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STRUCTURAL COMPLEXITY: QUANTIFICATION, VALIDATION AND ITS SYSTEMIC IMPLICATIONS FOR ENGINEERED COMPLEX SYSTEMS

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ABSTRACT

The complexity of today's highly engineered products is rooted in the interwoven architecture defined by its components and their interactions. Quantitative assessment of structural complexity is mandatory for characterization of engineered complex systems. In this paper, we develop a quantitative measure for structural complexity and illustrate its application to a real-world, complex engineered system. It is observed that low topological complexity implies centralized architecture and it increases as we march towards highly distributed architectures. We posit that the development cost increases super-linearly with structural complexity. Empirical evidences from literature and preliminary results from simple experiments strengthen our hypothesis. Preliminary experiments show that the effort increases super-linearly with increasing structural complexity (i.e., exponent, b = 1.69). We further introduce complicatedness as an observer-dependent property that links structural complexity to system level observables like the development cost. We further discuss distribution of complexity across the system architecture and its strategic implications for system development efforts.

Keywords: complexity, product architecture, development effort, complexity distribution

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1 INTRODUCTION

Today's large-scale engineered systems are becoming increasingly complex for numerous reasons including higher demands on performance levels and improved lifecycle properties. As a consequence, large product development projects are becoming more challenging and are falling behind in terms of schedule and cost performance [Bashir and Thomson, 1999]. For example, in 13 aerospace projects reviewed by the US Government Accountability Office (GAO) since 2008, large development cost growth of about 55% was observed. Such large development cost overruns/failures of large-scale system development projects can largely be attributed to our current inability to characterize, quantify and manage associated complexity [Bashir and Thomson, 1999, DARPA report 2011]. In order to deal with this issue effectively, quantitative metric for system complexity and its relation to development effort are needed. A quantified measure of complexity is imperative for systematic optimality search of system architecture. Such a quantitative measure of complexity can be evaluated and tracked during system development. A particular concern in the area of complexity estimation is that less than one-fifth of the studies even attempted to provide some degree of objective quantification of complexity [Tang and Salminen, 2001]. This is understandable as large system development projects are rare and definitely not repeatable, making empirical/experimental studies hard to perform. This has posed a significant roadblock to widespread adaptation of generic complexity quantification methods exist for engineered systems. In the context of engineered systems, the three main dimensions of complexity have evolved and they are grouped as (1) Structural Complexity, (2) Dynamic Complexity and (3) Organizational Complexity [Weber C. 2005, Lindemann 2009]. Structural complexity characterizes the system architecture, dynamic complexity refers to the complexity of the dynamical behavior of the system and organizational Complexity relates to the system development process and the organizational structure of the development team. All these dimensions are positively correlated in general [MacCormack et. al, 2011] and we decided to focus on the quantification of structural complexity and its relationship to system development cost/effort in this paper.

The structural complexity of systems depends on the heterogeneity, quantity and connectivity of different elements, and is a measurable system characteristic. This internal product architecture can be represented by complex networks, which are graph-theoretic representation of complex systems where components of the systems are the nodes and are connected by links if there exists an interaction between any pair of components. [Sheard and Mostashari, 2010]. In this paper, a rigorous and quantitative structural complexity metric for engineered complex systems, incorporating the fundamental underlying characteristics of system architecture, is proposed. We posit that the development cost varies non-linearly with structural complexity. Some empirical evidences of such behavior are presented from the literature. This hypothesis is further buttressed by preliminary results from simple experiments involving assembly of simpler structures. We introduce the notion of structural complexity distribution across the system architecture and how it can impact strategic decisions in system development efforts.

2 STRUCTURAL COMPLEXITY QUANTIFICATION

The structural complexity of technical systems depends on the quantity of different elements and their connectivity structure and is a measurable system characteristic. This quantity include contributions coming from the internal complexities of the components of the system; the complexities associated to the pair-wise interactions among the components and a quantity that encapsulates the complexity due to inherent arrangement of connections (i.e., structure) amongst the components. We propose the following functional form for estimating the structural complexity of an engineered complex system:

$$\textit{Structural Complexity, } C = C_1 + C_2 C_3$$

In the above formulation, the first term C_1 represents the sum of complexities of individual components alone (local effect). It relates to the component engineering activity within a system development effort and does not involve architectural information. The second term has two components: (i) number and complexity of each pair-wise interaction, C_2 (local effect) and it relates to interface design and management activity in a system development effort; (ii) effect of architecture or the arrangement of the interfaces C_3 (global effect) which reflects on the challenges associated with system integration. The individual component complexities can vary across the system (e.g., a low-pressure turbine is much more complex than the exhaust nozzle in a jet engine) and are designated by α's. This measure could be based on the widely used notion of component TRL (i.e., Technology Readiness Level) [Sadin *et al.*, 1988] or other similarly motivated measures. We propose a component complexity scale of [0, 5] and computed using component TRL level as:

$$\alpha = 5\left(\frac{TRL_{\max} - TRL}{TRL_{\max} - TRL_{\min}}\right)$$

Similarly we can represent interface complexities (i.e., β_{ij}'s) using a multiplicative model. Each interface complexity depends on the complexities of interfacing components (α_i and α_j) and a coefficient characteristic of the interface type (f_{ij}):

$$\beta_{ij} = f_{ij}\alpha_i\alpha_j \text{ where } \alpha_i, \alpha_j \neq 0$$

If there were multiple types of connections between two components (say, load-transfer, material flow and control action flow), it would have a high β value since it would be more 'complex' to achieve/design this connection compared to a simpler load-transfer connection. For large, engineered complex systems, it appears that β in [0,1] is a good initial estimate. Another alternative for estimation of component and interface complexities is to use pooling of experts opinion. Multiple expert opinions can be aggregated to define a final probability distribution that describes the component complexity [Babuscia and Cheung, 2012]. In such case, the resulting structural complexity will also have a probability distribution and not a deterministic value. The term C_3 represents the topological arrangement of the interfaces and defined as the topological complexity metric. Topological complexity originates from interaction between elements and depends on the nature of such connectivity structure. The adjacency matrix $A \in M_{nxn}$ of a network is defined as follows:

$$A_{ij} = \begin{cases} 1 & \forall[(i, j) \mid (i \neq j) \text{ and } (i, j) \in \Lambda] \\ 0 & \text{otherwise} \end{cases}$$

where Λ represents the set of connected nodes and *n* being the number of components in the system. The diagonal elements of A are zero. The associated *matrix energy* of the network [Nikiforov 2007] is defined as the sum of singular values of the adjacency matrix:

$$E(A) = \sum_{i=1}^{n}\sigma_i, \text{ where } \sigma_i \text{ represents i}^{th} \text{ singular value}$$

Matrix energy is used as a measure of topological complexity of the system architecture and is invariant under isomorphic transformations of the matrix. We define C_3 as:

$$C_3 = \gamma E(A)$$

where γ = 1/n acts as sort of a normalization factor. The topological complexity term C_3 quantity helps distinguish structural complexity of very different connectivity structures with the same number of components and interactions (see fig. 1).

Fig. 1: Two architectures having the same number of nodes and connections but are differentiated based on their internal structure with E(A1) = 4.9 and E(A2) = 6.83.

To check conceptual validity of the proposed topological complexity metric, we benchmarked it against the set of required properties prescribed by Weyuker [Weyuker 1988] and it can be shown to be fully compliant with Weyuker's criteria [Lindemann et al. 2008, Weyuker 1988]. The proposed structural complexity metric is defined below:

$$\begin{aligned} C &= C_1 + C_2C_3 \\ &= \sum_{i=1}^{n}\alpha_i + \left[\sum_{i=1}^{n}\sum_{j=1}^{n}\beta_{ij}A_{ij}\right]\gamma E(A) \end{aligned}$$

The effect of system architecture captured in C_3 represents a global effect whose impact could be first realized at the time of system integration and captures the challenges associated with system integration efforts [Sinha and de Weck 2012]. Topological complexity increases from *centralized* towards more *distributed* architectures (see fig. 2). A more distributed system is one that cannot be condensed/reduced, and such a system indicates higher topological complexity but it might also help achieve higher performance levels with high robustness and reliability [Carlson and Doyle, 2002].

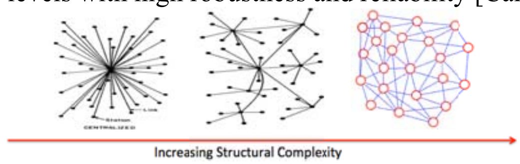
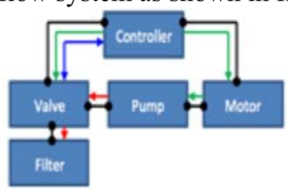


Fig. 2: Evolution of topological complexity based on their internal structure: (a) 'centralized' or bus architecture; (b) hierarchical architecture and (c) 'distributed' architecture.

According to fig. 2, highly distributed architecture would lead to high C_3 value and thereby imply high system integration effort. Note that C_3 is only a part of the structural complexity measure and the total structural complexity is also dependent on component and interface complexities. For example, assume a total *structural complexity budget* of C = 100. We can distribute this total complexity among its different components C_1, C_2 and C_3. There is an interesting tradeoff discussion of whether to opt for (i) complex components and simple architecture, or (ii) simpler components and complex architecture. Assuming we have both options open after considering other life-cycle considerations like *robustness* etc., the first option calls for excellence in component development and very high component reliability while the second option requires expertise in system architecting and integration. This may often be a strategic decision to be made by the development organization. In the following sub-section, we demonstrate operationalization of the proposed methodology using a simple example and also allude to a larger jet engine example where this methodology has been applied and reported in an earlier article [Sinha and de Weck 2012].

2.1 Illustrative Example

We present a small example of a hypothetical system for demonstrating the mechanics of the method, using a hypothetical fluid flow system as shown in fig. 3.



$$A = \begin{bmatrix} 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \end{bmatrix}$$

Fig. 3: (a) Sample system: it shows different connection types amongst components - physical/mechanical connection (black); material/fluid flow (red); energy flow (green) and information/control signal flow (blue); (b) aggregated adjacency matrix.

The graph energy is $E(A) = 5.6$. Now let us differentiate among components and let the component complexity vector be {(controller=5); (pump=2);(valve=1); (filter=1);(motor=3)}. The sum of component complexities C_1 = 5+3+2+1+1 = 12. Let us use the following connection complexities: $\beta^{mech} = 0.5$, □$\beta^{flow/energy} = 1.0$ and $\beta^{info} = 1.0$. Note that mechanical and information connections are bidirectional, while fluid and energy flows are unidirectional. Therefore, the sum of connection complexities C_2 = 2*5*0.5 + 1*5*1 + 2*1*1 = 12. If we use γ□□□□□n = 1/5, the structural complexity is (12+12*(5.6/5)) = 25.44. Here developing the system components is more complex than the connection complexities and it has the effect of increasing the contribution of component complexities in the structural complexity metric. The same method was applied to two different jet engine architectures, namely a dual spool turbofan and a geared turbofan engine. The specific details can be found in [Sinha and de Weck 2012]. The detailed sensitivity analysis revealed that primary functionality generators (e.g., those generating thrust) are significant contributors to component complexity while supporting systems (e.g., lubrication systems, accessory gearbox, robust control systems) are the primary contributors to topological complexity and have significant impact on system integration efforts [Denman et al. 2011, Sinha and de Weck 2012].

In practice, assignment of component and connection complexities could be uncertain during the conceptual stage or even after the product architecture is finalized. In such cases, the resulting structural complexity will not be a single number but a distribution, depending upon the distribution of individual component and connection complexities.

3 VALIDATION OF THE PROPOSED STRUCTURAL COMPLEXITY METRIC

While formulating the structural complexity metric, we performed formal mathematical consistency check and verification using Weyuker's criteria. This only looks at the mathematical validity of the proposed metric as a complexity measure. But in order to establish the proposed metric as a valid measure of structural complexity, a series of both empirical and experimental validations based on real-world applications is necessary. The first obstacle for validation is the inability to directly *measure* complexity. Therefore we have to depend on the indirect measures or well-accepted manifestation of complexity in terms of other system observables. The most visible of these system level observables is the system development cost. We state with the following hypothesis relating structural complexity to system development cost / effort.

Hypothesis: System development cost/effort correlates super-linearly with Structural Complexity (fig. 4).

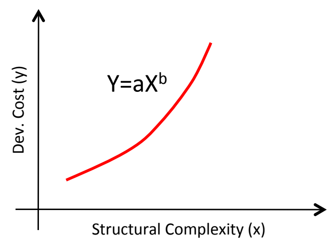


Fig. 4: Predicted super-linear growth in development cost with increasing structural complexity.

We start with showing examples from the literature, followed by an experimental validation (using natural experiments) and finally we discuss about the characteristics of parameters {a, b} in the proposed functional form in the stated hypothesis.

3.1 Empirical Evidence

We begin with some empirical evidence in support of the stated hypothesis. Here, we present three examples of empirical evidence from the literature [Wood et al. 2001, DARPA Report 2011]. They represent simpler systems (e.g., family of electrical drills) at one end and highly complex satellite systems at the other end. In all these cases the development costs are normalized and structural complexity is computed based on the underlying architecture. The component complexities were estimated on a scale [0,5] and interface complexities on a scale of [0,1]. The development costs were taken from the existing literature. In these cases shown, we have similar kind of products with the similar primary functionality.

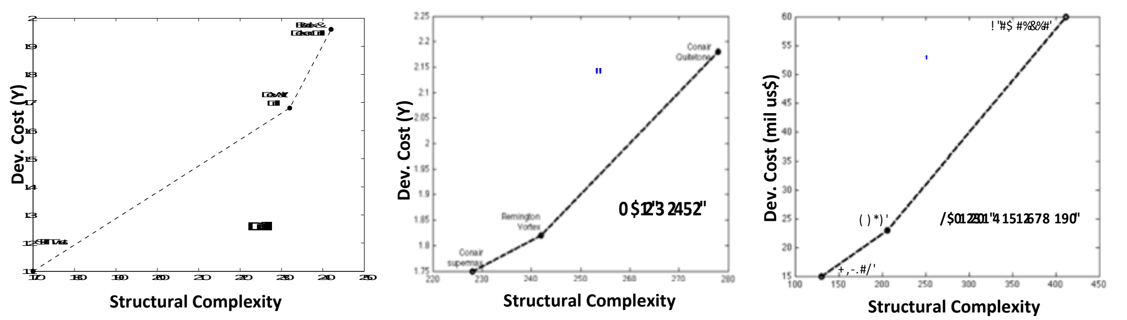
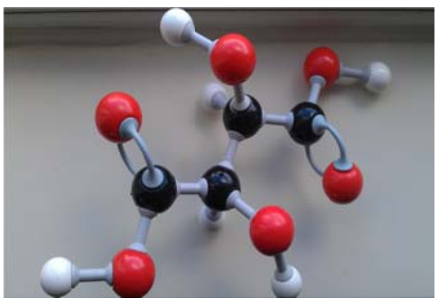


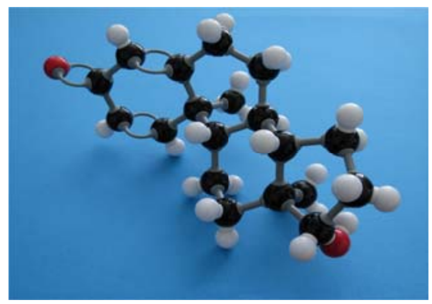
Fig. 5: Some empirical evidences of super-linear growth in development cost with increasing structural complexity from the literature.

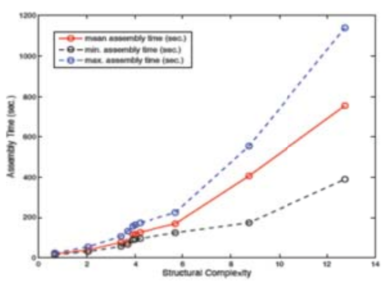
In all cases shown in fig. 5 above, if we were to fit a power law as per our hypothesis, we obtain R^2 = 0.99, indicating very strong correlation. The parameters of the model {a, b} depends on the nature and category of systems. For example, they are higher for satellite development compared to other kinds of systems. Please bear in mind that these numbers are based on just 3 data points and therefore not statistically significant. They only support the trend consistent with our hypothesis but are not enough for a statistically significant confirmation. Apart from such empirical evidence, we concentrated on conducting experiments with human subjects to see if we observe a similar behavior. These experiments were conducted as "natural" experiments as nearly as possible with a group of nearly homogeneous subjects, using simple ball and stick models as described in the following section.

3.2 "Natural" Experiments

There is not much publicly available data to validate our hypothesis for large, real-world complex engineered systems. Given the lack of available data, we choose to perform simple natural experiments related to assembly of simpler structural models by human subjects. We perform an experiment with a molecular modeling kit, used in chemistry for illustration of structure of organic molecules. The atoms are the components, and the bonds between them are the interfaces. Test subjects were required to correctly assemble structures given this molecular kit and a 2D picture of the structure to be built. We track the total assembly time for each structure as the observable and is used as a surrogate for system development effort. Any incorrect assembly involves rework and leads to increasing total assembly time. Notice that this is a natural experimental setting and the idea is to mimic the real-world assembly process. The sequence in which different subjects were given the molecular structures was randomized. In all cases, we assumed $\alpha = 0.1$ for all atoms, $\beta = 0.1$ for all links and $\gamma = 1/n$ where n is the number of atoms in a given molecule. This is because all atoms are used as is and there is no perceptible difference in assembling using different bond types (i.e., curved vs. straight bonds). We have looked at the sensitivities of component and interface complexities and found no significant impact on the nature of the Structural Complexity - Development Cost relationship.







Functional form:	$Y = aX^b$
Fitted parameters:	a = 10.23; b = 1.69
Model adequacy:	$R^2 = 0.9967$; adjusted $R^2 = 0.9962$
Significance test (parameters):	$t_a = 9.258 > t_0 = 2.306$; $t_b = 37.56 > t_0 = 2.306$
Significance of regression (F test):	$F = 1206.05 > f_{0.05,1,8} = 5.32$

Fig. 6: Some representative molecular structures that subjects were asked to assemble using a molecular kit and initial results based on a set of 10 structures with varying structural complexities. Here, the number of subjects, N = 12.

Initial results based on our experimental investigations show a similar relationship between structural complexity and molecule assembly time (see fig. 6) as in fig. 4. Also note that variation in assembly time increases as the structural complexity level increases. The statistical quality of the functional relationship is shown above in tabular format. All statistical significance analysis assumed 95% confidence level. The most interesting preliminary result is the exponent of the power law relation, b = 1.69. This suggests that effort increases super-linearly but is not quite quadratic with increasing structural complexity. This study will be expanded in future to include a larger sample size (i.e., number of test subjects) and assembly of additional structures from different complexity regimes.

3.3 Complicatedness function

Let us analyze the development cost vs. structural complexity model of the form $Y = aX^b$ where $\{X,Y\}$ stands for structural complexity and system development cost/effort respectively. At a given level of structural complexity $X = X_c$ we have a distribution of system development efforts as seen from fig. 6. Let us term the maximum development effort as Y_n and minimum development effort as Y_1. Also define the corresponding parameters as $\{a_n, b_n\}$ and $\{a_1, b_1\}$ respectively. Based on the data, we find the following relationship between structural complexity and spread in the system development efforts:

$$\frac{Y_n}{Y_1} = \left(\frac{a_n}{a_1}\right)\left(X_c\right)^{(b_n - b_1)} \sim 1.49\sqrt{X_c}$$

The parameters of the functional model emphasize two very different aspects associated to system development efforts. The parameter *a* characterize work efficiency of the actor (i.e. ability to perform known/specified work efficiently). The parameter *b*, on the other hand, relates to individual/ group's innate ability to synthesize solutions and cognitive capability plays a big role. This parameter becomes more significant at higher regimes of complexity. We observe this phenomenon at an individual level. The exponent parameter *b* increases significantly for higher complexity regimes vis-à-vis lower complexity regimes (see table 1 below).

Table 1: For an individual, the exponent b increases significantly as we move from lower structural complexity regime (0 – 4] to higher structural complexity region (4 – 12.7). The exponents were computed after segmenting the complexity regimes.

Exponent	Lower Complexity level (0 – 4]	Higher Complexity level (4.0 – 12.7)	Overall
b	1.13	2.58	2.39

We define *b* as *complicatedness function* of the actor (an individual or a group of individuals). *Complicatedness* is an observer-dependent property that characterizes an actor's / observer's ability to unravel, understand and manage the system under consideration. In contrast, *complexity* is an inherent system property and a complex system may represent different degrees of *complicatedness* depending on the observer. For example, the complexity of an automobile's automatic transmission may be hidden from a user and is perceived to be less complex. We can think of *complicatedness* as a conduit through which *complexity* manifests itself at the level of system-level observables like the *system development cost* [Tang and Salminen, 2001]. Complicatedness provides insights to the cognitive aspects of the observer and his/her ability to handle a certain level of complexity. We list the five main factors affecting complicatedness as (i) complexity; (ii) modularity or design encapsulation; (iii) novelty; (iv) cognitive capability and bandwidth. Effects of each of these four factors are as follows:

(i) Complexity: Complicatedness is the degree to which an actor or decision unit for the system is able to manage the level of complexity presented by the system. Assuming other factors being equal, complicatedness ***K*** can be written as a function of complexity, ***K=g(C)***. We expect monotonicity of complicatedness with respect to complexity and at ***C=0, K=0***.

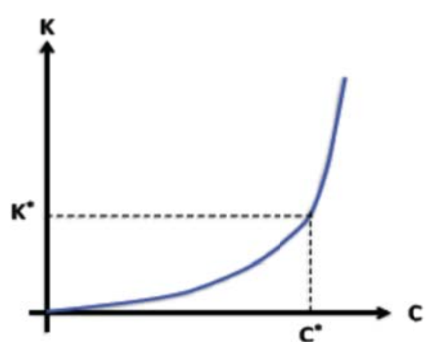


Fig. 7: Complicatedness vs. complexity: two different behavioral patterns, both with knee points defined by (C, K*).*

Intuitively, there is a level of complexity beyond which the observer can barely cope with the system and the system complicatedness becomes unmanageable (see fig. 7). Hence, $\mathbf{K} \rightarrow \infty$ for $\mathbf{C} > \mathbf{C}^*$.

(ii) Modularity or design encapsulation: Structural modularity or design encapsulation is a means of containing the complicatedness of a system. A well-architected system may hide inherent complexity in an effective fashion such that it appears less complicated. A good design or architecture always presents a less complicated system image to the actor's or decision units [Tang and Salminen, 2001]. Design encapsulation (notice that it also leads to information hiding) helps focusing attention on a subset of the system at a time. This is similar to ''chunking'' of information to circumvent the human cognitive span limitation [Hirschi and Frey, 2002].

(iii) Novelty: As an observer gains experience with a system, he/she starts developing knowledge and intuition about the system. A user can get more exposure with a system over time and deems it to be less complicated with passage of time, although the internal system remains unaltered. This seems quite natural if we view humans as *adaptive* systems. Humans continually update and adapt themselves as additional knowledge becomes available to new boundaries / constraints are discovered. This also applies in case of component or subsystem re-use in the new system, which drives the complicatedness down.

(iv) Cognitive bandwidth: Some actor's or decision units (i.e., group of individuals / team) may relate better to a more complex system than other actor's. This is reflective of the innate cognitive capability of an individual or a group of individuals to unravel the system, understand and manage the system. A high cognitive bandwidth on the part of the decision unit helps reduce complicatedness of a system for that decision unit.

Looking closely at the factors listed above, we observe that factors (i), (ii) and (iii) are related to the system architecture and design, while cognitive bandwidth relates to human ability to handle a given complexity.

4 DISTRIBUTION OF STRUCTURAL COMPLEXITY AND ITS SYSTEMIC IMPLICATIONS

Distribution of structural complexity across the system elements play a very significant role in achieving a set of system properties and often to programmatic success of the system development project. Knowledge of overall system architecture is absolutely critical to be able to quantify and track the complexity during the system development activity. This aspect can be best explained with a simple example as shown in fig. 8 below.

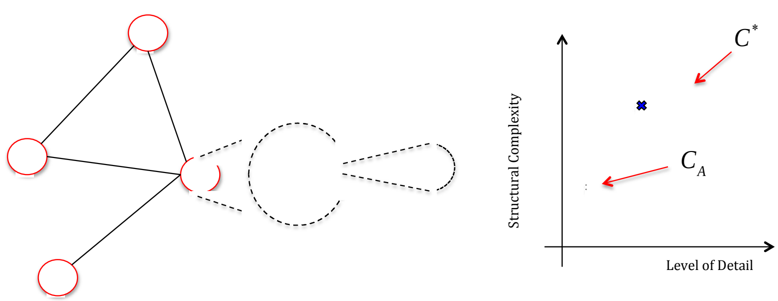


Fig. 8: Increasingly detailed view of the system and evolution of structural complexity if we assume components at each level to be of similar category.

At top level, each component actually represents a subsystem or module and their lower level details are shown in fig. 8. Complexity estimates are performed at each level of detail without considering the fact that at the top level, we do not have component, but we have subsystems and we cannot treat them as simple components. Doing that one might get the impression that structural complexity is only $\boldsymbol{C_A}$ while in reality, it is $\boldsymbol{C^*}$. This leads to a gross underestimation of structural complexity of the system. In order to extract information on complexity distribution we do need complete information about the internal structure of subsystems. This information is crucial for tracking and management of large, engineered system development efforts. Implication of the complexity distribution on system development effort can be best explored using case studies and development of *Boeing 787* (e.g., the

Dreamliner) is a good example [Cohan 2011]. Considered the largest industrial program in the world, Boeing chose to partner with 17 companies in 10 different countries and the outsourcing of the design and production amounts to 70% of the aircraft. Arguably, the decision to outsource so much of the design and production of the 787 played a large role in the project not meeting its ambitious goals in terms of reduced production cost and speed to market. By outsourcing both the design and the manufacturing, Boeing temporarily lost control of the development process since they had a clear view only at the level of primary modules, but not beyond. This view obscures what is inside the subsystems and made it difficult for Boeing to judge the total structural complexity of the system as it evolved. If a subsystem or module started to become too complex, it is possible that the outsourcing partner did not have the adequate capability for handling that level of complexity and this may have jeopardized the overall system development effort [Cohan 2011]. In this light, we argue that the importance of complete knowledge of the overall system architecture is crucial for decision-making during the development process and constitutes a core capability for the primary system development organization. This capability is essential for complexity to be tracked and actively managed during the process.

5 CONCLUSION

In this work, we formulated the structural complexity metric for engineered systems, which was shown to consist of three terms representing complexities of system components, connections among these components and topological complexity. We introduced the notion of *matrix energy* as a measure of topological complexity of product architecture and shown that it increases as we move towards more *distributed* architectures. We presented empirical evidence from real-world engineered systems and reported experimental validations to validate the proposed complexity metric. We have posited a super-linear growth in development cost with increasing structural complexity, presented confirmatory evidence from existing literature and also preliminary experimental validation of the same. Preliminary result suggests that effort increases super-linearly with increasing structural complexity with the exponent of the power law relation being 1.69. We also developed a *complicatedness function* for human decision units / actor through which structural complexity is manifested in terms of system development cost, which is a system observable. We further discussed distribution of complexity across the system architecture and argued that adequate knowledge and visibility of the overall system architecture is absolutely essential for matured complexity management capability. Distribution of overall complexity is a critically important facet and has a big impact on system architecting strategies. Knowledge of the relative subsystem complexities influences the selection / composition of the subsystem development team and might influence strategic decisions, including outsourcing options. It is imperative for every large-scale system development efforts to have active complexity distribution and management capability.

Going forward, the proposed structural complexity metric can serve future complexity-based product design and optimization framework and help explore important questions related to tracking, management and distribution of structural complexity across the system architecture and its impact on other system performance/lifecycle measures.

The relationship between structural and dynamic complexities presents an interesting area for exploration. Although there they are found to be positively correlated in general, there might be architectures where they might have to be traded against each other for attaining the ultimate goal of minimizing system development cost, compressing the schedule or mitigating risk.

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