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# Complexity in engineering design and manufacturing

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ABSTRACT

This paper reviews the breadth of complexity of the design process, products, manufacturing, and business. Manufacturing is facing unprecedented challenges due to increased variety, market volatility and distributed global manufacturing. A fundamental residue of globalization and market uncertainty is the increasing complexity of manufacturing, technological and economic systems. The nature and sources of complexity in these areas are reviewed and complexity modeling and management approaches are discussed. Enterprises that can mitigate the negative aspects of complexity while managing its positives should thrive on the continuous change and increasing complexity. To reap these benefits in the future, manufacturing companies need to not only adopt flexible technical solutions but must also effectively innovate and manage complex socio-technical systems.



## 1. Introduction

Increasing complexity continues to be one of the biggest challenges facing manufacturing today. It is manifested in products and manufacturing processes as well as company structures [162]. These systems operate in an environment of change and uncertainty.

The subject of this keynote paper is related to the complexity of the artifactual world humans have created. The breadth of complexity research in engineering is reviewed for a broad readership and with particular emphasis on engineered products and manufacturing. Engineers are justly proud of the many inventions and manufacturing technologies for which they are responsible. In the past, Henry Ford's zero complexity approach to automobile production proved to be a breakthrough, with the assembly line and mass production that have revolutionised the industry. Since then, many manufacturers have attempted to compete using this model of reducing or eliminating real and perceived complexities. This as well as other reductionist approaches, which were critically successful at a period of time of the development of industrialization, have reached their limit. The methods used by engineers to design, produce, and operate systems in the mid-to late twentieth century are insufficient to deal with the challenges of the future. The fierce global competition has focused on innovation and creating high value-added products at a competitive price in response to customer demands. The challenges facing industry now are characterized by design complexity that must be matched with a flexible and complex manufacturing system as well as advanced agile business processes. This is particularly true for manufacturers of high value, complex products that are multi-disciplinary in nature. This is quite a broad category as most industrial and consumer products these days are complex.

### 1.1. Sources of complexity

Modern complex products or equipment may have many thousands of parts and take hundreds of manufacturing and assembly steps to be produced. Most complex products and equipment now incorporate not only mechanical and electrical components but also software, control modules, and human–machine interfaces. Some equipment is connected on-line to the World Wide Web and "the internet of things" [10] for real time reporting and diagnostics. Although these additions have made equipment more versatile and dependable, significant complexity has been introduced to the product design [64]. Manufacturers have often responded to the challenges of globalization with mergers, consolidations and acquisitions. Fig. 1 illustrates the drivers and enablers for manufacturing complexity. Economic, technological and social aspects are included.

### 1.2. Perspectives on complex systems

Several different measures defining complexity have been proposed within the scientific disciplines. Such measures of complexity are generally context dependent. Colwell [27] defines thirty-two complexity types in twelve different disciplines and domains such as projects, structural, technical, computational, functional, and operational complexity. Systems complexity is invariably multi-dimensional. A complex system usually consists of a large number of members, elements or agents, which interact with one another and with the environment. They may generate

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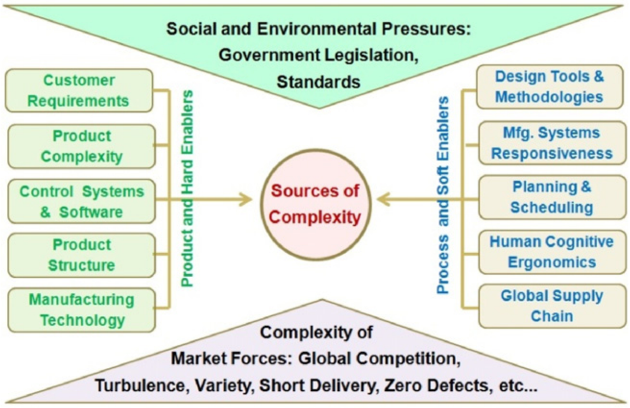


**Fig. 1.** Drivers of manufacturing complexity.

new collective behavior, the manifestation of which can be in one or more of the following domains: functional, structural, spatial, or temporal. A complex system is an 'open' system, in the thermodynamics sense, involving entropy principles, as well as involving nonlinear interactions among its sub-systems which can exhibit, under certain conditions, a degree of disorderly behavior. In particular, the future progression of events may become very sensitive to conditions at any given point of time and 'chaotic behavior' may emerge. For engineered systems, three views of product development complexity need to be considered [53]. The three relevant product development domains are product, manufacturing system and business organization. In this paper we consider complexity in each of these three domains.

Complexity in engineering design and/or manufacturing as well as operations management and global complex supply chains, has been the subject of numerous papers, Ph.D. dissertations and master theses in the last few years [1,4,5,7,19,20,22,32,36, 38,40,42,56,57,60,61,63,77,82,83,86,93,94,96,97,106,112,119,121, 129,139,141,156,160,165].

The state of the art and the research literature in complexity is reviewed from three perspectives: (i) complexity of engineering design and the product development process, (ii) complexity of manufacturing processes and systems, and (iii) complexity of the global supply chain and managing the entire business, as well as their intersections as illustrated in Fig. 2. Several textbooks in these areas have been published in recent years [17,34,54,65,79,89,98, 105,115,132,137], as well as several book chapters [13,35, 113,114].

## 2. The nature of complexity

The meaning of the word "complexity" is vague and ambiguous; there is no universal, precise (e.g., formal) and widely

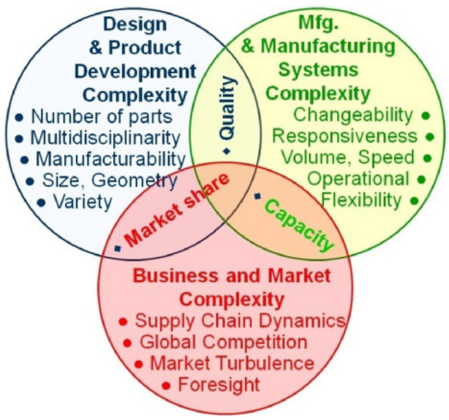


**Fig. 2.** Complexity of the design, manufacturing and business with examples of related the sub-topics.

accepted definition of it. The original Latin word "complexus" signifies "entwined" or "twisted together". This is similar to the Oxford Dictionary definition of "complex" as something that is "made of (usually several) closely connected parts". A system would be more complex if more parts or components exist, and with more connections in between them.

### 2.1. Computational and information complexity

*Computational complexity* is measured by the quantity of computational resources (e.g., time, storage, program, communication) which is required for solving a particular task. Here, the Turing-machines are used as a fundamental tool for analyzing algorithms and combinatorial optimization problems. The complexity of a structure is defined in the *Kolmogorov's complexity* [87] as its minimal description length, e.g., by a program on a universal Turing machine. Some other complexity measures, e.g., time-complexity, space-complexity and, for distributed systems, communication-complexity are associated with algorithms, e.g.,: Lovász and Gács [90].

Computational complexity comes from the number of elements (subsystems, components, or parts). This complexity becomes problematic, when the number of elements ($N$) grows, because the same algorithm that was able to solve a problem for a smaller $N$ cannot solve one for a larger $N'$ in a reasonable time (or with using reasonable memory). For example, assume every element in a system has a direct relationship with all other elements. The computational complexity in terms of the number of relationships in this case is $O(N(N-1)) = O(N^2)$, which is called polynomial complexity ($O(N^a)$, in which a is a positive constant). Practically, it is well known that computational complexity grows very quickly, when the complexity is $O(a^N)$ (exponential), $O(N!)$ (factorial), or $O(N^N)$ (double exponential). These are called non-polynomial (NP) complexity as opposed to polynomial cases (P). Some NP complexity classes (NP-complete or NP-hard) are known to be difficult or even impossible to manage and solve. In manufacturing, NP-complete problems can be found, for instance, in production planning problems and logistics problems. See [9,28] for further information about theoretical aspects of computational complexity.

### 2.2. Dealing with computational complexity

To deal with computational complexity, there can be three approaches. Reducing the number of elements is the most effective approach. However, this might not be always easy or even possible. The Divide & Conquer principles bundles elements into a manageable unit, although this principle might not directly reduce the number of elements. For example, rather than directly dealing with all elements in a flat organization, introducing an organized (hierarchical) organization would be a solution. However, this principle works well only when subsystems are independent and self-contained and no interactions among them (as a bundle of elements) exist except through well-defined interfaces.

When applied to product design, this approach leads to modular architecture rather than the so-called integral architecture [12,130,152]. There is a substantial number of reports on modular architecture that has advantages and disadvantages in dealing with complexity, cost, design quality management, variety, manufacturing, supply chain, risk management, and life cycle aspects, e.g., [55,109,154]. For further discussions about complexity and product architecture, see Sections 2.6 and 3.5.

Not only product architecture but also production architecture (organization) can be modular. For instance, in the aerospace industry before the end of the 1990s, typically an aircraft manufacturer had 2000–3000 suppliers to deal directly with. This number had a substantial impact on cost as well as lead-time of product development, supply chain management, and eventually production. To this end, the aerospace industry as a whole was forced to modify their supply chain structure to a more hierarchical one, with a handful first-tier suppliers down to third and fourth-tier suppliers. This reduced complexity to a manageable level by decreasing the number of suppliers the aircraft manufacturer had to deal with and by transferring the supply chain management responsibility of the second tier suppliers to the first tier suppliers, of the third to the second, and so forth. While this revolutionized aircraft production by allowing more modular production to be distributed on a global scale, it also resulted in drawbacks, including reduced transparency, traceability and controllability of the supply chain hierarchy.

### 2.3. IT solutions to deal with computational complexity and topological complexity

The third approach to deal with computational complexity is the application of intensive IT solutions. For example, if there are too many elements in the system or process that cannot be managed easily manually or semi-manually, then a practical solution is to introduce IT systems that can handle them (almost) automatically. Good examples are CAD, CAM, and CAE systems that help designers to define, manipulate, operate, and calculate design information. In addition to these "core capabilities", Product Data Management (PDM), Product Lifecycle Management (PLM), Enterprise Resource Planning (ERP), and Customer Relation Management (CRM) facilitate management of data, information, and knowledge throughout product life cycle in an enterprise context. These IT solutions help to tackle computational complexity, but it must be also noted that they have pitfalls if sufficient attention is not paid to computational complexity. For instance, total data amount currently required to define the complete geometry of a passenger car body is up to terabyte order. It is easy to imagine that data of this scale can create storage, processing and communication problems, because such IT solutions tend to lead to "proliferation of information" which increases complexity beyond a manageable size. Information complexity, similar to uncertainty complexity, i.e. entropy, tries to measure the randomness or disorder of objects. The amount of uncertainty about an event associated with a given probability distribution is characterized by information entropy, per Shannon [127]. The complexity of abstract algebraic structures, such as groups and semi-groups can be characterized by using the concept of homomorphism and wreath products (Krohn-–Rhodes complexity, introduced in the 1960s).

*Topological complexity* is used by the graph and network theories. The *complexity of such structures* can be described by symmetry-based measures frequently applying the concept of entropy, or by other measures including average- or normalized-edge complexity, sub-graph count, overall connectivity, total walk count, and others based on adjacency and distance.

### 2.4. Complicatedness, complexity and chaos

In simple terms for now, a simple system or artifact is easily knowable. A complicated system or product is not simple, but is knowable, e.g., a car is a complicated product/system. A complex system is one where uncertainty exists. For instance, the development of a car is complex; it requires engineering business knowledge in several disciplines, and collaborative work in teams. Details are not fully knowable to each development engineer. A complicated system could refer to a system having many parts, making it somewhat harder to understand, perhaps by virtue of its size, whereas complex refers to a system containing uncertainty during the development process or intrinsically in its design, the outcome not being fully predictable or controlled. Complexity may also be at the operational level such as during the manufacturing process itself. What is complicated is not necessarily complex, and vice versa, and what is complicated for one person, may be complex for another less knowledgeable individual or a group with less technological tools (Fig. 3).

In chaotic systems, small differences in initial conditions yield very different outcomes. Chaotic systems are difficult to manage and control, and long term prediction is generally impossible. A classical example is tacit knowledge which is made explicit when a scientific explanation is discovered. With this scientific knowledge and other engineering methods and tools, unexplained phenomenon become difficult, as opposed to complex or chaotic [115].

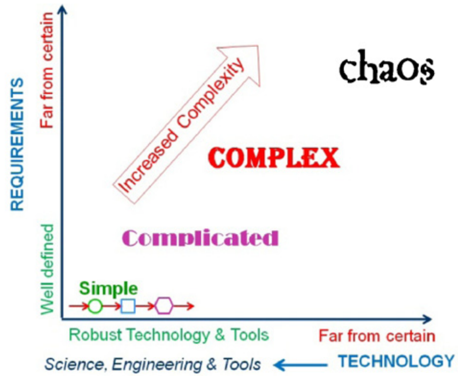


**Fig. 3.** The spectrum of process complexity.

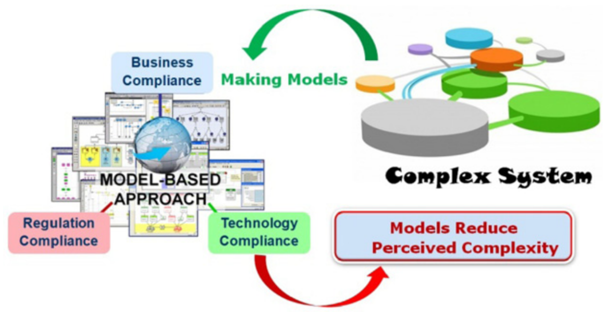


**Fig. 4.** Engineering approach to reducing the perceived complexity.

An application in manufacturing is machining chatter, a complex phenomenon, which could become chaotic if not for the work of industrial and academic researchers. Scientific theories have been researched, and practical applications proposed to control the vibrations, and eliminate the initiation of self-generated vibrations in conventional and high speed machining [6]. In general in engineering as we design new products and systems, we utilize science, and engineering methods and tools to manage the complexity by transforming the problem from complex to manageable and controlled. This then allows the elimination of the "perceived complexity", as illustrated in Fig. 4.

### 2.5. Complexity in engineering

Each field of science and engineering defines and views complexity in different ways in the absence of a unifying concept or general complexity theory. CIRP papers have addressed different aspects of complexity. Fig. 5 shows the CIRP keywords frequency. This is contrasted with the number of papers published in the related sub-fields of Design, Operations Management, Manufacturing Systems, and Sustainable Development in engineering published papers. These words were in either the keywords and/or the paper title. Fig. 6 illustrates the number of published papers in these categories.

As a result of the multi-disciplinarity and complexity of both the product development and manufacturing processes and their systems, several scientific technical committees (STCs) and working groups (WGs) within CIRP have researched complexity in design and manufacturing from several perspectives. These are illustrated in Fig. 7.

Researchers have studied complexity in engineering from different perspectives and with different foci. The source of complexity may be due to: (i) size, (ii) coupling, (iii) variety, and (iv) multi-disciplinarily. The type of complexity may be classified

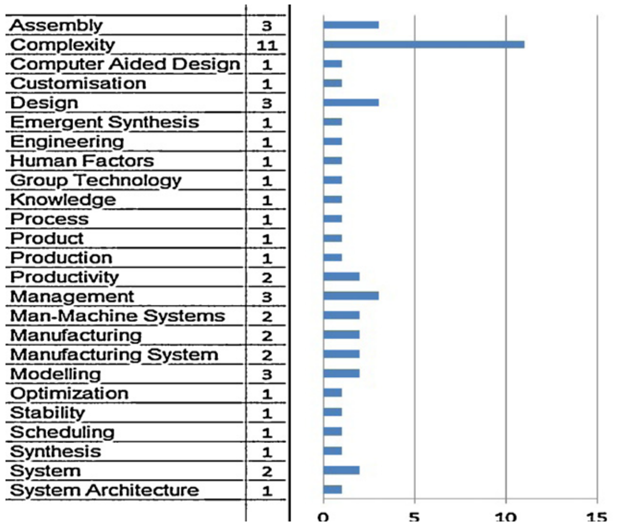


**Fig. 5.** CIRP keywords frequency in Annals papers published in years 2000–2011.

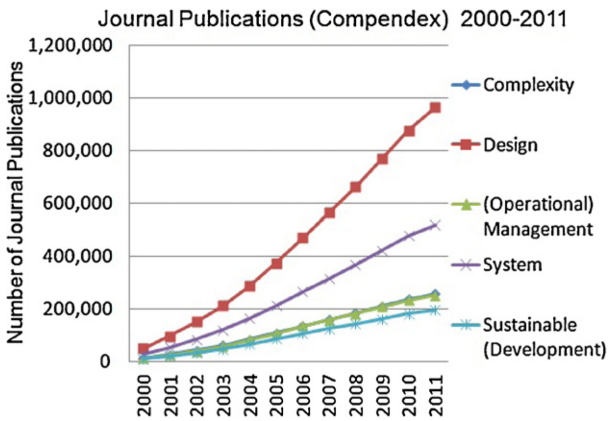


**Fig. 6.** Papers published years 2000–2011 (cumulative from Compendex).

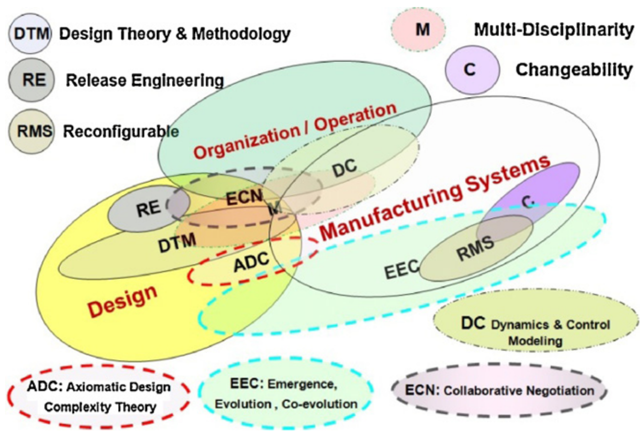


**Fig. 7.** Complexity related CIRP working groups and topics.

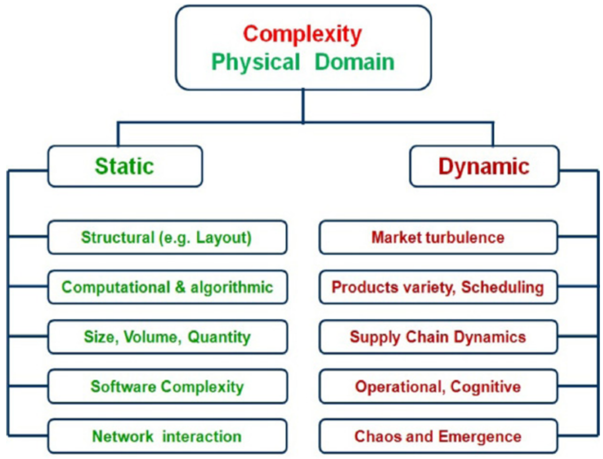


**Fig. 8.** Classification of engineering design and manufacturing complexity in the physical domain.

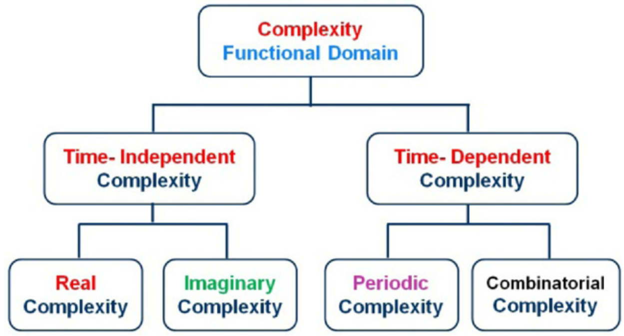


**Fig. 9.** Classification of the various types of complexity in the functional domain.

as: (i) static or (ii) dynamic. Static complexity is defined as the expected amount of information necessary to describe the state of an engineered system. Dynamic complexity is the expected amount of information necessary to describe the state of a system deviating from its design performance due to uncertainty. This classification of complexity in the physical domain is illustrated in Fig. 8.

The scope of complexity may be classified as: (i) part, (ii) product, (iii) system, and (iv) system of systems such as socio-technical systems. The research publications on complexity in engineering are divided into two groups: the first treats engineering complexity in the physical domain and the second treats complexity in the functional domain, e.g., the axiomatic design complexity theory. The latter [137] promotes the idea that complexity must be defined in the functional domain as a measure of uncertainty in achieving a set of tasks defined by functional requirements. This complexity theory aims to reduce the complexity of any system by taking the following actions: (i) minimizing the number of dependencies; (ii) eliminating the time-independent real complexity and the time-independent imaginary complexity; and (iii) transforming a system with time-dependent combinatorial complexity into one with time-dependent periodic complexity by introducing functional periodicity and by reinitializing the system at the beginning of each period. This theory has been successfully applied in the design of engineered systems including in manufacturing. Fig. 9 shows the classification of the various types of complexity.

Kim [75] illustrated the four causalities of complexity with respect to the design axioms (Fig. 10). Type I complexity is a result of heavy coupling of the functional requirements, which is a violation of the independence axiom. Time-independent complexity is a type II complexity and is a result of the information axiom violation. Time independent imaginary complexity is a type III complexity, which is a result of lack of understanding about the system. Time-dependent combinatorial complexity is a combined result of Type I, II, and IV complexities. Time-dependent periodic complexity is a smaller scale complexity.

While researchers adopting the axiomatic complexity theory argue that engineers should constantly be working to reduce the complexity of engineered systems to make them more robust, other disagree with this approach, and argue that the engineered system design should advocate complexity as a way to generate novelty and nurture creativity [158]. Indeed, chaos and bifurcation theories have been proposed as means for qualitative, structural

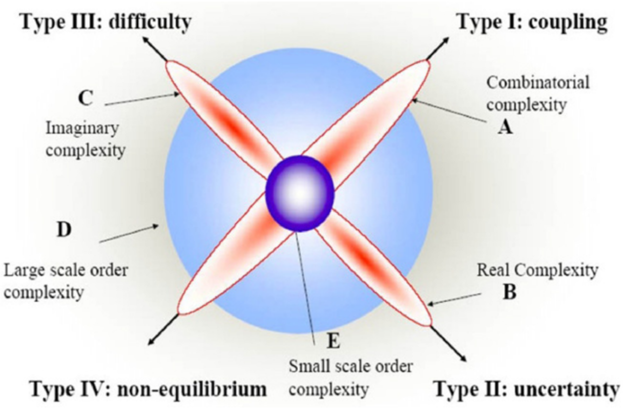


**Fig. 10.** Causality-based complexity radar chart [75].

changes in mathematics and social sciences, and creativity in engineering.

Furthermore, the researchers pursuing complexity research in the physical domain see its merit as being able to observe, model, manage and control phenomenon that do occur in the physical domain. Although complex systems are frequently unpredictable, they also often exhibit precise regularities and patterns that can be used to create strategies which can deal with uncertainty, reduce risk, and expand opportunities of contemporary business. This was observed with the support of an industrial case study by Buchanan [18]. In the model production management control is represented by a control function, which reflects the strategy used to adapt to varying demands and supplies Helbing et al. [66,67]. It was noted that a small change in strategy may have a large effect and increase the time required to adapt production rates to a changed demand. Finding the right strategy, in the context of any particular supply line, requires a detailed exploration of its dynamics, most likely based on computational simulations. In a reported industrial case study, while studying the scheduling conflict in the manufacturing line for semiconductors such exploration resulted in high dividends, when a counterintuitive, but highly successful scheduling strategy, that increased chip throughput by 30% was discovered [18]. Deif and ElMaraghy [35] used a control theoretic approach to research, plan and control the capacity of a dynamic and agile manufacturing systems, and demonstrated good results.

Peklenik [114] has proposed that the complexity of manufacturing systems be treated using cybernetics and feedback control. The complex manufacturing system is broken down into Elementary Work Systems (EWS), to which the concepts from control theory and information theory are applied to control the production processes. Ueda et al. [149] emphasized the importance of emergence for solving synthesis problems in manufacturing. Schuh and Eversheim [124] presented an approach to manage increasing system complexity of automotive systems, using "release-engineering" which is a methodology used in software engineering. Without reduction of the variants required by the market, a time-bundling strategy of component changes exponentially reduces the product planning and production system complexity. Papakostas et al. [110] investigated the stability of complex manufacturing systems, using discrete event simulation and nonlinear dynamics theory. With this approach, they were able to determine the sensitivity of a manufacturing system to workload changes and measure its complexity. Vrabic and Butala [159] presented a computational mechanics assessment and strategy for managing manufacturing systems complexity, illustrated with an industrial case study. The results suggest a clear relationship between complexity and throughput, and the impact of the tools used on managing complexity.

ElMaraghy and Urbanic [52] researched the effects of human worker attributes in relation to the complexity within the manufacturing system. They introduced a methodology for systematically modeling the product and process complexity for any manufacturing environment. They showed that to be effective, the system must balance human characteristics, needs, skills and capabilities within the technical and business environment. They developed a complexity model based on three elements: (i) total quantity of information, (ii) diversity of information and (iii) the information content which corresponds to the effort to produce a feature within a product. ElMaraghy and Urbanic [44] also addressed the manufacturing operational complexity. A systems analysis and design approach was utilized to integrate manufacturing technologies with the capabilities of human workers, in order to augment the performance of both. A framework and matrix methodology was created with a focus on realistic factors within the manufacturing environment such as information quantity, diversity and content; complexity (product, process and operational), task effort, and so forth. The developed models and metrics assess the three levels of manufacturing complexity: product complexity, process complexity and operational complexity. The latter includes modeling the operators' cognitive ergonomics and reaction time due to fatigue and environmental conditions. ElMaraghy et al. [47] developed a complexity coding system to classify and code the machines, buffers and material handling equipment that make up manufacturing systems. The code captures the amount and variety of information. The probability of a manufacturing system success in delivering the desired production capacity, as function of the availability of its components, is used as an additional measure of the system ability to meet the targeted forecast production volume with its variation, as a measure of complexity.

Hu et al. [70] presented a model for assembly systems and supply chain complexity in response to product variety. Assembly system design for product variety was also reviewed in a recent CIRP keynote paper [71]. In assembly systems, as in all manufacturing systems, the complexity may cause human errors and in turn impacts the manufacturing system performance. Complexity is defined as an entropy function of product variety. Wang and Hu [161] presented a measure of manufacturing complexity based on the choices of assembly activities that operators make in serial, manual mixed-model assembly lines, in response to the products variations.

### *2.6. Complexity of the product development process*

It is well known that companies that have a substantial edge in product development bring new products to market more quickly, consume fewer resources, and deliver higher quality designs, and therefore give much better returns to their share holders and the economy at large. Today and into the foreseeable future, companies that can successfully manage the product development and manufacturing of complex engineering products will have a definite competitive edge. Consequently, controlling and handling complexity in product development processes has turned into an important issue, as process diversity increases with the quantity of product variants and process steps become ever more intensely interconnected. The product development complexity, for complex products, has also continuously increased, and yet it has not been satisfactorily addressed in literature and practice. The quality problems and recalls in today's car industry give a striking example. Service engineering is also becoming a critical aspect of product design and development. Fig. 11 illustrated the integrated design and development of complex mechatronic and smart products.

As shown in Fig. 12, companies organizational structures, market, process and product complexity are interrelated. Market demands, product diversity and flexible business processes require new concepts and strategies in organizational design to meet increasing interdependencies between people acting in the development process [88]. Product adaptations, as they are required by product individualization or mass customization, affect all aspects of product generation and require appropriate complexity management.

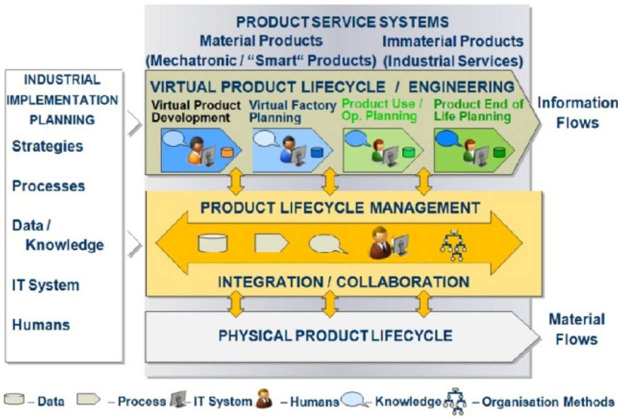


**Fig. 11.** IT in mechanical engineering research fields [3].


**Fig. 12.** Interactions in product development.

Summers and Shah [138] described the design process as an iterative problem solving process in which the designers typically externalize the design problem, process, and product. A model is built and then the adopted design process is used to find solutions satisfying the functional requirements. The resources of the process may include designer experience, rules, procedures, or domain knowledge used. The paper surveys and evaluates different approaches for defining complexity in the design process and the product. Three aspects to complexity are identified: size, coupling, and solvability. The methods are discussed with particular reference to parametric and geometric problems for "embodiment" design.

In today's highly connected technology-driven economy, the production industry must rely on the best practices of collaborative engineering to stay competitive when designing, manufacturing and operating complex machines, processes, and systems on a global scale. Designing complex technical systems is critical for sustaining a healthy economy, and innovation is one of the keys to success in engineering and business.

Given that the design process from conception, to embodiment and detail design, is complex, Lu et al. [91] proposed a new design paradigm capable of addressing and managing the complexity of design. The paper reports on collaborative efforts in developing a scientific foundation for Engineering as Collaborative Negotiation (ECN) based on a research hypothesis derived from observations of engineering teamwork, a socio-technical framework and a process to achieve participative joint decisions, and some implementation possibilities to make them operational. Collaborative engineering is the application of collaboration sciences to the engineering domain to accomplish complex technical tasks, which is the challenge currently faced by the engineering community including industry. Fig. 13 illustrates the Nature of Knowledge and Decisions in Collaborative Engineering.

Tichkiewitch and Pimapunsri [116,142] consider that a design problem is not complex, only solutions can be complex or non-complex. They describe a way to design non-complex products using integrated design, based on the just need notion. Actors

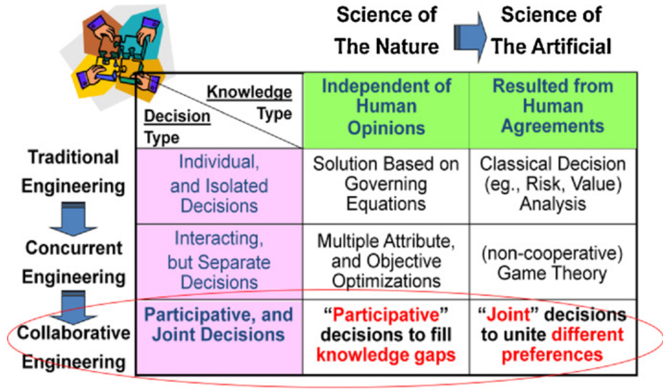


**Fig. 13.** The nature of knowledge and decisions in collaborative engineering [91].

involved in the life cycle of the product have to intervene in the design process as soon as they can specify a constraint but only if they can confirm the need for this constraint.

Most approaches for controlling product complexity focus primarily on its reduction [124,136]. Although it serves a purpose to avoid unnecessary complexity, it may not be advantageous to reduce complexity at any cost. Complexity often relates directly to attributes relevant to the customer; thus complexity reduction may decrease competitiveness. If a competitive product permits customization, it will appeal to more customer groups than a standardized product.

Another positive aspect of controlled product complexity is its use as a barrier to product plagiarism [88]. Competitors can imitate the specifications of the product delivered to the market; however, they cannot copy the core competence. Furthermore the understanding of the product structure is essential when interacting with a complex system. For example, system robustness is a feature that consists of a comprehensive combination of system elements. The demand for robust systems is directly related to the control of its complex interdependency network. Hence, the ability to control complexity rather than reducing it can be seen as a major competitive advantage.

Modern product design is characterized by shortened development cycles. Newly arising requirements are mostly realized by adapting existing products. The changes resulting from such adaptations may have an unexpected impact on a number of interrelated components. If such impact is not considered at the beginning of the development process, delays due to required iteration loops are inevitable. An effective system for controlling complexity permits the prediction of change impact that previously would have gone unnoticed [89]. One major requirement for defining such robust systems is to identify significant structural characteristics and then to derive suitable measures. Managing and controlling complexity in product development requires the understanding of the types and sources of complexity and developing appropriate metrics and methodologies for sustainable competitiveness. These include the introduction and application of innovative and scientific systematic engineering design methodologies as well as new collaborative engineering methods, e.g.,: using "Inventive Problem Solving – TRIZ" [74], design for manufacturing [120], and "Engineering Collaborative Negotiation – ECN – paradigm" within the general systematic design approaches. A framework for this was developed by [91]. Deloitte [37] completed one of the largest global manufacturing benchmarking initiatives, entitled "Mastering Complexity in Global Manufacturing", it shows that what most companies and industry analysts fail to realize is that "big and complex" can prove to be more profitable than "small and simple". The report states that a small number of global manufacturers that are known as "Complexity Masters" have managed complexity and have reaped the benefits of healthy profits and greater market share as well as good returns on capital investments.

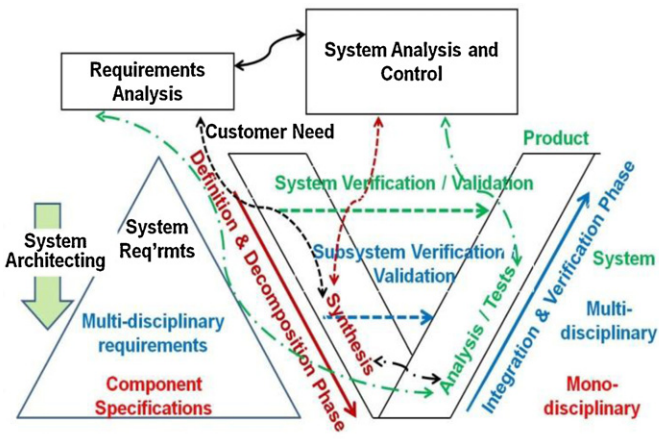


**Fig. 14.** The complex product/system development process V-model.

## 2.7. Framework and methodologies for complex product development and architecting

ElMaraghy [51] proposed a holistic design framework and architecture that is essential for product development of complex products from creativity to final design detailing. This process and architecture is an extension of the Zachman enterprise architecture framework [163] that was created to support the development of software.

In order to show bottlenecks of multidisciplinary design, we refer to two well-known procedures for product development: the V-model [58] and Muller's pyramid [105] as illustrated in Fig. 14. The V-model is divided into two paths. The left path represents the design phases and the right path represents the verification phases. For each design phase there is a corresponding verification phase. The right path of the V-diagram corresponds to integration and verification, which are later design phases where prototypes of the product are made and tested. Product architecting for modularization of products is a crucial concept for modularization and substructuring, and methods and metrics for automating this process are required.

In manufacturing, there exist cases in which geometry, topology, manufacturability and assembly factors cannot be estimated in the early stages. This may be possible through finding similar products. Jenab and Liu [73] conducted research aiming at developing analytical models to estimate the manufacturing complexity of a product. A method based on a utility function, has been developed and a design structural matrix (DSM) was constructed to relate the product design to needed skills, resources and costs. The case study was for a jet engine.

## 2.8. Complexity in manufacturing processes and systems

There are many different examples and methods dealing with complexity in manufacturing processes. Complexity in manufacturing processes is categorized as: (i) complexity of manufacturing complex parts, (ii) complexity in assembly, as well as (iii) combinatorial complexity costs due to product variety. The difficulty of particular manufacturing processes is related to the shape complexity of the manufactured components, and the number of additional processes required to achieve a specified tolerance or surface finish. The tolerance, size, material properties are also factors affecting the selection of particular manufacturing processes and technologies. The choice of manufacturing processes is also dependent on the formability properties of the component material as well as the minimum section thickness.

Manufacturability complexity is quantified through analyzing the assembly of a product using such methods as design for assembly (DFA), which have demonstrated reported success in reducing the assembly costs. Design for manufacturing (DFM) methods [117] have been developed to reduce the complexity and cost of manufacturing. These methods aim at evaluating and calculating a 'manufacturing index' to enable a simple comparison of alternative designs. The design for assembly methods generally suggests a reduction in the number of parts, with the possible result of increasing shape complexity of resulting composite parts. The difficulties and costs associated with the manufacture of complex shape parts are directly related to the number of types of manufacturing process required, the number of faces requiring each manufacturing treatment and the number of tool or orientation changes required during each phase of the manufacture. For example for manufacturing of small complex shapes, the metal injection molding (MIM) process competes favourably and economically with other traditional processes, such as machining [62]. In general, the process is particularly suited to small components, typically less than 100 g, and can produce complex-shaped, high-density, and high-performance metal parts at a low cost. MIM also enables the production of components with a density of up to 95–98%, a level of densification that is impossible with wrought materials from conventional powder metallurgy. The density improves the mechanical properties of the components, which in turn results in higher mechanical strength and ductility. Traditional metalworking processes often involve a significant amount of material waste, which makes MIM a highly efficient option for the fabrication of complex components consisting of expensive/special alloys: Cobalt-chrome, 17-4 PH Stainless Steel, and now Titanium as well.

Many manufactured parts are made of materials that have to withstand cyclic loading during their use. In materials with limited ductility, once a crack nucleates, it can continue to grow under cyclic loading until it becomes an unstable crack, leading to fracture of materials. This type of failure of materials due to crack propagation is an example of time-dependent combinatorial complexity. To prevent the crack propagation and fracture of materials, functional periodicity can be introduced to these materials to transform a system with time-dependent combinatorial complexity into a system with time-dependent periodic complexity [136]. This concept was utilized to produce microcellular plastics, where the periodicity is introduced in the material by tiny bubbles that are uniformly distributed throughout the material. Microcellular plastics technology was developed at MIT by means of introducing bubbles as small as 0.1 $\mu$m to as large as tens of microns. Microcellular plastics parts can be extruded or injection molded. These parts have minimal residual stresses, do not distort and are dimensionally accurate.

An application in nano-engineering has been reported by [76]. The axiomatic approach for systems design has been used to develop less complex manufacturing processes. The approach provides better understanding of the complexity in assembling products at micro-scale and guides development of proper assembling technology for nanostructures. The problem is that although many nanostructures have been developed and found to be very useful, there are very few tools to assemble them to a multi-scale system. This problem is similar to the challenge faced five decades earlier, when the solid state transistor was invented but no proper method to assemble them was available. A viable solution for nanostructure assembly, e.g., the assembly of carbon nano-tubes to deterministic locations, was developed via the axiomatic complexity theory to have reduced amount of real complexity. In order to minimize the complexity, the common range of the assembly process has been increased by moving the design range of handling carbon nano-tubes to have larger overlap with the system range of the existing micro-fabrication processes. The key idea is to embed individual carbon nano-tubes into a high aspect ratio pellet after growing single strand carbon nano-tubes on a flat substrate where E-beam processing is feasible [76].

Several researchers [25,41,100] proposed use of artificial intelligence, artificial neural networks, and machine learning techniques for managing complexity and uncertainties in manufacturing processing. There are various signals (force, torque, temperature, mechanical vibration, acoustic emission, etc.) which correlate to the condition of the manufacturing processes, and it is expected that sensor fusion or integration can offer significant benefits in controlling and monitoring of manufacturing processes. The complexity of the problem and the associated uncertainties necessitate the application of learning techniques to get closer to intelligent manufacturing [99]. The performance of present control and monitoring systems can be enhanced by the simultaneous processing of different signals. In order to illustrate the difficulty of the problem, cutting force components and mechanical vibration of the workpiece holder in face milling have been investigated [100]. Numerous statistical (e.g., mean value, quadratic mean value, variance, standard deviation, effective value, third and forth central moments, skewness, excess, etc.) and spectral features (e.g., absolute and relative power in frequency bands, frequency and power of the largest peak, normalized moment of the spectrum, and normalized central moment of the spectrum, etc.) have been computed from the measured signals.

In today's manufacturing systems, difficulties arise from unexpected tasks and events, non-linearities, and a multitude of interactions while attempting to control various activities in dynamic shop floors. The job-shop scheduling problem is generally an NP-hard optimization problem. Complexity and uncertainty seriously limit the effectiveness of conventional production control and (predictive) scheduling approaches. Distributed (agent-based) control architectures [15,95,104,157] offer prospects of reduced complexity, high flexibility and high robustness against disturbances in manufacturing. However distributed control architectures, usually banning all forms of hierarchy, cannot guarantee optimum performance and the system behavior can be unpredictable. In Monostori et al. [101], centralized and decentralized machine learning approaches were described for managing changes and disturbances in manufacturing systems, and to decrease the computational costs of the scheduling process [102]. Special emphasis was placed on the neurodynamics-based solution with a three-level learning structure (More details can be found in Csáji and Monostori [30]).

### 2.9. Complexity in engineering design and its measures

Qualitative approaches used by engineers to reduce complexity include value engineering, reduction of coupling, reduction of the number of parts, and use of modularization. In addition, complexity metrics have been developed to quantify and compare structural/static complexity. These metrics have their bases either in complexity theories, entropy or information theories. Furthermore, practical measures based on heuristics, empirical, and statistical models were developed.

The traditional branches of many disciplines, such as mathematics, statistical physics, biology, medicine and social sciences, as well as computer science and engineering face the problem of measuring complexity of a system, structure or problem and obtaining limits and quantitative relations of complexity. Complexity of products increases with: i) number and diversity of features to be manufactured, assembled and tested; and ii) number, type and effort of manufacturing tasks.

### 2.10. Information theory/uncertainty/entropy

There are different approaches found in the literature that describe system complexity and complexity measures. The first approach is based on Shannon's Information Theory/Entropy [128] where information is used as a measure of uncertainty. The second uses Information Content defined by axiom 2 in the Axiomatic Design Theory as a measure of complexity [135]. *Uncertainty Complexity* arises because future events can only be known and evaluated (at the most) using probabilities. It is often evaluated using probability theory and formalized in the context of Shannon's entropy. When an event $x$ occurs with a small probability $P(x)$ $(0 \leq P(x) \leq 1)$, the "impact" of this event is larger than events with a higher probability. This is evaluated by "expected value" of this event:

$$-P(x)\log(P(x)) \tag{1}$$

in which $-\log(P(x))$ is one way to evaluate such an impact. Therefore, the system entropy is defined as:

$$H = -\sum_{x} P(x)\log(P(x)) \tag{2}$$

A well-known application of this type of complexity is found in Suh's Second Design Axiom which minimizes information content (defined in Eq. (2)) to arrive at good designs [134]. Typically the value of design parameters has to be within the specified design range, $R_D$. and a design parameter instance would occur in a range defined by statistical distribution ($R_S$). Using the common range ($R_C$) defining the overlap between the design range and system range, information content ($I$) is given by:

$$I = \log\frac{R_S}{R_C} \tag{3}$$

For instance, the design parameter could be a dimension of a component, the design range signifies its tolerance, and the system range due to manufacturing errors is defined as a distribution. If the design range includes the system range ($R_C = R_S$), $I = 0$ meaning that functions realized by this design parameter would be realized without any effort. However, if the common range is smaller than system range, effort *should be made to keep* the design parameter within the required range.

In product development, requirements often change. Therefore, change management [26,43] would be needed, but since some changes go beyond "minor modifications" and may require major design changes; uncertainty and complexity should be dealt with.

### 2.11. Types of complexity (functional, static, and dynamic)

The complexity definition in the Axiomatic Design approach uses the Information Content as a measure of complexity, which is defined as uncertainty in achieving the functional requirements [135]. Frizelle and Woodcock [59] proposed a method using entropy to measure complexity in the structural and operational domains in manufacturing. There are two fundamental types of complexity: structural (static) complexity and operational (dynamic) complexity. Static complexity is time-independent complexity due to the product and systems structure. Dynamic complexity is time-dependent and deals with the operational behavior of the system. The static complexity can be reduced by simplifying the design of products and processes per Frizelle and Woodcock [59] as well as structural and functional complexity of a design process (Braha and Maimon [16]). The notion of operators and operands was introduced to describe a design and define the structural complexity by measuring the "design size" and "designing effort". In the functional level, the information content was used to measure complexity. In measuring the design size, Braha and Maimon [16] considered the total and unique number of operators and operands and measured the size and diversity of information where the design effort is a measure of mental activity to reduce a design problem, and effort is related to the reciprocal of information content.

### 2.12. Heuristics measures of complexity metrics

Complexity of design often is matched with increased complexity in configuration management as customers demand more exact specifications and more customisation. A brief summary of some published research in this area follows.

ElMaraghy and Urbanic [44,52] developed metrics that measure the three kinds of complexity in manufacturing systems: product, process, and operational complexity. In these metrics, an important factor is considered: the human operators and their perception of the tasks' complexity. These models capture the three elements of complexity: absolute quantity of information,

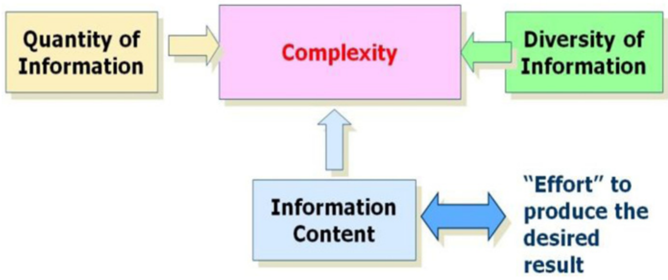


**Fig. 15.** Components of complexity [52].

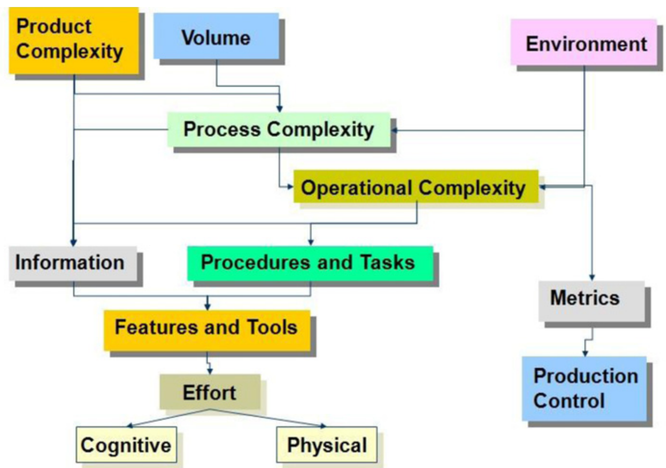


**Fig. 16.** Manufacturing complexity cascade [44].

diversity of information and information content (effort), as illustrated in Fig. 15. This information content is different from the one introduced by Suh [135] which measures the relative effort to achieve required tasks.

For process complexity, the same heuristics model used for product complexity is exploited [44]. The complexity of manufacturing systems, products, processes, and operations is related to the information to be processed in the system (Fig. 16). Increasing system size and variety leads to more information and higher complexity.

Kuzgunkaya and ElMaraghy [84] introduced a metric to measure the structural complexity of manufacturing systems based on the complexity inherent in the structure of its components: machines, buffers, and Material Handling Systems (MHS). It includes quantity of information (using the entropy) and diversity of information. The model uses the manufacturing systems classification code developed by ElMaraghy [45] to assess the contribution of each module to the overall system structural complexity.

### *2.13. Statistical complexity metrics*

Statistical complexity measures have been introduced recently in the context of chemical physics [29]. These computational mechanics metrics have been recently applied for managing complexity in manufacturing systems. Statistical complexity $C_\mu$ is defined as the Shannon entropy over the distribution of causal states. $P(S_i)$ denotes the probability of the ε-machine being in state $S_i$:

$$C_\mu = \sum_{S_i \in S} P(S_i) \log_2 P(S_i) \quad (4)$$

Statistical complexity $C_\mu$ is the average amount of historical memory stored in the process, in the units of bits. In a complex process, more information about the past is stored internally. Prediction therefore requires more information and is, in turn, more difficult [159].

### *2.14. Product modularity, platforms and complexity*

#### *2.14.1. Product modularity and its effect on complexity of the manufacturing process, the supply chain and the organization*

In the last two decades, the concepts of modularity and product platforms have been advanced as effective strategies to offset some of the increasing complexity faced by businesses in this era of frequent and rapid change. When a product or process is "modularized," the elements of its design are split up and assigned to modules according to a formal architecture or plan. From an engineering perspective, modularization generally has three purposes: (1) to make complexity manageable; (2) to enable parallel work; and (3) to accommodate uncertainty, present and future. Present uncertainty is reduced by using modules that have been proved successful in practice, and future uncertainty is accommodated because the particular modules or elements of a modular design may be changed easily after the fact, with new modules replacing older ones. It should be cautioned however that even when the design rules are observed, complexity may arise when there are unforeseen interactions between the new and existing modules. The overall design architecture and details should be checked for the possibility of the emerging of multi-disciplinary complexity. Baldwin and Clark [13] have shown that modularity is a financial force that can change the structure of an industry. Then, they explored the value and costs that are associated with constructing and exploiting a modular design, and they examined the ways in which modularity shapes organizations and the risks that it poses for particular firms. Avak [11] noted that the literature regarding the definition of modularity is vast, yet there is no single generally accepted definition of modularity. Somewhat similar to the definition of complexity itself, modularity is defined in either the functional or the physical domain. Modular product families have specified interfaces between modules and there are generally fewer interactions between than within modules. There is also a distinction between slot, bus, and sectional modularity depending on whether interfaces between modules are unique, all connect to a single bus module, or are standardized across all modules [11]. Modular product families have a deliberate product architecture [153]. Product architecture is the way in which the mappings are carried out from the functional to the physical domain. The functional domain, for instance, contains the functions and flows of the product. The physical domain contains the parts and assemblies, i.e. product structure, as well as the interfaces to fulfil these functions.

Parker [112] studied the relationship between modularity and complexity. Modularity refers to the hierarchical structure of a system whereby it is composed of smaller subsystems that can be designed independently, yet function together as a whole. The study applied a systems theoretic framework and Seemingly Unrelated Regression (SUR) to empirically analyze the effects of product modularity on production system complexity. The results suggest that the product modularity is positively associated with the complexity of internal manufacturing processes and supply networks in situations of high outsourcing and high environmental uncertainty.

#### *2.14.2. Product platforms*

To meet market needs and reduce production cost at the same time, product platform strategies have been utilized by many companies to maximize commonalities and utilize economies of scale across different product families. Using a core set of common platform elements and variant-specific unique elements, a family of products can be produced to satisfy various market segments [133].

The dilemma between economies of scale and scope which limits the potentials of platforms also was researched by Schuh et al. [125]. The paper focused on product innovation based on ''adaptive product platforms''. In this context, a new understanding of product platforms is embraced: platform standards are considered as pre-defined degrees of freedom for component design that allow the necessary room for innovation and product description, and technical solutions, as functional models. This perspective on standardization builds up on but exceeds mere physical commonality and also targets other levels of commonality such as identical product technologies, design concepts or manufacturing processes. Product functions are classified within a functional model, and a technological model provides the description of the degrees of freedom for each function variant, thus defining the design space for possible technical solutions of each function.

*2.14.3. Multi-discipline complexity of engineered systems*

Recent research has dealt with what is called complexity due to multi-disciplinarity [78,144]. Modern products and engineered systems are complex, due to several factors. One is the size represented by the number of components but also physical dimensions in two extreme directions (gigantic and macro/nano-systems). Increasing the number of functions physically packaged in a shrinking space has resulted in monotonically increasing functional density, which also translates to increasing interactions (or interferences) among subsystems. Second, more disciplines are involved, since multi-disciplinarity is considered one of the sources of innovation and superior added-value. A typical multi-disciplinary field is mechatronics that amalgamates mechanical engineering, electrical engineering, electronics, control engineering, and software engineering. This field is expanding further to incorporate such disciplines as optics, bio-technologies, and artificial intelligence. Third, more stakeholders are involved. Consider, for example, sustainability issues relevant to many products that can involve a wide range of stakeholders.

Multi-disciplinarity causes problems that were non-existing when products were mono-disciplinary, because multi-disciplinarity not only significantly increases the complexity of products but also that of the product development process [78,143,144]. Complexity resulting from multi-disciplinarity is different from other types of complexity such as computational complexity and uncertainty complexity, because it results from how our knowledge itself is formulated [144]. Simpler design problems can be first decomposed into simpler mono-disciplinary sub-problems with the classic divide-and-conquer strategy. These mono-disciplinary problems can be easily attacked and solutions for the entire problem can be synthesized. In contrast, multi-disciplinary problems cannot be solved in a straightforward manner. When a design problem involves multiple domains, unless there is a uniform theory that can attack the problem as a whole, we are forced to use a set of theories, each of which is valid only in one domain. While in principle these theories are independent from each other, they can have intrinsic interactions for a variety of reasons. These interactions among theories indicate the existence of cross-disciplinary problems. The complexity involving multiple disciplines is explained by examining the structure of knowledge represented by relationships among theories [143]. Tomiyama et al. [144] identified ''complexity by design'' and ''intrinsic complexity of multi-disciplinarity''.

Knowledge comes from education and training which are traditionally carried out mono-disciplinarily. In industrial settings, engineers are trained to work in a (mono-disciplinary) team environment, and these teams are supposed to collaborate with teams in different disciplines to tackle cross-disciplinary problems. Within many organizations, it is hard to identify experts who are multi-disciplinary and know ''everything''.

Due to size (computational complexity) and multi-disciplinarity, we apply the ''divide and conquer'' approach. However, due to very high ''functional density'', the approach can fail because it is almost impossible to decompose the whole system (particularly with high functional density) into subsystems that have the least interactions among them. Often, systems designers are surprised by ''unpredicted'' interactions that are hard to solve [32,33].

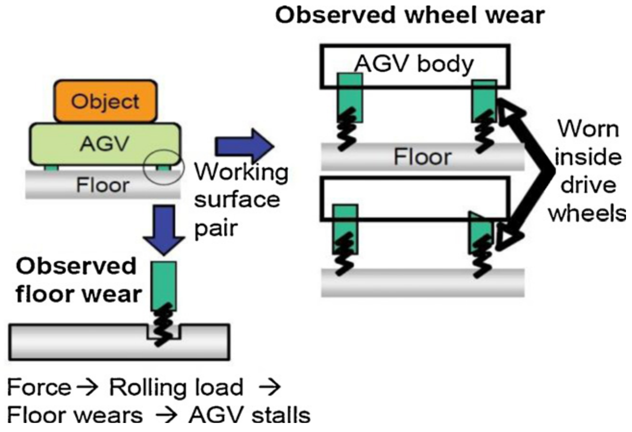


**Fig. 17.** Working surface pairs in AGV example [144].

Examples of multi-disciplinary complexity are illustrated in the design of an AGV material handling system (Fig. 17). Designers are concerned about design decisions made at the tactical level (e.g., the system design, vehicle requirements and the material management policies) and at the operational level (e.g., vehicle routing and traffic management).

Researchers explore the challenges associated with the tactical and operational issues, but the impact of equipment failures on the system is neglected in most literature [144]. For this example, AGVs with a fixed path guidance system utilized in a vehicle assembly plant operation are employed to illustrate the two types of complexity. This system was originally designed and installed before the required technologies had been fully developed. These AGVs are utilized to transport the engines, body and chassis components within the facility as part of the plant's flexible manufacturing system (FMS). The supervisory system tracks the AGVs and generates real time transport instructions to direct the traffic in an optimal manner. Routing directions from the supervisory system occur at communications junctions, which are located at each workstation, and at intervals along the guide paths. These junctions consist of induction loops to detect AGVs. During the launch cycle of the FMS, issues with respect to the vehicle scheduling, routing and conflict resolution were anticipated.

Unexpected couplings due to the two types of multi-disciplinarity complexity caused unpredictable and negative interactions within the AGV sub-systems and the environment.

Subtle failure modes, summarized in Table 1, emerged that made it difficult to trace a failure occurrence to a cause. Several avoidable problems were caused by the two types of complexity. The solutions were reactionary and implemented during the production launch. D'Amelio used a qualitative physics-based reasoning method to identify such interactions [32,33]. This type of ''no-fault'' failure has been on the increase in many complex multi-disciplinary products, and deserves more attention from designers and industrial enterprises [118].

## 3. Manufacturing systems complexity

Manufacturing companies operate in an uncertain and constantly changing environment driven by changes in customer demands, product design and processing technology. Uncertainty in manufacturing systems increases complexity, which is seen as a main challenge in many fields [46,79].

''It has been established that the real or perceived complexity of engineered products, their design and their manufacture is related to the amount of information to be processed. It arises due to increased product complexity and the uncertainty created by product variety and market fluctuations and their effects which propagate throughout their life cycle. Increased variety generates

**Table 1**
A summary of the selected cross-discipline problems for an AGV system [144].

| | Problem description | Disciplines | Parameters linking the domains | Resolution |
|---|---|---|---|---|
| Traverse route | Floor variations inhabiting progress (wear condition) | Mechanical civil | Force, cyclical loading fatigue, floor material properties, number of vehicles, production rate | Constant floor maintenance scheduled during periods of downtime |
| | False signals inhibiting progress | Electro-mechanical electrical, information Systems | Vehicle mass/wire physical properties/ induction/number of vehicles in an area | Modify induction coil loops in the floor |
| Perform accurate load positioning | Uneven wheel wear distorting the calculated travel distance (wear condition) | Civil mechanical electrical | Force, cyclical loading, fatigue, floor material properties, wheel diameter, travel distance counter, wheel wear pattern | Wheel maintenance procedures |

more information and provides opportunities for unexpected or unknown behavior of products, processes or systems. It increases the data, knowledge and effort needed for operating and managing the resulting consequences, anticipating them, designing or guarding against their effects or recovering from and rectifying their consequences. Manufacturing systems have evolved over time and new mechanisms and methods have been developed to cope with and manage the effects of increased product variety on process planning and production planning as well as the evolution of manufacturing paradigms'' [49].

Complex manufacturing systems consist of a number of machines, tools, logistics, computers, and human operators and managers with high dimensionality representing an extended space of possibilities. The interaction between the human operators and system modules and the resulting complexity (real or perceived) at the operational level is important to consider. Automation also influences complexity. Automated manufacturing systems are usually highly integrated with all levels of the enterprise, databases, products knowledge and resident expertise. The role of operators in automated systems may be reduced and, hence, easier but the system becomes more complex.

The layout of the various components in a system and connectivity among them also affect its complexity. Complicated products, processes and manufacturing systems cost more to design, implement, plan, operate, control and maintain and the associated cost is an important factor. The trade-off between simplicity and complexity and their effects on competitiveness and profitability are important reasons for more research.

### 3.1. Types of manufacturing systems complexity

The types of complexity discussed earlier, i.e.: Static and Dynamic are also found in manufacturing systems [39,59,60]. Frequent changes in markets, wide-spread mass-customization [164], and proliferation of variants all contribute to higher manufacturing complexity.

Dynamic complexity of a manufacturing system is time-dependent and relates to its real-time operation, material flow patterns, modules reliability and failures. Other factors related to the system operational aspects over a time period including deviation from the norm/steady-state, uncertainty of events, unpredictable behavior and adaptive responses also influence the system dynamic complexity [39,84]. The drivers of dynamic complexity may be internal (e.g., machines reliability, breakdown and maintenance and scheduling policies) or external (e.g., suppliers reliability causing variation in the quantity and timing of materials and tools).

The researchers at the University of Patras have contributed several studies and papers to the understanding of the complex and chaotic behavior of manufacturing systems [24,92,110,111]. Chryssolouris et al. [24] applied the concept of chaos in manufacturing systems for the scheduling of a simple manufacturing system with the help of commonly used assignment rules. The simulation results have been studied with the help of phase portraits, and a method for scheduling was proposed and tested against conventional rules. Papakostas and Mourtzis [111] presented a novel approach for modeling the adaptability of a Manufacturing System using a mathematical model for quantifying the adaptability of a system using real manufacturing data. The main objective was to quantify the ability of a manufacturing system to adapt to demand and to demonstrate that different operational policies for adaptability in a manufacturing system may be analyzed, by using non-linear and chaotic dynamics tools. Papakostas et al. [110] considered the complexity index (MECI) coupling the intrinsic structure of the system and the uncertainty related to the operations of the system. MECI depends heavily on the workload profile. They suggested that what engineers perceive as complexity in a real manufacturing environment may be heavily related to the load of the system. MECI is higher when more elements of the system operate close to their maximum capacity. Makris et al. [92] researched the supply chain control logic for enabling adaptability under uncertainty.

### 3.2. Complexity of engineered products and systems

The manufacturing system itself is a product to be designed, manufactured and assembled and it has its own life cycle including re-design, reconfiguration and evolution according to changing functional requirements [45]. Researchers in the field agree that key characteristics of complex systems include self-organization, adaptation and emergence [107]. However, manufacturing systems are designed to satisfy functional requirements and market demands in a robust manner. Robustness in the context of manufacturing systems typically means reliability of function and delivery in the presence of planned variations and failure of modules the probabilities of which can be estimated. ElMaraghy et al. [47] argue that self-adaptation and self-organization are not observed in manufacturing systems. Unplanned events affecting parts characteristics, workstations modules and supply of parts and tools are difficult to anticipate. Some hardware, software and control tools are available today and may be built into the system modules to impart a limited degree of adaptation and robustness. In response, characteristics such as sensors-based feedback and detected error correction, adaptive on-line control or buffers may be used to maintain successful operation of manufacturing systems in the presence of uncertainties which would have negatively impacted the desired function or output. These tools include use of artificial intelligence and expert systems, adaptive control methods and holonic agents and emergence principles. Nevertheless, autonomous, self-adapting, self-organizing emergent behavior is still far from reality in manufacturing systems used by industry.

Well-designed manufacturing systems, however, do have constructs and features built-in to achieve an ''*engineered evolution path*.'' Examples include: (1) modular physical and logical design features for ease of configuration and adaptation [49,80] and to facilitate plug and play operation at the machine or system level including their controllers, (2) cellular and other workstations arrangements to allow logical reconfiguration through re-routing and dynamic machine assignments, (3) buffers that act as physical de-couplers which help avoid bottlenecks and starvation and permit re-setting/re-initializing work cycles, and (4) flexible

Manufacturing Systems that can operate reliably for a range of anticipated functional requirements and variations. Therefore, ElMaraghy et al. [50] argued that the engineered manufacturing systems may be more accurately described as ''complicated'' rather than ''complex'' system. However, these two terms continue to be used interchangeably in the literature.

### 3.3. Measuring manufacturing systems complexity

Most research efforts concerned with defining and measuring complexity consider the physical embodiment of the product, process and system and endeavor to find an absolute measure of it in the physical domain. Shannon's information theory and entropy approach are commonly used for quantifying complexity in both the physical and functional domains [77,131]. Suh [4], on the other hand, stated that complexity is defined in the functional domain.

#### 3.3.1. Entropy and information content measures

Deshmukh et al. [39] and Frizelle and Woodcock [59] define the static and dynamic complexity using entropy-based formulation. The static complexity of a system S can be measured by the amount of information needed to describe the system and its components, as per Equation 5:

$$H(S) = -\sum_{i=1}^{M}\sum_{j=1}^{N} p_{ij}\log_2(p_{ij}) \quad (5)$$

where $M$ is the number of resources in S, $N$ is the number of possible states for the $i$th resource, and $p_{ij}$ is the probability of resource $i$ being in state $j$.

Suh's Axiomatic Design [135] utilizes entropy to measure complexity, based on the information content concept, and define it as a measure of uncertainty in achieving the set of functional requirements to be satisfied. Hence, $p$ in equation (6) represents the probability of success of design parameters in meeting the specified functional requirements. Information theory-based measures of systems complexity provide objective data. However, there are two major drawbacks in applying the entropy approach: (1) determining which event to use in order to describe the state of a component, and (2) the validity of the states independence assumptions made when using entropy formulation for simplification, when in reality it is not always true; hence, conditional probability should be used and that complicates the formulation particularly for large systems.

#### 3.3.2. Measuring manufacturing systems complexity in the functional domain

Consider three alternate configurations of manufacturing systems used in the heavy metal removal operations for a mass produced cast iron automobile engine cylinder block at the rate of 100/h. (Fig. 18). Systems designers synthesize the manufacturing system configurations and their modules capable of producing the desired product features, quality and quantity.

The designed system layout defines the connections and relationships, including parallel and series arrangements of machines and the flow of material between them.

Three different manufacturing systems may be used, as shown in Fig. 18: (1) serial line with 3 dedicated milling machines, (2) dedicated broaching operation, or (3) parallel system comprising 4-axis CNC machines [47]. They are all capable of producing the product, but there are major differences between them in the elements, characteristics, arrangement and complexity.

These systems must be robust and their planned capacity should meet fluctuating demands within a target range. The *functional requirement* is the forecast demand represented by a probability density function as illustrated in Fig. 19. The production capacity range has a probability density function the characteristics of which are based on the availability of various system components for production and the type of material flow in each layout. If all modules are assumed to be available 100% of the

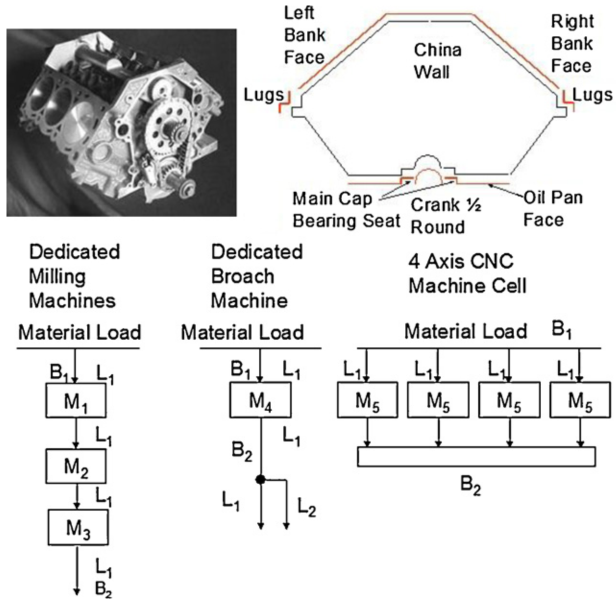


**Fig. 18.** Three systems for rough machining of an engine cylinder block Adapted from ElMaraghy et al. [47]

time, a uniform distribution may be used for the planned capacity within the desired range. A distribution can be defined to represent the manufacturing system modules availability based on the layout configuration, machines reliability, planned maintenance and repair and unplanned failure and downtime. If the demand and capacity distributions coincide perfectly (i.e. maximum commonality), the functional requirement is satisfied and the information content is zero.

The production rate is a function of available production time and throughput or takt time. If a system module is available for $n$ time units out of a total $m$ time units in the period of interest (e.g., shift, day, week, month), then the probability of this module being available for production is $p = n/m$, and the information content, $\log_2(1/p) = -\log_2(p)$.

We assume that the initial system configuration is designed to meet the demand requirements; therefore, the availability of the system would represent the success of meeting the design requirements.

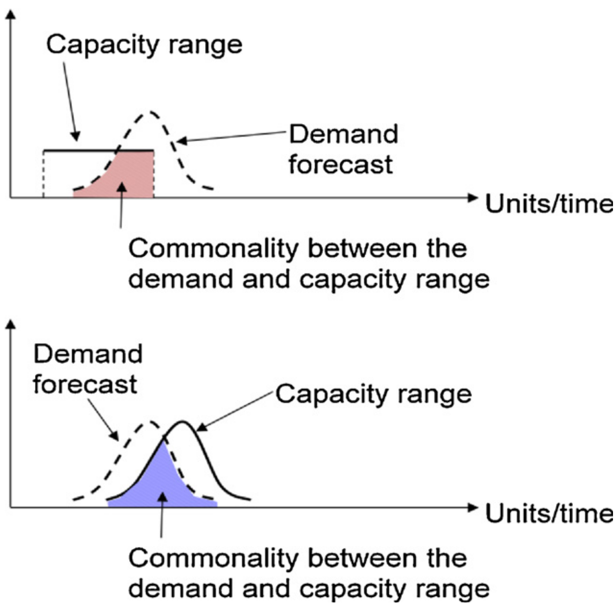


**Fig. 19.** Demand forecast vs. capacity.

The following index expresses the complexity arising due to machines availability:

$$I_{A\_M} = \sum_{i=1}^{M}\sum_{j=1}^{N} X_{ij}\log_2\left(\frac{1}{p_{ij}}\right) \tag{6}$$

where $p_{ij}$ is the availability of machine, $X_{ij}$ and $X_{ij}$ is the no. of machines in stage $i$, configuration $j$, $N$ is the number of machines installed in stage I and $M$ is the number of stages in a system configuration.

Assume that a machine fails if any of its modules (e.g., heads, spindles, etc.) fails since the modules are considered to be functionally serial. The following probabilities can be calculated for each machine configuration:

$$p_{ij} = |A^n|$$

where $p_{ij}$ is the availability of a machine with configuration ($j$) operating, $A$ is the availability of a module, and $n$ is the number of distinct components.

This complexity formulation, based on availability, is applicable to machines as well as buffers and material handling systems. The total manufacturing system complexity index is the sum complexity indices of all classes of system equipment.

The availability is assumed to be equal to 0.9 for each component in a configuration leading to machines availability for $M_1$ to $M_5$ being 0.349, 0.109, 0.282, 0.065 and 0.065 respectively. Accordingly, the complexity of the dedicated serial line is much higher than the other two system configurations. The CNC parallel line is the least complex system because of its parallel configuration, which also results in a more complex material handling system. It may be intuitively perceived that the broach line, having only one machine, would be the least complex system. However, its larger number of distinct functionally serial components results in a lower total availability, and hence, higher complexity.

This availability-based complexity, defined in the function domain, is static time-independent as it uses known properties of the system modules and components.

### 3.3.3. Measuring manufacturing systems complexity using heuristics and indices

A second approach to quantify system complexity uses heuristics and indices. Papakostas et al. [110] defined a manufacturing execution complexity based on the intrinsic structure of the system and the uncertainty related to its operation. Kim [77] found that in lean manufacturing, the system complexity, which is affected by increased product variety, is much less than in an equivalent mass production system. He proposed a series of system complexity metrics based on a complexity model developed using systems theory. These measures are: (1) relationships between system components (number of flow paths, number of crossings in the flow paths, total travel distance by a part, and number of combinations of product and machine assignments), and (2) number of elementary system components. These metrics include a mix of structure (static time-independent) and operation (dynamic and time-dependent) factors. No suggestion regarding their relative importance or how they may be combined into one system complexity metrics was offered.

Classification and coding systems were originally developed for manufactured parts. However, equivalent coding and classification systems for manufacturing systems did not exist until the development of the Structural Classification and Coding system (SCC) by ElMaraghy [45] to classify the various types of equipment in a manufacturing system, such as machines, buffers and transporters, as well as their layout (Fig. 20). Kuzgunkaya and ElMaraghy [84] used this classification code to assess the structural complexity of manufacturing systems configurations. The original equipment has been extended [48] to include the assembly specific structural features of typical equipment used in products assembly

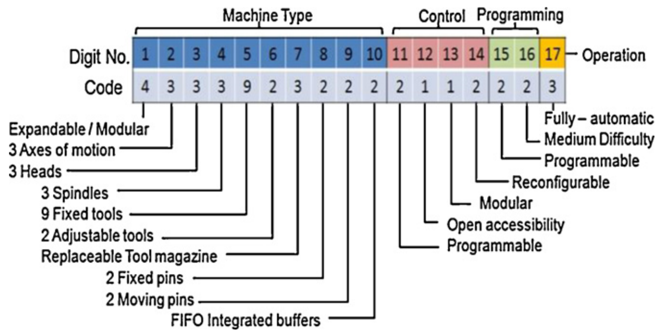


**Fig. 20.** Structural classification and coding system (SCC) ElMaraghy [45].

systems. It accounts for the number, diversity and information content within each class of the assembly system modules caused by the assembled products variety. The chain-type structure of the SCC coding scheme facilitated its extension (Fig. 20). The code characterizes the complexity of the various equipment within the assembly system such as machines, transporters, buffers, feeders and handling equipment. Equipment controls, programming, operation, power source, and sensors are common fields.

### 3.4. Products and assembly systems complexity

Modern manufacturing and assembly systems are becoming more complex. Some of this complexity is due to inherent structural characteristics of the equipment and layout configuration [48]. It is important to consider the manufacturing system as a product that has a life cycle and whose design, configuration and operation has to be managed. The increased complexity of such a product demonstrates a need for capturing and classifying its relevant information, facilitating information storage and retrieval and capitalizing on commonality and similarity to streamline its design, operation and control, and support decision making.

Introducing commonality into the assembly lines, such as common tools or fixtures for different product variants, can reduce complexity and simplify the assembly process. The complexity measures defined by Zhu et al. [166] focus on serial assembly lines. Wang and Hu [161] extended the complexity definition to mixed-model assembly systems with different configurations, including serial, parallel and hybrid of both.

Hu et al. [70] introduced a measure for variety induced manufacturing complexity in assembly and supply chains. by developing Models for characterizing the propagation of complexity in multi-state mixed-model assembly systems and multi-echelon assembly supply chains. They defined a complexity model based on product variety including station, system and supply chain complexity. It can be used to ensure robust performance of assembly systems and supply chains by reducing their complexity.

### 3.4.1. Assembled products complexity

Measuring the complexity of products' assembly supports assembly oriented product design and guides product designers in reducing assembly complexity and rationalizing the choice of various processes, sequences, equipment and system layouts. Samy and ElMaraghy [122,123] defined product complexity as the degree to which the individual parts/sub-assemblies have physical attributes that cause difficulties during the handling and insertion processes in manual or automatic assembly. They used design for assembly (DFA) principles to define a relative point scale of the different assembly attributes used in handling and insertion processes for both manual and automatic assembly. Each part is examined separately to identify their different handling and insertion attributes. The overall product assembly complexity index is based on the individual assembly complexity indices of all parts as shown in Fig. 21.

The product complexity model incorporates the assembly complexity resulting from the number and diversity of the parts

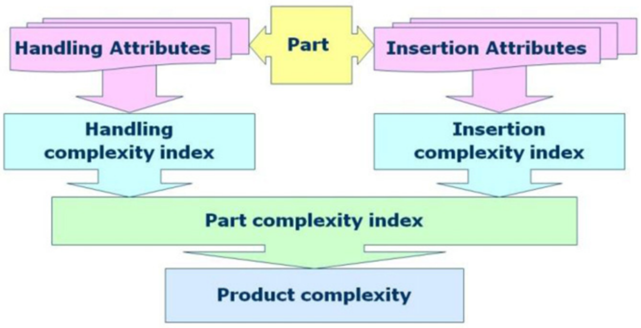


**Fig. 21.** Product assembly complexity.

and fasteners in the product assembly using a formulation that incorporates information content and diversity. In manual assembly, complexity is manifested in the added worker's effort to recognize, grasp, orient, insert and assemble the parts. In automatic assembly, complexity translates into additional equipment required to complete the assembly process. Their results show that higher complexity is proportional to longer assembly time in the case of manual assembly, and more equipment cost, in the case of automatic assembly.

### 3.4.2. Assembly systems complexity

Designing systems for less complexity and mapping between product complexity and system complexity are important issues for further research. Fig. 22 shows the decomposition of a product to its individual parts, each is related to its assembly equipment.

Samy and ElMaraghy [122,123] developed indices to measure the structural complexity of assembled products and their assembly systems. They established a mapping between the two to help design products and systems for complexity. This mapping establishes a relationship between the complexity of products and that of their assembly system. Predicting and estimating assembly

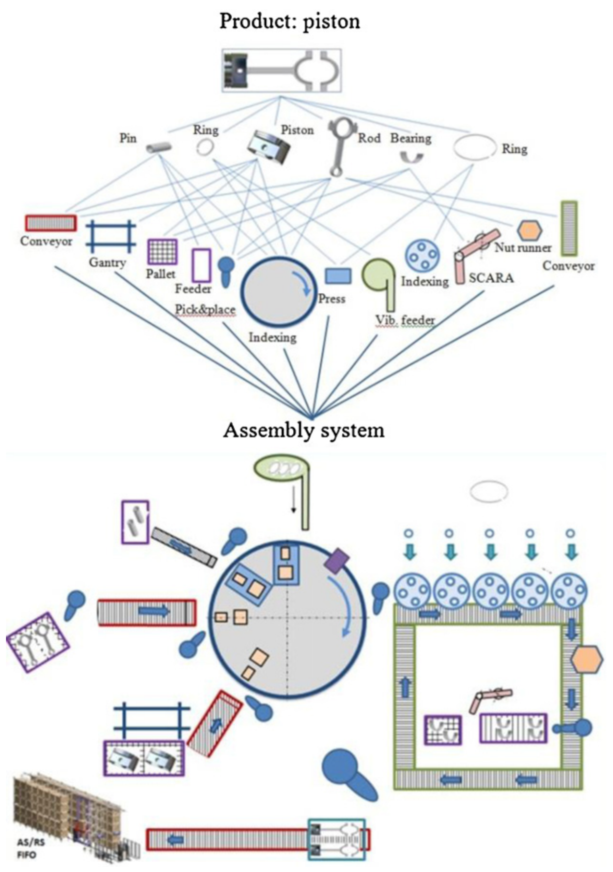


**Fig. 22.** Product and system mapping [121].

equipment complexity saves time and effort required to analyze system equipment and make the necessary design changes at early design stages.

As it is expressed in Eq. (7), the total complexity of a Reconfigurable Manufacturing System (RMS) is function of: (i) number, type, and state of machines; (ii) number, type, and state of buffers; and (iii) number, type, and state of the MHS and their components.

$$H_{RMS} = w_1 H_M + w_2 H_{Buffer} + w_3 H_{MHS} \quad (7)$$

where $H_M$ represents the complexity of machines, $H_{Buffer}$ is the complexity of buffer, $H_{MHS}$ represents the complexity of the material handling system, and $w_j$ is the relative weight of each element which may be assigned by users.

In order to measure the individual machine's complexity, they considered the availability and reliability of the machine modules as well as the base. For the buffer, the influential factors are the state of the buffer (empty or full, and the product variant in the system). For the complexity of MHS, the reliability of the MHS and the number of transformers in them are considered important factors. These proposed metrics exploit the entropy approach to measure the system structural complexity, and can be used as a comparative tool to design systems for the least complexity.

In designing any assembly system a number of trade-offs are made considering function, cost and complexity, which is known to affect performance, quality and reliability. The developed assembly system complexity metric can be used by system designers to compare and rationalize various system configuration alternatives and select the least complex assembly system that meets the requirements.

The economic importance of parts production and products assembly has led to extensive efforts to improve their efficiency and cost effectiveness. One way of achieving this is by managing their complexity. Measuring and understanding complexity of products and systems architectures is important for the whole product development and manufacturing cycle. More complex systems are associated with higher cost and more risky design, implementation and operation.

## 3.5. Manufacturing systems configuration and layout complexity

Manufacturing systems layouts have evolved from dedicated process-oriented lines to the more recent reconfigurable and changeable ones where work stations can be removed, added or moved as needed to adapt to product changes [46,79]. The arrangement of machines and other functional modules in a manufacturing facility, along with the processes and their sequence, define the material flow pattern which influences transportation efficiency and cost. The features of various layouts not only govern the movement of work pieces between workstations but also affect the decisions made on the shop floor during the system operation to ensure smooth flow and shortest travel distance and time, guard against workstation starvation, reduce bottlenecks and downtime which help enhance productivity, throughput and quality [47,72]. Plethora of research in the literature dealt with many aspects of manufacturing systems complexity e.g., [21,60,77], however, the complexity inherent in systems layout patterns has not been included.

This section focuses the effect of manufacturing systems configuration and layouts on their complexity. A manufacturing system configuration means the set of equipment that makes up the system and its characteristics. A system layout further defines their arrangement (e.g., in parallel, in series, linear, loop etc.), flow pattern between various pieces of equipment (uni- Bi- or multi-directional), their connectivity (direct or indirect) as well as decision points that govern the movement of material to allow branching, backtracking, looping, and flexible routing. A system layout is influenced by the process plans to be executed and their precedence constraints as well as the type of material handling

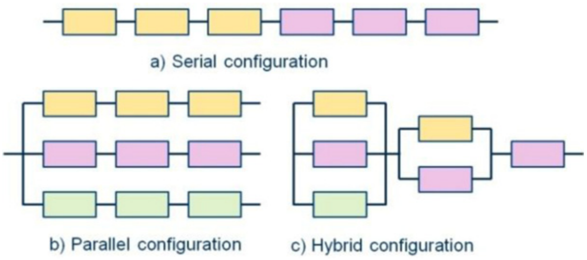


**Fig. 23.** Three machine configurations: (a) serial, (b) parallel and (c) hybrid.

system used and any restriction it may impose on the shape of the followed path (Fig. 23).

*3.5.1. The structural complexity of systems layout*

Gabriel [60] investigated internal static manufacturing complexity based on product line complexity, product structure and process complexity components. However, his complexity measure did not consider layout, arguing that it is difficult to quantify its complexity. Koren et al. [81] considered various system configurations, such as serial, parallel, and hybrid machining systems shown in Fig. 23. The configurations were analyzed as well as their effect on system performance in terms of reliability, productivity, quality and scalability, but did not consider their complexity due to configuration.

The layout of a manufacturing facility/system does not only shape material flow patterns and influence transportation cost, but it also affects the decision making related to movement of parts, material and tools between workstations on the shop floor.

The material flow patterns in any manufacturing system layout and the points where decisions are made, by system operators or control software, to determine the next destination and movement path/route for each work piece, should be considered. Tools and transporters in the system also have a direct effect on the information and knowledge required to make operating decisions. In a larger manufacturing system this can represent a large number of decisions that must be made and repeated many times to maintain satisfactory system operation. It can be hypothesized that the complexity of any system layout including all junctures is related to this information which in turn is a function of the attributes that characterize a system configuration layout.

Measuring the structural system complexity has received much attention, however, the system layout topology and its effect on its structural complexity were not considered. Manufacturing systems layouts may feature simple to elaborate patterns including

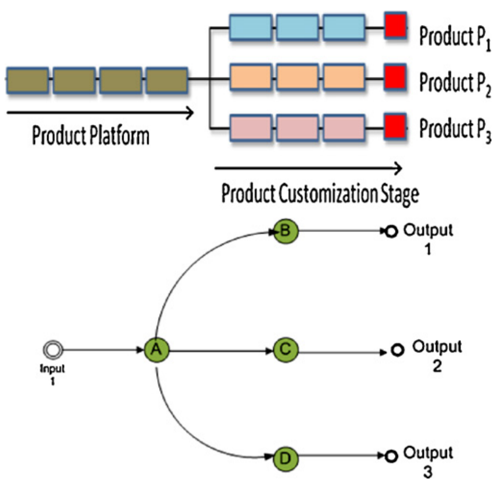


**Fig. 24.** Physical layout for delayed product differentiation and its graphic representation—input, output and decision nodes.
Adapted from [14].

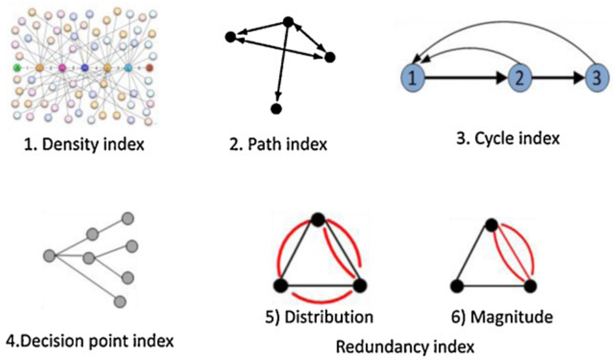


**Fig. 25.** Six manufacturing layout complexity indices [56].

serial, parallel and branching flow, repeated operations, backtracking and bypassing flows. The developed layout graph representation of a system layout with nodes and arrows representing the decisions made and the direction of the flow respectively as shown in Fig. 24. An adjacency matrix can be created to capture the relationships between nodes in the layout graph representation. Complexity indices are based on capturing the layout graph characteristics such as connections or number of nodes.

*3.5.2. Layout complexity indices*

A new method, which assesses the structural complexity of manufacturing system layout, was developed [56]. It introduces six complexity indices, based on the structural characteristics of the system layout which is represented by a graph. These indices are indicative of the *structural system layout complexity* and information content arising from its layout design. An overall complexity index, combining those individual indices, represents the *structural complexity of the system layout.* These indices are useful in the early system design stages to facilitate comparing and evaluating layout alternatives and identify potential flow problems but they do not assess complexities arising from the system dynamic behavior during operation.

The six complexity indices are: graph density, paths, cycles, decision points, redundancy distribution, and magnitude as shown in Fig. 25. They measure information content which increases or decreases the difficulty of making decisions regarding the flow of material in the system layout. All indices are normalized to range from 0 (minimum) to 1 (maximum) representing the layout information content and complexity and are defined as follows:

*Density index*: Number of connections between the nodes.

*Path index*: Number of paths.

*Cycle index*: Number of cycles in the graph.

*Decision points index*: Sum of all nodes between input and output nodes.

*Redundancy Distribution Index*: Number of occurrences of redundancy between adjacent nodes (regardless of the number of the redundancy branches).

*Redundancy Magnitude Index:* Number of redundant parallel arrows in the system layout.

*The layout complexity index* (LCI) aggregates and combines the individual complexity indices into an overall complexity index of the system layout [56].

*3.6. Biological manufacturing systems models and emergent synthesis*

Biological manufacturing systems models that can deal with the complexity of the manufacturing environment using the ideas of self-organization, evolution and learning have been studied by Ueda et al. [146,147,150]. The models handle the uncertainty in the perception, action and inner structure of agents by introducing bounded rationality in their characteristics.

Emergent synthesis methodologies have been reviewed in a CIRP keynote paper by Ueda et al. [149]. The paper clarifies the importance of emergence in solving synthesis problems. Ueda et al. [145,148,151] presented applications in process planning and scheduling. The effectiveness of the proposed methods is confirmed by demonstrating, through benchmark problems, high productivity resulting from role-sharing among machines.

## 4. Business/enterprise complexity

Organizational structures of companies are affected by increased complexity. Market demands, product diversity and flexible business processes require new concepts and strategies in organizational design. Product adaptations, as they are required by product individualization or mass customization, affect all aspects of product generation and require appropriate methods of complexity management.

A recent study carried out by IBM Corporation [108], which is based on face-to-face conversations with more than 1500 chief executive officers worldwide, revealed the following three widely shared perspectives: (1) the world's private and public sector leaders believe that a rapid escalation of complexity is the biggest challenge confronting them, (2) their enterprises today are not equipped to cope effectively with this complexity in the global environment; and (3) they identify creativity as the single most important leadership competency for enterprises seeking a path through this complexity. In addition, global shifts have compounded the situation as interactions and supply chains are more multi-faceted, interconnected and structurally different.

### 4.1. Global supply chain complexity

For industrial organizations to succeed and survive in volatile fast changing markets, they should build a reliable architecture that allows them to develop a sustainable competitive advantage, in an era of globalization [2,79,132]. Building such reliable architecture automatically reduces their organizational flexibility. As a result, any current successful capability contains risk of rigidity and bureaucratic grid lock in the face of the continuous changing environment and short windows for opportunities. Enterprises are confronted with a dilemma: on the one side, developing reliable patterns of selecting and linking resources to attain better performance and competitive advantages, and on the other side, risking becoming locked into exactly these "successful reliable capabilities."

From a system thinking perspective, the competition/cooperation boundaries govern the evolution of a firm's adaptive strategic behavior and drive it towards its desired objectives. Strategic flexibility is considered a sustainability advantage in today's global competitive environment.

On 11 March 2011, an earthquake of Richter scale 9.0 followed by Tsunami hit the east coastal area of Japan. Besides immediate losses of human lives and materialistic damages, one of the nuclear power plants in this region suffered a disastrous meltdown in its three reactors. Since this region had a number of factories producing industrially critical components and materials, the disruption and stoppage of their production caused chain reactions of disruption in the supply chains of many companies around the world. Some examples are: Renesas had factories producing semiconductor chips for embedded systems. Their customers were the automobile industry, and the disruption at Renesas factories resulted in reduction and stoppage of world-wide automotive production, in particular of Japanese automotive companies. Merck had the only factory in this region that was producing pigment (Xirallic) used for car painting. The damage by the earthquake resulted in shortage of paints and further production stoppage of a Chrysler factory in North America.

This suggests many lessons to manufacturers. First, the importance of risk management of the supply chains should be more emphasized. The Renesas case was clear because Renesas was a first tier supplier for many automotive companies, while Merck case was tricky, because Merck was not a direct supplier to Chrysler. This means the management and control of secondary, tertiary, and even downstream suppliers is necessary. In both cases, the trouble became bigger than it first appeared and resulted in production disruption for a long period of time, because they were the sole suppliers of critical components. In addition, another important issue emerged. Traditionally (particularly Japanese) automotive industries relied on the so-called "keiretsu" supplier relationship which means on one hand a single supplier (without a second source) and on the other very close relationships that allow design-in activities for better quality. While this type of relationships had been reviewed and in certain cases reduced to some extent due to further cost-down pressures, it also contributed to more competitive products by having an integral architecture through "custom-designed and custom-made" components. Some custom ICs critical for car production were not available as "industry-standard". This earthquake revealed the weakness of this design philosophy.

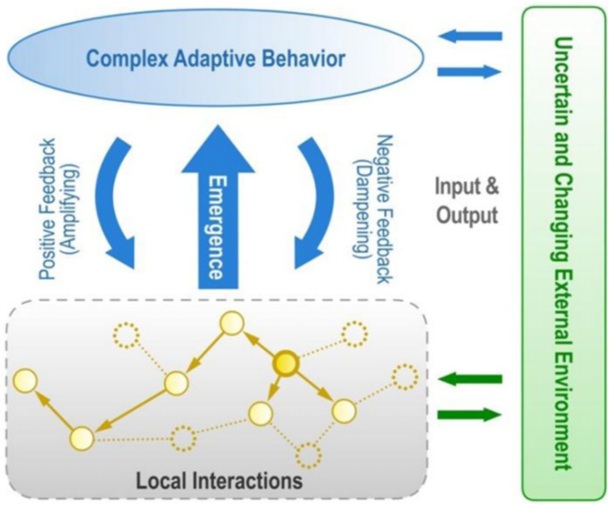


**Fig. 26.** Emergence in Complex Adaptive Systems [31,126].

The most important elements of an enterprise collaboration are probably dynamic and, therefore, hard to model and analyze. Complex Adaptive Systems (CASs) were suggested for modeling the dynamic behavior of enterprise networks [31,103,126,140]. CASs constitute one of the newest complexity approaches [68,69] with the goal of studying the structures and dynamics of systems and examining how the adaptability of the system creates complexity. A CAS can be considered as a Multi-Agent System (MAS), where the agents cooperate and compete for the same resources or for achieving a given goal. Consequently the environmental conditions are changing, which, in turn, changes the behavior of the agents themselves. The most remarkable phenomenon of CASs is the emergence of highly structured collective behavior over time from the interactions of simple subsystems, usually, without any centralized control [149]. The simultaneous co-evolvement of the CAS and its environment results in a state of quasi-equilibrium. Fig. 26 illustrates the emergence of a collective complex adaptive behavior from the local interactions of agents.

Designing CAS is an extremely difficult assignment where, among other issues, non-linear phenomena, incomplete data and knowledge, combinatorial explosion of states, dynamic changes in environment and the problem framework are to be faced. In order to manage such systems, an appropriate balance between control and emergence must be found [23]. It is hard to understand the effects of individual characteristics of agents on their collective behavior. Consequently, while designing and optimizing such systems, a proper balance between simulation and theory is desirable [140]. In order to successfully set up and manage a

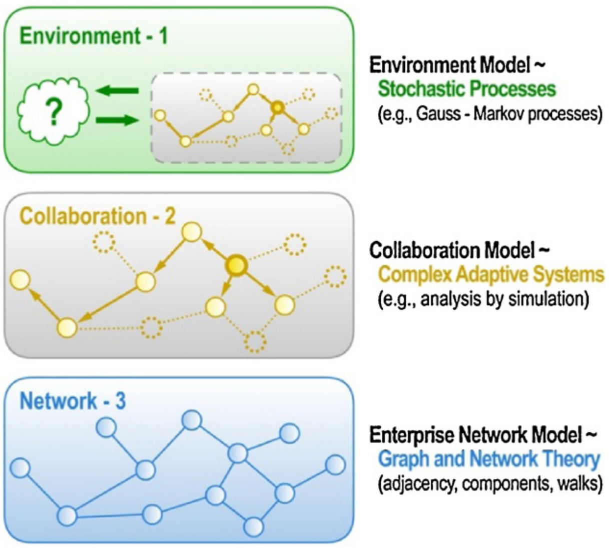


**Fig. 27.** Conceptual overview of the semi-formal model [31,126].

network of collaborative agents, it is important to experimentally and theoretically study collaborations. Based on computer science and mathematics, a collaboration network description model was proposed based on well-developed theories from statistics, discrete mathematics and artificial intelligence [31,126]. It consists of three different sub-models for modeling different parts of the problem (Fig. 27). The n*etwork structure* of supply chains (lower level of Fig. 27) can be treated as *quasi-static* and, therefore, can be adequately described by graph theory. Graph vertices can represent companies (or their functionalities), while the edges can indicate connections or relations between them (such as potential cooperation). The properties of the companies, which are important from the modeling point of view, can be encoded into the nodes, while the features of the connections (such as physical distance or trustiness) can be described by edge weights in scalar or in vector form. The use of graph representations offers the application opportunity of graph related complexity measures for characterizing the complexity of a manufacturing enterprise network, at least its static parts.

The *dynamic parts of the cooperation* (middle level of Fig. 27) can be modeled as a Complex Adaptive System, where the agents are primarily associated with enterprises. Each agent can have its own goal and the ability to cooperate with other agents. A complex adaptive behavior can emerge from local interactions of the agents, even for simple agents strategy or behavior rule. Computer-based simulation can be used for analyzing such systems and the results can serve as the basis of a collaboration network design or a decision support tool for managing them.

The *environment* is the most abstract part of the proposed approach (upper part of Fig. 27).

In order to keep the complexity of the proposed model at a manageable level, those phenomena that are not to be investigated in detail, but still affect the collaboration (e.g., macro economy, customers, culture, politics, geography and weather), are roughly modeled as multivariate random variables with potentially different marginal distributions. Mathematically, the environment is treated as a stochastic process, namely, as a sequence of multivariate random variables. In order to simplify the analysis, this process can be assumed to be stationary or Markovian. Its complexity can still be measured, e.g., by information entropy.

This triple-level model offers a simple yet effective approach for modeling collaborative enterprises. The approach is fundamentally built upon existing and well-developed theories from computer science and mathematics and offers complexity measures that could help investigate potential problems in networks of collaborating enterprises.


**Fig. 28.** The socio-technical system of systems model.

## 4.2. The socio-technical systems

Socio-technical systems are systems in which both human and non-human elements interact, and where the social or management dimensions tend to be significant, stressing the philosophy of shaping both the technical and the social conditions of work. The notion of "system" has also been used in general systems theory, and in system of systems (SoS) modeling. The concept includes sustainability, environmental, and ecological systems in the model.

Complexity management is a business methodology that deals with the analysis and optimization of complexity in enterprises. Effects of complexity pertain to all business processes along the value chain and hence complexity management requires a holistic approach. Complexity in manufacturing enterprises appears in the following fields: Products, Markets, Customer portfolio, Material/Components, IT systems, Processes, Maintenance, Technologies and Organization as illustrated in Fig. 28.

## 4.3. Managing the dynamic business landscape

The complexity economics concept considers economic systems as evolutionary systems, which tend to develop toward levels of higher internal self organization. This new model of economic decision making suggests replacing perfect rationality with more realistic assumptions of inductive decision making and bounded rationality for individuals, where individuals might not conclude the same output even if they have the same inputs [85]. Arafa and ElMaraghy [8] explored the link between the manufacturing objectives and their effect and quantified the strategic effect of applying five different strategies on the enterprise strategic flexibility capability.

By modeling and analyzing different scenarios using a system dynamics simulation approach and considering the market competitive dynamics, the model introduces the volume flexibility as a macro strategic measure that affects the firm's intended production capacity. The effect of enterprise volume flexibility on its market share was studied and reported. The global competition conceptual model is illustrated in Fig. 29. The volume flexibility dynamics submodel is illustrated in Fig. 30. The research explored how operations management theory on volume flexibility can be linked to the dynamic capability theory to develop new macro measures for the enterprise manufacturing strategy [8]. Results show that matching between the firm capabilities and its external environment is a critical factor for organizational success. While the intensity of competition governs the product life cycle duration, success level is proportional to the competitor simultaneous actions and reactions, which is different in different market conditions.

## 4.4. Sustainability and evolution of engineering systems

The growing global population, demographic shifts, climate change and increasing pressure on natural resources have all

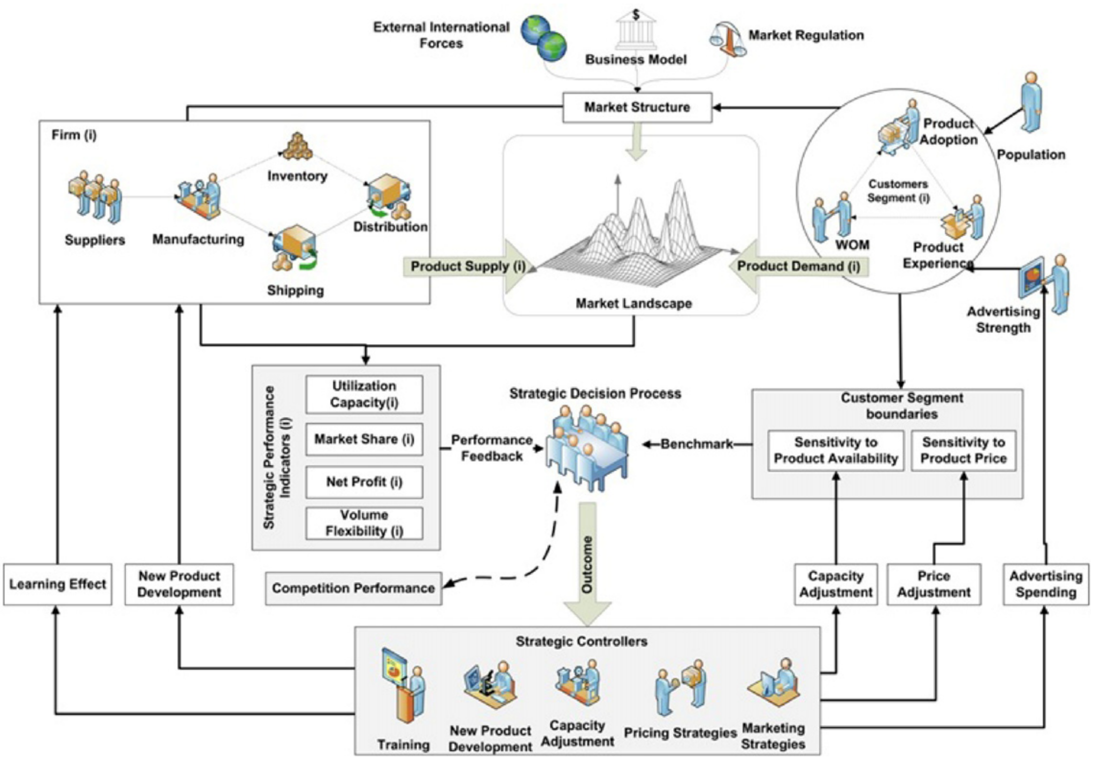


**Fig. 29.** Global competition conceptual model structure [7].

brought sustainability to the top of the political, social and business agenda. Sustainability is the capacity to endure. Limited attention has been accorded to the social dimension of sustainability as envisioned by the United Nations Division for sustainable development [155] articulated the objectives: "Recognizing that countries will develop their own priorities in accordance with their needs and national plans, policies and programmes, the challenge is to achieve significant progress in the years ahead in meeting three fundamental objectives: a) to incorporate environmental costs in the decisions of producers and consumers; b) to move more fully towards integration of social and environmental costs into economic activities; and c) to include, wherever appropriate, the use of market principles in the framing of economic instruments and policies to pursue sustainable development".

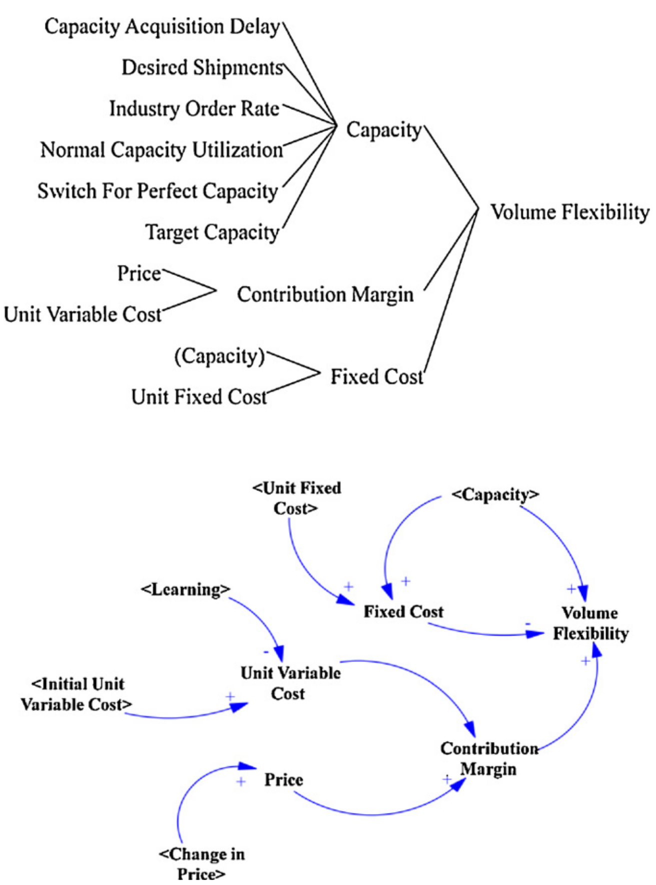


**Fig. 30.** Volume flexibility dynamics sub-model [7].

Sustainability, similar to "complexity", presents both major challenges and tremendous opportunities for businesses. Many companies have realised that by investing in energy-efficiency measures, responding to changing consumer buying patterns and ensuring sustainable business practices in their supply chains, they can operate more efficiently and create value in new ways.

## 5. Current directions

The subject of complexity in engineering design and manufacturing is quite involved in its breadth and depth. Researchers in all fields of science, social sciences and engineering have been concerned with complexity for many years. In industry, interest is growing as industry is faced with fierce global competition and complexity in all areas.

Pavard and Dugdale [114] analyzed some of the conceptual and methodological contributions that complexity theory can make to the study of socio-technical cooperative systems. The theory of complex systems has developed along two complementary, but nevertheless distinct, axes. Chronologically, the first unifying concepts of the complexity paradigm resulted from the study of non-linear systems. Later, the study of distributed self organizing systems made it possible to widen this initial approach to the analysis and modeling of social cognitive systems. They discussed the four specific properties of complex systems in relationship to their usefulness to socio-cognitive modeling:

(1) non-determinism;
(2) limited functional decomposability;
(3) distributed nature of information and representation; and
(4) emergence and self-organisation.

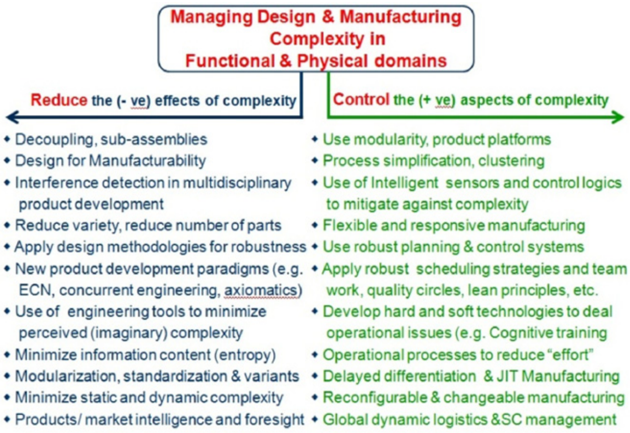


**Fig. 31.** Managing complexity in design and manufacturing.

### 5.1. Embracing complexity in engineering and business

Whilst the focus until recently was to reduce complexity, the new trend in engineering and business is to embrace it. Engineering complexity comes in different types and magnitudes, in all domains, and in different stages of the life cycle. Successful companies take each of these types into account. On the most basic level, there are two types of complexity. Good complexity creates value for consumers, customers, channels, and the company. It has positive impact on buying decisions and helps increase the company's revenue and profit margins. Bad complexity, by contrast, brings little value and leads to reduced revenue, excessive costs, and lower margins. Simply put, companies need to manage good complexity while minimizing or eliminating bad complexity as shown in Fig. 31.

Complex systems concepts provide a unity of approach to many different problems. These concepts originate from efforts to understanding physical, biological and social systems, and have been extended to applications in science, medicine, engineering, management and education.

According to [34] Engineering Systems is defined as: ''A class of systems characterized by a high degree of technical complexity, social intricacy, and elaborate processes, aimed at fulfilling important functions in society''. Systems Engineering has been defined by the consensus of the International Council on Systems Engineering (INCOSE) Fellows: ''Systems Engineering is an engineering discipline whose responsibility is creating and executing an interdisciplinary process to ensure that the customer and stakeholder's needs are satisfied in a high quality, trustworthy, cost efficient and schedule compliant manner throughout a system's entire life cycle. This process is usually comprised of the following seven tasks: State the problem, Investigate alternatives, Model the system, Integrate, Launch the system, Assess performance, and Re-evaluate. These functions can be summarized with the acronym SIMILAR: State, Investigate, Model, Integrate, Launch, Assess and Re-evaluate.'' Engineering for much of the twentieth century was about artifacts and technical systems. Now it is increasingly about complex systems, as large-scale socio-technical systems converge and interact. As scale, scope, and complexity increase, engineers must consider technical and social issues in a highly integrated way as they design flexible, adaptable, robust systems that can be reconfigured and changed to satisfy changing requirements and new technological opportunities. In a recently published book, de Weck et al. [34] offer a comprehensive examination of such systems and the associated emerging field of ''Engineering Systems'', which is at the intersection of engineering, management, and social sciences. This approach is needed for engineers to participate, even take a lead role, in addressing the grand challenges ahead including productivity, competitiveness, sustainability, health, security, and the joy of living. Through scholarly discussion, concrete examples, and history, the authors consider the engineer's changing role, new ways to model and analyze these systems, the impacts on engineering education, and the future challenges of meeting human needs through the technologically enabled systems of today and tomorrow.

### 5.2. Chaordic manufacturing systems

The paper by van Eijnatten et al. [158] is about the management of novelty creation in modern manufacturing systems considering complexity as a central concept in this respect. Earlier engineering research and practice tend to consider complexity a negative phenomenon. The central thesis in the paper is that in order to create novelty, complexity should not be eliminated but nurtured instead in manufacturing systems design and development. The authors propose to apply chaordic systems thinking (CST), which is a recent, qualitative framework in the domain of complexity that both combines and generalizes existing ideas from various disciplines, rather than inventing new concepts. Its name is derived from the technical term chaord, which is an amalgamation of the wordings chaos and order.

### 5.3. Trends in managing the business complexity

The global supply chain is now more integrated than ever, exposing companies to interdependence risk. Conventional theories of management lack the tools to describe, analyse, and manage growing complexity, and can, in turn, no longer cope with the issues it gives rise to. Manufacturing companies do work in competing and collaborative modes, while working in an uncertain and volatile global market [7]. Their main challenge is to survive, and better yet to thrive in increasingly uncertain times. A possible approach is offered by socio-technical complex systems research [65]. Another is by using system dynamics methods and tools to tackle these very large and complex problems [8]. Learning to deal with discontinuity requires more than mere diversification or efficient exploration of possible products. Often organizations face the difficult task of thinking differently; of breaking habits and questioning long-standing conceptual and cultural commitments. Some firms have learned to capitalize more directly by harvesting the lucrative returns associated with some discontinuities. In many industries, a few products dominate all others in terms of their returns on research and development investment.

## 6. Conclusions

The approach to complexity in design or manufacturing varies from coping with it, and trying to manage it to advantage, to minimizing or eliminating it. Regardless of the objective, it is essential to characterize it, develop metrics to measure it and models to study how it propagates from products to operations and processes and ultimately to manufacturing systems and their design and operation. The ultimate goal is not only to mitigate potential negative effects of complexity but also to maximize the benefits from it, such as using it to gain a competitive edge in the market. The increase in complexity by design is only justifiable if it improves system capabilities and performance, but should otherwise be minimized. Regardless of the objective, it is important to characterize and measure complexity at all levels.

Given the grand challenges facing engineering, which are of increasing complexity in breadth and depth, it is realized that companies must consider complexity in technical as well as in other multi-disciplinary domains. To reap the benefits in the future, manufacturing companies will need to not only to adopt flexible technical solutions, but they must also effectively innovate and manage complex socio-technical systems.

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