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MODULARITY, ROBUSTNESS, AND CHANGE PROPAGATION: A MULTIFACETED RELATION

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Abstract

Increased system robustness is one of the promises of modularity. However, research on the topic has provided conflicting findings. By generating more than 2000 system architectures, this paper shows that the relation between modularity and robustness is multifaceted: Modularity decreases topological robustness, increases robustness to change propagation, and provides economic benefits. Results here confirm the importance of modularity, enable reconciliation of opposing findings from prior research, and guides researchers and practitioners in the selection of appropriate robustness measures.

Keywords: *modularity, robustness, complex systems, network approaches, design structure matrix (DSM)*

1. Introduction

Many systems, both natural and artificial, exhibit a modular organisation (Gershenson et al., 2003; Lorenz et al., 2011; Newman, 2003). That is, their elements are interrelated such that they form groups with high internal cohesion and loose external coupling, giving rise to a nearly decomposable structure (Gershenson et al., 2003; Schilling, 2000; Simon, 1962). Modularity has been associated with many advantages and desirable properties. Systems with higher modularity show higher adaptability to changing environments (Clune et al., 2013; Sanchez and Mahoney, 1996; Suh et al., 2007). Higher modularity can promote higher changeability as an effect of the loose coupling between modules, which makes it possible to substitute or upgrade a module in isolation or with fewer local changes (Hölttä and Otto, 2005; Thomke, 1997; Ulrich, 1995; Worren et al., 2002). As changes, errors, and perturbations can remain localised without being propagated to the whole system, modularity can increase system robustness (Giffin et al., 2009; Pan and Sinha, 2007; Piccolo et al., 2019; Suh et al., 2007). Finally, the presence of loosely coupled or independent modules makes it possible to implement parallelisation (Gershenson et al., 2003; Parraguez et al., 2019; Yassine and Braha, 2003).

Explanations of the origins of modularity can be found in economics, evolutionary biology, and multiple constraint optimisation. Economic arguments suggest that modularity reduces costs (Baldwin and Clark, 2000). Computational biology experiments show that systems that evolve to optimise performance and to minimise cost achieve better performance than systems that evolve only to optimise performance (Clune et al., 2013). Finally, modularity can arise from the need to satisfy multiple constraints. For instance, networks that at the same time minimise the number of edges and the distance between any two nodes while maximising robustness exhibit a modular organisation (Pan and Sinha, 2007).

Given all the advantages discussed, one might be tempted to conclude that modularity is an unequivocally useful and universal design rule; however, certain results go into an opposite direction. For instance, it was shown that dividing a system into too many subsystems, with the purpose of increasing the concurrent development or parallelising the search of design solutions, can lead to systems with suboptimal performance and can reduce the gains of concurrency (Ethiraj and Levinthal, 2004; Hoedemaker et al., 1999). This has been interpreted as both a problem of over-modularisation and as an intrinsic limit in concurrency (Ethiraj and Levinthal, 2004; Hoedemaker et al., 1999). Moreover, it was shown that modular networks break apart more easily if subject to physical node removal than their non-modular counterparts. This is a result of loose coupling between the modules, which reduces robustness of the network topology (Bagrow et al., 2015; Walsh et al., 2019).

Why such conflicting findings? If modularity does not bring the advantages we discussed above, why is it so common in many systems? In this paper, we answer these questions through the analysis of the relation between modularity and robustness. Unlike previous literature that has analysed this relation by considering mainly a single definition of robustness, we consider two of the most common perspectives: a dynamic robustness to disturbance or change propagation (Ahmad et al., 2013; Braha and Bar-Yam, 2007; Clarkson et al., 2004; Piccolo et al., 2019, 2018a); and a topological robustness to physical failures (Albert et al., 2000; Bagrow et al., 2015; Piccolo et al., 2018a; Walsh et al., 2019). In order to obtain results for general systems, we take the perspective of system architecture (Crawley et al., 2016; Steward, 1981) through network science. Here, we generate 2100 comparable network configurations, characterised by the properties found in many real technical and engineering networks, with increasing degrees of modularity and evaluate the resulting robustness.

We find that higher modularity reduces robustness to physical node removal; however, higher modularity also reduces the number of nodes where robustness needs to be improved. Therefore, modularity can have the aforementioned economic advantages. At the same time, higher modularity increases the dynamic robustness to disturbance propagation: the system becomes less prone to catastrophic cascades and the clustered structure of the network slows the propagation down. This supports the framework of *axiomatic design* (Suh, 1990) and relates our work to the insights of system stability from *Work Transformation Matrices* (Smith and Eppinger, 1997; Yassine et al., 2003). Our results suggest the existence of a trade-off between topological and dynamic robustness. This also explains the conflicting findings on the relation between modularity and robustness. Showing that the two definitions of robustness are not interchangeable, we also discuss how to select the one most appropriate. Finally, we found a negative relation between modularity and number of modules that shows how the number of modules is not necessarily a good measure of modularisation. In fact, modularity depends on high cohesion within modules and low coupling between modules; the number of modules does not account for any of these properties. As the aforementioned problems of over-modularisation are the result of the increased coupling between modules as the number of modules increases, this is effectively a type of suboptimal modularisation. Specifically, the division of the system into more modules than those suggested by the system architecture has the effect of increasing coupling between modules.

In sum, this paper makes the following novel contributions: 1) it shows that the relationship between modularity and robustness is multifaceted and that there is a trade-off between topological and dynamic robustness; 2) it brings a framework to engineering design that generates comparable system architectures (i.e. networks) in order to perform rigorous experiments; 3) it provides recommendations on how to measure robustness and modularity in real systems; 4) it offers actionable insights on how to choose between competing system architectures; and 5) it explains and reconciles conflicting results from prior research, and confirms modularity as a useful design principle that satisfies multiple constraints, including robustness.

2. Methods

2.1. Preliminaries on graph theory

The architecture of a system (i.e. the way in which its elements are connected) can be modelled as a network. A network is a pair $G = (V, E)$ where V is the set of N nodes that represent the elements of the system and E is the set of M edges that represent the connections between the elements of the

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system. Each edge connects two nodes. For each graph we can define its adjacency matrix A, defined as $A_{ij} = 1$ if nodes i and j are connected and $A_{ij} = 0$ otherwise. In the remainder of the paper we will consider networks without self-loops (i.e. $A_{ii} = 0$) and undirected (i.e. $A_{ij} = A_{ji}$). The degree of a node i is the number of nodes connected to it, and it is defined as $k_i = \sum_j A_{ij}$. From the adjacency matrix we can define the Laplacian matrix $L = K - A$, where K is the diagonal degree matrix ($K_{ii} = k_i$). The Laplacian matrix is useful for studying diffusion processes on a graph; therefore, we will use it to understand the robustness of a system architecture to error/change propagation.

2.2. Generating networks with varying degrees of modularity

Newman and Girvan (2004) defined a measure of network modularity that captures how well the network exhibits a clustered structure such that the connectivity is high within the clusters and low between them. Network modularity is defined as (Equation 1):

$$Q = \frac{1}{2M} \sum_i \sum_j \left[A_{ij} - \frac{k_i k_j}{2M} \right] \delta(i, j) \tag{1}$$

where $\delta(i, j)$ is 1 if nodes i and j are in the same cluster or 0 otherwise. In order to apply this equation, one needs to find the cluster structure of the network. To this end, we apply the Louvain method (Blondel et al., 2008), a clustering algorithm for networks that finds partitions with high Q.

We generate comparable networks with different values of Q by sampling the statistical ensemble of graphs $\{G\}$ with probability measure $\mu(G) \propto e^{-H(G)}$ induced by the Hamiltonian $H(G) = -J \times Q$, where J is a constant that govern the final degree of modularity Q for the generated network. The general procedure to sample network configurations according to $\mu(G)$ is the following: we start with an initial network G and produce a new configuration G' by swapping two randomly selected edges. We accept G' with probability $\min\{1, e^{-\Delta H}\}$ where $\Delta H = H(G') - H(G)$. We repeat the procedure until convergence. This procedure is a way to produce exponential random graphs (Park and Newman, 2004) with a given value of modularity. It preserves the number of nodes and the degree distribution of the original network, and produces comparable network configurations.

We obtain the initial network through the Barabási-Albert model (Barabási and Albert, 1999) by setting the number of nodes $N = 100$ and the average degree $m = 2$. This choice produces sparse networks with broad degree distribution. These characteristics are common in many technological and engineering networks (Albert and Barabási, 2002; Braha and Bar-Yam, 2007). We empirically determined that, in our case, the sampling procedure discussed above converges after 4000 rewiring operations. We explored 21 equally spaced values of J in [-1000, 1000] producing 100 independent configurations for each J. The value of modularity Q increases monotonically with J (Figure 1A).

2.3. Characterising the synthetic networks

Understanding how certain network properties change with respect to modularity provides insights that complement the following analysis and supplies pointers to compare our work with previous literature. We discuss three measures here, which are relevant because of their relation to modularity and widely used to characterise networks. The first one is the average shortest path length (Watts and Strogatz, 1998), which measures the average shortest distance between any two nodes. Let $d(i, j)$ be the shortest distance in terms of number of edges between node i and j, the average shortest path length (l) is defined as follows (Equation 2):

$$l = \frac{1}{N(N-1)} \sum_{i \neq j} d(i, j) \tag{2}$$

The second one is transitivity (Newman, 2003), which measures network cohesiveness as the probability that two nodes are connected given that they share a common neighbouring node. Let a triangle be a cycle between three nodes (i.e. $\{(i, j), (j, k), (k, i)\}$) and a triplet be a path between three nodes (i.e. $\{(i, j), (j, k)\}$), the transitivity (T) is defined as follows (Equation 3):

$$T = \frac{3 \times \text{number of triangles}}{\text{number of triplets}} = \frac{3N_\Delta}{N_\wedge} \tag{3}$$

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If a network exhibits an average shortest path of length similar to the one that is expected from a random graph with the same number of nodes and number of edges and a transitivity higher than the one expected from such a random graph, such a network is called ‘small world’ (Watts and Strogatz, 1998).

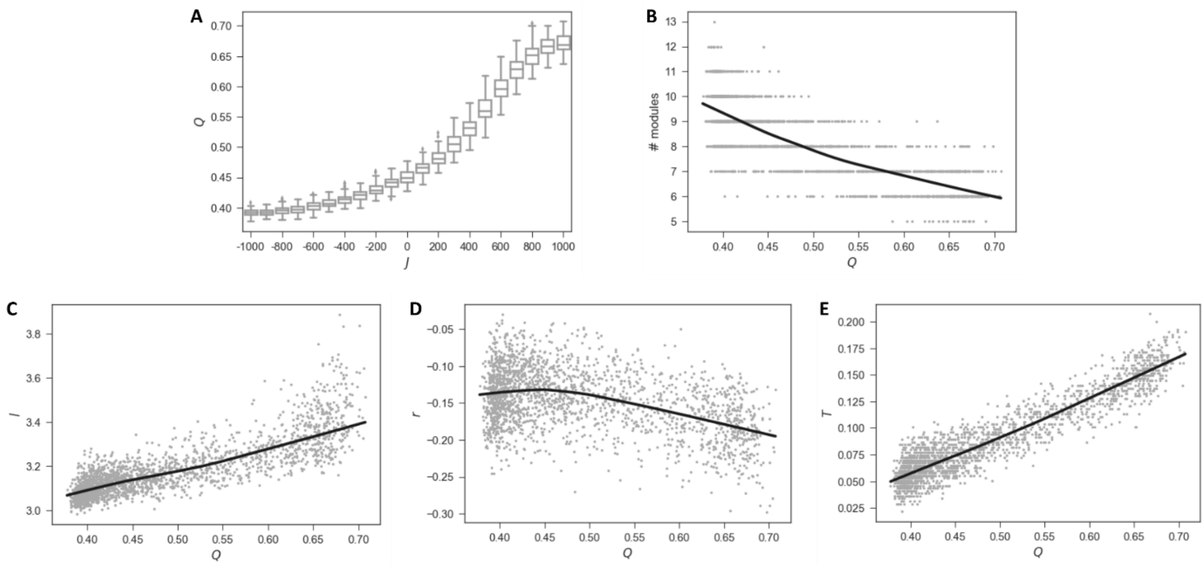

Figure 1. A) The value of modularity increases monotonically with J. B) The number of inferred modules decreases with modularity. C) The average shortest path length (l) increases with modularity. D) Degree assortativity (r) is negative throughout and decreases with modularity. E) Transitivity (T) increases with modularity. Trend line computed with LOESS smoothing.

The third property is the degree assortativity (r), which measures the degree mixing in a network (Newman, 2002). It is the Pearson correlation coefficient between the degrees of the nodes at either end of an edge over all edges (Equation 4):

$$r = \frac{M^{-1}\sum_{i,j\in E} k_i k_j - \left[M^{-1}\sum_{(i,j)\in E}\frac{1}{2}\left(k_i k_j\right)\right]^2}{M^{-1}\sum_{(i,j)\in E}\frac{1}{2}\left(k_i^2 k_j^2\right) - \left[M^{-1}\sum_{(i,j)\in E}\frac{1}{2}\left(k_i k_j\right)\right]^2} \quad (4)$$

Assortativity has implications for both topological robustness (Newman, 2002) and robustness to propagation dynamics (D’Agostino et al., 2012).

With respect to the 2100 synthetic networks, we find that the number of modules is in a negative relation with modularity (Figure 1B), showing that the raw count of modules is not necessarily a good indicator of the system modularity. This negative relation was found also in an empirical analysis of the evolving topology of a design process as the process unfolds (Parraguez et al., 2019). As modularity increases, both the shortest average path length (Figure 1C) and transitivity (Figure 1E) increase. This is a consequence of the increase in modularity, which increases the cohesion of the nodes within the same modules and lowers the coupling of the nodes across different modules. Although positively correlated with modularity, transitivity is not a proper measure of modularity as it only measures the cohesion of the network but does not account for the coupling between the modules. In fact, transitivity takes its maximum value for the fully connected graph, which is the stereotype of an integrative architecture. As the average shortest path length that we would expect from a random graph with N = 100 nodes and average degree m = 2 is 3.44 and the expected transitivity is 0.04, the synthetic networks exhibit the small world property. Finally, the synthetic networks tend to become more disassortative as modularity increases (Figure 1D). In many important respects, therefore, the synthetic networks generated through the procedure described above are realistic enough to exhibit the properties found in many real systems.

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3. Modularity decreases topological robustness

A stream of literature defines robustness as the ability of a system to maintain its functions even after the failure of some of its components (Albert et al., 2000; Piccolo et al., 2018a; Schneider et al., 2011; Walsh et al., 2019). The operationalisation of this definition to measure the robustness of a network uses percolation theory (Albert and Barabási, 2002; Newman, 2003). In the percolation framework, nodes are progressively removed from the network in order to simulate failures and the relative size of the giant connected component is measured after each removal. This procedure defines a decay curve that characterises the topological robustness of the network. If we compute the area under said curve and normalise it for the theoretical maximum (the linear decay given by the fully connected graph), we obtain a numerical indicator of topological robustness. With $S(G,q)$ as the relative size of the giant connected component after the removal of q nodes, we can define the following coefficient of topological robustness (Equation 5):

$$R(G) = 2\int_0^1 S(G,q)\,\delta q \approx \frac{1}{N}\sum_{q=1}^{N}[S(G,q-1)+S(G,q)] \tag{5}$$

This measure lies in the range [0, 1]. The case $R(G) = 0$ is reached when G does not exhibit a giant connected component even when no nodes have been removed at all. The case $R(G) = 1$ is reached for the fully connected graph.

Typically, nodes are removed according to two strategies: 1) a random removal procedure, which simulates random failures, 2) a targeted removal procedure, which removes higher degree nodes first to simulate targeted attacks or adverse scenarios. We simulate both random and targeted failures and compute the robustness index for our synthetic networks. For the random removal, we average over 50 simulations. We find that as modularity increases the topological robustness is reduced (Figure 2). This holds true for both random (Figure 2A) and targeted failures (Figure 2B).

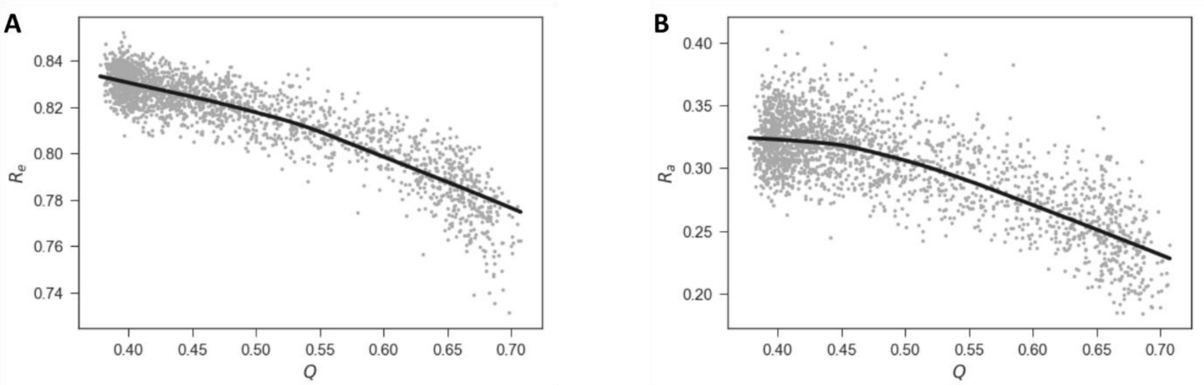

Figure 2. Relation between modularity (Q) and topological robustness to random failures (R_e) and robustness to targeted failures (R_a). Trend line computed with LOESS smoothing.

Relative to networks with the lowest modularity, networks with the highest modularity exhibit, on average, a robustness to random failures that is about 7% lower and a robustness to targeted failures that is about 24% lower. Our findings integrate those from Walsh et al. (2019); in addition, we control for the number of nodes, edges, and the same degree distribution. Therefore, we are able to isolate the effect of modularity from other quantities such as network density. Failures of targeted central nodes generate higher damage on modular networks as the probability of removing nodes that connect different modules is higher. Therefore, if the probability of failure for these nodes can be reduced, or if redundancy can be added, modularity can actually offer a strategy to minimise the number of nodes on which to intervene, providing an economical advantage.

Topological robustness is a useful concept when the failure of a component of a system is approximated with its physical removal or absence *and* when the connectedness of the system is the parameter of interest. This is the case, for instance, in a computer network where the failure of a server is roughly equivalent to a node being removed from the network, and packets cannot flow in a disconnected network. This situation is also the case in a design process, whose architecture can be

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interpreted as a bipartite network of people working on (i.e. connected to) given tasks (Piccolo et al., 2018a). In such a network, the absence of some people might make some tasks disconnected from the network and, therefore, said tasks cannot be completed. For other systems, this way of understanding robustness is not useful. For instance, an integrated circuit where the failure of even one component can compromise the whole circuit regardless its connectedness. In such cases, other approaches (i.e. Gohler et al., 2016) are more appropriate.

4. Modularity increases robustness to error or change propagation

Certain phenomena, such as error or change propagation, cannot be approximated with the removal of nodes in the network and, to understand these situations, we need a different model than topological robustness. Such phenomena need a model that can capture the transmission of failures among nodes. Epidemic and diffusive models on networks (Pastor-Satorras et al., 2015) offer a systematic way to study these propagation dynamics. In epidemic models, a given node has a certain probability β to propagate a change or an error to its neighbouring nodes. The affected neighbours, in turn, can propagate to their neighbours and so on. Additionally, each node has a certain probability γ to correct the error or implement the change and, therefore, to stop the propagation to its neighbours. If the ratio $\frac{\beta}{\gamma} \leq \tau$, where τ is the critical threshold (also known as epidemic threshold), errors or changes are resolved fast and no propagation happens. Conversely, if the ratio $\frac{\beta}{\gamma} > \tau$ then errors or changes propagate and affect a fraction of the system. Therefore, we are interested in understanding how the critical threshold changes as a function of modularity. It has been shown that the critical threshold in networks depends only on the connectivity and it is equal to $\tau = \frac{1}{\Lambda_1}$, where Λ_1 is the maximum eigenvalue of the adjacency matrix A (Chakrabarti et al., 2008). A higher critical threshold (τ) means that, the probability of resolving an error or a change (γ) being equal, a higher probability of transmission (β) is needed in order to propagate changes in the system. Thus, a higher critical threshold lowers the systemic risk by reducing the probability of catastrophic propagations. We found that high values of modularity [0.51, 0.71] increase the epidemic threshold (Figure 3A). We note that there is almost no effect for low values of modularity [0.38, 0.50].

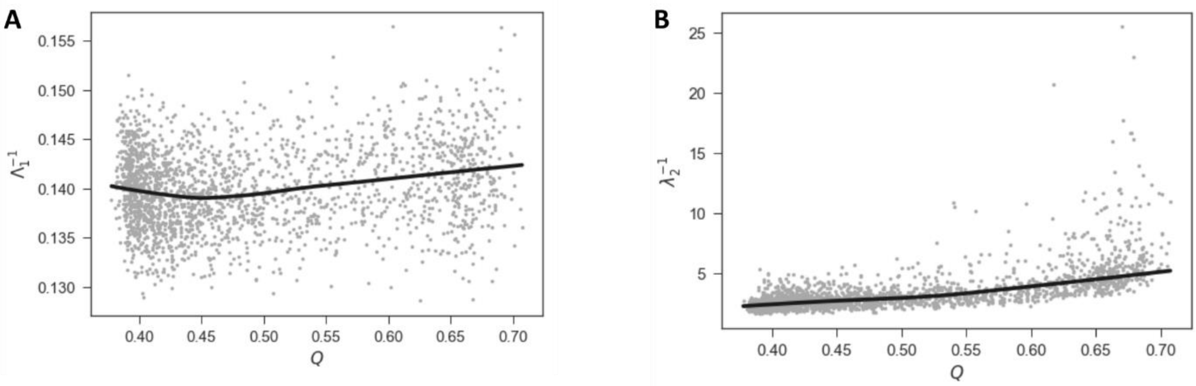

Figure 3. Relation between modularity (Q) and critical threshold (Λ_1^{-1}) and diffusion time (λ_2^{-1}). Trend line computed with LOESS smoothing.

We are also interested in understanding how the system architecture affects the speed of propagation on the network. In fact, even if we increase the epidemic threshold, the probability of catastrophic propagation will hardly be zero. Therefore, a system in which the propagation is slower, or that offers more time for intervention, is more robust/resilient than a system in which the propagation is fast. We can understand the speed of propagation by computing the first non-zero eigenvalue λ_2 of the Laplacian matrix L. The Laplacian matrix L describes both the diffusion process $\partial_t \rho = L\rho$ and the dynamics of a network of harmonic oscillators $\partial_t^2 x = -\sum_j A_{ij}(x_i - x_j) = -L\boldsymbol{x}$. The ratio $\frac{1}{\lambda_2}$ describes the period of the slowest oscillatory mode, or the longest timescale after which a perturbation will spread through the

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whole network. The higher the ratio $\frac{1}{\lambda_2}$, the higher the time a diffusion process needs to spread to the whole network. We find that increased modularity increases the diffusion time and, therefore, decreases the speed of propagation (Figure 3B). To be concrete, the networks with the highest modularity exhibit, on average, a propagation time up to 187% higher than the networks with the lowest modularity. Regarding the critical threshold, modularity has a much lower effect (around 2% increase) and the highest critical threshold is 20% higher than the lowest. This difference is mostly explained by the negative assortativity. In fact, D'Agostino et al. (2012) have shown that decreasing the assortativity (that is, avoiding direct connections between nodes with high degree) increases the critical threshold. However, they have also shown that decreasing the assortativity increases the speed of propagation, thus having a detrimental effect. We also show that modularity decreases the speed of propagation even in disassortative networks. Therefore, combining modularity with disassortativity is a strategy to both increase the critical threshold and to decrease the speed of propagation. This deserves more investigation and we will pursue it elsewhere. Here, however, we can formulate the following heuristics to choose between two architectures with respect to robustness to error- and change propagation: between two system architectures with similar value of modularity, the architecture with lower assortativity will tend to be more robust in terms of propagating phenomena.

5. Discussion

Our analysis investigated the relations between modularity and robustness in an ensemble of synthetic networks with many realistic properties. Through network analysis, we took the perspective of system architecture in order to generate insights that are potentially applicable across many systems.

We analysed robustness using both a topological (static) and a dynamic definition. Considering both definitions turns out to be crucial, as our results show that modularity has opposite effects on the two types of robustness. Increasing system modularity tends to make the system more vulnerable against failures of specific components that are situated between different modules. In terms of networks, this means that a network with higher modularity is less robust against node removal in terms of connectedness than a network with lower modularity and, therefore, breaks apart more easily. As such, a higher modularity will tend to produce a system with lower topological robustness.

However, increasing the system modularity tends to make the system more robust to iterations and error or change propagation phenomena. In fact, the clustered structure of the system architecture and the sparsity of linkages between modules tend to slow down propagation. Additionally, modularity might lower the probability of catastrophic propagations. We analysed the dynamic robustness by considering the eigenvalues of the adjacency matrix and the Laplacian matrix as in D'Agostino et al. (2012). Our analysis shares similarities with the eigenvalue analysis carried out on *Work Transformation Matrices* (Smith and Eppinger, 1997; Yassine et al., 2003) in the context of process analysis. In particular, the critical threshold (also known as epidemic threshold) analysed here is the reciprocal of the first eigenvalue of the adjacency matrix, which is related to the first 'controlling feature' or design mode (Smith and Eppinger, 1997). Therefore, as modularity can increase the critical threshold, we confirm that modularity can increase the stability of a system. To these approaches, we added the study of the second smallest eigenvalue of the Laplacian matrix, which gives information about the speed of propagation and network synchronisability.

As the two definitions of robustness are not interchangeable, we advise practitioners and researchers to carefully consider which definition of robustness applies to their systems. Otherwise, the results generated through considering the wrong definition might be misleading and inconsistent. In some systems, it might be desirable to have both high topological and dynamic robustness. The variance in our results (it is still possible to have high, although not necessarily maximal, values of robustness for high modularity) suggests that it might be possible to reconcile modularity and the two definitions of robustness. Future research should explore this trade-off systematically to understand the properties of the system architectures that satisfy such a trade-off.

Our work also provided an important related result. The negative relation between modularity Q and the total number of modules shows that the simple count of the number of modules of a system is not a reliable measure of overall modularity. This is especially important in the early stages of system design,

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when the system engineers define the system architecture. The number of modules should be determined as a function of the system architecture, not a priori. In fact, previous theoretical research on concurrent engineering has found that the best performance is found for an intermediate number of modules, and too many modules can have detrimental effects (Ethiraj and Levinthal, 2004; Hoedemaker et al., 1999). This issue, termed 'over-modularisation', occurs because too many modules increase the integration/coordination cost between the modules, and such a cost exceeds the gain of concurrent processing. If instead of considering the number of modules, we consider a measure of modularity that takes into account both internal cohesion and low coupling between modules, it is evident that this issue is not 'over-modularisation' but a suboptimal level of modularity. Therefore, we advise that researchers and practitioners use modularity measures that take into account the system architecture and that account for both the high cohesion within modules and the low coupling between modules.

Our analysis did not consider directed and weighted networks. This limitation is addressable in future research; however, the results about topological robustness are not affected by edge directionality and weights, as the definition we used considers only the size of the giant component. Our results on dynamic robustness, instead, are similar to previous findings on both directed networks (Braha and Bar-Yam, 2007) and weighted directed networks (Smith and Eppinger, 1997; Yassine et al., 2003). Therefore, we do not expect significant departures from the findings obtained here.

Taking a system architecture perspective allows us to interpret our findings in multiple domains. Therefore, we would like to conclude this discussion by interpreting our findings in three domains of interest in engineering design: product, process, and organisation. With respect to a product architecture, our findings point to the importance of few components that bridge different modules: while modularity might decrease topological robustness, at the same time it gives an economic advantage as it minimises the number of bridging nodes, which are the nodes to strengthen and improve. The findings on dynamic robustness, instead, suggest that modular product architectures receive fewer iterations or changes and are robust to their propagation. This is congruent with empirical research that has shown that modularity is associated with a decrease in the number of errors, changes, and iterations (MacCormack et al., 2006; Piccolo et al., 2019; Sosa et al., 2013). With respect to a process architecture, our research suggests that modularity can add stability to a process and can help to confine iterations inside process modules, thus avoiding catastrophic cascades. Additionally, it points to the importance of the tasks that integrate different modules. Again, this is corroborated by empirical research (Giffin et al., 2009; Piccolo et al., 2019; Smith and Eppinger, 1997; Wynn and Eckert, 2017). With respect to an organisational architecture, our research points to the importance of people who are located between different teams, as these people can either facilitate or hinder the information flow (Piccolo et al., 2018a). Finally, our results on dynamic robustness suggest that modularity in organisations might have the effect of hindering the process of reaching consensus. This relates to misalignments in organisational communication (Maier et al., 2008; Piccolo et al., 2018b), and suggests that when reaching fast consensus amongst the members of an organisation is of great importance, communication should become more integrative. This view has also received both theoretical and empirical support (Lazer and Friedman, 2007; Pentland, 2012).

In sum, modularity might not be the universally best choice when we want to optimise one single constraint, such as topological robustness. However, when we deal with multiple constraints and requirements, as we commonly do in design, we can regard modularity as a powerful design rule, one that trades between multiple constraints, has economic advantages, and tames complexity by reducing the risk of catastrophic cascades.

6. Conclusions

In this study, we analysed how modularity affects robustness. We used networks to represent system architectures and to measure modularity and robustness. In order to systematically study the effect of architectural modularity on robustness, we borrowed an approach from statistical mechanics to generate a number of comparable networks with the same number of nodes, edges, and same degree distribution, with increasing values of modularity. We considered two definitions of robustness: 1) a topological robustness, defined as the ability of a network to stay connected after node removal, and 2) a dynamic robustness, defined as the ability of a network to suppress or slow down error or change

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propagation. In such a way, we bridged a somehow split literature that tends to consider only one kind of robustness. Most importantly, we demonstrated that modularity affects the two types of robustness in opposite ways. Increasing modularity decreases the topological robustness as an effect of the lower coupling between modules, which makes the network more fragile to node removal. At the same time, and again due to lower coupling between modules, increasing modularity increases the resistance to error or change propagation. In fact, changes or errors tend to remain 'trapped' inside the modules. As such, our results suggest the presence of a trade-off between the two types of robustness, explain earlier conflicting findings, and confirm modularity as a strategy to reduce costs and to suppress change propagation.

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