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MANUFACTURING SYSTEMS COMPLEXITY AN ASSESSMENT OF PERFORMANCE INDICATORS UNPREDICTABILITY

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ABSTRACT

In the modern interconnected environment, manufacturing systems, in their pursuit of cost, time and flexibility optimization, are becoming more and more complex, exhibiting a dynamic and non linear behaviour. Unpredictability is a distinct characteristic of such a behaviour and affects production planning significantly. This paper presents a novel approach for the assessment of unpredictability in the manufacturing domain. In particular, the fluctuation of critical manufacturing performance indicators is studied with the help of the Lempel-Ziv Kolmogorov complexity measure in order for the complexity of a manufacturing system to be evaluated. Finally, the method's potentiality is examined with the application of the proposed approach to an automotive industrial use case.

KEYWORDS

Manufacturing complexity, unpredictability, production planning, performance indicators

1. INTRODUCTION

In the globalized and interconnected market, demand fluctuation along with the requirements of high product quality, low cost, short lead time and high customization lead to a manufacturing complexity increase (Chryssolouris, 2006). Unpredictability, a typical characteristic of a complex system, may have a negative impact on a production system's design, planning and operation, in a quite significant manner. Determining the complexity quantitative metrics is considered as a prerequisite for understanding complexity mechanics and managing efficiently complexity (Hon, 2005, Wiendhal and Scheffczyk, 1999). The scope of the current study is the examination complexity in manufacturing systems, by assessing the unpredictability of performance indicators with the use of the Lempel Ziv complexity measure.

The rest of the paper is organized as follows. Chapter 2, presents a review of the existing literature on manufacturing modelling approaches. Chapter 3, describes the proposed methodology for the assessment of unpredictability, by introducing the application of the Lempel Ziv complexity measure to manufacturing performance indicators timeseries analysis. A case study from the automotive industry that illustrates the efficacy of the approach to real industrial environments is provided in chapter 4. In the case study, the complexity assessment of an assembly line and the relationships among flexibility, production mix and unpredictability are studied. Chapter 5, concludes the basic outcomes from this work and proposes future research direction.

2. LITERATURE REVIEW

Over the past years, several approaches, utilizing

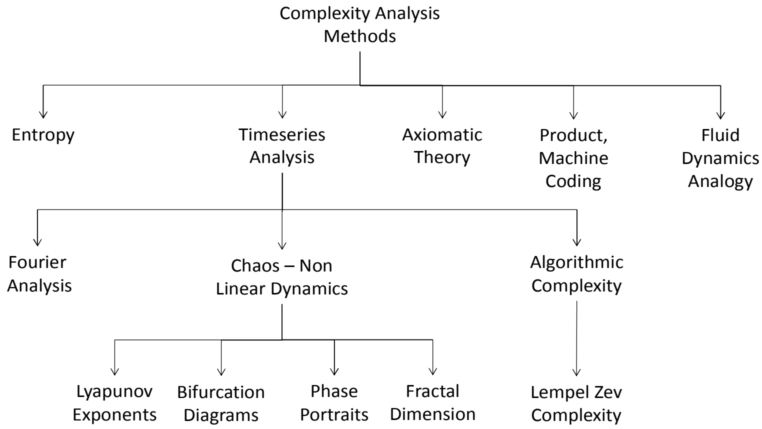

Figure 1 – Classification diagram of the main manufacturing complexity analysis methods

different methods and tools, have been proposed for modelling and measuring the manufacturing complexity. Most of the approaches can be classified into five main categories, based on the tools used for the complexity analysis. The first category of methods follows the information theory approaches, having as fundamental measure this of Shannon's entropy. The second category is related to timeseries analysis techniques, such as the Fourier analysis and non-linear dynamics tools. In the third category, several approaches study complexity having as a basis the axiomatic theory. The fourth category includes methods that attempt to address complexity by defining a coding system for machines and products. The last category concerns methods inspired by ideas from fluid dynamics and aim to introduce a Reynolds number namely the metric to manufacturing in order for the complexity to be assessed by defining a threshold between a steady and a turbulent manufacturing behaviour. The diagram of Figure 1, schematically illustrates the classification of the aforementioned categories and their subcategories.

Entropy, as it is introduced in the information theory (Shannon and Weaver, 1949) is associated with the uncertainty of the occurrence of a series of events. In the manufacturing domain, the information entropy approach is utilized in order for the complexity of a production system to be assessed, and it is regarded as the sum of individual entropy rates for each process and product variant. Following this approach, in (Deshmukh et al, 1998), a theoretical framework is proposed for assessing the static complexity of manufacturing systems. Static complexity is associated with the different types of resources and different types of parts in the system and it can be regarded as the measure of information, required to describe the system and its components. Similarly, in (Hu et al, 2008) the effect of product variability and assembly process information on the manufacturing system complexity, is studied with the help of entropy based metrics. Entropy metrics are also used in (Frizelle and Woodcock, 2008) for studying input-output systems, in particular on focusing on queues' measurements. The mixed model assembly lines complexity is analysed in (Zhu et al, 2008), where the entropy of each station is computed as the entropy, caused by the introduced variants and the entropy induced by preceding stations. Based on (Zhu et al, 2008) the complexity metric, the complexity effect on the throughput of different assembly system configurations is studied in (Wang, 2010).

In (Suh, 2005), complexity is considered as "the measure of uncertainty in satisfying the aims (functional requirements) of a system" and it is classified into the following types: real and imaginary, time dependent and time independent, periodic and combinatory. A series of axioms, concerning complexity are defined, and within the resulting framework relations, between design parameters and functional requirements, are established in a matrix form. In terms of manufacturing, the objective is the maximization of productivity by reducing the complexity of the manufacturing system, following a process called "Design-Centric Complexity (DCC) theory". According to (Lu and Suh, 2009) the introduction of functional periodicity, by reinitializing the system's function on a periodic basis, is suggested in order for the continuous drifting of system ranges to be disrupted.

In a timeseries analysis, chaos and non-linear dynamics techniques are used for the assessment of complexity in manufacturing systems. Phase portraits and time delay plots are utilized in order to examine the scheduling of a simple manufacturing

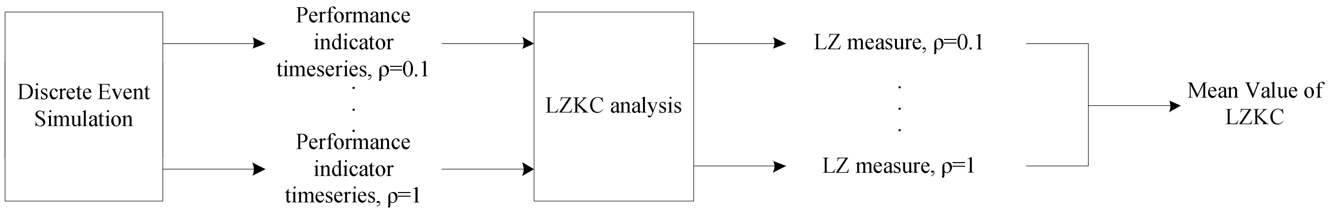

Figure 2 – Proposed Manufacturing Complexity Assessment Methodology based on LZ complexity analysis

system (Giannelos et al, 2007). Based on this analysis, a new dispatching rule is proposed presenting promising results in terms of time performance characteristics. Time delay plots i.e. the Poincare maps are also used in (Peters, 2003) for studying the effect of buffer size on the performance of a manufacturing system. The adaptability to demand of a steel construction industry, under different operational policies and parameters, is studied, utilizing the maximal Lyapunov exponents and bifurcation diagrams (Papakostas and Mourtzis, 2007). Similarly, the maximal Lyapunov exponents are also utilized in (Alfaro and Sepulveda, 2005) along with the Fourier analysis and fractal dimensions for examining the chaotic behaviour of a production system, based on buffer index timeseries. In (Papakostas et al, 2009), a simulation based method, along with a regression analysis and a non-linear dynamics analysis is proposed. The aim of the present methodology is the determination of a manufacturing system's sensitivity to workload changes, the measurement and the control of the system's complexity. In another work, a sensitivity analysis is performed in order to identify the system's chaotic behaviour, by introducing small perturbations in the initial conditions (Schmitz et al, 2002).

A coding system for classifying information of major components of industrial systems is proposed. In the context of this coding framework, complexity is defined as a function of the quantity and the uniqueness of information (ElMaraghy et al, 2005 and ElMaraghy and Urbanic, 2003).

In (Efthymiou et al, 2010) the introduction of the Reynolds number concept to a manufacturing system as an indicator of complexity is proposed. The aim of this, is the identification of the transition regime between the behaviour of steady and turbulent manufacturing operations in analogy to laminar and turbulent flows. Similar concepts, coming from the fluid dynamics domain are also proposed in (Schleifenbaum et al, 2010) for production systems and in (Romano, 2009) for supply chain.

Although the existing approaches of the manufacturing complexity analysis may lead to useful results, they do not provide a direct assessment of unpredictability of the manufacturing performance indicators that are significant parameters for decision making during the design, planning and operation of manufacturing systems (Chryssolouris, 2006). Additionally, a series of difficulties arise in applying the existing approaches to real industrial problems. These obstacles are mentioned within the paragraph hereafter.

Entropy based approaches require the definition of the different states of a system's components. In addition, a series of assumptions related to the independence of the system's states should be made. Finally, there is the problem of inserting subjectivity into the analytical association of the entropy measures with the system's performance (Papakostas et al, 2009). The complexity approaches, based on a coding system, insert the subjective definition of the codes that subsequently lead to a subjective assessment of complexity. Moreover, in case that a code of a component or a part is missing, the complexity assessment is not feasible. The axiomatic theory methods demand the knowledge of uncertainty for a system's specific requirement. This uncertainty is connected with the estimation of a probability that should be known or assumed. The chaos and non-linear dynamics theory tools are useful only when the system under study is chaotic. The phase portraits and the bifurcation diagrams provide a schematic way of presenting a system's irregularity but they do not provide a specific value that can be easily compared with the values of other systems. Finally, the approaches inspired by fluid dynamics are still in an early stage of development

3. MANUFACTURING COMPLEXITY ASSESSMENT METHODOLOGY

In the present method, complexity is approached as the unpredictability of manufacturing performance indicators. The assessment of the unpredictability is performed by applying the Lempel-Ziv complexity analysis to manufacturing performance indicators timeseries.

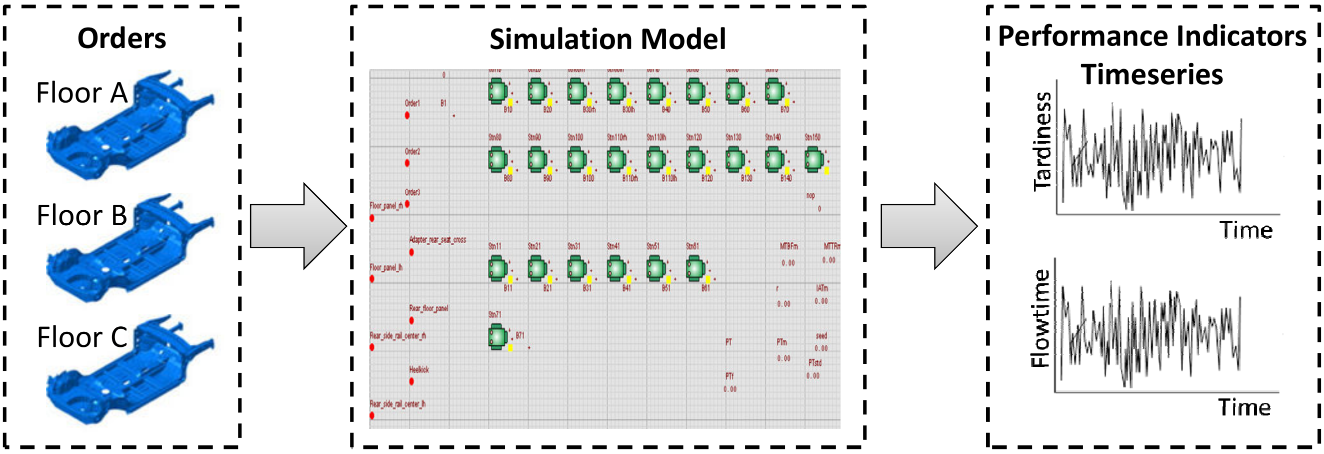

Figure 3 – Case Study inputs and outputs of the discrete event simulation model

In (Lempel and Ziv, 1976), a complexity measure (LZ) based on symbolic dynamics and on Kolmogorov's work (Kolmogorov, 1978) is introduced. LZ is a nonparametric measure for finite sequences, related to the number of distinct substrings and the rate of their occurrence along the sequence that assesses the degree of disorder or irregularity of a sequence. The LZ values close to zero indicate a system presenting the least complex behaviour, while systems with LZ values near one are related with stochastic, unpredictable behaviour (Ferreira et al, 2003). The LZ presents several advantages in comparison with the timeseries complexity techniques. First, the LZ can be applied both to deterministic and to stochastic (and chaotic) systems. Second, the stationarity of the timeseries under investigation is not required for the application of LZ. Third, the LZ provides a universal measure of complexity, facilitating the comparison of different manufacturing systems.

The proposed methodology consists of three main steps, namely, the simulation of the manufacturing system, the LZ analysis of performance indicators timeseries and the estimation of the mean value of LZ measures. In the first step, the simulation model of the manufacturing system under study is developed. The system is examined under a range or ρ varying from 0.1 up to 1. The idea is to study the system under a wide range of order's pressure from low demand rates up to high. So, a series of simulations are performed as many as the range or ρ. The output of this step is the performance indicators timeseries. Each performance indicator corresponds to a ρ. In the next step, the timeseries are analyzed with the use of Lempel Ziv and a complexity measurement for each timeseries that occurs. In the last step, the mean value of the LZ measure of performance indicator timeseries for the range of ρ from 0.1 up to 1 is estimated. The mean value is considered as weighted indicator of the manufacturing system's unpredictability and it is left as $\overline{LZ}$. The flowchart of the proposed methodology is presented in Figure 2.

3.1. UNPREDICTABILITY ASSESSMENT WITH LEMPEL-ZIV KOLMOGOROV COMPLEXITY

The LZ analysis of a performance indicators' timeseries, which is denoted $\{I_i\}$, $i \varepsilon Z^+$ consists of two phases: a. the timeseries preparation, and b. the computation of complexity. The first phase includes: a. the transformation of the performance indicators' timeseries into a sequence of 0 & 1 and b. the definition of two subsequences of the produced sequence. The {Ii} timeseries is transformed to a sequence S including 0 and 1. The S sequence is written as s(i), $i \varepsilon Z^+$ according to the rule:

$$s(i) = \begin{cases} 0 \ if \ I_i < I^* \\ 1 \ if \ I_i \geq I^* \end{cases} \quad (1)$$

, where I^* is the mean value of the timeseries.

The definition of two subsequences follows, so let,

- P and Q be two subsequences of S,
- PQ be the concatenation of P and Q,
- PQπ be a sequence derived from PQ after the last character is deleted,
- v(PQπ) denote the vocabulary of all different subsequences of PQπ

Table 1: mean values of the Lempel Ziv Kolmogorov complexity

Product Mix (A%, B%, C%)	System type	Mean LZ measure, $\overline{LZ}$	Total	Underbody A	Underbody B	Underbody C
Product Mix A (20%, 30%, 50%)	Assembly Line A	Flowtime	0,48	0,44	0,50	0,49
		Tardiness	0,11	0,11	0,08	0,05
	Assembly Line B	Flowtime	0,45	0,42	0,48	0,46
		Tardiness	0,10	0,09	0,07	0,04
Product Mix B (33%, 33%, 33%)	Assembly Line A	Flowtime	0,45	0,39	0,48	0,51
		Tardiness	0,07	0,07	0,06	0,07
	Assembly Line B	Flowtime	0,43	0,37	0,45	0,49
		Tardiness	0,06	0,07	0,06	0,06
Product Mix C (10%, 80%, 10%)	Assembly Line A	Flowtime	0,20	0,07	0,43	0,35
		Tardiness	0,19	0,18	0,03	0,17
	Assembly Line B	Flowtime	0,19	0,06	0,44	0,34
		Tardiness	0,17	0,17	0,03	0,16

In general, the P and Q subsequences can be denoted as,

$$P = s(1), s(2), ..., s(r) \tag{2}$$

$$Q = s(r+1) \tag{3}$$

$$PQ\pi = s(1), s(2), ..., s(r) \tag{4}$$

where, rε[1,n]

The second phase is the computation of the complexity. Sequence S is scanned from left to right and a complexity counter c(n) is increased by one unit every time a new subsequence of consecutive characters is encountered. The steps followed are described hereafter.

1. At the beginning of the computation c(n)=1, P=s(1), Q=s(2), PQ=s(1), s(2) and PQπ=s(1). In general

$$P = s(1), s(2), ..., s(r) \tag{5}$$

$$Q = s(r+1) \tag{6}$$

$$PQ\pi = s(1), s(2), ..., s(r) \tag{7}$$

   If Q belongs to v(PQπ), then Q is a subsequence of PQπ.
2. Renew Q to be s(r+1), s(r+2) and check if Q belongs to v(PQπ).
3. Repeat the steps 1 & 2 until Q does not belong to v(PQπ) and increase c(n) by 1.
4. Renew P to be the sequence P=s(1),…, s(r+i) with Q=s(r+i-1).
5. Repeat the steps 1, 2, 3 & 4 until Q is the last character, i.e. up to the point that r equals n. The complexity counter c(n) at this point defines the number of different subsequences in P.

In order for the LZ measure to be made independent of the sequence length, the c(n) is normalized with respect to the complexity of a random binary sequence,

$$b(n) = n / \log_2 n \tag{8}$$

Thus, the normalized LZ used within the current study is given by:

$$LZ\, measure : C(n) = \frac{1}{n} c(n) \log_2 n \tag{9}$$

The mean value of the LZ measure of a performance indicator timeseries for a set of ρ is given by:

$$\overline{LZ}(Performance\, Indicator) = \frac{1}{w} \sum_{\rho=1}^{w} CF\rho_i \tag{10}$$

, where w is the number of the examined ρ

4 INDUSTRIAL USE CASE

The efficacy of the proposed approach is presented with the help of an industrial use case from the automotive sector. Two identical assembly lines (AL) consisting of 17 consecutive stations are simulated with the discrete event simulation SW Witness 2007. Each line produces three different types of car floors, namely underbody A, B and C. The only difference between the two assembly lines is that the setup times of the second assembly line are the double of the first assembly line setup times. Thus, the first assembly line is considered being more flexible than the second one.

The output of the assembly lines' discrete event simulation models is the performance indicators' timeseries. Two types of performance indicators are provided by the simulation and are further analysed

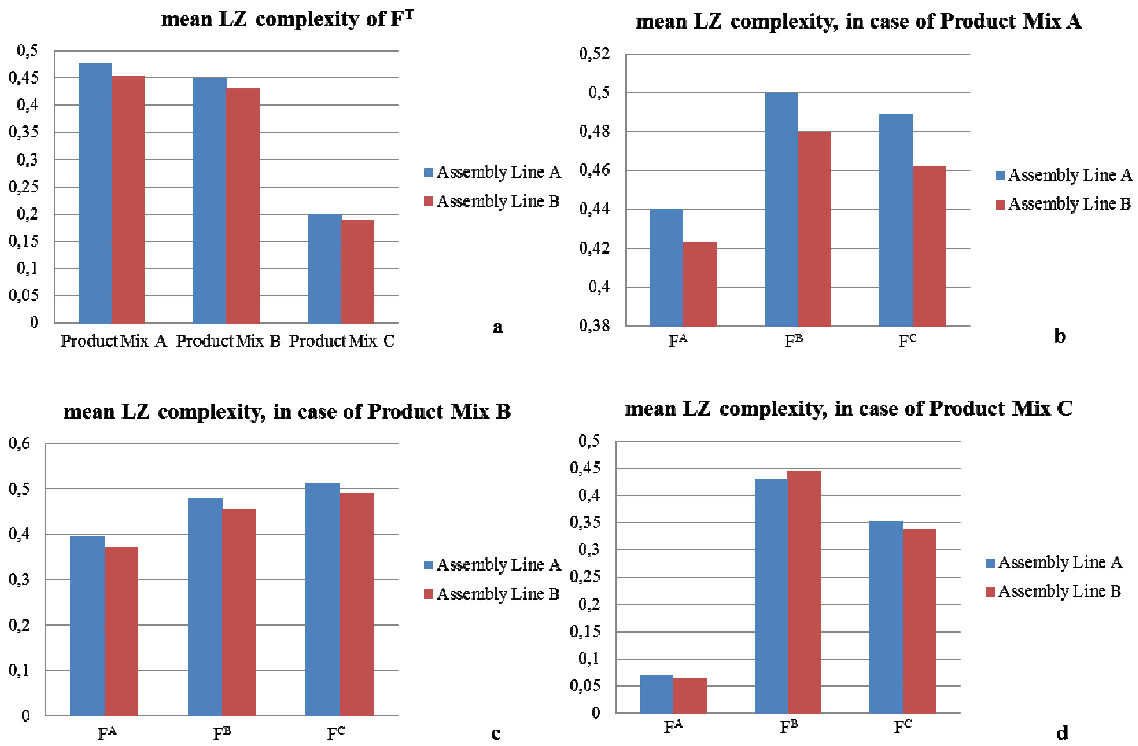

Figure 4 – Mean LZ complexity measures of flowtime analysis

with LZ, namely, flowtime and tardiness and are given by the following equations.

$$F_n^i = ET_n - AT_n \qquad (11)$$

, where F_n, ET_n and AT_n, represent the flowtime, the completion (end) time and the arrival date of job n at time step i, respectively.

$$T_n^i = \max(0, DD_n - ET_n) \qquad (12)$$

, where T_n and DD_n represent the tardiness and the due date of job n at time step i, respectively. Flowtime and tardiness timeseries are further divided into three timeseries for underbody A, B and C. In particular, the notations are:

- F^A/T^A: flowtime/tardiness timeseries of underbody a
- F^B/T^B: flowtime/tardiness timeseries of underbody b
- F^c/T^C: flowtime/tardiness timeseries of underbody c
- F^T/T^T: flowtime/tardiness timeseries of all the underbodies

Three different groups of experiments are carried out (Table 1) for three different product mixes. Each group consists of 10 different experiments for 10 different values of ρ, ranging from 0.1 up to 1, with a step of 0.1.

The results of the analysis are presented with the help of Table 1 and the diagrams of figures 3 and 4. Table 1, includes the mean values of the Lempel Ziv Complexity for the flowtime and tardiness timeseries for both the assembly lines, of three different product mixes. The diagrams in Figure 4 illustrate the mean value of the LZ, coming from the analysis of the flowtime timeseries for both the assembly lines under three different product mixes. In particular, the diagram a presents the weighted complexity indicator, based on the flowtime of all the underbodies. Figure 4b, illustrates the mean LZ of the flowtime timeseries of underbody a, b and c in the case of product mix a. Similarly to diagram b, the diagrams c and d show the mean LZ in the case of product mix b and c respectively. Figure 5, includes diagrams similar to those in figure 4, but in figure 5, it is a tardiness timeseries analysis illustrated, instead of the flowtime.

4.1. ASSEMBLY LINES' UNPREDICTABILITY

The maximum mean value of the LZK complexity, i.e. 0,51 occurs in the case of product mix B for the assembly line A, based on the analysis of flowtime timeseries. In general, the mean values of the LZK complexity of assembly line A, coming from the flowtime timeseries analysis, range from 0,07 up to 0,51. Similarly, assembly line B is characterized by the same range of the LZ flowtime mean values,

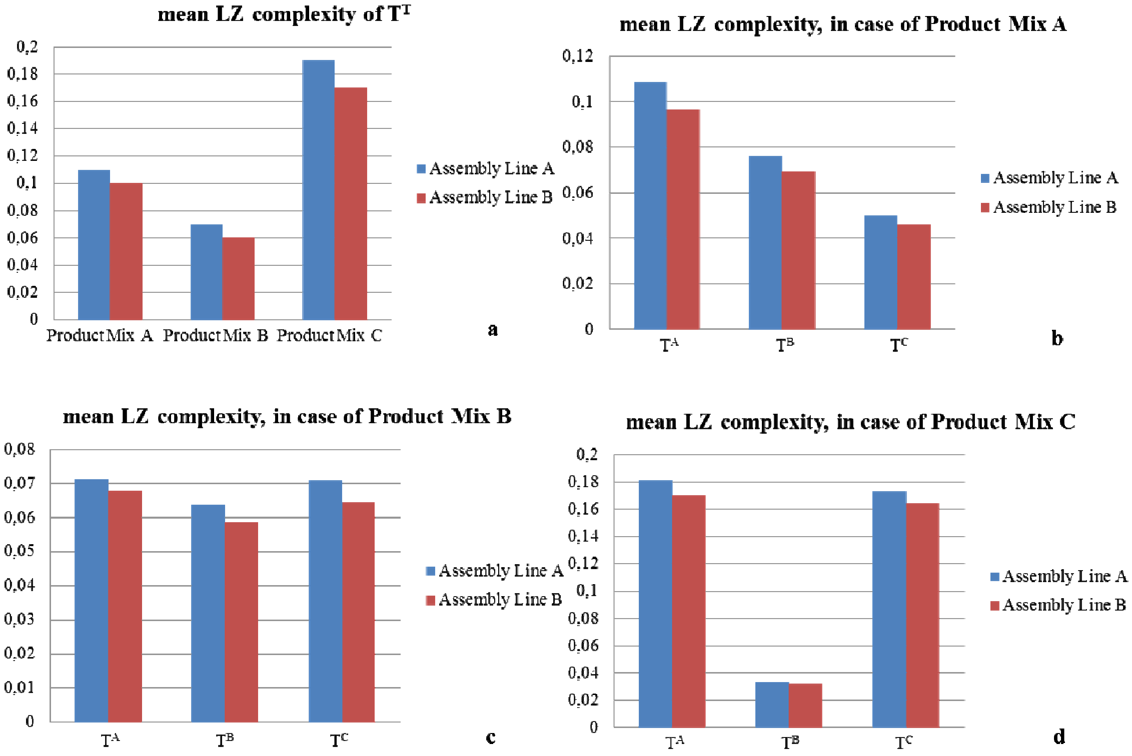

Figure 5 – Mean LZ complexity measures of flowtime analysis

in particular, the LZ fluctuates between 0,06 and 0,48. Additionally, the average of LZ of the tardiness timeseries is characterized by low values. Specifically, the values are significantly close to zero, with a maximum of 0,18.

A process that is least complex and predictable has an LZ value close to zero, whereas a process with the highest complexity and unpredictability-randomness will have an LZ close to one. A value of the LZ near to zero is associated with a simple deterministic process such a periodic motion, in contrast to a value near to one that is related toa stochastic and unpredictable process (Ferreira et al, 2003). Thus, both assembly lines A and B can be considered as deterministic systems of a low complexity and a high predictability, since the average LZ values are close to zero. This ascertainment is in agreement with the characteristics of the assembly lines, since the process and setup times are deterministic fixed values, while the demand rate is also deterministic and periodic.

4.2. FLEXIBILITY AND UNPREDICTABILITY

The setup times of assembly line A are two times smaller than the setup times of assembly line B. This difference leads A to have higher flexibility than B. In order for flexibility to be quantified, the FLEXIMAC (Alexopoulos et al, 2008) indicator is utilized and A and B are characterized by 0.2242 and 0.0632 respectively. It is evident from the diagrams of both figures 4 and 5 that flexibility is proportional to complexity. Apart from one case in Figure 5b, the mean value of LZ of assembly line A is always higher than the respective LZ mean values of assembly line B. Both flowtime and tardiness unpredictability is affected by flexibility. Thus, a strong correlation between flexibility and complexity, in terms of unpredictability and randomness, is identified. The relationship between flexibility and complexity can be useful during the design or the planning of a manufacturing system, indicating flexibility thresholds that should not be reached in order for any unpredictable running of the manufacturing system to be avoided. Avoiding randomness in a manufacturing system, facilitates its successful monitoring and controlling.

4.3. PRODUCT MIX AND UNPREDICTABILITY

Assembly lines A and B are studied under three different product mixes. The product mix A, consists of orders of underbodies a, b and c, in a ratio of 20%, 30% and 50% respectively. The product mix B consists of equal underbody orders with a ratio of 33%. Finally, in the case of the product mix C, the underbody b orders ratio is much higher than that of the other two underbodies' orders ratio. Specifically, the underbody orders of floor b is almost 80% while the ration of the underbodies a and c is 10%.

The diagrams of figure 5, presenting the mean values of the LZ analysis of tardiness timeseries, indicate a relationship between the product mix and the unpredictability. It is observed that the lower the underbody order ratio is the higher the mean LKZC value. In particular, in the figure 5b, unpredictability is inversely proportional to the underbodies' ratio. A similar correlation is also shown in figures 5c and 5d. In figure 5c, unpredictability fluctuates around 0,06 for all the underbodies, whose orders ratio is 33%. The diagram d shows that tardiness unpredictability of the underbodies a and c is almost the same and much greater than the unpredictability of underbody b. The underbodies a and c share the same orders' ratio of 10% and the underbody orders ratio is 80%. It should be noted that this correlation, between unpredictability and product mix is observed only with the tardiness and not with the flowtime. The diagrams of figure 4 that present the mean values of LZ of the flowtime timeseries do not reveal a connection between unpredictability and product mix.

The relationship between the mean LZ of F^T and the mean LK complexity measure of F^A, F^B & F^C can be studied with the help of table 1. The F^T timeseries exhibit behaviour similar to that of the F^A, F^B & F^C in terms of unpredictability. The same remark can be made for the tardiness timeseries as well. The values of the mean LZ of T^T T^A, T^B and T^C timeseries fluctuate in the same range, without presenting great differences.

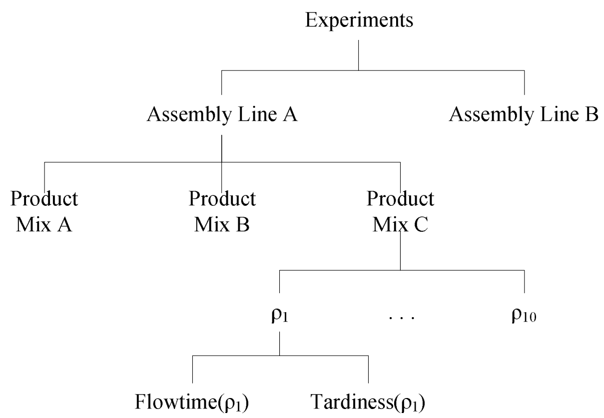

Figure 6 – Design of Experiments

5. DISCUSSION

This paper proposes a new method of modelling and analysing the complexity of manufacturing systems from a performance indicators unpredictability point of view. The assessment of unpredictability is based on the performance indicators timeseries analysis, with the use of the Lempel Ziv Kolmogorov Complexity measure. The efficacy of the approach is presented with a case study from the automotive industry. Two assembly lines, characterized by different flexibility, producing three underbodies are examined, under a range of demand rates and three different product mixes. Both assembly lines present high predictability and can be characterized by low complexity. The values of the mean LZ are in line with the characteristics of both the assembly lines which are deterministic. A proportional relationship between the flexibility and the unpredictability is observed, after analysing the flowtime and tardiness timeseries. This correlation of flexibility and complexity, in terms of unpredictability, can be useful for monitoring and controlling manufacturing systems, and it should be further and thoroughly studied. Another correlation is also identified, this of the product mix and the unpredictability, but only in the case of the unpredictability of tardiness. It is observed that the lower the ratio of the underbody orders is the higher its unpredictability.

6. ACKNOWLEDGMENTS

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REFERENCES

Hu. S.J., Zhu, X., Wang, H., Koren, Y., "Product variety and manufacturing complexity in assembly systems and supply chains", CIRP Annals - Manufacturing Technology, Vol. 57, No.1, 2008, pp.45-48

Frizelle, G., Woodcock, E., "Measuring complexity as an aid to developing operational strategy", International Journal of Operations and Production Management, Vol. 15, No. 5, 1995, pp.26-39

Desmukh, A., Talavage, J., Barash, M., "Complexity in manufacturing systems - Part 1: Analysis of Static Complexity", IIE Transactions, 1998, pp.645-655

Nam P. Suh "A theory of complexity and applications", Oxford University Press, USA, 2005

Stephen C.-Y. Lu and Nam P.Suh, "Complexity in design of technical systems", *CIRP Annals - Manufacturing Technology*, Vol 58, No 1, 2009,pp 157-160

ElMaraghy, H.A., Kuzgunkaya, O., Urbanic, R.J., "Manufacturing systems configuration complexity", *CIRP Annals - Manufacturing Technology*, Vol.54, No.1, 2005, pp.445 - 450

ElMaraghy, H., Urbanic, R.J., "Modelling of manufacturing systems complexity", *CIRP Annals - Manufacturing Technology*, Vol. 52, No. 1, 2003, pp.363 - 366

Shannon C. E. and Weaver W,"A Mathematical Theory of Communication", 1st Edition, University of Illinois, Press, Urbana, 1949, p

Papakostas N and Mourtzis D, "An Approach for Adaptability Modeling in Manufacturing - Analysis Using Chaotic Dynamics", *Annals of CIRP-Manufacturing Technology*, Vol. 56, 2007, No. 1, pp 491-494

Giannelos N, Papakostas N, Mourtzis D and Chryssolouris D., "Dispatching policy for manufacturing jobs and time-delay plots", *International Journal of Computer Integrated Manufacturing*, Vol. 20, No. 4, 2007, pp. 329-337

Papakostas N, Efthymiou K, Mourtzis D and Chryssolouris G, "Modeling the complexity of manufacturing systems using nonlineas dynamics approaches", *CIRP Annals - Manufacturing Technology*, Vol 58, No.1, 2009, pp 437-440

Wiendahl H P, Scheffczyk H, "Simulation based analysis of complex production systems with methods of nonlinear dynamics", *Annals of the CIRP*, Vol. 48, 1999

K. Peters, J. Worbs, U. Parlitz and H.-P. Wiendahl, "Manufacturing systems with restricted buffer sizes", *Nonlinear Dynamics of Production Processes*, 2004, pp. 39-54

Alfaro, M.D., Sepulveda, J.M., "Chaotic behaviour in manufacturing systems", *International Journal of Production Economic*s, 2006, pp. 150-158

Efthymiou K, Papakostas N, Mourtzis D and Chryssolouris G, "Fluid Dynamics Analogy to Manufacturing Systems' 42nd CIRP Conference on Manufacturing Systems, Grenoble, France, 2009

Schleifenbaum H, Uam JY, Schuh G and Hinke C., "Turbulence in Production Systems – Fluid Dynamics and its Contributions to Production Theory", Proceedings of the World Congress on Engineering and Computer Science 2009 Vol II

Romano P, "How can fluid dynamics help supply chain management?" *International Journal of Production Economics,* Vol.118 No.2, 2009, pp. 463–472.

Zhu X., Hu., S., Koren, Y., Marin, S.P., "Modeling of manufacturing complexity in mixed model assembly lines", *Journal of Manufacturing Science and Engineering, Transactions of the ASME*, Vol. 130, No. 5, pp. 0.510131 - 05101310

Wang., H., Hu., S.J., "Manufacturing complexity in assembly systems with hybrid configurations and its impact on throughput", *CIRP Annals - Manufacturing Technology*, Vol. 59, No. 1, 2010, pp. 53 – 56

Lempel A and Ziv J, "On the complexity of finite sequences". *IEEE Trans Inform Theory*, Vol. 22 No. 1, 1976, pp. 75–81

Ferreira FF, Francisco G, Machado BS and Murugnandam P "Timeseries analysis for minority game simulations of financial markets" *Physica A* Vol. 321 No X, 2003, pp.619–632

Hon K K B, "Performance and Evaluation of Manufacturing Systems", *CIRP Annals – Manufacturing Technology,* Vol. 54, No 2, 2005, pp. 139-54

Chryssolouris G, "Manufacturing Systems: Theory and Practice",2nd Edition, Springer-Verlag, New York 2006

Alexopoulos K, Papakostas N, Mourtzis D, Gogos P, Chryssolouris G., "Quantifying the flexibility of a manufacturing system by applying the transfer function", *International Journal of Computer Integrated Manufacturing*, Vol. 20, No. 6, 2007, pp. 538-547

Schmitz J P M, Beek van D A, Rooda J E, "Chaos in discrete production systems",*Journal of Manufacturing Systems,* Vol. 21, No. 3, 2002, pp. 236-246