacturing systems.

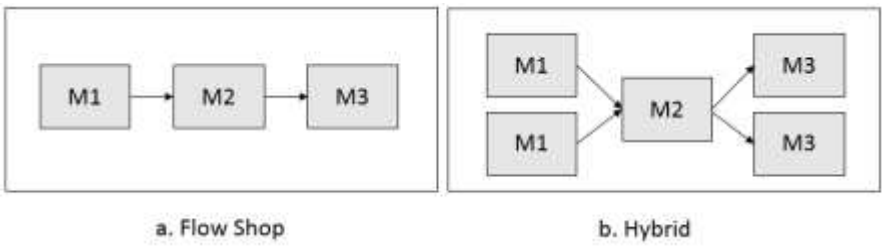
3 Method

The method to carry out the research is developed in five stages, (i) Structural modeling of the systems, (ii) Measurement of the complexity in the systems, (iii) Hypothesis, (iv) Experimental and factorial statistical analysis.

3.1 Structural modeling of systems

In manufacturing systems, operations must follow a route that involves the use of resources. According to [16] products are processed through a series of production stages and the number of machines is different from one stage to another, some stages have only one machine, while others have more than one. As organizations grow and expand to meet their demand, they tend to have increasingly complex manufacturing operations [6], varying their structure from Flow shop (FS) to Hybrid (H) environment, according to [17] the more complexity exist in the systems, factories seek to expand their production capacity, acquiring additional parallel machines in each of the stages, transforming the flow line system to a hybrid flow line. Figure 1 shows a schematic view of the FS structure in comparison with the H [16].

Fig. 1. Flow Shop and Hybrid Structure



According to [17][18] there are some characteristics of these types of structures, (i) the products follow the same linear path throughout the system, (ii) the jobs go from a first stage to the last one in order, (iii) the number of machines per stage can be different, (iv) buffers are present to store intermediate products, (v) the process flow for each job is known in advance, (vi) each part is processed on at most one machine at each stage, and (vii) the processing time for each job at each visiting stage is known in advance and is constant. Table 1 presents several application cases found in the literature, where most of them belong to the process industry.

Table 1. Literature review of application cases

Industry	Year	Author
Pharmaceuticals	2017	Bouras, A., Masmoudi, M., Saadani, N. E. H., & Bahroun, Z. [19]
	1996	Guinet, A.G.P., Solomon, M. [20].
Energetics	2021	Ho, M. H., Hnaien, F., & Dugardin, F. [21].
	2016	Yan, J., Li, L., Zhao, F., Zhang, F., & Zhao, Q. [22].
	2013	Dai, M., Tang, D., Giret, A., Salido, M. A., & Li, W. D. [23].
Automotive	2020	Marichelvam, M. K., Geetha, M., & Tosun, Ö. [24]
	1997	Agnetis, A., Pacifici, A., Rossi, F., Lucertini, M., Nicoletti, S., Nicolo, F., Oriolo, G., Pacciarelli, D., Pesaro, E., [25].
Printed circuit boards	2003	Alisantoso, D., Khoo, L. P., & Jiang, P. Y. [26].
	1994	Piramuthu, S., Raman, N., Shaw, M.J. [27].
	1993	Tsubone, H., Ohba, M., Takamuki, H., & Miyake, Y. [28].
Glass	2020	Wang, S., Wang, X., Chu, F., & Yu, J. [29].
	2017	Liu, M., Yang, X., Zhang, J., & Chu, C. [30].
	1997	Leon, V.J., Ramamoorthy, B. [31].
Petrochemicals	2016	Rahmani, D., & Ramezanian, R. [32].
	1998	Riane, F. [33]
	1973	Salvador, M.S. [34]
Electrical and Electronics	2005	Quadt, D., Kuhn, H. [35].
	1988	Wittrock, R.J. [36].

For the development of the structural modeling, in this work all possible combinations were generated considering three stages within a process and a maximum of two machines per stage. Likewise, different indicators were established to evaluate and analyze each of the instances.

3.2 Measuring complexity in systems

Entropic methods are based on analytical equations to measure complexity, facilitating entropic analysis in different types of scenarios and providing a quantitative basis for decision making. One applied method is Shannon's information entropy, which is a quantitative, objective technique that allows measuring both static and dynamic complexity. All the information used in this section is defined by [37] who based his work on a mathematical theory of information. Consequently, [38][39] take this theory as a basis and use it to measure

complexity in industrial organizations. The necessary information comes from the process, from two work focuses, (i) planning, the information collected should contain set-up times of each operation at each workstation, production times and non-production times and (ii) the scheduling of activities, the information should be captured from the same development of the process. The results obtained are analyzed mathematically, formula 1 measures the static complexity in manufacturing systems and formula 2 measures the dynamic complexity.

$$C_{static}(Cs) = -\sum_{i=1}^{M}\sum_{j=1}^{N} P_{ij}\, log_2 P_{ij} \tag{1}$$

$$C_{dynamic}(Cd) = -\sum_{i=1}^{M}\sum_{j=1}^{N} P'_{ij}\, log_2 P'_{ij} \tag{2}$$

Where:

Cs: Static complexity
Cd: Static complexity
Pij: Probability of status of a given resource
M: Amount of resources
N: Number of possible states

3.3 Hypothesis

This section identifies the factors that significantly influence the characteristics associated with the complexity response variable, (i) structural design of the system, (ii) variability in the time of each stage of the process, (iii) variation in the frequency of arrivals and (iv) variation in the number of arrivals of the entities. Therefore, the following hypotheses are proposed:

H0 (A): The effect of the structural design factor is equal when comparing different structures of flow shop (FS) and Hybrid (H) environments.
H1 (A): The effect of structural design factor is different when comparing different structures of flow shop (FS) and Hybrid (H) environments.

H0 (B): The effect of the time variation factor per stage is equal when different time levels are compared.
H1 (B): The effect of the time variation factor per stage is different when comparing different time levels.

H0 (C): The effect of the arrival frequency variation factor is equal when comparing different frequency levels.

H1 (C): The effect of the arrival frequency variation factor is different when comparing different frequency levels.

H0 (D): The effect of the variation factor on the number of arrivals of the entities is the same when comparing different quantity levels.

H1 (D): The effect of the variation factor on entity arrival quantities is equal when comparing different quantity levels.

Similarly, taking into account the results obtained in the performance indicators of each of the structural systems, such as (i) Finished products, (ii) Cycle time, (iii) Products in process, (iv) Throughput, (v) Productivity, (vi) Efficiency and (vii) Production cost. With respect to the measurement of complexity, the following hypothesis is made:

H0 (E): The performance indicators presented are not correlated with respect to the total system complexity measure.

H1 (E): The performance indicators are correlated with respect to the total system complexity measure.

H0 (F): The silver performance indicators are not correlated with respect to the static complexity measure of the system.

H1 (F): The silver performance indicators are correlated with respect to the static complexity measure of the system.

H0 (G): The performance indicators presented are not correlated with respect to the dynamic complexity measure of the system.

H1 (G): The performance indicators are correlated with respect to the dynamic complexity measure of the system.

3.4 Experimental statistical analysis

The technique used is that of experimental design, to determine the level of significance of the following factors: (i) structural design of the system, (ii) variability in the time of each stage of the process, (iii) variation in the frequency of arrivals and (iv) variation in the number of arrivals of the entities. With respect to the response variable Total complexity. The study is based on the results obtained in the analysis of variance or anova table.

3.5 Factor analysis

Based on a multivariable correlation matrix between the performance indicators of each of the structural systems, such as (i) Finished products, (ii) Cycle time, (iii) Products in process, (iv) Throughput, (v) Productivity, (vi) Efficiency and (vii) Production cost. With respect to the Total, Static and Dynamic Complexity variables, it is possible to determine if there are correlations between them and the variables of interest.

4 Results

This section presents the results obtained separated by sections, (i) structural modeling, (ii) complexity measurement and (iii) experimental and factorial statistical analysis.

4.1 Structural modeling

The structural modeling considers three stages within the process and a maximum of two machines per stage. Varying the times in each one, where the yellow color represents a high level and the blue color a low level. Similarly, there is a variation in the frequency of arrivals (F) and the number of arrivals of the entities (Q), where the red color represents a high level and the green color a low level (See figure 2).

The modeling of the scenarios generated 256 possible combinations, providing as a result for each one, the evaluation of the performance indicators, (i) Finished products - Pt, (ii) Cycle time - Tc, (iii) Products in process - Wp, (iv) Throughput - Th, (v) Productivity - Pr, (vi) Efficiency - Ef and (vii) Production cost - Cp. The models were implemented with the help of the ProModel software (Manufacturing Systems Simulator), which allowed the evaluation of each structure, considering 1 replica, a 24-hour run and a 2-hour break. Figure 3 shows a higher performance and upward trend of Pt, Cp, Pr, Th and Wp when working in wide H structures. Regarding Tc, the trend is downward and favorable for H structures, unlike Ef, which has a downward trend with higher performance in Fs environments.

Fig. 2. Types of structures for modeling

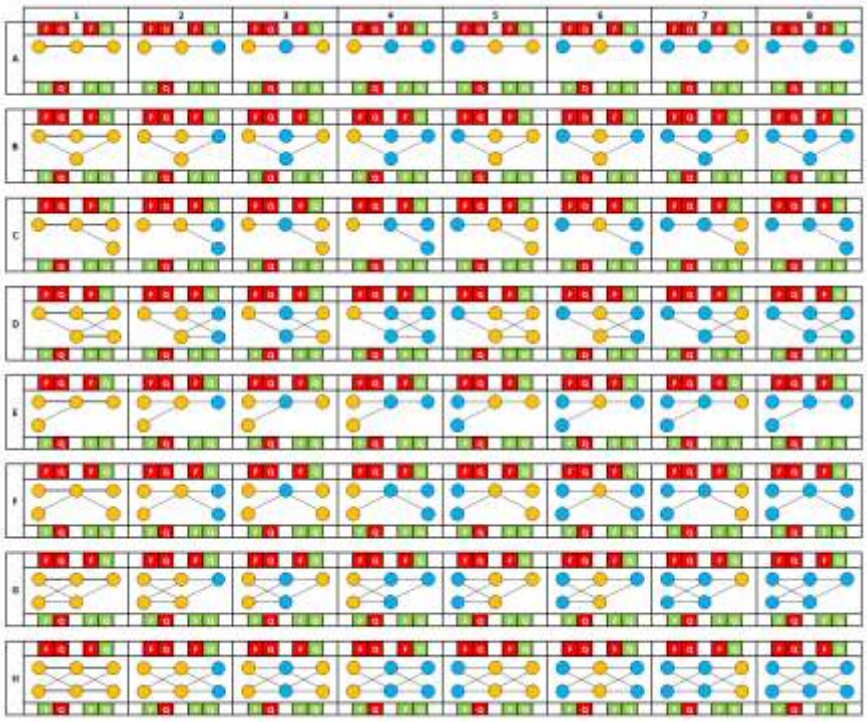
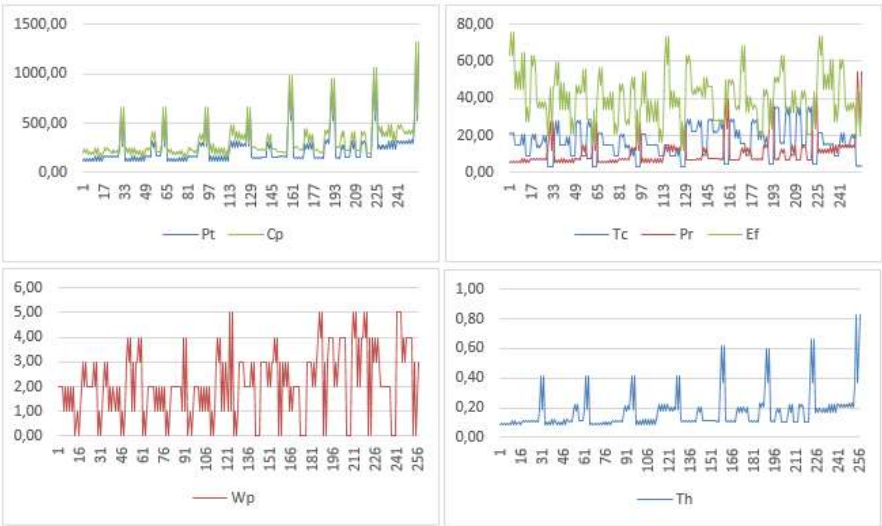


Fig. 3. Performance Indicator Results



4.2 Complexity measurement

From the results obtained and from formula 1, the static complexity (Cs) is calculated, considering the observed frequency (Fo), probability (Pr) and entropy (E) of each of the structures. The last structure of block H8 with environment H is taken as an example for a better understanding (See Table 2). The calculations show a Cs equal to 1,983 bits.

Table 2. Static complexity measurement results

	Station A			Station B			Station C			
	Fo	Pr	E	Fo	Pr	E	Fo	Pr	E	Cs
Machin1	22	0,92	0,12	22	0,92	0,12	22	0,92	0,12	
Machin2	22	0,92	0,12	22	0,92	0,12	22	0,92	0,12	
Break	4	0,17	0,43	4	0,17	0,43	4	0,17	0,43	
Total	48	2,00	0,66	48	2,00	0,66	48	2,00	0,66	1,983

$$C_{static}(s) = -\sum_{i=1}^{M}\sum_{j=1}^{N} P_{ij}\, log_2 P_{ij}$$

$$C_{static}(Cs) = (0{,}12 + 0{,}12 + 0{,}43) + (\,0{,}12 + 0{,}12 + 0{,}43) + (0{,}12 + 0{,}12 + 0{,}43)$$

$$C_{static}\ (\mathrm{Cs}) = 1{,}983\ bits$$

Consequently, taking into account formula 2 and the results obtained in the simulation, the dynamic complexity (Cd) is calculated. Considering the percentages of Operation, Setup, Idle, Waiting, blocked and Down (See table 3). The calculations show a Cd equal to 7.4055 bits.

Table 3. Simulation results for stations in structure H8

		Operation	Setup	Idle	Waiting	Blocked	Down
Station A	Machine 1	45,45	0,00	45,45	0,01	9,09	0,00
	Machine 2	45,45	0,00	34,65	10,81	9,09	0,00
Station B	Machine 1	45,45	0,00	54,55	0,00	0,00	0,00
	Machine 2	45,38	0,00	44,77	9,85	0,00	0,00
Station C	Machine 1	45,40	0,00	54,60	0,00	0,00	0,00
	Machine 2	45,30	0,00	54,70	0,00	0,00	0,00

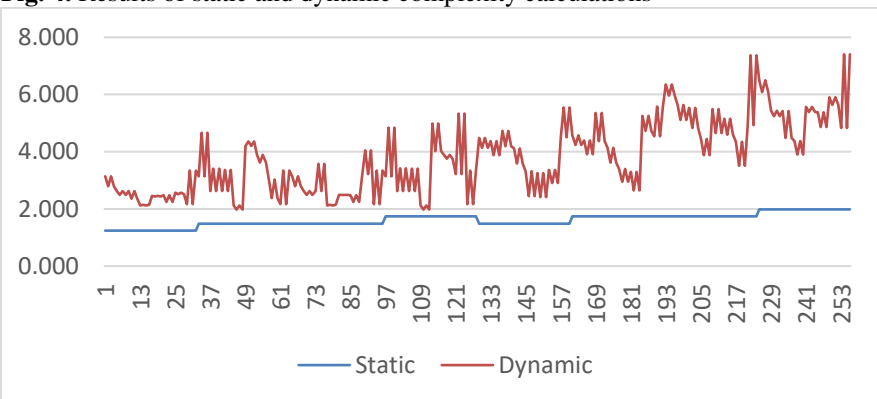
$$C_{dynamic}(Cd) = -\sum_{i=1}^{M}\sum_{j=1}^{N} P'_{ij}\, log_2 P'_{ij}$$

$$\begin{aligned} C_{dynamic}(Cd) = -\sum_{i=1}^{M}\sum_{j=1}^{N} & [0{,}4545 * log_2(0{,}4545)] \\ & + [0{,}4545 * log_2(0{,}4545)] + [0{,}0001 * log_2(0{,}0001)] \\ & + [0{,}0909 * log_2(0{,}0909)] + [0{,}4545 * log_2(0{,}4545)] \\ & + [0{,}3465 * log_2(0{,}3465)] + [0{,}1081 * log_2(0{,}1081)] \\ & + [0{,}0909 * log_2(0{,}0909)] + [0{,}4545 * log_2(0{,}4545)] \\ & + [0{,}5455 * log_2(0{,}5455)] + [0{,}4538 * log_2(0{,}4538)] \\ & + [0{,}4477 * log_2(0{,}0985)] + [0{,}0985 * log_2(0{,}0985)] \\ & + [0{,}4540 * log_2(0{,}4540)] + [0{,}5460 * log_2(0{,}5460)] \\ & + [0{,}4530 * log_2(45{,}45)] + [0{,}5470 * log_2(0{,}5470)] \end{aligned}$$

$$C_{dynamic}(Cd) = 7{,}4055 \text{ bits}$$

Figure 4 shows the results obtained for the calculation of Cs and Cd of all the modeled structures. It is evident that the greater the amplitude in the H environments, the higher the Cs and Cd.

Fig. 4. Results of static and dynamic complexity calculations



4.3 Experimental and factorial statistical analysis

The design of experiments technique was used to determine the level of significance of the factors by means of an analysis of variances or anova table. Table 4 shows that the factors structural design and production time per stage have a p-value of less than 0.05, both in the main effects and in the interactions; therefore, the null hypotheses - H0(A) and H0(B) - are rejected. The opposite case occurs with

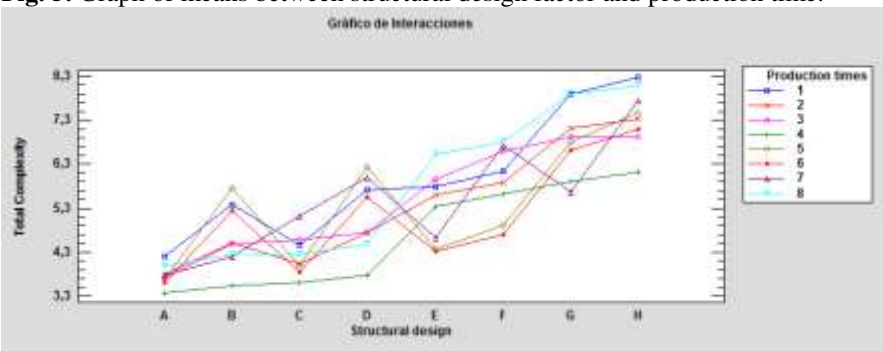
the factors time of arrivals and number of arrivals, which present a p-value greater than 0.05; therefore, the null hypothesis - H0(C) and H0(D) - are accepted. Given the above, it can be inferred that factors A and B have a significant influence on total complexity in manufacturing systems, with a 95% confidence level.

Table 4. Results of the analysis of variance - Anova for total complexity

Source	Sum of Squares	Gl	Medium Square	F-Ratio	P-value
MAJOR EFFECTS					
A:Structural design	349,261		49,8945	488,74	0,0000
B:Production times	36,0067		5,14382	50,39	0,0000
C:Arrival time	0	1	0	0,00	1,0000
D:Number of arrivals	0,122063	1	0,122063	1,20	0,2758
INTERACTIONS					
AB	75,4261		1,53931	15,08	0,0000
AC	0		0	0,00	1,0000
AD	8,20386		1,17198	11,48	0,0000
BC	0		0	0,00	1,0000
BD	21,0011		3,00016	29,39	0,0000
CD	0	1	0	0,00	1,0000
WASTE	16,4361		0,102087		
TOTAL (CORRECTED)	506,457				

A graphical analysis using Statgraphics Centurion v19 software allows comparing the different levels of the factors with respect to the total complexity variable. Regarding the structural design factor, the results indicate that there is a significant difference when comparing the types of structures, with A, B and C generating the lowest total complexity and F, G and H generating the highest total complexity (See Figure 5). Given the above, it can be inferred that the greater the number of machines in the different stages, the greater the total complexity.

Fig. 5. Graph of means between structural design factor and production time.



Regarding the production time factor by stages, the results obtained indicate that there is a significant difference when comparing the variation of times by stages. Being structure type 4 the one that generates less total complexity (See figure 5). Given the above, it can be inferred that when the times vary progressively from higher to lower, a lower total complexity is generated. Finally, the assumptions of the model were verified, taking into account the tests of normality, homogeneity of variances and independence of the data. These tests show that the model complies with these assumptions.

Consequently, a factor analysis is developed to find correlations between the variables. A matrix is used to locate the correlations between all the variables considered (performance indicators) with respect to the total complexity (see figure 6). This graph shows the Pearson product moment correlations between each pair of variables. These correlation coefficients range from -1 to +1, and measure the strength of the linear relationship between the variables. The following pairs of variables have a p-value below 0.05 at the 95% confidence level, indicating correlations significantly different from zero. Therefore, the alternative hypothesis H1(E) is approved, which establishes that the performance indicators presented are correlated with respect to the total system complexity measure, with greater strength with respect to production costs (Cp).

Fig. 6. Correlation matrix of performance indicators for Ct.

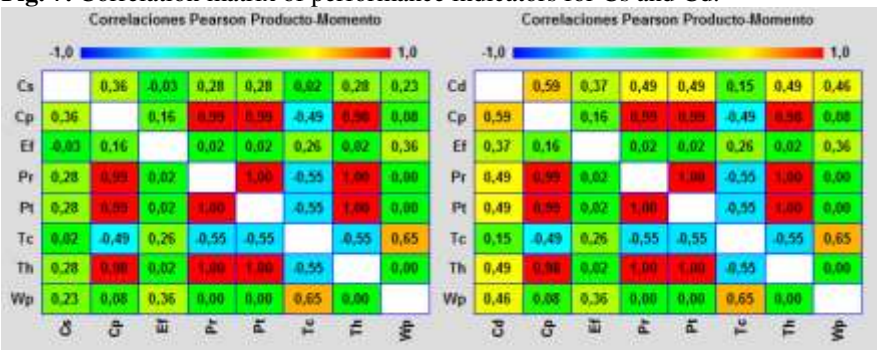
Correlaciones Pearson Producto-Momento

-1,0 1,0

	Ct	Cp	Ef	Pr	Pt	Tc	Th	Wp
Ct		0,58	0,33	0,48	0,48	0,13	0,48	0,45
Cp	0,58		0,16	0,99	0,99	-0,49	0,98	0,08
Ef	0,33	0,16		0,02	0,02	0,26	0,02	0,36
Pr	0,48	0,99	0,02		1,00	-0,55	1,00	0,00
Pt	0,48	0,99	0,02	1,00		-0,55	1,00	0,00
Tc	0,13	-0,49	0,26	-0,55	-0,55		-0,55	0,65
Th	0,48	0,98	0,02	1,00	1,00	-0,55		0,00
Wp	0,45	0,08	0,36	0,00	0,00	0,65	0,00	

With respect to static complexity (Cs), the same test is applied. Figure 7 shows that the variables Tc and Ef are not correlated with respect to the measure of static complexity, so the null hypothesis H0 (F) is approved. Unlike the variables Ct, Pr, Pt, Th and Wp; which have a correlation with the static complexity measure, corroborating with a confidence level of 95% the alternative hypothesis H1(F).

Fig. 7. Correlation matrix of performance indicators for Cs and Cd.



In relation to dynamic complexity (Cd), the correlation matrix indicates that all the performance indicators presented are correlated with respect to the system's dynamic complexity measure (see Figure 7), with greater strength with respect to production costs (Cp). Therefore, the alternative hypothesis H1(G) is corroborated with a confidence level of 95%.

5 Conclusion

This research focuses on the measurement of static, dynamic and total complexity, based on Shannon's entropy method, considering different structures and factors in a flow shop and hybrid environment. Structural modeling is initially developed taking into account 256 possible combinations in a three-stage configuration with a maximum of two machines in each one. Allowing an analysis with respect to performance indicators, experimental and factorial statistics. The results obtained corroborate the hypotheses proposed, where statistically the structural design factors and the variation of the production time per stage, significantly influence the response variable. Inferring that the greater the number of machines in the different stages, the greater the total complexity. In turn, when the times vary progressively from higher to lower, a lower total complexity is generated. Similarly, the existence of correlation between the indicators and the studied variable is evidenced, in which the incidence with the production costs stands out.

Acknowledgements

Thank you to the Fundación Universitaria Tecnológico Comfenalco (FUTC), Research Group Ciptec, Universidad de la Costa (CUC) - Colombia and to the Universidad Nacional Lomas de Zamora (UNLZ) - Argentina, for the support of their academic and scientific group.

Ethics declarations

Conflict of interest
The authors declare that they have no conflict of interest.
Ethics approval
The authors hereby state that the present work is in compliance with the ethical standards.
Consent to participate
Not applicable.
Consent for publication
The manuscript has not been published before and is not being considered for publication elsewhere.

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