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System Architectures Assessment Based On Network Metrics

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Abstract: Characterising system architectures and describing a system's properties using quantitative metrics is required for the comparison and evaluation of engineering systems. The aim of this article is to discuss the assessment of system architectures based on network metrics derived from literature. In this paper, network metrics such as interaction density, Newman modularity index *(Q),* centrality measures, cyclomatic number, and graph energy measure are included into a methodological approach for evaluating five hypothetical system architecture patterns: bus-modular, sequential, hierarchical, core-periphery and integral. Network and graph theory offer a conceptual approach to model and analyse engineering system architectures. The contribution of the article is a network metrics assessment founded on describing emergent system architecture properties as integrality, modularity, centrality, cyclicality and complexity for holistically assessing system architectures. The network metrics offer quantitative tools to gain valuable insights and can function as decision aid tools during the redesign and early development of engineering systems.

Keywords: integrality, modularity, complexity, cyclicality, centrality, integral, core-periphery, hierarchic, sequential, bus-modular, product architecture.

1. Introduction

Characterisation of system architectures through the description of their properties is a prerequisite for analysis, comparison and evaluation. Crawley et al. (2004) defined system architecture as "an abstract description of the entities of a system and the relationships between those entities", though in most instances system architecture can be abstractly depicted as a network. By representing complex systems as networks a collection of quantities or measures that describe distinct properties of the network topology can be deduced. Sturtevant (2013) advocated that networks encapsulate patterns such as integrality, modularity, cyclicality and hierarchy and networks as natural means of depicting and studying architectural patterns.

There is a growing body of literature implementing network and graph theory in product and system architectures (Baldwin et al., 2014; Sarkar et al., 2014; Sinha, 2014; Sosa et al., 2007). Although researchers adopted a broad network approach, they implemented different metrics and measures to assess system architectures. In spite of the fact that network and graph theory offer a conceptual, and have mathematically rigorous foundation that captures the general description of system architecture, a general network theory metrics approach in evaluating system architecture as an aid in analysis of engineering systems is just emerging.

This paper presents an examination of the literature of applications of network theory metrics in product and system architectures and a quantitative evaluation of a set of architectural patterns by the use of network metrics derived from existing literature.

Section 2 presents a literature review on the different types of network metrics such as node degree, graph energy, centrality, cycles and modularity metrics applied in product and system architectures. Section 3 describes an assessment network metric methodological approach whilst Section 4 presents computed results and discussion. Finally, Section 5 presents conclusions, limitations and future research directions for the use of network metrics in the analysis and evaluation of engineering systems.

2. Literature review

Network theory is a mathematical field of studying networks represented as nodes (vertices) of actors or elements and edges (arcs) as the connections between the actors or elements. It builds on graph theory originated by Leonhard Euler (De Weck et al., 2011). Literature suggests methodologies in relation with classification of system architectures and design changes based on network theory (Giffin et al., 2009; Pasqual and de Weck, 2011; Baldwin et al., 2014; Dong et al., 2016). Network theory, combined with its mathematical background, has reinforced the use of network metrics (Bounova and Weck, 2012) as quantifiable means for measuring system architectural properties. Nonetheless, like Browning (2016), recommended "researchers should continue to draw upon the advances in closely-related areas such as graph theory, network analysis, complexity, and other types of architectural models". An outline of the network metrics found in system and product architectures literature is presented in Table 1. Sosa et al. (2007) suggested the in-degree and out-degree of modularity metrics are derived from in-degree and out-degree graph theory metrics of a node respectively. Moreover, Luo (2015) used the interaction density metric *(K)* to study product architecture's impact on product evolvability and interpreted as the "reverse indicator of product modularity". Raz and DeLaurentis (2017) proposed a modified Singular value Modularity Index (SMI) originally developed by Hölttä-Otto and de Weck (2007) and adopted it in a network theoretical approach. Sinha (2014) calculated modularity by adopting Newman's modularity index (*Q*) to compare between two (old and new) product architectures of an aircraft engine. Sarkar et al. (2014) proposed an approach based on graph energy for identifying hierarchical modularity in product architectures. In addition, Sosa et al. (2007) used the closeness centrality and betweenness centrality in the product architecture context, and developed the distance modularity metric and bridge modularity metric. Sarkar et al. (2014) used eigenvector centrality in an aero-engine component to measure the degree of the overall influence of component into the system. In the realm of management science, Gokpinar et al. (2010) employed subsystem centrality to test a hypothesised inverted-U relationship between subsystem complexity and quality. Also, Van Eikema Hommes (2009) applied degree, closeness and betweenness centrality measures and concluded that they are effective tools for identifying areas of architectural improvements. Furthermore, in the literature (Braha, 2016; Luo, 2015; Sosa et al., 2013; Tamaskar et al., 2014) the role of cycles in system architectures is acknowledged. This unique role is emphasised by Sosa et al. (2013) suggesting that cyclicality as a property is "distinct from, and no less important than, modularity". Therefore, cycles characterised idiosyncratically system architectures. Tamaskar et al. (2014) noted that cycles enable components to be interconnected without direct connections, and therefore, cycles are critical characteristics of architectures because of the decisive consequences of their presence in systems. An older network metric is the cyclomatic number which is a recognised complexity metric in software engineering (McCabe, 1976; Harrison, 2016). Nevertheless, recent literature such as Sosa et al. (2013) developed the construct of component cyclicality which they consider to have a direct relationship with quality. Luo (2015) proposed cyclic degree metric "percentage of directed influence links that are in at least one cycle" for measuring the cyclic inter-component dependencies in product architecture. Lastly, Sinha (2014), suggested that graph energy function as a measure of structural topological complexity.

Table 1: Network metrics use in product and system architectures (*italics network theory term*)

	Network metric	**Description of metric**	**Reference**
Modularity	*node degree* in and out degree modularity	"in-degree of component *i*, equal to the number of other components that *i* depend on for functionality, whereas out-degree is equal to the number of other components that depends on component *i"*	(Sosa et al., 2007)
Modularity	*average node degree* interaction density *(K)*	"average number of components that each component influences", indicator of integrality, reverse indicator of product modularity	(Luo,2015; Dong,2002)
Modularity	*adjacency matrix* modified SMI	modified SMI is updated by introducing a modularity matrix in place of a design structure matrix, which is the sum of an architecture adjacency matrix and system functional contribution.	(Raz and DeLaurentis, 2017)
Modularity	*Newman modularity index (Q)* modularity	"a subsystem is a module when the number of edges within the subsystem is much higher than the expected number of edges derived from an equivalent random network model with the same number of elements and similar distribution of links between elements with no modular structure"	(Newman, 2010; Sinha, 2014)
Modularity	*eigenvalue spectra* modularity	large eigenvalue gap shows modularity and eigenvalue cluster gaps shows hierarchical modularity	(Sarkar et al., 2014)
Centrality	*eigenvector* (x_v)*, closeness* (C_i)*,betweenness* (x_i)*, centrality* distance and bridge modularity	indicator of overall influence of component or areas for improvement in the system, "the more distant a component is the other component, the further its design dependencies have to propagate and, the more modular the component is", "distance modularity of component *i* based on the number of times it appears in the path between two other components"	(Sarkar et al. 2014;Van Eikema Hommes, 2009; Sosa et al., 2007)
Cyclicality	*acyclic* cyclomatic number *v(G)*	the number of edges required to be removed to become acyclic, meaning that nodes and edges no longer create cycles in the graph.	(McCabe, 1976)
Cyclicality	*cyclicality* component cyclicality	is the degree of which a component is dependent on itself through other components	(Sosa et al., 2013)
Complexity	*modified version graph energy E(G), sum of singular values of adjacent matrix* Structural topological complexity	encapsulates the impact of topological differences in the connectivity structures, function as measure of topological complexity	(Sinha, 2014; Min et al., 2016)

3. Methodological approach

A methodological approach incorporating existing network metrics derived from the literature review for assessing system architectures is presented herein. Interaction density, Newman modularity index (*Q*), graph energy, cyclomatic number, and centrality measures were used to evaluate the architecture patterns. The selected metrics are based on representative literature examples of network metrics which capture a variety of intrinsic system architectural properties such as integrality, modularity, centrality, cyclicality, and complexity. However, the suggested approach is not limited to the selected metrics. The approach primarily claims network theory metrics as a comprehensive toolbox for application to assess system architectures. Determination of system architectural properties by the use of multiple network metrics supports analysis and comparison among different system architectures. The approach allows progressive scaling in size of the patterns to investigate the influence of size on properties and metrics. A set of hypothetical binary design structure matrix (DSM) architectural patterns were generated. The patterns are bus-modular (BM), sequential (SE), hierarchical (HI), core/periphery (CP) and integral (IN) inspired from literature (Borgatti and Everett, 1999; Hölttä-Otto et al., 2012; Min et al., 2016; Sharman and Yassine, 2004). In this paper, the generated patterns are based on binary and symmetrical design structure matrices, therefore, have symmetrical adjacency matrices, and are undirected and unweighted graphs. This paper adopts similar justifications as Sarkar (2014). The main argument is that undirected graphs are the most commonly used in modelling complex networks. In addition is argued that they are the most used in product architecture examples in the existing literature, and that the weighed versions can be studied in following research.

3.1. Methodological steps

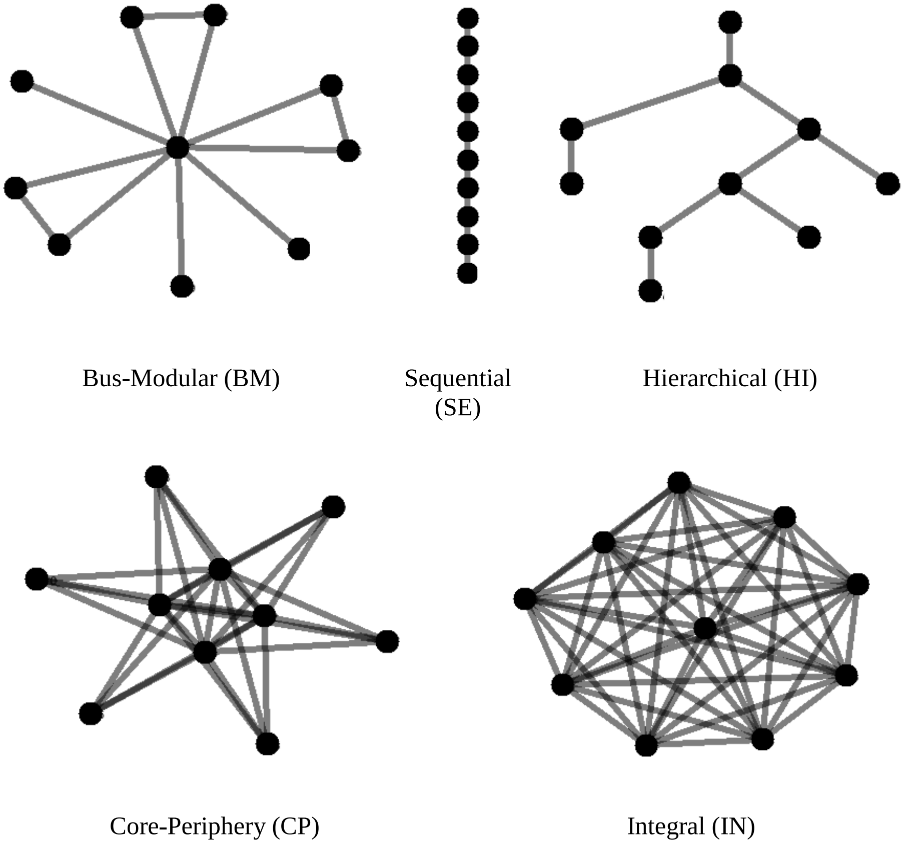
Step 1: Represent design structure matrix (DSM) as networks.

DSM is a traditional tool for depicting product system architectures. The DSM is analogous to an adjacency matrix in network theory. The nodes of the network account for the heading of rows and columns of a DSM, and the edges represent the interactions inside the DSM. System architecture as a network is defined as G= (C, E), where C= {c_1, c_2, c_3…) are the components forming the system and E= {e_1, e2, e3…} edges. An adjacency binary matrix, A_{ij}=1, if the edges (interconnections) exist between nodes (components), and A_{ij}=0 if there are no connections. The DSMs generated are transformed into an adjacency matrix and graphs as shown in Figure 1 following this approach.

Step 2: Compute a set of network metrics for each architectural system pattern.

Interaction density, Newman modularity index (*Q*), eigenvector, closeness, betweenness centrality measures, cyclomatic number and graph energy are calculated (utilising MATLAB and MIT Strategic Engineering, 2006). Girvan and Newman (2002) partitioning approach is used based on assumption of the number of modules and then *Q* is computed.

Figure 1: Hypothetical networks (pattern size 10 i.e. nodes: bullet, edges: line)



Step 3: Scale the patterns in size and repeat step 2.

Each metric was calculated for each of the patterns of sizes 10, 100, 1000 nodes. The 10 and 100 size patterns are derived from the literature (Luo 2015; Min et al., 2016). The 1000 nodes are based on scaling factor of ten to represent a highly complex system with many components. The reason behind adding a process of the system scaling in the methodological approach is to investigate the system architectural properties across a range of sizes.

4. Assessment of architectural patterns

Characterising system patterns is based on describing system properties. The computation network metric results of the methodological approach explained in Section 3, allows the description of properties and discussion of the various pattern characteristics.

4.1. Description of computed results

A Monte Carlo simulation layer was applied on the top of the described methodological approach in Section 3. Multiple instances of networks (sample 500) were generated. Table 2 presents the summary of computed results. The columns label the architectural patterns and the rows the various network metrics. The white rows shows results for pattern size 10, light grey results for pattern size 100, and dark grey results for pattern size 1000. The computation generates centrality values for each node, the highest values calculated and the respective node are only presented in Table 2, for the specific patterns depicted in Figure 1.

Table 2: Methodological approach computed results, {n} = node, (CI)=confidence interval, notations as per Table 1

	BM	**SE**	**HI**	**CP**	**IN**
Mean K	2.690 (2.690, 2.700)	0.900 (±0)	0.873 (0.859, 0.886)	2.880 (2.820, 2.960)	4.500 (±0)
	2.070 (2.069, 2.070)	0.990 (±0)	0.809 (0.791, 0.827)	28.420 (28.250,28.590)	49.500 (±0)
	2.007 (2.006, 2.007)	0.990 (±0)	0.990 (0.997, 1.00)	287.110 (285.390, 288.830)	499.500 (±0)
Mean Q	0.420 (0.419, 0.420)	0.401 (±0)	0.463 (0.455, 0.471)	-0.0495 (-0.052, -0.047)	-0.053 (±0)
	0.442 (0.376, 0.508)	0.579 (±0)	0.823 (0.813, 0.833)	≈0	≈0
	0.502 (0.483, 0.511)	0.598 (±0)	0.889 (0,811,0.920)	≈0	≈0
x_v	0.23 {1}	0.14 {5&6}	0.18 {5}	0.13{1- 4}	0.1 {1-10}
	0.09 {1}	0.02 {50&51}	0.14 {1}	0.01{1- 40}	0.01 {1-100}
	0.30 {1}	0.001 {275-726}	0.08 {1}	0.001{1-400}	0.001{1-1000}
C_i	0.11{1}	0.04 {5&6}	0.06{5}	0.11{1-4}	0.11{1-10}
	0.01 {1}	0.0004 {50 & 51}	0.0028{1}	0.01 {1-40}	0.01 {1-100}
	0.0010 {1}	4E-06 {500-501}	0.00027{1}	0.001{1-400}	0.001{1-1000}
x_i	33 {1}	20 {5&6}	24 {5}	3.75 {1-4}	0 {1-10}
	4818 {1}	2450 {50 &51}	4410 {1}	44.25 {1- 40}	0 {1-100}
	498168{1}	249500{500-501}	494010 {1}	449.25{1-400}	0 {1-1000}
Mean $v(G)$	2.60 (1.91,3.2)	0	0	19.800 (19.12, 20.48)	36 (±0)
	24.80 (13.49,36.10)	0	0	2742.89 0 (2726, 2760)	4851 (±0)
	250.5 (142.50,358.49)	0	0	286109.9 (284390,287830)	498501 (±0)
Mean $E(G)$	10.71 (9.47,11.95)	12.1 (±0)	11.29 (11.25, 14.36)	12.50 (11.23,13.77)	18 (±0)
	69.02 (46.63,91.41)	126.60 (±0)	117.35 (117.24, 135.50)	136.93 (127.35,146.52)	198 (±0)
	458.03 (286.43,629.61)	1272.51 (±0)	1175.89 (1170.98, 1360.80)	1397.31 (1317.21, 1477.41)	1998 (±0)

4.2. Observations and discussion

The following discussion provides observations about characteristics and properties of the various system architectural patterns. In the discussion, the patterns are compared, evaluated and characterised based on the resulted values calculated by the network metrics.

4.2.1. Integral and core-periphery patterns

The IN pattern exhibits high values calculated by the interaction density, graph energy and cyclomatic number metrics. These computed results support the arguments that an IN is integral, complex and cyclic pattern, a description that agrees with the understanding of integral architectures existing in the broader literature. The interaction density metric as an indicator of integrality and reverse indicator of modularity distinctively distinguish the IN among the other patterns.

Table 2 shows that the IN pattern has the greatest cyclomatic number, followed by the CP. The cyclomatic number describes the number of independent cycles in the network, therefore, indicates that the IN is highly cyclic pattern compared with the other patterns. The interaction density, graph energy and cyclomatic number computed values increase with the growth of the size of pattern (number of nodes) of IN and CP patterns, endorsing that pattern size directly influence their architectural properties. Moreover, it was observed that in the IN pattern; components have equal centrality measures values. Therefore, network theory's centrality measures have the potential to be used as ancillary indicators for characterising patterns. The Newman modularity index (*Q*) calculates approximately zero and negative values for IN pattern. Newman (2010) defined "modularity is supposed to be largest for the best division of the network, no matter how many groups that division possesses". Newman modularity index (*Q*) measures the quality of the particular divisions of the network. The *Q* values calculated approximately, as zero and negative, signify that IN pattern cannot be readily divided into modules, because of the high interconnectedness among the components in the pattern. However, this metric requires further investigation to allow its establishment as modularity metric in the system and product architecture's literature domain. The CP pattern has the second highest computed values for interaction density, cyclomatic number and graph energy values. The computed results point toward the characterisation of the CP pattern as medium to high complex system architecture. Comparable with the IN pattern, the CP pattern scaling in size, results in an increase in the values of interaction density, graph energy and cyclomatic number, so can deduce that architectural properties of integrality, complexity and cyclicality are amplified with size. Similarly, with the IN, also for the CP Newman modularity index, (*Q*) values are calculated approximate as zero and negative, meaning that also the CP cannot be readily partitioned, as core elements are highly interconnected with the periphery elements. Lastly, the IN pattern is deterministic in nature, as is defined on the principle of a full interconnectedness among the nodes and edges. On the contrary, the CP pattern is stochastic in nature as the number of nodes located in the core and numbers of nodes in the periphery have possible different configurations for a number of different instances. This quantitatively investigation concludes that CP and IN are high complex, integral, cyclic, and low modular patterns in line with the general understanding in the literature.

4.2.2. Hierarchical, sequential and bus modular patterns

It is observed that the outcomes computed by the interaction density remains moderately constant for the increase in the size (10-100-1000 nodes size patterns) of BM, SE and HI patterns. The cyclomatic number metric results are zero for HI, and SE, which affirm that these patterns do not contain any cycles. Cycles, as an architectural property, characterised patterns in a unique manner. With regards to graph energy, the results of Table 2 are in agreement with Min et al.'s (2016) remarks that the SE pattern has higher graph energy which reflects higher topological complexity than the BM pattern. The Newman modularity index (Q) for BM, SE and HI calculates positive values. Therefore, the positive values of Q signify the pontentials for good quality of partitioning into modules, meaning internally highly densely connected components within modules and weakly connected across modules. The results calculated by the centrality measures, demonstrate that an important component can be identifiable within the HI and BM patterns. This signifies the existence of a prominent element of the system architecture. However, the medium or low levels of centrality could also provide useful insights into system architectures, and centrality value motifs could be used as indicators of architectural patterns. Van Eikema Hommes (2009) suggested ways centrality values can be interpreted in DSM for example; high closeness centrality signifies component engagement in pattern long interface sequences in the system. Another example is that a high betweenness centrality shows a component holding a central bridging position. This is desired if it is the main bus module of architecture; otherwise, such a bridge component may become a bottleneck in the system. Finally, HI and BM patterns are stochastic in nature, as the patterns can be configured randomly for a number of instances. Then again, the SE pattern is deterministic in nature, as the pattern is defined on the principle of linear connection among sequential nodes. In general, the computed results characterised the HI, SE and BM patterns as medium to high modular, medium complex and integral, whereas, the BM is a medium to low cyclic pattern, SE and HI are not cyclic patterns.

5. Conclusion

The work presented in this paper applies network metrics for assessing system architectures. A network metrics evaluation offers advantages in obtaining a comprehensive assessment of system architectures and gaining an understanding to support design and development of system architectures. One of the findings of this work is the acknowledgement that metrics complement each other, as each metric provides distinctive knowledge regarding the inherent character of the system architecture. Thus, establishment of a network-based metrics evaluation framework that incorporates a collection of various network metrics will deliver a holistic system architecture assessment. Moreover, interaction density, centrality metrics, cyclomatic metric, and graph energy provided reasonable measures about modularity, centrality, cyclicality, and complexity of the system architectural patterns, endorsing their usefulness as instruments for evaluating and characterising system architectures. However, the Newman modularity index (Q) requires further investigation for use in this field. Network metrics have evolved as important tools for ascertaining system architecture properties, as standalone metrics, or as segments of advanced formulations. In general, the approach of the application of network metrics in a DSM offers opportunities for an objective assessment of system architectures. Hence, a better understanding of systems architectures can support understanding and recognition of vulnerability in systems. Architects, designers and engineers, can use network metrics when making decision trade-offs and choices in early conceptual phases.

In addition, system architecture pattern's characterisation by network metrics can accommodate a mix and match approach for accomplishing desired design objectives. Qualification of patterns derived from the use of a collection of different network metrics can produce insights regarding systemic architectural characteristics. Such knowledge can offer avenues for developing a library of reusable set based engineering system patterns with known established system properties and characteristics. This can allow the generation of engineering systems by synthesising based on an assemblage of these patterns. This mix and match approach could assist in aligning system architectures with design goals.

Moreover, a network based evaluation approach can function as decision aid tools during the evaluation, redesign, and improvement of engineering design processes. Network theory' mathematical background and the valuable examples in the areas of physics, biology, computers, economics, and sociology can assist in the extension of their implementation in system and product architectures. The limitations in the network theory approach include the high level of abstraction and the general assumption of equality among components, such as nodes, of a system network.

Future research avenues include empirical verification through case study validation and the modification of network metrics and methodology for specific applications in practical engineering system designs. Another avenue of future research is an in-depth investigation of the random graphs to gain theory and knowledge for the engineering design domain.

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