RESILIENCE AND NETWORKS

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Abstract

The purpose of this paper is to apply network science to the field of resilience engineering. Starting with the trade-off between prepared versus deliberated knowledge, I argue that socio-technical systems are first and foremost networked systems that need to connect modules of prepared knowledge or instances of deliberated knowledge by means of protocols. I hypothesize that particular frameworks for organizing protocols, or 'architectures', are more resilient than others. In network science terms, protocols are interaction patterns that may lead to sustained adaptability in the face of unexpected events. Research in a variety of domains has shown that scale-free network structures, with a power-law degree distribution, have the highest resilience. The relevance of this finding for social networks and for the concept of resilience as sustained adaptability remains to be demonstrated. It is clear, however, that social network analysis in particular, as a novel research methodology in this field, offers a more quantitative base to establish resilience engineering research upon.

1 THE PREPARATION VERSUS DELIBERATION TRADE-OFF

One of the main issues within the field of resilience engineering is the question how systems deal with surprise events. More generally, systems are able to perform under a variety of conditions by drawing upon a mix of prepared knowledge or deliberated knowledge (Newell, 1990). Prepared knowledge facilitates the recognition of familiar events and results in efficient, robust, and rule-based performance. Deliberated knowledge is required when systems are confronted with surprise events. In this case, the emphasis is on thoroughness and analysis of multiple options. The variety of situations leads to a specific mix of deliberation and preparation, and the architecture of a specific system determines the extent to which a response stems from deliberation or preparation. Humans, for instance, generally rely on prepared knowledge, as demonstrated by the finding that at least 80% of their decisions are recognition-primed rather than analytical. The human cognitive architecture, as well as the externally fixed time to respond, simply do not allow for much deliberation. Intelligent computer systems have different architectures and are able to engage in extensive search, comparing millions of situations per task, but generally have little prepared knowledge to bring to bear.

There is thus a preparation versus deliberation trade-off that has been known for some time for intelligent systems (see Newell, 1990) and is depicted below:

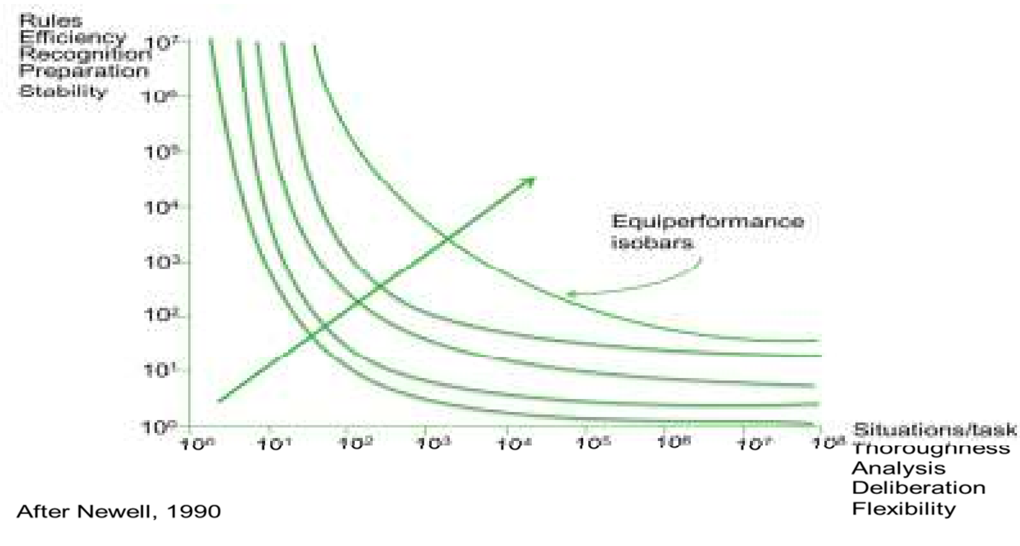

Figure 1 *Preparation versus deliberation trade-off (after Newell, 1990)*

Figure 1 shows that different systems may reach the same performance (on a single equiperformance isobar) by a different mix of either preparation or deliberation. The arrow denotes the optimal-mix points where cost-isobars (not depicted) touch the highest-performance isobar. These points constitute best trade-offs between amount of problem search and amount of knowledge search.

It is also clear from figure 1 that resilient performance should be in the area depicted by the optimal-mix points, along the arrow. Humans, taken as individual intelligent systems, are positioned in the top-left quadrant (lots of preparation, little deliberation), which results in robust, yet fragile (Doyle et al., 2005) behavior. Automated systems are positioned in the bottom-right corner (lots of deliberation, little preparation), which results in flexible, yet vulnerable behavior. The bottom-left corner is the brittle zone where systems run a high risk of saturation (Woods, 2015). The top-right corner is the area far from saturation where resilience should be positioned. The question is what architecture allows a system to balance the preparation versus deliberation trade-off (Woods, 2015).

2 MODULES AND PROTOCOLS AS THEY RELATE TO RESILIENCE

The concepts of 'modules' and 'protocols' may now be added to explain how systems deal with surprise events. Originally developed by Doyle and Csete (2002) in the area of biological systems and later extended to engineered systems, modules are defined as well-structured layers with high internal complexity that display robust behavior, while protocols are the rules that describe allowed interfaces between the modules. Protocols are generally fixed and small in number compared to modules, but they are the most vulnerable to attacks by viruses and other parasites. Modules may be compared to packets of prepared knowledge that yield robust behavior in the face of familiar events, but may fail catastrophically in the face of surprise events. In the face of surprise events, therefore, we need protocols to connect various modules in order to arrive at a less fragile response pattern.

Network science deals with the description of phenomena in terms of nodes and edges/arcs (relations or links between nodes). From a network perspective, modules are the nodes, whereas protocols are the links between the nodes. In social networks, protocols provide the information flow that is necessary to connect modules of prepared knowledge (information is taken to be an external phenomenon, whereas knowledge is an internal phenomenon; see Zins, 2007). I hypothesize that in order to be resilient, unrestrained information flow is a necessary condition. Particular frameworks for organizing protocols, and thus for managing information flow in networks, are more likely to demonstrate sustained adaptability than others (Woods, 2015).

From a cognitive science perspective, adaptive systems are what they are from being ground between the nether millstone of their physiology or hardware and the upper millstone of a complex environment in which they exist (Simon, 1980). To paraphrase Simon (1980), networked systems are what they are from being ground between the nether millstone of their limited channel bandwidth, which sets inner limits on their adaptation, and the upper millstone of a complex environment, which places demands on them for change. Networked social systems are capable of adapting to complex environments, but hardly ever perfectly. They could be called 'resilient' if they would demonstrate sustained adaptability over longer scales (Woods, 2015), but the reality is that most networked systems do not. Just as cognitive systems are boundedly rational, due to information processing limitations, networked systems are boundedly resilient, due to channel bandwidth limitations. These limitations are partly hardwired, but are also partly due to variations in absorptive capacity, centralized network position, tie strength, trust, and shared vision and systems (Van Wijk, Jansen, & Lyles, 2008). These factors have demonstrable positive effects on organizational knowledge transfer, yet can also impede knowledge transfer when they are less well developed.

If resilience engineering is taken to be the study of networked systems that operate in an unpredictable world, then the search for relative invariants must be found in the inner and outer environments that bound the adaptive processes. The inner environment of networked systems poses constraints on the types of information that can be transmitted. One relative invariant that has been found is the diversity-bandwidth trade-off (Aral & Van Alstyne, 2011), stating that high diversity of information exchange inevitably results in low channel bandwidth, whereas low diversity of information exchange results in high channel bandwidth. Resilience may be viewed as managing the trade-off between increasing a diversity of perspectives versus increasing homogeneity of perspectives. A choice within this trade-off space is determined by characteristics of the outer environment, such as the time available to reach a decision. Increasing a diversity of perspectives may be required when ample time is available, in situations where it pays off to be proactive, for instance in planning teams. A deliberate choice for increasing homogeneity of perspectives may be required in situations of time pressure, when it pays off to be highly responsive, for instance in action teams. This trade-off is similar to the trade-off many organizations face—that between exploration of new possibilities versus exploitation of known opportunities (March, 1991). As Rivkin and Siggelkow (2007) have shown, the patterns of interaction that exist in organisational, social and technological systems strongly determine how much to invest in long-run exploratory efforts. For instance, a centralized pattern of interaction results in a few decisions and the remaining choices are obvious, thus further exploration is not required. On the other hand, a dependent structure, in which a handful of decisions are affected by virtually every other decision, yet those decisions exert very little influence themselves, will substantially benefit from exploratory activities. Rivkin's and Siggelkow's (2007) study indicates that particular network structures may determine the long-term resilience of complex systems.

3 EMPIRICAL EVIDENCE FOR RESILIENT ARCHITECTURES

Given that we live in an unpredictable world, the question is how we prepare for and anticipate surprise events. By studying examples of organizations that have done so successfully, we may gain insights in successful architectures, taken in Doyle's sense of 'frameworks for organizing protocols'. I will make a first attempt at answering these questions by providing illustrative examples from various domains, ranging from technical to social systems.

3.1 Supply network disruption and resilience

Kim, Chen, and Linderman (2015) recently studied supply network disruptions from a network-level perspective. A supply network can be viewed as a collection of nodes (facilities) and arcs (transportation linking facilities). A disruption of a node or an arc sometimes has little effect on the supply network, but at other times can bring down the entire network. Kim, Chen and Linderman (2015) define supply network resilience as "a network level attribute to withstand disruptions that may be triggered at the node or arc level" (p. 50). Resilience is therefore an emergent structural property of a supply network that has to do with the extent to which a network stays connected.

Kim, Chen and Linderman (2015) studied four basic supply network structures that frequently occur in real-world supply chain management settings and that each may have different degrees of resilience: block-diagonal, scale-free, centralized and diagonal (see Rivkin & Siggelkow, 2007 for more detail and other network structures). To calculate supply network resilience for each of these four network structures, the authors randomly removed nodes and arcs and estimated the likelihood of a network disruption. The results showed that the *scale-free* network structure had by far the highest resilience. Denser networks and networks with the most walks were not the most resilient. Also, the network level metrics of betweenness centrality and centralization did not correlate with resilience. These results suggest that *degree distribution* of a supply network plays a critical role in determining its resilience. In particular, networks that display a power-law distribution are likely to be more resilient. In networks with a power-law distribution, most nodes lie on few paths between others. Therefore, random node/arc removal rarely affects the overall connectedness of a network with this structure, as already shown by a large body of research initiated by Albert, Jeong, & Barabasi (2000).

3.2 Resilience in industrial symbiosis networks

Industrial symbiosis networks are networks of industries that use each other's waste and by-products to achieve a mutually beneficial relationship. For instance, a power plant and refinery may use groundwater and surface water for industrial purposes, while the power plant may in addition use seawater as cooling water for electricity production. Subsequently, wastewater and the cooling water are reused as well as recycled within industries to reduce the extraction of groundwater and surface water. Chopra and Khanna (2014) studied the industrial symbiosis network at Kalundborg, Denmark and used network metrics and simulated disruptive scenarios to understand the resilience of this network. They were also interested in how the network developed over time, from 1960 to 2010. They found that a single node in the network, the Asnaes power plant, was the most central and therefore critical. Time trends revealed, however, that the network became less susceptible to single points of failure over time. Chopra and Khanna (2014) found a pattern of preferential attachment, as new industries that joined primarily attached themselves to the Asnaes power plant. This results in a network structure that has a power-law degree distribution. As mentioned in the previous paragraph, these networks tend to be robust to random removal of nodes, but they are vulnerable to targeted removal of central nodes (Albert, Jeong, & Barabasi, 2000).

3.3 Resilience in medical and military teams

By using social network analysis techniques, my colleagues and I have gained insight in the communication structures at the team level, and have related these dynamic structures to the demands of the environments in which the teams operate. For instance, we have studied the response of a paediatric cardiac surgical team to surprise events (Schraagen, 2011; Barth, Schraagen, & Schmettow, 2015) and found that communication patterns are dynamically adjusted in the face of such events (communication becomes less hierarchical and more heedfully interrelated). We have also studied the network structures displayed by this particular team as a function of the phase in the surgical procedure, for instance whether the patient was going on or off cardio-pulmonary bypass (a highly critical phase in the cardiac surgical procedure that requires close cooperation between the surgical team members). We found that in any given phase, there were always two team members linked to many others, thus scoring high on total degree centrality. Not surprisingly, the primary surgeon was always one of these, with the anaesthetist and perfusionist being the second actor, depending on the surgical phase. We also looked at complex versus non-complex procedures and found that during complex procedures the role of the assisting surgeon increased relative to the role of the primary anaesthetist, especially when going on or off cardio-pulmonary bypass. Although the primary surgeon still scored highest in total degree centrality in virtually all cases, the assisting surgeon filled in the role of communicator to the rest of the team whenever the workload of the primary surgeon prevented him from speaking to the rest of the team. This form of 'heedful interrelating' (Schraagen, 2011) shows that this team is at least adaptive, if not resilient. It is also a very important observation vis-a-vis the Albert, Jeong, & Barabasi (2000) finding that scale-free networks are highly vulnerable to targeted attacks. Capable people, such as the assisting surgeon, may compensate for the virtual 'elimination' of the most connected node in the network, the primary surgeon, whenever he is overloaded. Note that the assisting surgeon only took over the communication processes, while the primary surgeon continued with the physical work.

So far, we have not looked in detail at the precise structure adopted by this team. However, the results clearly display a power-law distribution of the total degree centrality, for both complex as well as non-complex procedures (see figure 2), leading us to suspect that this team displays a scale-free network.

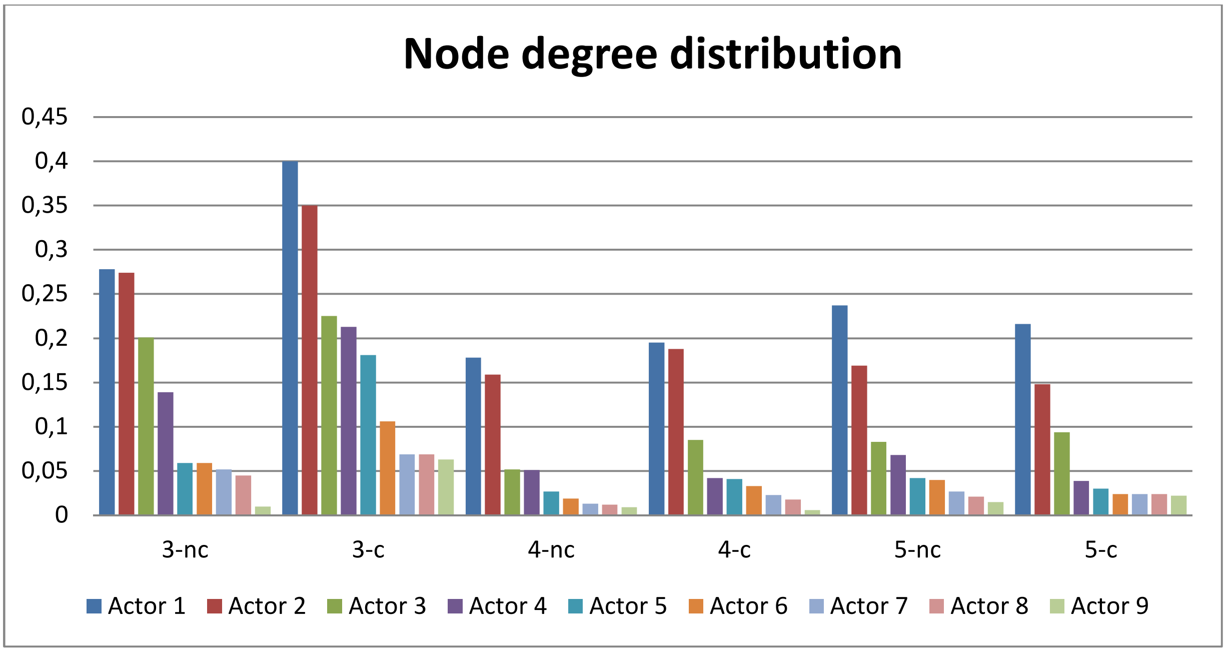

Figure 2 *Distribution of total degree centrality for each node (medical actor) in the network. The figure only shows the three most critical phases in the surgical procedure (3-5), for both non-complex (nc) and complex (c) procedures*

As a second example, a study of communication patterns in two separate naval internal battle teams showed that the more experienced team displayed more centralized communication patterns than the less experienced team, an example of a protocol evolving over time (Schraagen & Post, 2014). The central actor in the more experienced team, the Resource Manager, displayed significantly higher scores on total degree centrality than the other actors, as compared to the less experienced team. Most significantly, however, is the fact that distribution of total degree centrality displays a power curve for the more experienced team compared to the less experienced team (see figure 3), again suggesting a scale-free network structure.

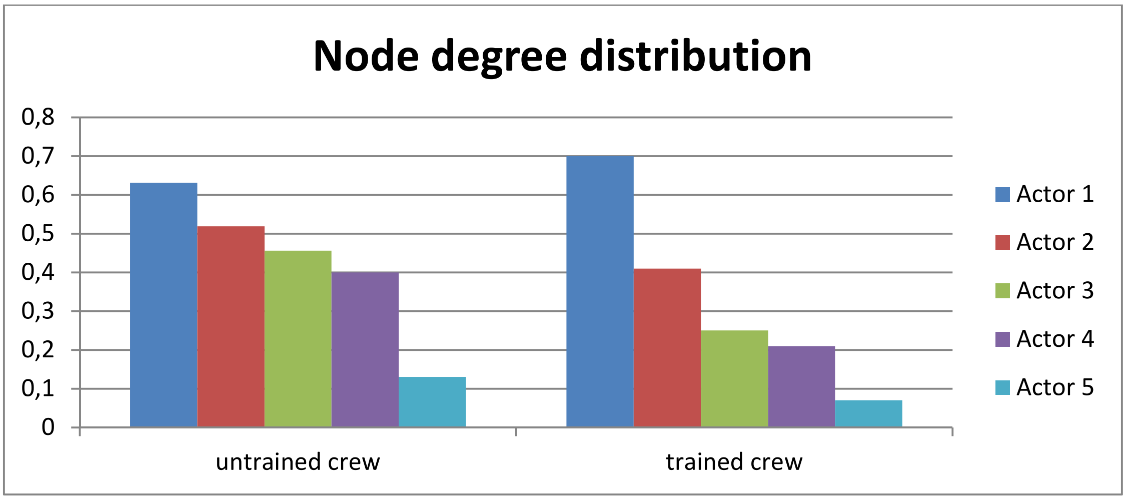

Figure 3 *Distribution of total degree centrality for each node (military actor) in the network, for both the untrained crew (left) and the trained crew (right)*

4 CONCLUSIONS

Complex socio-technical systems are first and foremost networked systems. In order to achieve their goals, these systems will select information from their networks using a limited number of protocols. Resilient performance in such systems is characterized by the flawless selection of such protocols, delivering information to the nodes in the network as needed to respond to a variety of conditions. Surprise events will be dealt with at local levels (through prepared knowledge or processes of improvisation) to the largest extent possible, thus maintaining the flow of the operation at the higher level. In a variety of domains, scale-free network structures have been shown to be resilient architectures, in the sense of being robust to the (random) removal of nodes. Specifically, in such resilient architectures the degree distribution of nodes follows a power law. This provides a direction for future research in resilience engineering, as it focuses attention to protocols and network characteristics of resilient networked systems. Moreover, it provides an impetus to the empirical investigations of such network structures using techniques such as social network analysis (Barth, Schraagen, & Schmettow, 2015).

However, we have also seen that there is a difference between social networks on the one hand and physical or biological networks on the other hand. Due to the adaptability of people in social networks, the results obtained with simulation models and random removal of nodes and arcs in physical networks may not generalize to social networks. Thus, the Robust Yet Fragile (Doyle et al., 2005) nature of many large-scale complex physical networks may be dampened in social networks, as people are flexible in taking over each other's roles, provided there are sufficient levels of trust and mutual understanding.

The question remains why we found that the degree distribution of nodes followed a power law in our social systems (at the team level), just as was found for the physical systems discussed. It may well be that this finding is a consequence of limited bandwidth constraints on human communication, making it simply impossible for actors to maintain communication links with many other simultaneously. A scale-free network may be the natural consequence of such constraints rather than a cause of resilience or sustained adaptability.

What, then, does resilience have to do with particular network structures? We hypothesize that this particular structure is able to deal with disturbances that are not well modelled, unexpected events that an OR team or a naval team such as we have studied needs to deal with as the occasion arises. In our research on communication processes within the OR, we have shown that the medical team adapted its communication structure to the external task demands, such as the complexity or the phase of the procedure (Barth, Schraagen, & Schmettow, 2015). In fact, the team blended a bureaucratic structure, with a central role for the surgeon, with a flexibility-enhancing structure, adding team members to the surgeon as the situation demanded. This results in a small-world or scale-free network structure, where supporting actors such as the anaesthetist, perfusionist or assisting surgeon switch roles in being the second-most-linked actor depending on the surgical phase. Also, the team as a whole adopted a flatter structure as procedures became more complex. We believe therefore that, in fact, these are network architectures that can sustain the ability to adapt to future surprises as conditions evolve (Woods, 2015). Future research needs to show whether scale-free networks are better able to deal with fundamental trade-offs such as the diversity-bandwidth trade-off than other architectures. It may very well be that there is a curvilinear relationship between scale-free networks and performance, such that too much connectivity may decrease the level of diversity of information exchanged (Uzzi & Spiro, 2005).

REFERENCES

Albert, R., Jeong, H., & Barabasi, A.-L. (2000). Error and attack tolerance of complex networks. *Nature, 406*, 378-382.

Aral, S., & Van Alstyne, M. (2011). The diversity-bandwidth trade-off. *American Journal of Sociology, 117(1),* 90-171.

Barth, S., Schraagen, J.M.C., & Schmettow, M. (2015). Network measures for characterizing team adaptation processes. *Ergonomics*. DOI:10.1080/00140139.2015.1009951

Chopra, S.S., & Khanna, V. (2014). Understanding resilience in industrial symbiosis networks: Insights from network analysis. *Journal of Environmental Management, 141*, 86-94.

Csete, M.E. & Doyle, J.C. (2002). Reverse engineering of biological complexity. *Science, 295*, 1664-1669.

Doyle, J.C., Alderson, D.L., Li, L., Low, S., Roughan, M., Shalunov, S., Tanaka, R., & Willinger, W. (2005). The "robust yet fragile" nature of the Internet. *Proceedings of the National Academy of Sciences, 102,* 14497-14502.

Kim, Y., Chen, Y.-S., & Linderman, K. (2015). Supply network disruption and resilience: A network structural perspective. *Journal of Operations Management, 33-34*, 43-59.

March, J.G. (1991). Exploration and exploitation in organizational learning. *Organization Science, 2,* 71-87.

Newell, A. (1990). *Unified theories of cognition*. Cambridge, MA: Harvard University Press.

Rivkin, J.W., & Siggelkow,N. (2007). Patterned interactions in complex systems: Implications for exploration. *Management Science, 53(7),* 1068-1085.

Schraagen, J.M.C. (2011). Dealing with unforeseen complexity in the OR: The role of heedful interrelating in medical teams. *Theoretical Issues in Ergonomics Science, 12(3),* 256-272.

Schraagen, J.M.C., & Post, W.M. (2014). Characterizing naval team readiness through social network analysis. *Proceedings of the Human Factors and Ergonomics Society 58th Annual Meeting* (pp. 325-329), Chicago, Il., October 27-31, 2014. Santa Monica, CA: Human Factors and Ergonomics Society.

Simon, H.A. (1980). Cognitive science: The newest science of the artificial. *Cognitive Science, 4,* 33-46.

Uzzi, B., & Spiro, J. (2005). Collaboration and creativity: The small world problem. *American Journal of Sociology, 111*, 447-504.

Van Wijk, R., Jansen, J.J.P., & Lyles, M.A. (2008). Inter- and intra-organizational knowledge transfer: A meta-analytic review and assessment of its antecedents and consequences. *Journal of Management Studies, 45,* 830-853.

Woods, D.D. (2015). Four concepts for resilience and the implications for the future of resilience engineering. *Reliability Engineering and System Safety*, http://dx.doi.org/10.1016/j.ress.2015.03.018.

Zins, C. (2007). Conceptual approaches for defining data, information and knowledge. *Journal of the American Society for Information Science and Technology, 58(4),* 479-493.