Manufacturing Systems Complexity Review: Challenges and Outlook

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Abstract

In the globalized and interconnected market, demand fluctuation along with the requirements of high product quality, low cost, short lead time and high customization may lead to an increase in manufacturing complexity. Over the past years, several methods, following different theories and approaches, have been proposed to analyse the manufacturing complexity. In this paper, the concepts of a manufacturing system’s complexity are discussed. This study is a systematic and rigorous attempt to identify and synthesize the research done in the manufacturing systems’ complexity domain. Special emphasis is given to the approaches based on a theoretical analytical framework that provide a quantitative analysis of manufacturing systems complexity. These approaches and their applications to industrial problems are presented, classified, and discussed.

Keywords: Manufacturing systems; Complexity; Chaos; Unpredictability

1. Introduction

During the last decades, manufacturing systems in pursuit of cost and time reduction without decreasing quality and flexibility are becoming more and more complex. The main reason for the investigation of manufacturing complexity is to understand and control the non-linear behavior of production systems that will finally make manufacturing systems more productive and predictive [1]. A prerequisite for the comprehension of a manufacturing system’s complexity and its management is the determination of quantitative metrics of manufacturing complexity either static or dynamic [2]. The intricate relationships and interrelations among the system’s elements, along with the stochastic nature of the system, characterized by unpredictability, make the mathematical modeling of a manufacturing system quite challenging. In particular, it has not yet been possible to establish relations, in a set of closed form analytical equations, which could describe the dynamic behavior of a manufacturing system. The queuing theory, mathematical programming and optimization techniques have been used extensively, over the past years, for the purpose of modeling and analyzing production systems [3], however, understanding and controlling complexity by conventional methods, is becoming more and more difficult [4]. It is, therefore, apparent that the study of manufacturing complexity that will provide us the metrics and the analysis methods cannot rely only on the existing traditional approaches. During the last years, the complexity theory, including approaches such as the information theory, the chaos theory and the non-linear theory provide methods that seem to be useful for the analysis of a manufacturing system’s complexity.

Complexity can be divided into two types dependent upon the domain, namely the physical and the functional domains. In the functional domain, complexity is defined as a measure of uncertainty in achieving the functional requirements. This type of complexity is close to the manufacturing systems design and is further divided into time independent and time dependent [5]. Time-independent complexity is the result of not satisfying the functional requirements of a system at all times, including the uncertainty that arises because of the designer lacking in knowledge or understanding of the system and its components [2][5]. Time-dependent...
complexity, on the other hand, may be either combinatorial, increasing as a function of time, due to the continuous expansion of possible combinations of states with time, or periodic complexity, which exists in a finite time period, with a limited number of possible combinations of states [2]. In the physical domain, manufacturing complexity is also further classified into two types namely, static and dynamic [7]. Static complexity, also termed as structural complexity, is concerned with the system’s structure and configuration, the number and the variety of the products, the system’s variety of components, such as labors, machines, buffers, transportation mechanisms, their interconnections and interdependencies. Dynamic or operational complexity is related to the uncertainty of the system’s behavior for a specific time period and deals with the probability of the system to be in control [5][8].

This paper presents a review concerning the physical domain complexity of discrete manufacturing systems, focusing on production operations. The approaches that provide a theoretical framework of understanding and controlling complexity are only considered in this paper. These kinds of approaches are selected because they can provide an analytic, quantitative, systematic foundation for the understanding of a manufacturing system’s complexity.

In Section 2, the approaches and the methods of analyzing a manufacturing system’s complexity are presented. A taxonomy of the methods, based on the origins of their theoretical approach, is proposed. In section 3, the main advantages and drawbacks of each approach and method, as well as the main challenges of a future work, concerning the manufacturing systems’ complexity are discussed. The last section concludes the paper highlighting the main issues.

2. Manufacturing Complexity Analysis

In this work, there is a taxonomy proposing five categories, based on their theoretical origin. The first category is based on the methods and the concepts coming from the chaos theory and non-linear dynamics theory. The second category relies on the methods founded on the information theory approaches, having as a fundamental measure the Shannon entropy. The third category includes hybrid methods that attempt to address complexity by combining information theory approaches along with a coding system for machines and products. The fourth category concerns methods that cannot be directly classified into one of the above categories that address physical domain complexity and range from computational mechanics up to fluid dynamic analogies. In the last category, the approaches presented follow the complexity theory that is based on axiomatic design and are related to the functional domain complexity.

2.1. Chaos & Non Linear Dynamics Theory

The chaos and non-linear dynamical systems theory offers a solid theoretical and methodological foundation for interpreting a wide class of nonlinearity, instability and uncertainty that characterize the increasing complexity of systems [9]. According to the definition provided in [10], “Chaos theory is the qualitative study of unstable aperiodic behavior in deterministic nonlinear dynamical systems”. First, the term dynamical, indicates the evolution of the system over time. Second, unstable and aperiodic behavior is related to the absence of repetitive patterns. Third, the nonlinearity implies that the system does not conform to the principle of additivity, meaning that the output is not necessarily proportional to the input of the system. Fourth, the term deterministic means that the system does not include stochastic elements, although it presents an unstable and aperiodic behavior. Finally, a key characteristic of a chaotic system is its sensitivity to the initial conditions.

Chaotic systems may exhibit patterns that are well hidden and need to be discovered. These patterns are observed in the form of attractors. Phase portraits and the recurrence plot are two tools utilized in order to detect the attractors of chaotic systems. Lyapunov exponents and bifurcation diagrams are also used in order to detect a chaotic system and to measure its stability. The maximal Lyapunov exponent is often employed for obtaining a measure of the sensitive dependence upon initial conditions. Lyapunov exponents are the average exponential rates of divergence or convergence of nearby orbits in phase space. A system that contains at least one positive Lyapunov exponent is defined to be chaotic, and the magnitude of the exponent reflects the time scale on which system dynamics become unpredictable [11]. As it is already stated, a key characteristic of chaotic systems is their sensitivity to small differences in the initial conditions. For example, a delay in an order is a variable change, while selecting another dispatching rule of the system is a parameter change [12].

One of the first studies on the manufacturing systems complexity that introduces chaos concepts is [13]. Simulation models are employed in order to assess the effect of several factors on the output of wafer fabrication facilities. The system’s performance was evaluated using the distribution of throughput times and the patterns of interdeparture times. It is concluded that each of the investigated factors contributes to the complexity required for the onset of chaotic behavior. The behavior of complex systems is evaluated utilizing the chaos theory methods in [14]. The chaotic behavior
of a simple closed loop system is investigated through the phase plane trajectories, the Poincaré maps, the spectrum analysis, the phase graph analysis and the Sugihara May test and Lyapunov exponents. It is stated that although the spectrum analysis proved useful for its analysis, the proof of the existence of chaos should be based on the Lyapunov exponent testing. Similar in [15] the chaotic behavior of a simple production model is examined and production costs are optimized. The dynamic behavior of manufacturing systems with restricted buffer sizes is analyzed by means of the Poincaré maps and the bifurcation diagrams [16]. In [17] a product lot sizing method of chaotic demand is developed. Chaotic demand is identified using the maximal Lyapunov exponent and a modified Wagner method. The simulated model of a reentrant paint-spraying system for sheet metal is studied by means of non-linear dynamics [4]. In [19] the logistics networks of cooperating manufacturers are studied via discrete event simulation models and methods from non-linear dynamics. In [20] the effect of complexity on the performance of Flexible Manufacturing Systems (FMS) is evaluated and is related to the number of numerically controlled machine tools and robots present in each FMS. In [21] evaluation of the time series of the queue length was performed with the use of the Lyapunov exponents and the fractal dimension, as well as the spectrum analysis and the autocorrelation analysis. The non-linear dynamics of a simple production system are discussed, and the possibilities of assessing and regulating WIP levels are depicted [22]. In [12] the chaotic behaviour of several discrete production systems appearing in the literature is questioned. In [23] the scheduling of a simple manufacturing system, with the help of commonly used assignment rules, has been simulated first. The results have been studied with the help of phase portraits. A new dispatching rule, based on phase portraits, was proposed and tested against the aforementioned rules. It is argued that since there is no dispatch rule that has been found to perform best in all situations [3], different settings will have to be examined. Phase portraits are also used for the analysis of manufacturing systems, assembly systems in particular, in order for the impact of random processing time to be investigated into the inter arrival time patterns [25]. In [26], a model is proposed for assessing a manufacturing system’s adaptability to demand and the potential ways of investigating different adaptability policies demonstrated, by using a non-linear time series analysis tools, such as the bifurcation diagrams and the maximal Lyapunov exponents. In [8] a simulation-based approach for assessing the complexity of manufacturing systems in the execution stage is introduced. It takes advantage of ideas pertaining to the nonlinear dynamics, based on the maximal Lyapunov exponents, sensitivity and structural analysis.

2.2. Information Theory

A measure for the quantification of information, choice and uncertainty, in the context of the communication theory, is introduced in [27]. The entropy measure is used for the quantification of the uncertainty that characterizes manufacturing or the information required for the description of a system’s components. The machine states such as busy, idle, breakdown, product variety, and queue length are used as an input for the entropy assessment. Apart from the entropy measure, entropy rates are also used for the assessment of manufacturing complexity primarily for the dynamic complexity. The entropy rate is a Kolmogorov complexity measure that assesses the average growth of the Kolmogorov complexity of a random sequence [28]. The entropy rates in general, can be viewed as a time series analysis of the conditions of the manufacturing system’s components.

An assessment of a production and a commercial system’s complexity, based on entropy rates of queuing length is proposed in [28]. This work focuses on the dynamic characteristics of systems; therefore, the introduced measure is more related to the dynamic rather than the static complexity. In accordance to [7] the complexity assessed is viewed as the evolution over time of the defined queue and the state conditions of a resource. The entropy rates are computed following the Kolmogorov complexity of a random sequence. An entropic measure of the decision making complexity for alternative layouts and operating characteristics is introduced in [29]. The proposed measure is supported by an expert system that works as a mediator between the program and the organization. In [30], a measure of the supplier customer system operational complexity is proposed. Operational complexity is viewed as the uncertainty, related to managing dynamic variations in time or quantity across information and material flows. The introduced entropic measures similar to [29], aim to capture the queue variability in terms of length and composition. The work of [31] focuses on the manufacturing systems’ modelling of static complexity. In [28], the static complexity of manufacturing systems is understood as a function of the systems’ structure, the variety of components and the interconnections. The information required for the description of a system, i.e. structure, components and interconnections can be considered as the system’s static complexity and is assessed with entropic measurements. A measure of the manufacturing complexity for assembly systems is introduced in [32]. The proposed complexity measures are related to the product mix, the assembly system
complexity at station and system level and the supply chain complexity. The basis for their mathematical formulation is the Shannon theorem. Manufacturing complexity in human based assembly systems is also examined in [34], with a special emphasis given to the impact of complexity on throughput. Finally, this study [35] correlates the system’s complexity with the assembly throughput. They provide an example of simple serial, parallel and hybrid assembly lines verifying the positive correlation between complexity and throughput.

2.3. Axiomatic Design Theory

In [5], complexity is considered as “the measure of uncertainty in satisfying the aims (functional requirements) of a system”. In terms of manufacturing, the objective is that productivity can be maximized by reducing the complexity of the manufacturing system, following a process called “Design-Centric Complexity (DCC) theory”.

2.4. Other

In [36], the Reynolds number concept was introduced to a manufacturing system as an indicator of complexity. The aim was the identification of the transition regime between the behavior of steady and turbulent manufacturing operations in analogy to laminar and turbulent flows. Similar concepts having derived from the same Reynolds analogy were also proposed [37] for supply chain and in [38] for manufacturing systems. In [39] another classification of complexity is proposed: time-related, organizational and systemic. Each type is represented by a vector that assesses the complexity manufacturing system. The three types can be seen as three axes, thus creating a complexity cube.

In [40] there is a method proposed for the assessment of dynamic complexity, following the notions of statistical complexity. Dynamic or operational complexity, as it is termed in this study, is determined as the difficulty of predicting a sequence. This definition is very close to the [41][42] that dynamic complexity of manufacturing systems can be understood as the unpredictability of the manufacturing system’s performance indicators. In [40] the statistical complexity is estimated by analyzing finite lengths of the symbolic sequence of inter departure times by utilizing the Causal-State Splitting Reconstruction algorithm. In [41][42], the assessment of unpredictability is based on the analysis of the performance indicators timeseries, with the use of the Kolmogorov Lempel Ziv [43] complexity measure algorithm. The approach is validated through an example of two simple manufacturing systems, exhibiting unpredictable behavior, due to stochastic breakdowns. The efficacy of the approach is presented with a case study from the automotive industry. A weak but positive correlation, between the product mix and the complexity, is observed. The lower the product mix ratio is the lower the unpredictability.

2.5. Hybrid

A hybrid approach, following a combination of the entropy measure, based on the information theory, as it is described in the relevant chapter and a heuristics index based method is proposed in a number of studies [44][45]. In [46] product complexity is modelled as a function of the product information entropy and a product manufacturing complexity index and represents the complexity of a product, associated with the material, design, specifications and components. In [47], the approach introduced in [46] is also applied to the case of operational complexity when considering human characteristics. The complexity of manufacturing systems is investigated in [44] by introducing a structural complexity measure, based on the manufacturing systems’ coding, and on an information entropy measure that takes into consideration the availability of the system. The two approaches, followed in [44] are integrated into one complexity measure in [47]. Alternative configurations are assessed presenting different results of the complexity measure, showing that the proposed measure is sensitive to changes in manufacturing system configuration components and their relationships.

3. Discussion and outlook

The approaches that are based on the chaos and the non-linear dynamics theories were originated from the work of [13] in 1994. Since then, a lot of studies have been presented trying to identify and measure chaos in manufacturing systems. As it is noted in [12], the presence of chaos in discrete manufacturing systems, in a strict theoretical sense, has not been solidly proven. A number of works [14][18][26] identify chaos in manufacturing systems by utilizing the maximal Lyapunov exponents, but they have arbitrarily modelled the manufacturing systems utilizing the logistic function for a range of parameters that indeed exhibit a chaotic behaviour. In addition, the methods based on the chaos and the non-linear dynamics theories, such as the maximal Lyapunov exponents, the bifurcation diagrams and the phase portraits are capable of identifying and measuring only chaos. However, a manufacturing system may present unpredictability, due to the stochastic nature system, e.g. machine breakdowns, but this stochastic behaviour can not be identified by chaos.
theory. Furthermore, even if the manufacturing system is chaotic, it can be measured by the maximal Lyapunov exponents but not by the bifurcation diagrams of phase portraits. The maximal Lyapunov exponents method provides a quantitative measurement, a specific value that can be easily compared with the values of other systems and it can be considered as a complexity metric, for dynamic complexity. In contrast to the maximal Lyapunov exponents method, the other two approaches are restricted to presenting the system’s irregularity in a schematic way only. However, any future work can be based not only on the strict approaches but also on the notions of the chaos theory and provide a series of metrics that can measure dynamic or static complexity [8].

Information theory approaches have been extensively applied to the assessment of static and dynamic complexity. Entropy based measurements are employed for the assessment of static complexity, but they require the definition of the different states of a system’s components, whilst a series of assumptions related to the independence of the system’s states should also be made. Moreover, a complexity value by itself does not provide any contribution to the understanding of the manufacturing system. Dynamic complexity, also termed as operational complexity, is assessed with the help of entropy rates. In contrast to the Shannon entropy, entropy rates are randomly applied and do not rely on specific assumptions about underlying probability distributions [28]. Moreover, the dynamic complexity assessed with entropy rates provides an almost direct insight of the manufacturing systems’ performance, by facilitating the identification of bottlenecks [28]. Although there is not a direct connection between the static complexity and the manufacturing systems performance, there are a number of studies that attempt to provide a relationship between them. Complexity is associated with the throughput in [34] in the context of the investigation of mixed assembly systems. Although such connections, between the manufacturing performance and complexity are ad hoc and lack in generality, they can be considered as a first step.

Hybrid approaches share the same difficulties with the information theory approaches, since they are mainly based on the Shannon entropy for the assessment of complexity. In addition, the introduced codes that are used by the hybrid methods do not cover the entire area of manufacturing systems. Therefore, such approaches are restricted to the area that has been covered so far. However, taking into account the increase in the standardisation of manufacturing systems, the hybrid approaches can be considered as promising. Finally, the proposed metrics, based on hybrid approaches, may be more preferable for the assessment of a “complicated” system rather than a “complex” one [44].

Other approaches include the fluid dynamic analogies, complexity cube, computational mechanics and Lempel Ziv complexity. The approaches inspired by fluid dynamics are still at an early development stage and they do not provide any quantitative measurement either of static or dynamic complexity. They remain only at a conceptual analogy level between manufacturing systems and fluid dynamics that need to be further explored. The complexity cube is an interesting approach, whose metrics are restricted to counting the number of machines in a manufacturing system. Computational dynamics and the Lempel Ziv complexity approaches seem to share the same understanding on dynamic complexity. In both approaches, the dynamic complexity is understood as a system’s unpredictability and in [41][42], there is emphasis on the way of assessing complexity by calculating the unpredictability of performance indicators time series.

4. Conclusion

In this paper, the main approaches and methods that provide an analytical assessment of manufacturing complexity, in the physical domain, have been presented. Four main categories of approaches are identified on the basis of their theoretical foundations, namely chaos and non-linear dynamics theory, information theory, hybrid, and other. The complexity theory, based on the axiomatic design theory, is also included in the proposed taxonomy due to its high significance, although it is mainly applied to the functional domain. Special emphasis has been given to the application approached apart from the description of the theoretical background. The advantages and the drawbacks of each approach have been discussed, and the main future challenges have been proposed. In particular, the need for developing a connection between the performance of manufacturing systems and the complexity metrics has been identified and highlighted as one of the future challenges.

References
