Immunity and Information Sensitivity of Complex Product Design Process in Overlap Decomposition

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Structural decomposition of large scale systems into subsystems or agents has been a method of simplifying decision making for the complex systems. In most complex system designs the overlap decomposition of the systems is employed, which leads to overlap design tasks between design teams and more synchronous information transfer between them. A method for measuring the overall complexity of a system after being overlap decomposition is presented. It is shown that this measure is useful in deciding on an appropriate decomposition strategy which influences the design process efficiency. A combination of random or in some cases exhaustive search with spectral graph partitioning is proposed for extracting the decompositions with the dual objective of low overall complexity with maximized overlapping parts.

1 Introduction

Most contemporary design problems tend to be large, necessitating decomposition to reduce the problems complexity in order to make design problem solving more tractable [Li et al., 2005]. The parametric and detail design phases of product design mainly focus on identifying and classifying the specific design parameters. The parametric design problem is decomposed into smaller tractable sub-problems which can be solved separately and in parallel [Ulrich and Epping, 2004]. This is usually referred to a Structural or Functional decomposition approach. There is however a considerable difference between functional decomposition and structural decomposition. Functional decomposition is concerned about interactions between the components in the form of energy, materials, or signal interchanges between the sub-functions or components [Ulrich and Eppinger 2004]. Where as structural decomposition takes decomposition as the clustering of the different system or design parameters, objectives and constraints into subsystems which are also referred to as agents [Kusiak, 1999]; the term agent here is used mainly as the design of these subsystems are performed independent from each other. Therefore we can refer to the decomposed system as a multi agent system (MAS) [Efatmaneshnik and Reidsema, 2007b]. In the complex product development, the parameter determination of each of the subsystems (design of each of the agents) is assigned to different design groups or teams.

An efficient design process is defined as a cheaper, faster process leading to better products in terms of quality. In order to increase the efficiency of the design process it is suggested that, many development teams work at the same time and concurrently. To render the detail design of the subsystems parallel processes, it is ideal that these subsystems/agents be as independent as possible [Kusiak, 1999]. For coupled systems the design process is iterative, and the number of iterations at each stage is directly proportional to the degree of dependence or couplings of the subsystems [Eppinger and Sialman, 2001]; the iteration is accompanied by design negotiation and conflict resolution to arrive at a compromise solution and to maximize the joint payoff for the two design agents or subsystems [Ulrich and Eppingger, 2004]. Managing the network of interactions across the subsystems is the task of system engineering specialists of many kinds [Eppinger, 1997] and is usually referred to as design coordination [Duffy et al., 1999].

However, in the case of complex systems, the intrinsic characteristic of which is interdependency, the perfect decomposition and decoupling of the agents/subsystems is virtually impossible. This threatens the integration of the entire system, and renders centralized coordination impractical. For severely coupled systems collaborative design is suggested; Collaborative design is performed by multiple participants representing individuals, teams or even entire organizations each potentially capable of proposing values for design parameters and/or evaluating these choices from their own particular perspective [Klein et al, 2003]. The key challenge raised by the collaborative design of complex artifacts is that the design spaces are typically huge, and concurrent search for design solutions by the many participants through the different design subspaces can be expensive and time-consuming because design issue interdependencies lead to conflicts when the design solutions for different subspaces are not consistent with each other [Klein et al. 2003]. Klein et al. further state that collaborative design is challenging in that strong interdependencies between design issues make it difficult to converge on a single design that satisfies these dependencies and is acceptable to all participants.

The design teams can be collaborative only when the design space or problem space is decomposed in an overlapped manner, so that the design teams share some of their parameters, problems, and tasks (figure 1). Taking the information processing view to product design process, Krishnan et al. [1999] has argued that overlap decomposition of the problems can lead to faster information acquisition and more frequent information exchange between the subsystems enabling the concurrent execution of coupled activities in an overlapped process.

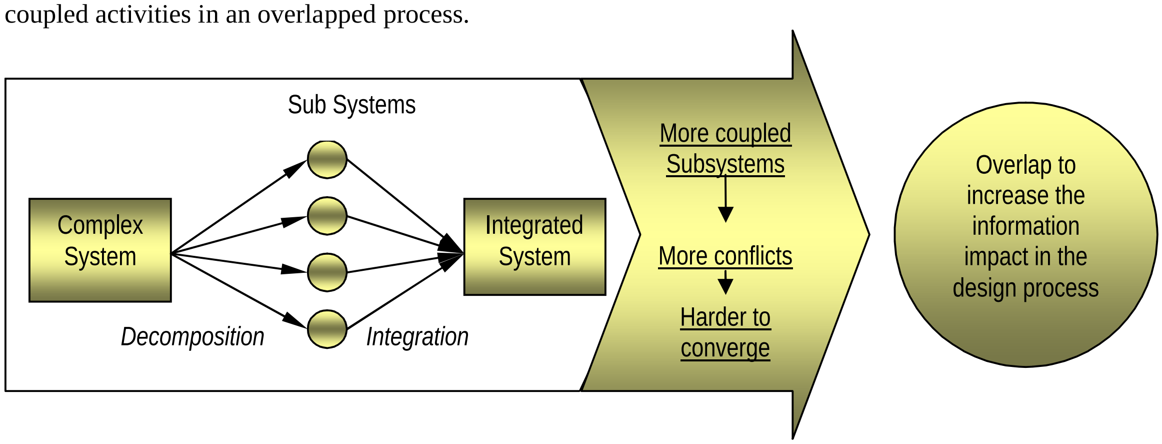

Figure 1. The complex system design process which includes decomposition and integration can be collaborative if the design space decomposition is overlap.

Several operation researchers have addressed the overlapping decomposition and have emphasized its quality improving, lead time and cost reducing benefits [Roemer and Ahmadi, 2004, Terwiesch and Loch, 1999, Krishnan et al. 1997] to the extent that design efficiency can be regarded as proportional to the amount of the overlap between the subsystems [Clark and Fujimoto, 1989]. Krishnan et al. [1997] has however noted that the overlap decomposition of the system must be performed very carefully as without careful management of the overlapped product development process, the development effort and cost may increase, and product quality may worsen.

Despite this caveat, they have reported that, no appropriate measure has yet been proposed to distinguish the overall behavior of the systems under a range of possible overlap decompositions. In this paper we propose an overall complexity measure for the system overlap decomposition. By knowing that design efficiency is directly proportional to the overall complexity of the system and that decomposition affects the design efficiency (Ulrich, and Eppinger, 2003), this measure can be used to evaluate the efficiency of the different possible decompositions. We define an immune overlap structural decomposition as one that leads to relatively low overall complexity. By measuring this complexity and presenting a spectral method for searching and extracting the immune structural decomposition of the large scale systems, it is argued in this paper that better, cheaper and faster complex products and production systems are feasible.

2 Real Complexity of Overlapped Decompositions

Every design problem consists of determining the design parameters (inputs) according to some objectives and constraints (outputs). The design system's structure is the defined as the map that shows the parameters and their relationship which is the way different parameters affect each other. We refer to this structure as the system's "self" as opposed to the set of the inputs and outputs which are the environment that the systems self perceive. Typically, the "self" is represented via an undirected or directed graph which can be weighted or un-weighted. Note that this graph is not identical for the nonlinear design spaces and is established based on the information from the repository of past products and/or the models that describe the underlying structure of the system's parameters. Complexity is measured for the "self" of the system, and is a graph theoretic measure that characterizes the total entropy (uncertainty) in a system. Complexity is a "holistic" measure of the systems that enables us to study the system as a "whole" and characterizes the intensity of emergence in a system [Efatmaneshnik and Reidsema, 2007a]. If complexity is too high the system becomes chaotic and uncontrollable and likely to lose its structure, and if too low the system loses the intrinsic characteristics of the entity it was intended to describe, and fails to emerge as an organized self or spontaneous whole. Thus, complexity materializes the system's self in the emergence of the structure when agents or subsystems interact. This emergence is spontaneous and is referred to as spontaneous self-organization, which can be seen in the formation of societies, molecules, bird flocks, etc.

Complexity of a system before decomposition is referred to self complexity which is different from the overall system complexity after decomposition. When a system is simplified it is unavoidable to lose some of the information contained in the system [Klir, 2002]. In other words decomposition leads to information lost and thus increases the amount of uncertainty about the behavior of the system. This means an increase in the complexity of the system [Efatmaneshnik and Reidsema, 2007b] from an outsider's point of view. We refer to this overall complexity as the real complexity. Even though this complexity-based method can be generalized to systems with unilateral relationships between parameters, for our purpose (complexity analysis) all graphs suffice to be considered undirected, and it is also true that, in general, most of any system's parameters mutually affect each other. The most natural matrix to associate with a graph is its adjacency matrix [Diestel, 2005].

A block diagram is the graph representation of a partitioned graph [Diestel, 2005]. A block diagram of a system is in fact a more abstract representation of the system and is the graph of the subgraphs or the graphical representation of the corresponding MAS or partitioned system. Consider partitioning a graph, into k subgraphs or blocks, with the complexity of each subgraph determined by the proprietary complexity measure of Ontonix s.r.l.[1] Company. In Efatmaneshnik and Reidsema [2007b] we have defined the "Super Adjacency Complexity Matrix" (SCAM) $B = [b_{p,\,q}]$ for the block diagram:

$$b_{p,\,q} = \begin{cases} C_p & p = q \\ L_{p,q} = \sum a_{i,\,j} & p \neq q,\ i \in p,\ j \in q \end{cases} \tag{1}$$

Or

$$B = \begin{bmatrix} C_1 & L_{1,2} & . & \cdots & . & L_{1,k} \\ L_{2,1} & C_2 & . & \cdots & . & L_{2,k} \\ . & . & . & & & . \\ \vdots & \vdots & & \ddots & & \vdots \\ . & . & & & . & . \\ L_{k,1} & L_{k,2} & . & \cdots & . & C_k \end{bmatrix} \tag{2}$$

[1] This measure is a combination of the graph theoretic complexity and kolmogorov-Sinai's entropy. Visit www.ontonix.com for more information.

With C_i s as the complexity of each of the k subgraphs, L_{ij} as the number of links between each pair of blocks, and $a_{i,j}$ as the elements of the adjacency matrix of the system's self graph.
The real complexity of the system after decomposition is then a function of k, C_is and $L_{i,j}$s. One of the striking results of this definition is that the resulting complexity is very sensitive to the weight of links to the most complex subgraph; this suggests why complex systems of certain complexity mostly posses a few hubs that are the most complex subsystems as well, the effect which is usually referred to as the power law in complex systems.

2.1 Extended Landscape

In overlap decomposition of graphs, vertices are allowed to be shared between the subgraphs. Base on the formulation of the decentralized control strategies for overlapping information sets [Ikea et al., 1981], we introduce the measurement of the overall real complexity of the overlapping multi agent systems. Ikead et al. states that the simple underlying idea is to expand the state space of the original system(design space or landscape in case of the product design) so that the overlapping subsystems appear as disjoint. The expanded system contains all the necessary information about the behavior of the original system which then can be extracted using conventional techniques devised for standard disjoint decompositions.

We use the method introduced in Efatmaneshnik and Reidsema [2007b] which was briefly explained earlier as the convention for complexity measurement of ordinary/disjoint decompositions. Below figure shows the extraction of the SCAM for the overlapping subsystems. It can be tested that the dimension of the SCAM is four where as the number of subsystems are two.

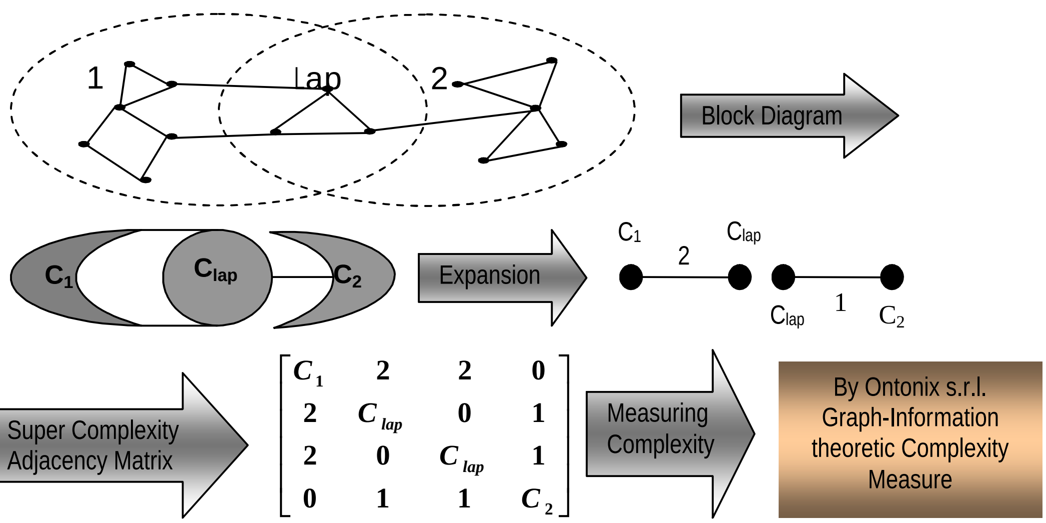

Figure 2. Partial representation of real structural complexity measurement for overlapped subsystems.

In general the Super Adjacency Complexity Matrix of the block graph with elements B = $[b_{ij}]$ where subgraphs share some vertices is defined as:

$$b_{i,j} = \begin{cases} C_i & i = j \text{ for unshared blocks} \\ C_{overlap} & i = j \text{ for overlapping blocks} \\ L_{ij} & i \neq j \\ 0 & i \neq j,\ i \text{ and } j \text{ are the expansions of the same block} \end{cases} \quad (10)$$

2.2 Innovative or Routine Design Process

Bar-Yam [2003] states that There are two effective strategies for achieving quality criteria for the design of large scale systems: (1) restricting the complexity of the problems (immunization of the process against chaos), and (2)adopting an evolutionary paradigm for complex systems engineering. The designs with high structural complexity need to be assigned to innovation groups. The evolutionary process of design relies on radical innovative solutions provided by design groups [Bar Yam, 2003]. Examining many design alternatives and avoiding premature commitment to routine solutions, innovative design groups have the ability to reach higher global optima and robustness: the solutions are tested for wider adoption to the other solutions from other design teams. On this basis the real structural complexity of a design problem provides the design process planners with the insight required for the selection of the design process (figure 3).

Figure 3. : Structural Complexity informs us about the required design process.

3. Routine Design Process Fragility and Sensitivity to Information

Risk and information are two important concepts of design theory and for the routine design processes have the following definitions and implication:

Risk: In the design process system, "performance risk" is defined as uncertainty in the ability of a design in its current state to meet desired quality criteria (along any one or more dimensions of merit) and the consequences thereof [Browning, 1999]. Here, design performance is defined broadly, including system functionality, reliability, cost, design process lead time, product conformance to specifications and perceived quality. As Browning [1999] states the performance risk increases with product and problem complexity and complex system product development involves enormous risk; because complexity in the presence of the uncertainty leads to fragility [Marczyk ,2006]. Complex systems which are referred to as "robust yet fragile" systems tend to be robust to some variations, but as soon as the uncertainty in the system increases from a certain amount, chaotic properties (oversensitivity) make the system fragile and likely to sudden collapse. This is why the design of complex product usually fails as has been reported by bar Yam [2003].

Information: Braha and Maimon [1998] defined (functional) "information" a distinct notion, and independent of its representation which allows the designer to attain the design goals. Therefore information has a goal satisfying purpose. Design can be regarded as an information process in which the information of the design increases by time: making progress and adding value (to the customer) in system product development compares to producing useful information that reduces performance risk [Browning et al., 2002].

Decomposition increases the overall complexity and by that leads to more risk being involved in the entire design process, and reducing the ability of the design groups to measure the overall performance with certainty. Thus it leads to information lost about how to satisfy the overall design goals [Efatmaneshnik and Reidsema, 2007b]. A decomposition that has lower real overall complexity, obviously leads to less risk and less information lost of the design process (figure 4). To such decomposition we refer to as immune (against chaos).

The effect of overlapping on the design efficiency is very subtle. The integration phase of the design process is often accompanied by inadvertent information hiding due to the asynchronous information exchanges between the design teams which is referred to as "design churn effect" [Eppinger, 2002]. Design churn delays the design process convergence to a global solution. The remedy to this effect lies in overlapping the design tasks. Overlapping leads to faster and "in time" information transfer between the design teams. This is to say that overlapping increase the design process response and sensitivity to new information reducing design lead time and increasing design process efficiency (Figure 4).

As can be tested in figure 4 overlapping leads to more real complexity in comparison with the disjoint decomposition of the design space, since overlapping increases the dimensionality of the problem space. Thus, it is not recommended to simply overlap the subsystems as much as possible because it may lead to high overall complexity. We propose two seemingly conflicting objectives when overlapping subsystems: first to minimize the real complexity of the whole (extracting immune decompositions), and second to maximize the sum complexity of the overlapped parts. The complexity sum of the overlapped parts (C_{lap}) is representative of how much the system is overlapped.

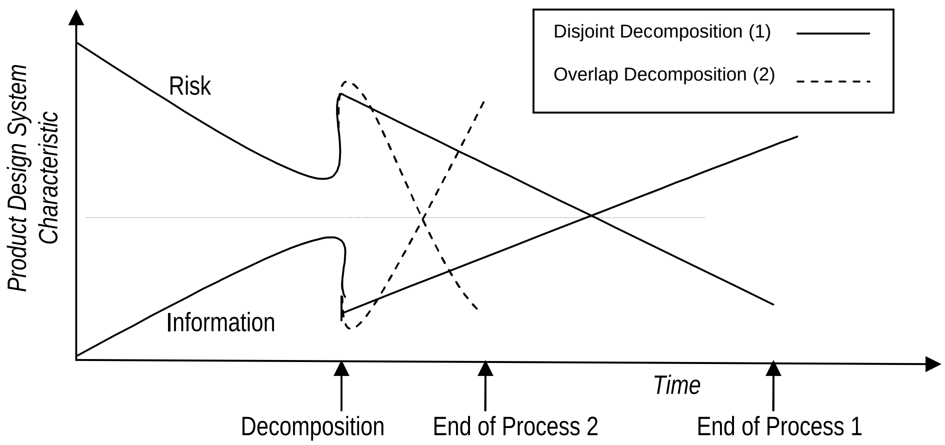

Figure 4. Decomposition increases risk and reduces information. Overlap decomposition makes the system to converge faster.

3.1 A Spectral Method

The eigenvectors of both the adjacency matrix and laplacians are useful in extracting the desirable decompositions of system's graph/self . This method of decomposition is called spectral partitioning and is explained here. Consider A to be the adjacency matrix of an undirected, weighed graph (G). An automorphism of a graph G is a permutation g of the vertex set of G with the property that, for any vertices u and v, we have ug ~ vg if and only if u ~ v [Cameron, 2004]. vg is the image of the vertex v under the permutation g. Automorphisms of graph G produces isomorphic graphs. The first step in spectral partitioning of graphs is to sort the eigenvectors of the adjacency or laplacian matrix of the graph in ascending order, and to permute G by those indices of the sorted vector. Some of the resulting isomorphic graphs would then be diagonalized [Alpert, 1999].

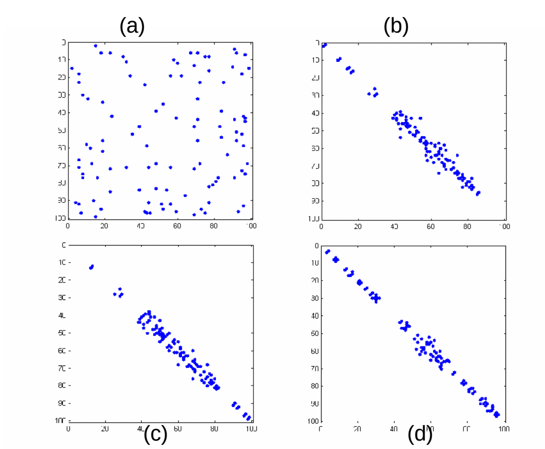

Figure 4. Shows the adjacency matrices of a graph (a) and its spectral permutations that are automorphisms of the graph and are be diagonal (b,c,d).

To find the appropriate decomposition, we propose the random partitioning of the diagonalized automorphisms. Figure 5. demonstrates the real complexity and the degree the decomposition renders the system overlap (complexity sum of the overlap parts) for many random decompositions. These decompositions, in the first glance, seem impossible to be compared to each other. This figure shows the desired region for the decompositions, the characteristic of which is minimum overall real complexity (maximum efficiency, minimum fragility of the corresponding design process or immunity) and maximum overlapping complexity (high sensitivity of the design process to new information).

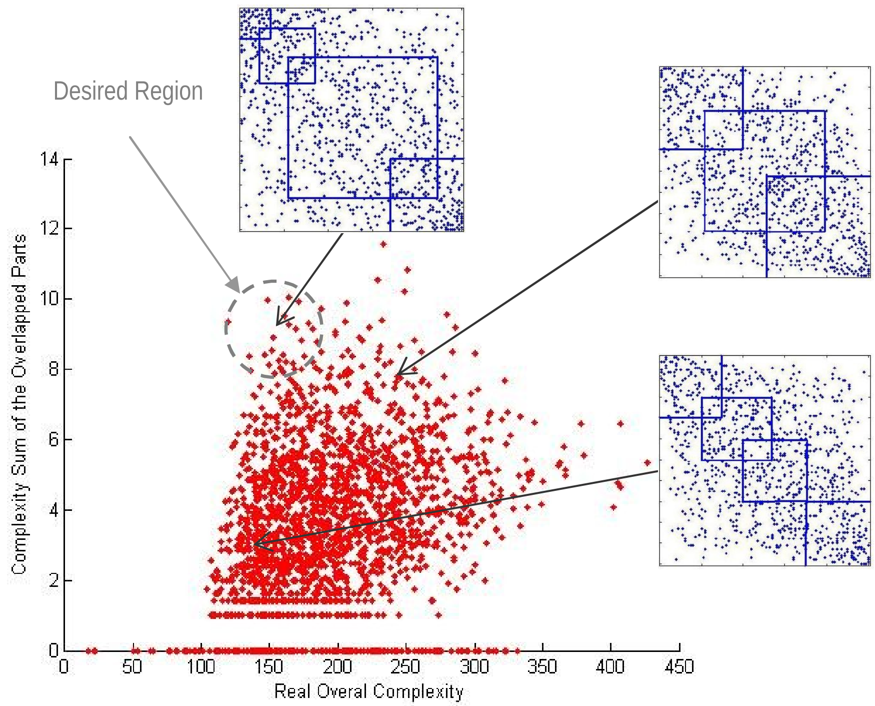

Figure 5. The suitable overlap decompositions for routine design process of complex systems by random search and spectral diagonalization.

4 Conclusion

Real overall complexity of the overlapped structural decompositions of the design problems was defined which characterizes the tendency of the system to show the emergence properties. The emergent properties which can be positive (robustness) or negative (fragility) help us to decide on the type of design process that needs to be utilized by the design process planners. Innovation based and evolutionary design processes are suitable for the design of the systems with large overall complexity values. Whereas, low overall complexity systems favor routine design processes. It was shown that decomposition always increases the overall complexity of the system and that overlap decomposition, relative to the corresponding disjoint decompositions, adds extra complexity to the system's whole. However overlap decompositions are favorable in that they lead to design processes with increased rate of convergence to the overall design solution. Consequently the higher the complexity of the overlapped parts, the design process would be closer to a collaborative format with more synchronous information transfers between the design teams which grantees the faster convergence to the global design solution between all design teams. It was shown that arbitrary overlapping of the systems can have adverse effects on the design efficiency and can lead to high real structural complexity which sheds more complexity on the system and system design process.

Acknowledgement

We would like to thank Dr. Jacek Marczyk, and Ontonix s.r.l. Complexity Management Group for their support.

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