PAPERS

Self-Organizing Networks in Complex Infrastructure Projects

Stephen Pryke, *School of Construction and Project Management, University College London, United Kingdom*
Sulafa Badi, *Faculty of Business and Law, British University of Dubai, United Arab Emirates*
Huda Almadhoob, *School of Construction and Project Management, University College London, United Kingdom*
Balamurugan Soundararaj, *Department of Geography, University College London, United Kingdom*
Simon Addyman, *School of Construction and Project Management, University College London, United Kingdom*

ABSTRACT

While significant importance is given to establishing formal organizational and contractual hierarchies, existing project management techniques neglect the management of self-organizing networks in large-infrastructure projects. We offer a case-specific illustration of self-organization using network theory as an investigative lens. The findings have shown that these networks exhibit a high degree of sparseness, short path lengths, and clustering in dense "functional" communities around highly connected actors, thus demonstrating the small-world topology observed in diverse real-world self-organized networks. The study underlines the need for these non-contractual functions and roles to be identified and sponsored, allowing the self-organizing network the space and capacity to evolve.

KEYWORDS: infrastructure projects; team communication; self-organization; social network theory and analysis

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INTRODUCTION

Large-infrastructure projects are characterized by technical, organizational, and environmental complexity (Bosch-Rekveldt, Jongkind, Mooi, Bakker, & Verbraeck, 2011). Organizational complexity particularly arises from the need to manage the relationships among a large number of actors with multiple interests and objectives (Flyvbjerg, 2009). Infrastructure projects are also subject to multiple types of uncertainties: internally, such as duration estimations, a firm's financial capabilities and efficiency, performance of project participants—and externally, such as governmental and regulatory changes, economic turbulence, legal changes, and natural disasters (Love, Holt, Shen, Li, & Irani, 2002). In an effort to manage project uncertainty, clients rely heavily on contractual agreements for the management of project risks. This often results in situations in which the behaviors of project participants become aligned with resolving contractual obligations, rather than working collaboratively for the resolution of issues as they arise during the course of the project. Pryke (2012) contended that traditional organizational and contractual models, in other words, those based upon the published standard forms of contract, for infrastructure project delivery do not reflect the magnitude of complexity or the need for effective management of relationships. Indeed, despite the significant attention placed on establishing formal organizational and contractual hierarchies in large, complex infrastructure projects, much of the decision making related to project uncertainties are made through non-contractual multifunctional networks of individuals temporarily brought together by project-related common interests or tasks (Pryke, 2012).

The focus of this article is on the concept of "self-organization." According to Heylighen (2013) complex systems have an inherent tendency to spontaneously self-organize. Self-organization can be defined as the emergence of collective and coordinated global patterns as a result of the agents' local interactions, without any single agent being in control of the process (Heylighen, 2013). The emergent self-organized structure is dynamic, yet exhibits higher stability and greater flexibility and resilience in dealing with internal and external events (Heylighen, 2011). Complexity theory postulates that any sufficiently fragmented, diverse, and coordinated activity (Tavistock Institute, 1966), such as in the case of complex infrastructure projects, is inherently equipped with a natural evolutionary capacity that is sufficient enough to activate the self-organizing process. This can take place at any given point in time irrespective of the project's life cycle (Stacey, 2001). This inevitable self-organizing process is underpinned by the fact that megaprojects involve a large number of actors with a multitude of authority, power, values, and objectives (Wild, 2002), resulting in large-infrastructure projects being 'unmanageable' (Mintzberg, 1982) in the traditional sense. The magnitude of conflicting forces associated with resource allocation and approaches used to reach desired goals may increasingly amalgamate over time, tipping the project into what has been termed by complexity theorists as the 'edge of chaos' (Kauffman, 1996). This is the transitionary stage at the intersection of the project either succumbing to true chaos, in other words, complete system disintegration, or being reshaped by an inner "anti-chaos" force that pulls it back toward order (Stacey, 2001). Consequently, the project's continuity and success largely depend on the capacity to manage these nonlinear and unpredictable interactions at the edge of chaos (Bertelsen, 2003). Such a state is remedied, according to complexity theory, by the gradual emergence of cooperative relationships, often termed "informal organizations" that transcend contractual boundaries. These informal relationships bring about order and stability through increased collaboration, behavioral coordination, and goal alignment, thus improving problem solving and decision making (Anvuur & Kumaraswamy, 2008; Bertelsen, 2003).

Despite their importance, Cross, Borgatti, and Parker (2002) argue that most organizations are oblivious to the importance of informal ties as reinforcements to contractual and formal relationships. Given their greater adaptability, complexity theorists go as far as to contend that navigating these informal networks can be the difference between surviving and succeeding in projects (Bertelsen & Koskela, 2003). While traditional project management literature has placed great emphasis on technical issues such as planning, scheduling, risk analysis, and project management techniques (Winter, Smith, Morris, & Cicmil, 2006), there have been recent calls for more attention to be placed on the "relational" and "social" dimensions of project management (Müller & Martinsuo, 2015; Zhang, Cheng, & Wang, 2015). This is largely driven by the growing recognition of "informal" and "relational" forms of governance in projects with management scholars increasingly viewing projects as complex networks of multiple interdependent actors (Dubois & Gadde, 2000; Eloranta & Turunen, 2016). Having said that, studies adopting a network analytical perspective remain scarce in the project management domain (Kratzer, Leenders, & Van Engelen, 2010; Hossain & Wu, 2009) compared to other management disciplines (Balkundi & Harrison, 2006). This knowledge gap (Sandberg & Alvesson, 2011) needs to be dealt with in order to develop adequate managerial understanding of self-organization in large infrastructure projects.

The central premise of this article is that large infrastructure projects are temporary and can be complex both technically and organizationally. Technical complexity arises from the need to deliver non-standard solutions with complex technological interfaces, whereas organizational complexity stems from the involvement of a diverse set of actors from multiple organizations with often conflicting objectives (Flyvbjerg, 2009). Transition is necessary as a project moves from procurement of resources to the delivery of a complex project. The temporary organization involves transient and iterative roles (Pryke, 2012), additional factors influencing the tendency toward "self-organizing." This article puts forward the view that the success of the project rests therefore with the success or otherwise of the evolution and maintenance of these self-organizing systems. Specifically, we pose the following questions:

1. What is the social network structure observed in large infrastructure projects? We hypothesize that the structure will represent a self-organizing network.
2. Are these structural characteristics similar to, or do they differ from, those observed in non-project-based settings?
3. How does the self-organized network structure (i.e., topology) relate to the functioning of the project?

It was to answer these research questions that a study was conducted on a large and complex infrastructure project, the Bank Station Capacity Upgrade Programme. We adopted social network theory and the associated social network analysis (SNA), with the purpose of obtaining an understanding of the structure and the functioning of the project networks. Based on quantitative network data collected through an online questionnaire with 60 project participants, the study examined the network characteristics of density, path lengths, community structure, clustering, and actor centrality, looking at their connectivity (degree centrality), influence (eigenvector centrality), and brokerage potential (betweenness centrality). Embracing a network view allowed the comparison of the formally prescribed project organization with the self-organized organization and underlines the importance of the informal social structures that operate 'behind the chart' (Krackhardt & Hanson, 1993) in large-infrastructure project organizations. The study also provided a deeper understanding of the various network roles that actors acquire as a function of their positions within a given project's self-organized network. It should be noted that the term "informal" refers in this study to the set of emergent relationships that do not follow the official reporting structures prescribed in contractual documents. It is referred to by other scholars as "non-contractual," "non-hierarchical," or "embedded" ties as opposed to "contractual" and "arm's-length" relationships (Rooke, Koskela, & Kagioglou, 2009; Uzzi, 1997; El-Sheikh & Pryke, 2010). These relationships shape the way work gets done, in reality, through project actors' informal behavior, rather than by compliance with formal contractual roles.

The contribution this article makes is to extend the concept of self-organization to the management of large-infrastructure projects. It promotes a management approach founded in complexity theory, which views large infrastructure projects as complex systems with an inherent tendency to spontaneously self-organize (Stacey, 2001; Heylighen, 2013). Identifying the structural characteristics of these self-organized networks will offer insight into how the network's function and topology may affect each other—the function of the network dictating the topology. With increased managerial understanding, these non-contractual self-organized network functions and the associated network roles need to be identified and actively sponsored, allowing the self-organized network the space and capacity to evolve.

We begin this article by introducing self-organization and outlining the main structural characteristics and analytical measures used to observe self-organization. We then describe the case study and discuss the findings of the empirical investigation. The conclusion summarizes the findings, discusses the contribution of the approach to management practice, and underlines directions for future research on project networks.

Conceptual Underpinnings

The Concept of Self-Organization

In the traditional Newtonian paradigm, organizations are viewed as machines—processing information and producing predictable and repeatable solutions through prescribed, stable, and linear processes (Taylor, 1911). Organizations are viewed as determinist closed systems and managed through high levels of bureaucracy, hierarchy, and standardization. Such a view may work effectively in environments of high certainty and stability. However, the increasing complexity and uncertainty of today's business environments have rendered such a view of organizations unrealistic (Hamilton, 1997). Indeed, such a traditional understanding of organizations has been challenged over the years by chaos theory, which views organizations as dynamic systems in a constant state of change and inhabiting an increasingly unpredictable environment (Bertelsen & Koskela, 2003). Of particular interest is the seminal work of Stacey (2010, 2001), Englehardt and Simmons (2002), Lewin and Regine (2000), and Pascale, Millemann, and Gioja (2000), which conceptualized organizations as complex adaptive systems (CAS). CAS view organizations as self-organizing, complex, emergent, and interdependent systems. The system continually co-evolves with its constituent agents loosely restricting the agents' behavior, while agents are shaping the system by their interaction within it. Such a perspective is heavily grounded in complexity theory and offers a more superior insight into the structure and dynamics of evolving organizations.

In particular, the concept of "self-organization" has been growing in popularity in a wide range of fields, including biology (Capra, 1996), management (Hülsmann, Grapp, & Wycisk, 2007), social systems (Helbing, Yu, & Rauhut, 2011), telecommunications (Aliu, Imran, Imran, & Evans, 2013), and opinion formation (Habermas, 1994). The main premise of self-organization is that a system is not only capable of maintaining a stable state, but can also evolve and transform itself into a higher degree of order and complexity (Capra, 1996; Kauffman, 1996; McMillan, 2006). For instance, in economics Adam Smith's "invisible hand," which refers to the processes that help a market's supply and demand forces to reach equilibrium, is frequently seen as a self-organizing mechanism (Helbing et al., 2011). The self-organization process is characterized by the following central principles (Cooke-Davies, Cicmil, Crawford, & Richardson, 2008; Mahmud, 2009; Stacey, 2010):

- The process occurs spontaneously over time, driven intrinsically and collectively, without prior planning, controlling, external direction, or imposed order;
- With communication as its central mechanism, it is based on joint action and mutual understanding by the system's constituents for the achievement of a common goal;
- The consequences of the self-organizing process are unpredictable, as each system is capable of exercising choice and behaving in an idiosyncratic manner; and
- The emergent new self-organized structure is more coherent, stable, and with higher adaptive capability.

A common misunderstanding prevails in relation to the self-organization concept, in that managers and leaders are widely believed to have no role to play in the self-organization of networks or teams (Foerster, 1984; Mahmud, 2009). This is largely founded on the traditional Newtonian paradigm, which views the management function as solely maintaining an organization's stability and equilibrium (Foerster, 1984; Mahmud, 2009). However, in the context of the complexity paradigm, management is seen as a social function with managers and leaders performing as catalysts and cultivators of the self-organizing processes (Foerster, 1984; Mahmud, 2009; Stacey, 2010).

Characteristics of Self-Organizing Networks

Self-organizing networks can be viewed as 'complex networks that are not regular but they are not random either: their linking patterns do obey certain regularities, albeit not strictly' (Heylighen, 2011, p. 12). This study focuses particularly on social networks of actors engaged in the delivery of large-infrastructure projects—but what is a social network?

To answer this question we need to visit the realm of social network theory, a dominant theoretical paradigm in management research, as well as other disciplines, including communication, knowledge transfer, marketing, and organizational studies (Borgatti & Foster, 2003; Brass, Galaskiewicz, Greve, & Tsai, 2004; Freeman, 2004; Contractor, Wasserman, & Faust, 2006). Wasserman and Faust (1994) describe a "social network" as a set of actors connected through a set of clearly specified relationships. These relationships can be directed, in that they flow from one actor to the other, such as information, trust, and affection, or undirected; sharing an office, for example. Network theory focuses on uncovering the patterned and structured interrelationships among actors and exploring their antecedents and consequences both for the individual actor and for the network as a whole (Knoke & Young, 2008; Emirbayer & Goodwin, 1994). The associated SNA offers a powerful analytical tool for capturing, analyzing, and visualizing complex infrastructure projects and their interacting organizations (Wasserman & Faust, 1994).

Returning back to the focus of this study on self-organization, complexity researchers have examined a diverse set of complex self-organizing real-world networks, such as metabolic networks[1] (Wagner & Fell, 2001), the World Wide Web (Albert, Jeong, & Barabási, 1999), power grids (Watts & Strogatz, 1998), scientific collaboration networks (Newman, 2001a, 2001b), and engineering problem-solving networks (Braha & Bar-Yam, 2004). Table 1 offers an illustrative example of three of these studies, chosen for comparison because they represent seminal work in their respective fields, and gives a brief summary of their substantive findings.

Most significantly, these studies observed that self-organized networks often exhibit a high degree of sparseness (low density), relatively short path lengths, and clustering around actors of high connectivity with small-world typology (Baker, 2014; Braha & Bar-Yam, 2004; Hassas, Marzo-Serugendo, Karageorgos, & Castelfranchi, 2006; Heylighen, 2011; Saha, Mandal, Tripathy, & Mukherjee, 2015; Watts, 1999). These structural properties can be defined mathematically using SNA, and are described in detail as follows.

Density

A key dimension of social networks is density, which represents the proportion of all possible ties that are actually present, calculated by the number of ties, divided by the total number of possible ties. The values range from 0 to 1; in other words, 0 denotes that network actors are unconnected, whereas 1 indicates full connectivity. Within social networks, density is an indicator of the speed at which information diffuses in the social network and the extent to which network actors can reach each other (Kadushin, 2011; Hanneman & Riddle, 2005). It also represents "cohesion"—a reflection of redundancy taking place within a group. Higher cohesion, which is the existence of a large proportion of redundant ties between actors, is often associated with increased team performance (Beal, Cohen, Burke, & McLendon, 2003; Evans & Dion, 2012). This is explained by cohesion representing many trusted relationships through which valuable resources such as knowledge, information, and opportunities can flow. The work of Wise (2014), however, has contested this view, showing that group performance was maximized at an optimal point of group cohesion, and any decrease or increase beyond this point would result in suboptimal performance, "group think," and limited innovation.

Density of self-organizing real-world networks seems to be contingent on the function of the network in question. A dense, well-connected network was observed in Newman's (2001a) study of scientific collaboration networks and was viewed as an essential feature of a functional scientific community, whereas sparseness was a feature of metabolic networks (Wagner & Fell, 2001) and engineering problem-solving networks (Braha & Bar-Yam, 2004). For metabolic networks, a sparse structure means that a minimum number of active reactions takes place, hence, resulting in efficient use of cellular resources (Öksüz, Sadikoğlu, & Çakir, 2013). On the other hand, the low density of engineering problem-solving networks indicates that effective information transfer among engineers is more dependent on the pattern of network interactions, rather than the sheer number of information ties across the network (Braha, 2016).

Path Length

Path length is another network-analytical measure that indicates the distance between two actors in the network in question calculated by the minimum number of ties, which must be crossed to get from one actor to another. A large path length between two actors would indicate that several intermediary actors would have to transfer information between the communication originator and the receiver. This may result in extended time periods for processing the information, higher potential for miscommunications, and an increase in the boundaries between the two actors. Self-organized networks are often characterized by short average path lengths (Wagner & Fell, 2001; Newman, 2001a; Braha & Bar-Yam, 2004; Foukia & Hassas, 2004). This was found to increase the efficiency of information transfer between tasks in Braha and Bar-Yam's (2004) study of engineering problem-solving networks as well as result in new knowledge and discoveries traveling faster among scientists in Newman's (2001b) analysis of scientific collaboration networks. In a project context, short path lengths may reflect

[1]Cellular metabolism is essential for maintaining life. In a metabolic process, some materials are broken down to produce energy, whereas others, vital for life, are synthesized. A metabolic network is defined as "a characteristic complex network including all metabolites and enzyme catalyzed reactions occurring within a living cell, as well as the interactions between the reactants and enzymes" (Zhao, Yu, Luo, Cao, & Li, 2006, p. 1529).

	Metabolic Networks (Wagner and Fell, 2001)	Engineering Problem-Solving Networks (Braha and Bar-Yam, 2004)	Scientific Collaboration Networks (Newman, 2001)
Network constituents (also known as actors or nodes)	– 'Metabolites' present in the biological organism of *E Coli* (a type of bacteria that normally live in the intestines of people and animals).	– 'Tasks' in distributed product development (PD) problem-solving teams.	– 'Authors' of scientific papers in bibliographic databases in physics, biomedical research, and computer science.
Network relationships (also known as ties or links)	– The biochemical pathway connecting metabolite *i* and metabolite *j*.	– The information flow between task *i* and task *j*.	– Two authors *i* and *j* are considered connected if they have co-authored one or more scientific papers together.
Nunber of networks studied and size	– Four networks of sizes ranging from 275 to 315 metabolites that represent the small building blocks of *E Coli*.	– Four networks of size ranging from 120 to 899 tasks.	– Seven networks of size ranging from 8,361 to 1,520,251 authors.
Network structural characteristics:			
Density	Sparse networks with local high density in clusters.	– Sparse networks with average density of 0.011	– Each collaboration network has one giant, dense component filling 80%– 90% of the total network and a number of much smaller components filling the rest.
Path length	– Short average path length of 3.88.	– Short average path lengths ranging from 2.628 to 3.700.	– Short average path lengths ranging from 4.01 to 9.74.
Community structure (clustering)	– High clustering coefficient of 0.32 to 0.59. – Small-world typology observed. This is seen to minimize the transition time between metabolic states.	– High clustering coefficient of 0.205 to 0.449. – Small-world typology observed. This is seen to increase the efficiency of information transfer between tasks.	– High clustering coefficient of about 0.3 to 0.4, with the highest reaching 0.726. – Small-world typology observed showing that most scientists are connected through collaborations.
Centrality	– High centralization.	– High centralization.	– A strong funneling effect was observed. For most authors, the bulk of the paths between them and other scientists in the network (about 64%) go through just one or two of their collaborators.
Source: Wagner and Fell, 2001; Braha and Bar-Yam, 2004; Newman, 2001b			

Table 1: Example studies of complex self-organized networks.

the effectiveness with which temporary multi-organizations deal with the sharing of information and knowledge (Hansen, 2002).

Community Structure

The property of community structure identifies network actors that are joined together in densely connected clusters with looser connections to other parts of the network. Communities may be formed based on common interest, occupation, or co-location. The degree of 'clustering' in a network is the probability that two of an actor's connections are themselves connected (Newman, 2001b). High clustering that is linked by cross-cluster ties relates to the 'small-world' concept (Baker, 2014; Watts, 1999) with its origin in the idea of 'six degrees of separation—all human beings on this planet are only six steps away from each other.' This characteristic produces networks of regional specialization and efficient yet wide-ranging information transfer (Watts, 1999). The small-world topology has been found to be common not only in social networks but also in a wide range of large, sparse real-world networks such as those observed by Watts and Strogatz (1998) in their mapping of the power grid network of the western United States. The small-world properties (short path length and high clustering) were seen to contribute to the robustness of power networks through greater signal-propagation speed, computational power, and synchronizability. Newman (2001b) equally showed a very strong clustering effect in the scientific community: two scientists typically have a 30% or greater probability of collaborating if they have both collaborated with another third scientist. This indicates, according to Newman

(2001b), an important mechanism in the development of scientific communities: scientists introducing their collaborators to one another and hence brokering new collaborations among their acquaintances. Wagner and Fell (2001) also observed a small-world topology in their study of metabolic networks, which was found to optimize metabolic functions by reducing the time between metabolic states. All these studies point to the superior performance of small-world topologies as rapid transmitters of whatever needs to flow between network actors. Braha and Bar-Yam (2004) also argue that the high clustering of product development networks may suggest the inherent 'modularity' of the process; in other words, the organization of the product development process in clusters that contain most, if not all, of the interactions internally while minimizing or eliminating the interactions or links between separate clusters. Despite their superior performance as cultivators of innovative activities, small-world networks can be damaged by the targeted removal of nodes with high connectivity, particularly cluster-spanning ties (Hassas et al., 2006; Lizardo & Pirkey, 2014).

Actor Centrality

The position actors occupy in a network can enhance or constrain their access to valuable network resources (Freeman, 1979). An isolated position on the periphery of the network is unfavorable, as it offers limited opportunity to access other network actors and their resources. On the other hand, occupying a central position is associated with status, power, and influence, as it provides the actor with direct access to many other network members and increases his or her visibility (Scott, 2012). Three different concepts of centrality are traditionally differentiated (Freeman, 1979): Degree centrality is an indicator of the "connectivity" of an actor, based on measuring an actor's direct connections. Degree indicates power within one's own group, but not necessarily beyond that (McCulloh, Armstrong, & Johnson, 2013; Wasserman & Faust, 1994) and is associated with primary links. Self-organizing networks were found to exhibit high centralization (Wagner & Fell, 2001; Braha & Bar-Yam, 2004) with most network actors having a low degree (i.e., the number of actors a particular actor is connected to), while a few actors have a very large degree. This pattern is often referred to as power law ~or "scale-free" networks and is closely related to the concept of 'preferential attachment,' which explains inequalities in the process of network growth when new actors joining the network preferentially establish ties with those actors who have already a large number of connections (Heylighen, 2011). This may represent a weakness in communication networks, as the removal of such well-connected actors (i.e., hubs) may fragment the network into separate "islands" that no longer communicate with each other (Heylighen, 2011).

An extension to the degree centrality measure is eigenvector centrality, which acts as an indicator of influence by identifying actors who are well connected to other well-connected actors. Actors with high eigenvector centrality have the power to connect to other influential individuals and have the power to build norms and expectations that others in their group will relate to (McCulloh et al., 2013; Wasserman & Faust, 1994).

Finally, betweenness centrality is an indicator of "brokerage potential" based on identifying actors on the path between most of the other nodes in the network (Alojairi & Safayeni, 2012; Wasserman & Faust, 1994). Actors with high betweenness have the best opportunity to filter or change information flowing to others in the network, and thus information can be delayed, changed, or stopped at these points in the network. They could act as "funnels" through which most communication travels across the network (Newman, 2001a, 2001b), or as "choke" points, filtering or passing a particular view of the information, or even misinformation (McCulloh et al., 2013). Indeed, a strong 'funneling' effect was observed in Newman's (2001b) scientific collaboration networks—for most authors the bulk of the paths between them and other scientists in the network (about 64%) go through just one or two of their collaborators. In a project context, those key individuals can act as "boundary spanners" crossing organizational boundaries and connecting otherwise disconnected groups (Long, Cunningham, & Braithwaite, 2013); their removal may fragment the network and prevent the flow of information (McCulloh et al., 2013).

Research Method

Case-Study Approach and Context

SNA is fundamentally a positivist approach that favors a structuralist perspective, mainly due to its emphasis on understanding the functioning of systems through the mapping of the interrelationships between its role-holding actors. SNA requires, as a starting point of analysis, a holistic and rigorous description of relationship patterns, in order to structure a useful understanding (Knoke & Young, 2008). An exploratory single case-study approach was adopted examining the case of the underground rail-network station in London, England, serving the Bank of England, and known as Bank Station. The project was chosen because it offered a unique setting as part of a number of pilot projects for Transport for London (TfL) that aimed to promote collaborative working arrangements in order to drive down the cost of risks associated with successful project delivery. The research team was also provided with the opportunities for extended research access as part of a Knowledge Transfer Partnership (KTP) between University College London and TfL. The aim was to investigate the network structure in project delivery–related communication, to compare this structure with that prescribed in formal contractual agreements, and to underline the structural characteristics of the observed self-organized network.

The project comprised major upgrading work for the railway station,

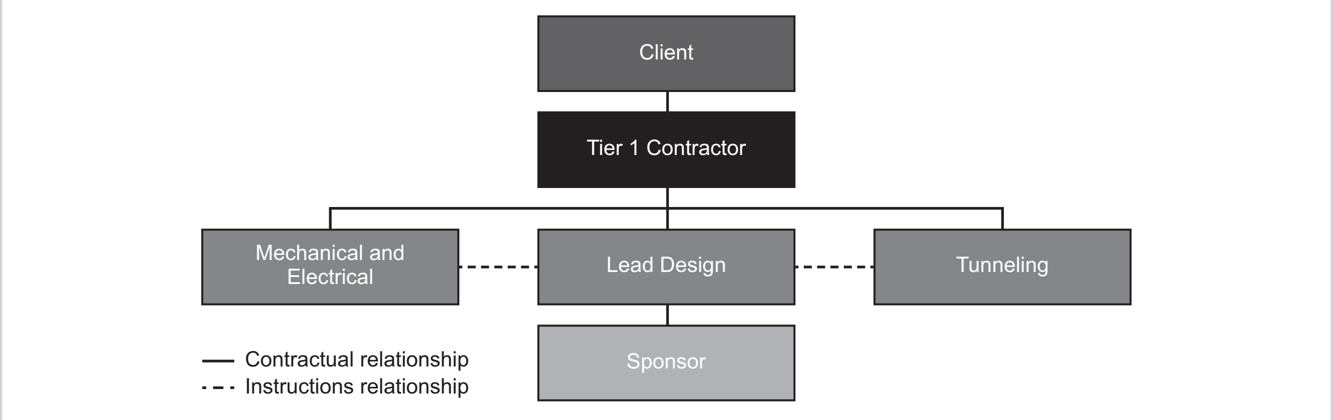

Figure 1: The contractual structure between organizations for the Bank Station Capacity Upgrade Programme (April 2014).

operated by TfL. At an estimated cost of £563 million (US$760 million equivalent), the project was initially launched in 2003 and went through the development of a number of options, before arriving at a base case in 2011 and entering tender process in 2012. The conceptual design was completed, application for permission under Transport and Works Act Order was submitted in September 2014, and construction started in autumn 2016. The project at the conceptual-design stage involved contributions from six organizations, with the contractual structure consisting of the client (Transport for London) and three tiers of contractors as shown in Figure 1. The formal organizational structure for the project is hierarchical (Mintzberg, 1981) with a limited degree of mixed teams and responsibilities as shown in Figure 2.

Data Collection

A major decision that a network researcher is faced with is how to delineate the case under study—in other words, what belongs to the case (the network)? This is termed the "network boundary" and two approaches are commonly used for its definition: a realist approach, with the actors deciding for themselves who belongs to their network; and a nominalist approach, in which the researcher decides who belongs to the network for the purpose of his or her research (Laumann, Marsden, & Prensky, 1992). In this study, a nominalist approach was adopted for network definition, in that the boundary of the network was established by the researcher as the team involved in the design of the Central Line escalators. A total of 60 individuals were identified to meet this criterion and were invited to take part in the study. As the researcher commenced the investigation, the project was gradually moving from the procurement stage, in which firms were brought together as an assemblage of specialist resources bound together through formal contracts, to the design-development stage. A specific "event" was of significance as the data was collected. This was in relation to the resolution of issues surrounding the impact on settlements and reaching agreement on switchgear, maintenance, and space-proofing requirements. The focus on a key event follows the work of Mahmud (2009), which argues that self-organization is best studied within the context of an event, organization change, or adaptive challenge.

Data were collected through an online questionnaire sent by email to the 60 project actors and took place between January 2014 and April 2014 during the design and approvals stage of the project. Table 2 lists the main questionnaire items. As communication is considered to be the central mechanism for the iterative interaction that drives self-organization (Mahmud, 2009), actors were asked to identify the individuals with whom they communicated in relation to issue resolution. Emails, telephone calls, letters, and face-to-face conversations are collectively represented as relationships between two actors. Likert scale values were recorded (low, medium, or high, scoring one, two, or three, respectively) for frequency and quality of the communication. Quality was operationalized using six measures: importance, clarity, accuracy, timeliness, understanding, and reliability. The scores for frequency and quality were multiplied and used, following Pryke (2012), as a proxy for tie strength.

The data collected represents networks of actors involved in resolving issues during the design of the Central Line escalators. However, several challenges were experienced during the data collection process, particularly the need to re-administer the survey using a modified survey questionnaire. The initial questionnaire adopted the "snowballing method" with which participants were identified progressively and added to the list by early completers of the survey; however, the initial response rate for the survey was low, with respondents struggling to remember accurately individuals by name. Subsequently a

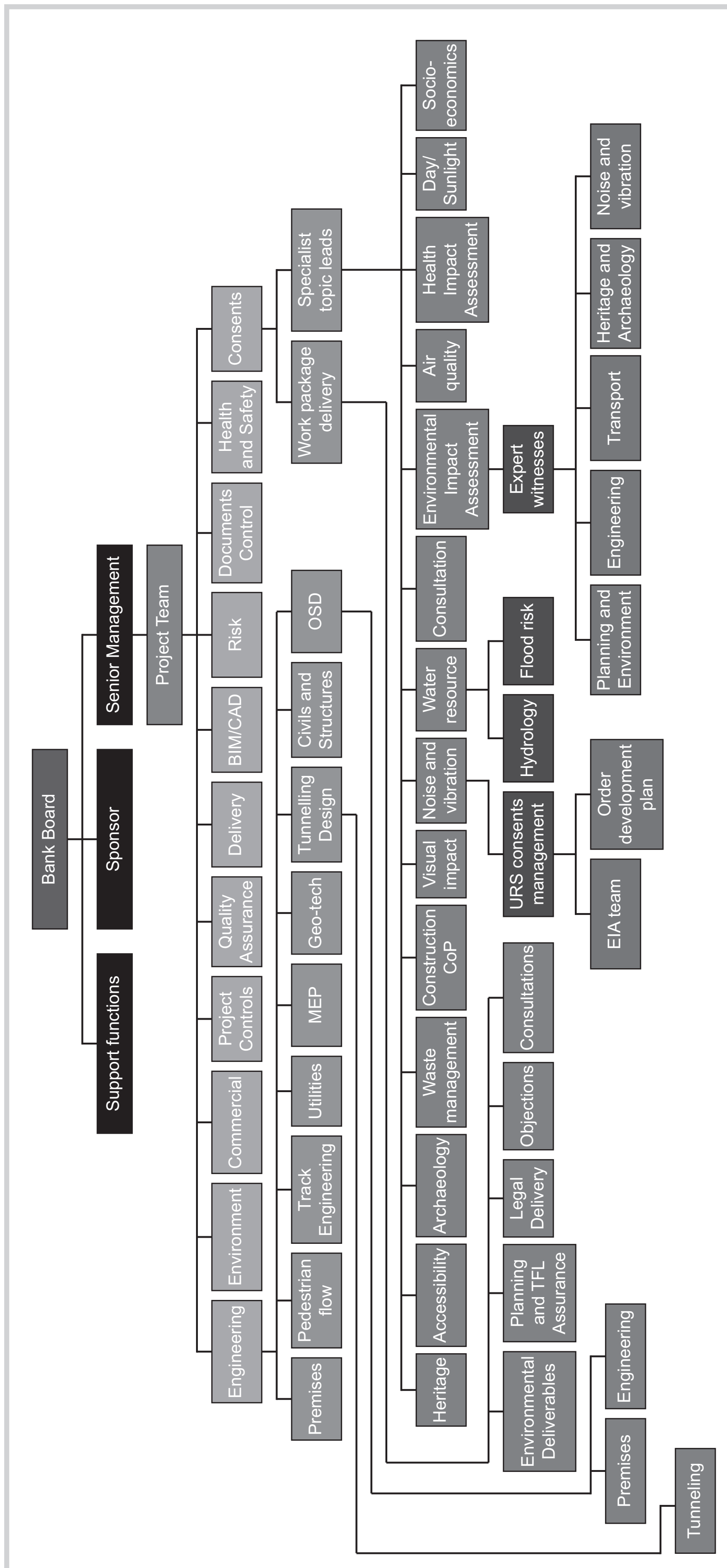

Figure 2: The formal organization of individuals and roles for the Bank Station Capacity Upgrade Programme (April 2014).

Questions	Details
Details of the respondent	**Name, organization, role, time spent in the Bank Station Capacity Upgrade Programme [%]**
Were you involved in the design of the Central Line escalators?	Yes/No
With whom did you communicate in resolving issues during the design of the Central Line escalators? (Please consider all types of communication including email, telephone call, letter, and face-to-face conversations).	Selected from an expandable list of individuals [yes/no]
How often did you communicate with this person?	Frequency [Nominal]
Please assess the quality of this communication.	Importance, Clarity, Accuracy, Timeliness, Reliability, Understanding [Ordinal -2:2]

Table 2: Questionnaire items.

number of measures, including designing an easier questionnaire, conducting drop-in sessions, following up with target respondents over email and in-person, were taken up to improve the response rate, finally reaching 100%. Adopting a nominalist approach, the redesigned survey was easier to be completed by participants, as a list including all 60 target respondents was presented with their organizations, roles, and contact details pre-listed, which made it easier for respondents to complete the questionnaire and addressed the problems of respondent recall.

Data Analysis

The data collected through the online questionnaire was stored in an SQL database. This data was retrieved using PHP Hypertext Processor and combined into one network by merging the overlapping links in each survey response and calculating the weights of the links from the responses on frequency and quality of the links. While creating a weighted network, the link weight was determined from the information collected on the quality of the link and was normalized to a continuous value between 0 and 1, when 0 denotes no link and 1 denotes the strongest possible link between the corresponding nodes. In this case, the strength of a link is defined by two variables—frequency and quality. The strength of communication between the actors i and j is thus expressed as (Equation 1):

$$E_{ij} = F_{ij} \times Q_{ij}$$

$$\text{Where, } F_{ij} = \frac{f_{ij}}{6} \text{ and } Q_{ij} = \frac{\Sigma q_{ij}}{30} \quad (1)$$

F_{ij} is the frequency of communication normalized to be between 0 and 1 and Q_{ij} is the quality of each communication, which is the mean of all six individual parameters q_{ij}, shown in Table 2 normalized to be between 0 and 1. The final value E_{ij} is calculated for all the links in each record in the data. The resulting network is then analyzed using igraph library (Csardi & Nepusz, 2006) in R Programming language to identify the characteristics of the network—density, average path length (West, 1996), and communities (Pons & Latapy, 2014) as well as the characteristics of the actors—degree centrality (Freeman, 1979), eigenvector centrality (Bonacich, 1987),[2] and betweenness centrality (Brandes, 2001) shown in Table 3.

The Gephi software was used to convert the mathematical values of the data into network diagrams—also known as "sociograms" (Moreno, 1953). A force-directed layout, Force Atlas 2 (Jacomy, Venturini, Heymann, & Bastian, 2014), was used for all the visualizations (see Figures 4, 5, and 6) except for Figure 3, showing the community structure when a manually created layout was used. The force-directed layout algorithm treats all nodes as objects with mass and links as 'springs' with strengths (link weights) suspended in space and uses a gravitational model to calculate their relative positions. This produces a network diagram in which nodes are placed relative to each other, depending on the existence and strength of the links between them. This is beneficial, in that the resulting network diagram is legible with less overlap of nodes and links.

Validating the Tie-Strength Measures

In order to validate the tie-strength measures, a Multiple Regression Quadratic Assignment Procedure (MRQAP) was performed among the six individual parameters constituting the quality of communication (see Table 4). MRQAP is preferred for the analysis of relational data, such as social network data. The results have shown that all six parameters are strongly correlated, hence their aggregation by simple means is justified.

The data for degree, eigenvector, and betweenness centrality were analyzed for correlation with tie strength, frequency, quality, and values for the population studied in this case study as shown in Table 5.

There was a modest correlation (0.44) between betweenness centrality and overall tie strength, with weak correlations for the individual tie-strength elements of frequency (0.21) and quality (0.17), indicating that it is the *combination* of frequency and quality that is important and provided

[2]Degree centrality was calculated based on the total of incoming and outgoing links an actor has (Freeman, 1979). Eigenvector centrality, on the other hand, was calculated, following Bonacich (1987) based on only incoming links by which lower value is given to an incoming link from an isolated actor and higher value is given to an incoming link from a more "well-connected" actor. Hence, the importance of an actor, according to eigenvector centrality, is dependent upon both the number of links he or she has and those links are weighted according to the importance of the sender.

Sn	Role	Organization	Connectivity (degree centrality)	Influence (eigenvector centrality)	Brokerage (betweenness centrality)
1	Lead Architect	Architecture	0.41	0.48	0.03
2	CPC Project Services	Client	0.61	0.45	0.06
3	Program Manager	Client	0.25	0.23	0.01
4	Planning-Consents Manager	Client	0.05	0.01	0.00
5	Operational Task Manager	Client	0.25	0.89	0.00
6	Profession Head: Tunnels	Client	0.49	0.41	0.02
7	Power Engineer	Client	0.39	0.13	0.03
8	ADE for Systems Engineering	Client	0.32	0.07	0.01
9	Asset-Protection Discipline	Client	0.05	0.22	0.00
10	Environment Manager	Client	0.00	0.00	0.00
11	Delivery Manager	Client	0.37	0.54	0.02
12	Tunnel Engineer	Client	0.36	0.28	0.01
13	Lead Program Engineer	Client	0.41	1.00	0.06
14	HSE Manager	Client	0.15	0.35	0.01
15	Project Sponsor	Client	0.32	0.31	0.01
16	TWA Work-Package Manager	Client	0.19	0.36	0.00
17	Lead Discipline Engineer—Lifts	Client	0.10	0.16	0.00
18	Lead Premises Engineer	Client	0.41	0.39	0.03
19	Lead Premises Engineer	Client	0.02	0.01	0.00
20	Lift-User Acceptance Manager	Client	0.02	0.01	0.00
21	Lift and Escalator	Client	0.15	0.50	0.00
22	Project Engineer	Client	0.12	0.27	0.00
23	Principal-Systems Engineer	Client	0.03	0.08	0.00
24	Lead Power Engineer	Client	0.12	0.25	0.00
25	Lead Fire Engineer	Client	0.08	0.15	0.00
26	Other	Client	0.02	0.04	0.00
27	Other	Client	0.10	0.32	0.00
28	Lead Tunnel Engineer	Client	0.02	0.06	0.00
29	Other	Client	0.02	0.06	0.00
30	Lead E&M Engineer	Client	0.07	0.11	0.00
31	Other/Unspecified	Client	0.02	0.03	0.00
32	Other/Unspecified	Client	0.02	0.05	0.00
33	Other/Unspecified	Client	0.02	0.05	0.00
34	Other/Unspecified	Client	0.02	0.01	0.00
35	Design Manager	Lead Design	0.05	0.00	0.00
36	Interface Manager—Systems Integration	Lead Design	0.00	0.00	0.00
37	Building-Services Coordinator	Lead Design	0.34	0.50	0.00
38	Railway Systems Assurance Engineer	Lead Design	0.05	0.11	0.00
39	Permanent Way Lead	Lead Design	0.00	0.00	0.00
40	Engineering Manager	Lead Design	0.20	0.96	0.00

(continued)

Sn	Role	Organization	Connectivity (degree centrality)	Influence (eigenvector centrality)	Brokerage (betweenness centrality)
41	Senior Power Engineer	Lead Design	0.54	0.08	0.04
42	E&M Engineering Manager	Lead Design	0.05	0.17	0.00
43	Other/Unspecified	Lead Design	0.07	0.33	0.00
44	Senior Project Manager	MEP (Mechanical and Elec Plant)	0.05	0.20	0.00
45	Other	Other/Unspecified	0.02	0.07	0.00
46	Other/Unspecified	Other/Unspecified	0.02	0.01	0.00
47	Other/Unspecified	Other/Unspecified	0.02	0.01	0.00
48	Other/Unspecified	Other/Unspecified	0.02	0.02	0.00
49	Project Director	Tier 1 Contractor	0.15	0.36	0.00
50	Project Manager	Tier 1 Contractor	0.36	0.52	0.02
51	Engineering Manager	Tier 1 Contractor	0.58	0.73	0.10
52	Construction Manager	Tier 1 Contractor	0.12	0.11	0.01
53	Other	Tier 1 Contractor	0.10	0.19	0.00
54	Other/Unspecified	Tier 1 Contractor	0.05	0.14	0.00
55	Other/Unspecified	Tier 1 Contractor	0.02	0.08	0.00
56	Other/Unspecified	Tier 1 Contractor	0.02	0.08	0.00
57	SCL Tunneling Lead	Tunneling	0.31	0.54	0.02
58	Other/Unspecified	Tunneling	0.03	0.17	0.00
59	Other/Unspecified	Tunneling	0.02	0.10	0.00
60	Other/Unspecified	Tunneling	0.02	0.02	0.00

Table 3: Centralities of actors within the information-exchange network.

some validation of using information-exchange frequency and quality combined as a measure of tie strength in project networks. Correlation between degree and eigenvector centrality values and the weight or the link is weak and in the case of quality there is a negative correlation. This indicates that if we are looking for a useful measure of prominence of actors engaged in iterative communication, then betweenness may represent the most appropriate measure.

Reporting of SNA Results

All the generated network visualizations (see Figures 3 through 6) were visually inspected for consistency with the actual practices in the project work. This was validated by consultation with the research respondents and key individuals in the senior management team for the Bank Station Capacity Upgrade Programme. This took the form of a three-hour workshop in which the researcher presented the results of the study and invited interpretations from the project team. This enabled the research respondents, as well as the senior management team, to evaluate the network structurally and relationally. This process provided insight into the functioning of the project network, as will be discussed in the following sections.

Results

This section presents the SNA analyses and interpretation of the case-study project. We argued that the study of self-organized temporary project-delivery networks is facilitated by an understanding of the overall structure and the number of ties that link network actors together through the SNA measure of density. Density is, however, transient and the identification of relative density variations in the network, through the identification of communities, is valuable in identifying self-organizing systems that contractual roles have not identified. The path lengths existing between the project actors in their information acquisition and dissemination activities are also important, because they affect the speed and accuracy of communication. The three measures of actor centrality relate to prominent network roles that actors acquire in the self-organizing project network, rather than their formal roles.

Density

The network is sparsely connected with a low relational density of 0.076, thus characterized by fragmentation, low levels of "noise," and limited access to

Measure 1	Measure 2	R Squared	Adjusted R Squared
Frequency	Importance	0.6872	0.6871
Frequency	Accuracy	0.6935	0.6934
Frequency	Clarity	0.6841	0.6840
Frequency	Understanding	0.6880	0.6879
Frequency	Reliability	0.6722	0.6721
Frequency	Timeliness	0.6820	0.6819
Importance	Accuracy	0.9800	0.9800
Importance	Clarity	0.9806	0.9806
Importance	Understanding	0.9764	0.9764
Importance	Reliability	0.9708	0.9708
Importance	Timeliness	0.9744	0.9744
Accuracy	Clarity	0.9894	0.9894
Accuracy	Understanding	0.9842	0.9842
Accuracy	Reliability	0.9781	0.9781
Accuracy	Timeliness	0.9782	0.9782
Clarity	Understanding	0.9840	0.9840
Clarity	Reliability	0.9784	0.9784
Clarity	Timeliness	0.9806	0.9806
Understanding	Reliability	0.9837	0.9837
Understanding	Timeliness	0.9715	0.9715
Reliability	Timeliness	0.9709	0.9709

Table 4: QAP correlation among the six individual parameters of quality.

resources (Pavlovich, 2003). This sparseness resonates with the density of four design-development communication networks examined by Pryke (2012), which ranged from 0.066 to 0.214. While the size of the networks examined by Pryke is not identical to our network—he examined four networks of a size ranging from 32 to 74 actors, hence restricting comparability—low density seems to characterize such complex self-organized networks. For example, the study of Braha and Bar-Yam (2004) of large engineering problem-solving networks has identified this sparseness characteristic with an average density of 0.011 observed. Kastelle and Steen (2010) pointed to the cost of seeking higher network density through increased connectivity, in other words, the effort needed from actors to establish and maintain relationships as well as transfer information and knowledge through these links. Thus, as Pryke (2012) argues, such low-density networks are more efficient in transaction cost terms. Central actors within less-dense networks may reap the advantage of enjoying greater power in a dispersed structure and acting as network 'commanders' (Pavlovich, 2003).

There are three isolated actors in the network, which indicate that these poorly connected members of the project were not communicating with other members of the network in resolving this particular issue, despite being a part of the design team. It is worth noting, however, that while these actors were isolated in the network under study, the actors could be well connected in other networks that are not included within the scope of the research reported here.

Path Length

It could be observed that the structure of the network is such that any two actors are connected within a maximum of 5 steps (or links) and an average of 2.23 steps. The average path length is relatively small, which, in a design environment, may indicate efficiency in communication and decision making, since information travels quickly because actors need to make fewer links in order to communicate with other actors.

Community Structure

The analysis and identification of communities help in the identification of the underlying hidden project-delivery structure of a network based on the smaller groups formed by individual relationships between actors. The communities were identified using a feature of Gephi community identification as shown in Figure 3. The important point is that having used the software to identify communities, the data analysis was taken back to the original research respondents and it was *the respondents* who classified the activities of the actors within each community. The number, size, and connections of communities help to understand how project team members form informal groups to resolve the design-development issues at stake. It is worth noting that these structures are self-organized and not designed by

	Degree	Eigenvector	Betweenness
Tie strength (value)	0.082	0.210	0.442
Frequency	0.102	0.161	0.208
Quality	−0.049	−0.062	0.173

Table 5: Coefficient of correlation by centrality measure.

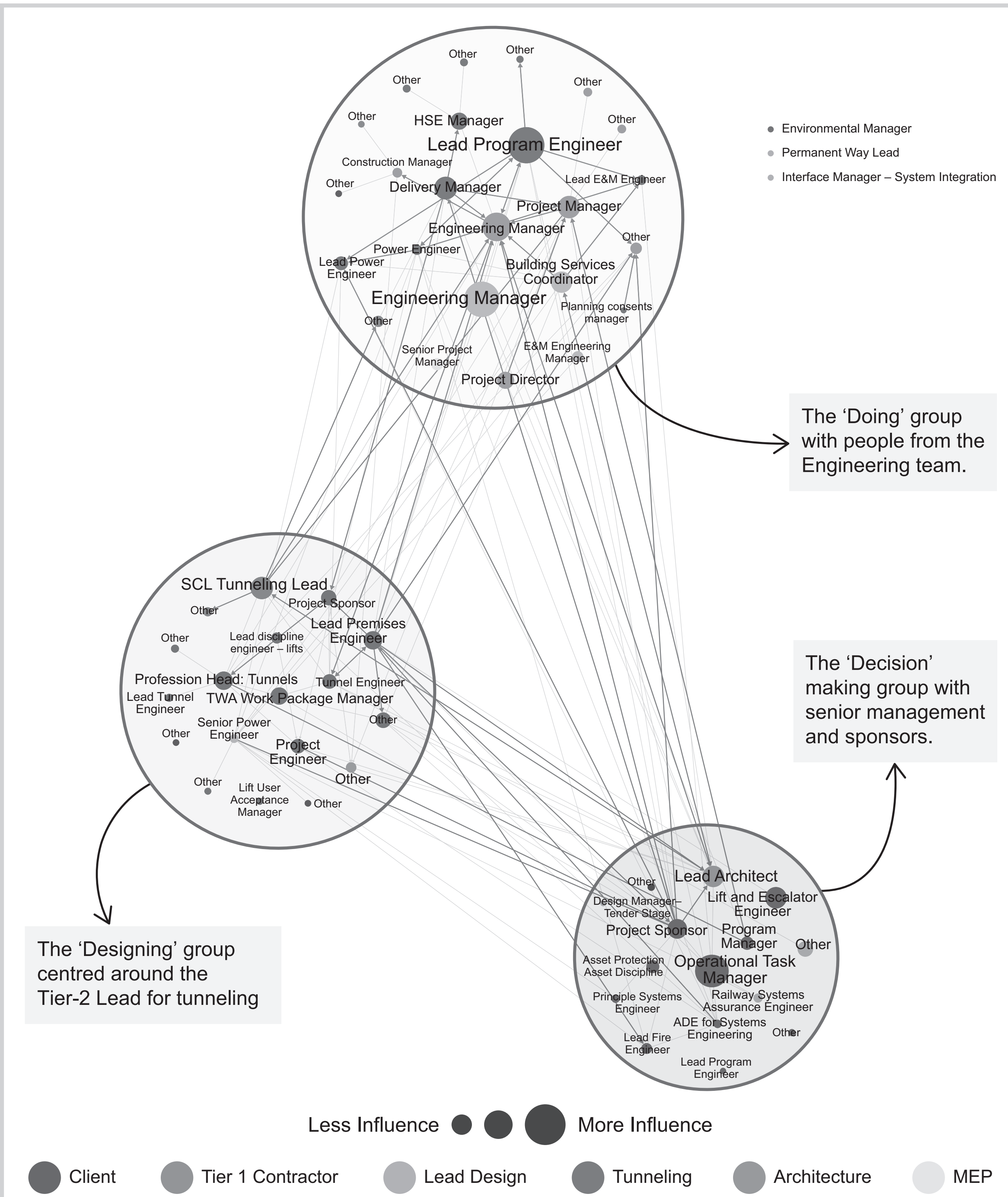

Figure 3: Communities' substructures within the network (layout manually created). (A larger format, full-color version of this figure is available for viewing at https://www.ucl.ac.uk/bartlett/construction/sites/bartlett/files/pmj-networks-figures-3-6.pdf)
Source: Pryke, Badi, Soundararaj, Watson, and Addyman (2015, p. 9). Figure 3 is reproduced in color in Pryke (2017, p. 153).

the project management team. In the network, three distinct communities (see Figure 3) were found, consisting of individuals from different organizations but working under the same community theme. The themes identified were: "doing," "decision making," and "designing," and these classifications came about in consultation with the original network respondents. "Doing" comprised the gathering and dissemination of information; "decision making" comprised the problem-solving and strategy formulation; and "designing" comprised the processing of information to produce "artefacts" for use by other project actors, in dealing with the design or production function. It is also notable that the communities are formed around certain actors of high influence (eigenvector centrality), such as the Lead Program Engineer (doing), SCL Tunneling Lead (design), and Operational Task Manager (decision making).

In addition, the network could be observed to exhibit a number of "small-world" properties derived from the following observations:

1. Low average path length (2.23) in the network compared to a random network of the same size and average degree (2.83);
2. The "fat-tailed" distribution of the degree in the network compared to a normal distribution in a random network; and
3. The high clustering coefficient (0.464) of the network compared to a similar random network (0.133).

These small-world characteristics have been consistently observed in a diverse set of real-world self-organizing networks such as Wagner and Fell's (2001) metabolic networks, Newman's (2001a, 2001b) scientific collaboration networks, and Braha and Bar-Yam's (2004) engineering problem-solving networks. Braha and Bar-Yam (2004) underlined the key factors that such small-world topology is optimizing in product-development networks, including the reduction of development times, an increase in product quality, and a decrease in development costs. The inherent iterative nature of the design process means that inevitable changes and rework need to be implemented throughout the network. To minimize rework and delay and to achieve a shorter design-development time, efficient communication is required throughout the network. The small-world topology supports this through clusters that encompass internally most—if not the entirety—of the interactions required, with minimum cross-cluster ties that facilitate swift information transfer throughout the whole network via short path lengths.

In our case study, the small-world typology increased the efficiency of communication between the three identified heterogeneous communities of "doing," "decision making," and "designing," with each "functional" community made up of a group of actors with their own distinct routines, mental models, and cognitive map, also termed 'epistemic communities' by Kastelle and Steen (2010). The small-world structure allows the integration of these actors' resources by short path lengths for the resolution of the design-development issues at hand. The structure is also highly robust and error-tolerant to the random removal of actors; however, it is vulnerable to the targeted removal of those who are well connected. Such actors with cluster-spanning ties are the network's critical points, and their removal, perhaps by dismissal or retirement, may weaken the network by splitting it into dispersed "islands" that no longer communicate with one another.

Actor Centrality

The position and importance of the actors in the network were measured in terms of the three measures of centrality, including degree centrality (connectivity), eigenvector centrality (influence), and betweenness centrality (brokerage). Table 3 classified the prominence of each of the 60 actors within the network. The knowledge of the position of the actors within the network enables a better understanding of their relative importance in the network and also underlines any differences from their contractually prescribed roles.

Connectivity or degree centrality measures an actor's direct connections, representing his or her communication activity within the network. In our case, high connectivity translates to the individuals who are the most visible or outspoken to others in the team. Since we are focusing on a network resolving a technical problem, we expect the individuals who are dealing with the technical aspects to be more significant in terms of connectivity. The network is shown in Figure 4. It was noted that this was not always the case; the lead for Lifts and Escalators was at the periphery of the network with low prominence, whereas the Asset Discipline Engineer for Premises and Systems was enjoying more connectivity in the network. Along with the weak communication between the Delivery Manager and Engineering Manager, these were identified as problems in the network and were confirmed to have a real impact in resolving the issue from the senior management team. It can also be observed that the network has high centralization derived from the existence of 10 (out of 60) actors with significantly higher degree centrality than other actors (see Table 3), in which connectivity values form two distinct groups. In other words, the network has few actors with much higher connectivity than other actors, including the lead managers of the engineering disciplines and the project sponsor. This could be explained by team members joining the design-development, issue-resolution network preferentially attaching themselves (Albert & Barabási, 2002); in other words, choosing to communicate with those well-connected actors from the engineering disciplines. The high connectivity of the project sponsor indicates their active involvement by establishing and maintaining a large number

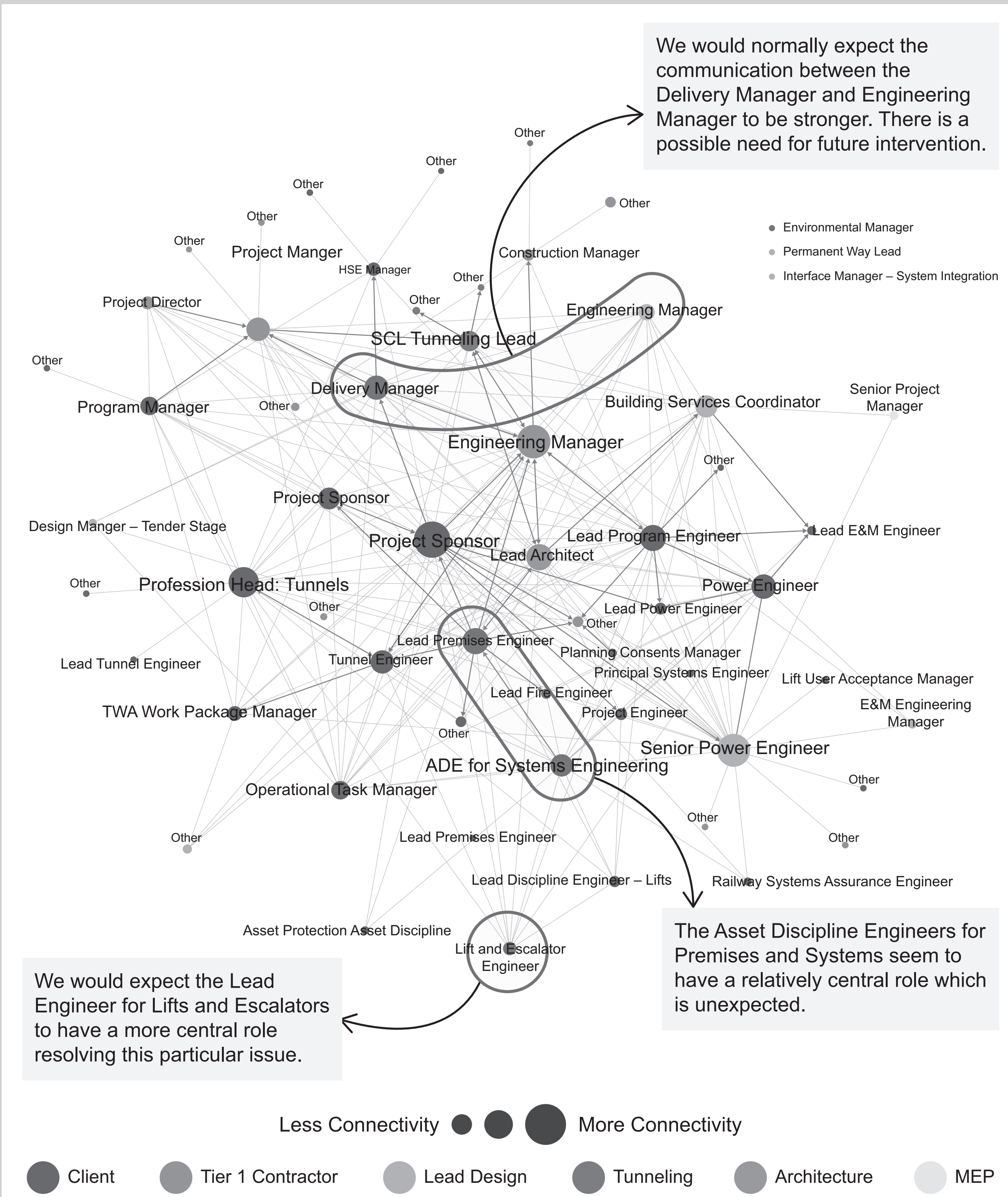

Figure 4: Connectivity of actors within the information-exchange network. (A larger format, full-color version of this figure is available for viewing at https://www.ucl.ac.uk/bartlett/construction/sites/bartlett/files/pmj-networks-figures-3-6.pdf)

of ties in the self-organized network (Kloppenborg, Tesch, & Manolis, 2014). Following discussions with the project team using the network sociograms, it was explained that the “Senior Sponsor” for the project was included within the senior management team and, as owner of the clients’ business case, is the final arbiter for “changes” to any part of the design that influenced the project requirements or the business-case outcome of the project. Such issues would be escalated to the senior management team for final change authority as determined within corporate management structures and the main contract. The Senior Sponsor oversees a number of projects within the client organization. Embedded within the management structure of the delivery team was a “Sponsor,” who reports to the Senior Sponsor, and is mandated with the day-to-day integration with the design, construction, operational, and maintenance teams to ensure that the clients’ requirements are properly heard and met in the development of the design. Often in projects we do not see that sponsor so closely embedded with the day-to-day management, so the network illustrations provided confidence to the project team that the discussions being held to develop the design were inclusive of this important project role from a client’s perspective. If the sponsor sat outside these day-to-day discussions, it would be expected that this would lead to potential delays on final submission of the design.

Influence or eigenvector centrality weights a node’s degree according to the centrality of the nodes it is connected to. Eigenvector weights both direct and indirect ties of every length (Borgatti, 2005). In our case, high influence relates to the individuals who are close to highly connected individuals in the network (shown in Figure 5). It was observed that the Tier 2 leads for functional disciplines have the most influence in the network compared with their positions in the organizational hierarchy, in which we expect the Tier 1 managers to assume this prominence. It was also noted that contrary to expectations, the Asset Protection and Discipline Engineer for maintenance had much less influence in the network solving a problem closely related to his responsibilities. Another important observation is that the senior management team sits on the periphery of the network, whereas the project sponsors enjoyed more influential positions, as explained above. This indicates that the influence of an actor in a self-organizing network is more closely associated with their active communication with other well-connected actors rather than merely the actor’s position in the organizational hierarchy. Actors with high eigenvector centrality have the power to connect to other influential actors and have the power to align objectives within the project network, creating social norms and expectations that other network members will appreciate (McCulloh et al., 2013).

Brokerage, or betweenness centrality, represents an index of potential control over communication, because actors with high betweenness can restrict the flow of information (Kadushin, 2011) or otherwise control and/or influence individual actors (Burt, 2000). In our case, high brokerage potential related to individuals with strategic links between unconnected communities in the network (as shown in Figure 6). It was observed (see Table 3) that individuals with high connectivity (degree centrality) managing the process of resolving the issue also have a relatively high brokerage role in the network, such as the Engineering Manager, Lead Program Engineer, and Project Sponsor. Actors with high Degree as well as betweeness centralities often act as network coordinators synchronizing the activities of the different network actors (Pauget & Wald, 2013). This positional advantage also equips those actors with the power to act as leaders; building, communicating, and imposing rules in the network (Pauget & Wald, 2013). It is also interesting to note that the Tier 2 leads on premises and tunneling and the operational task manager, despite having significant influence in the network (high eigenvector centrality), had low brokerage roles in the network. This shows that the structure of the self-organizing network makes these individuals bypassable in terms of communication flow, thus reducing their power in the resolution of the design-development issue.

Discussion

This study sought to illuminate the “relational” and ‘social’ dimensions of project management and advocates a management approach rooted in complexity theory, which views large infrastructure projects as complex systems with an inherent tendency to spontaneously self-organize (Stacey, 2001; Heylighen, 2013). It also builds on previous work on construction project networks (Pryke, 2004; 2005; 2012), which used SNA to underline the effects of changes in procurement strategy on project governance and project management systems. Our findings provide further insight into the self-organized functions and the roles of managing projects that are not formally procured. Our results have shown that the network of communication in resolving issues could significantly differ from the formal organizational hierarchies defined by contract procurement. It is argued that as a result of the organizational and technical complexity of the large engineering project presented here (Flyvbjerg, 2009; Bosch-Rekveldt et al., 2011), individual project actors form self-organizing networks to facilitate project delivery. These informal ties represent help-seeking behavior and could be seen as communication shortcuts overcoming overly bureaucratic and prescribed channels to provide the necessary, and at times, critical information. As time passes, informal support communities gradually and legitimately emerge when the established structures are not functioning efficiently (Bertelsen, 2003; Emmitt & Gorse, 2003). But what might be the functional significance of

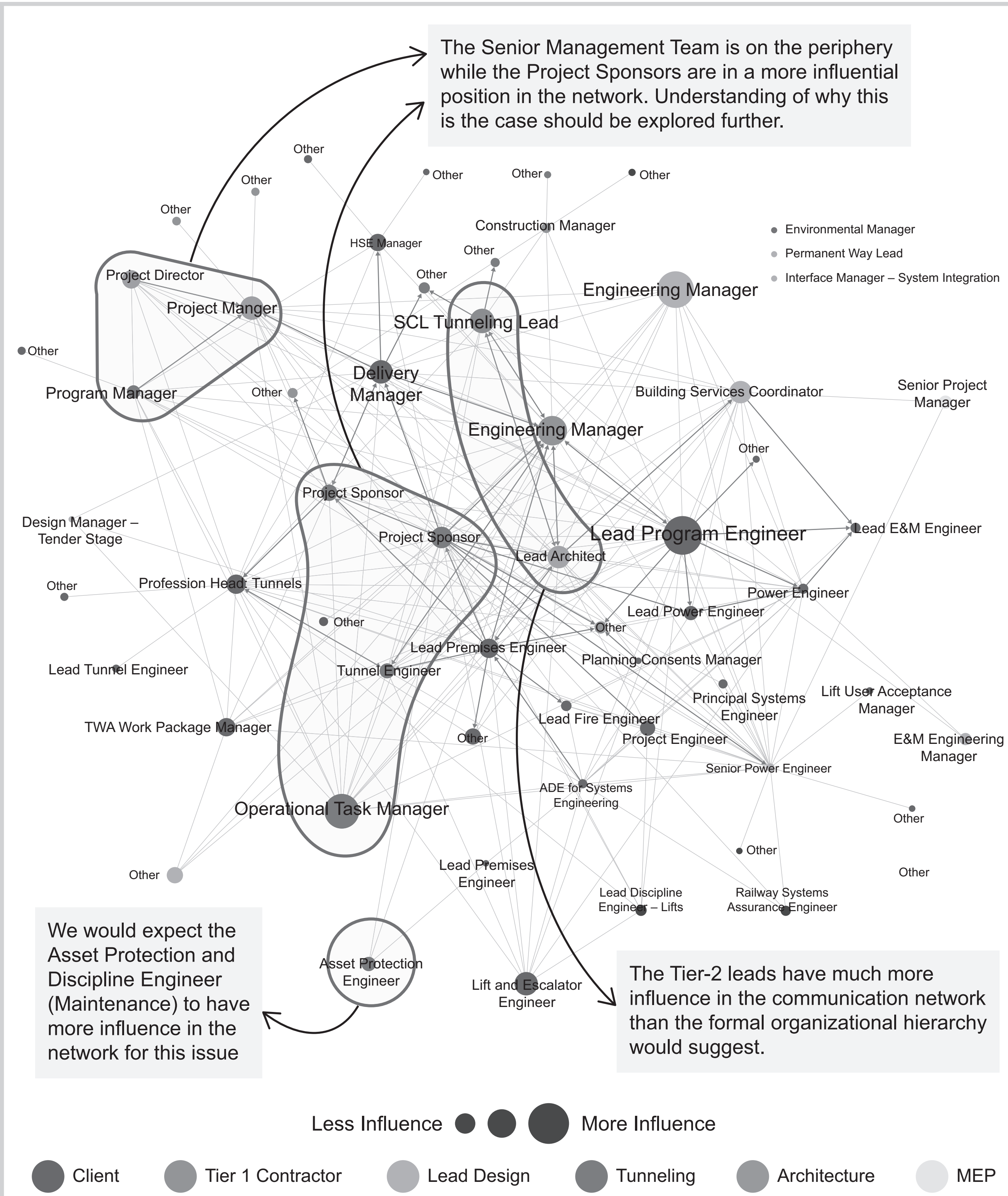

Figure 5: Influence of actors within the information-exchange network. (A larger format, full-color version of this figure is available for viewing at https://www.ucl.ac.uk/bartlett/construction/sites/bartlett/files/pmj-networks-figures-3-6.pdf)

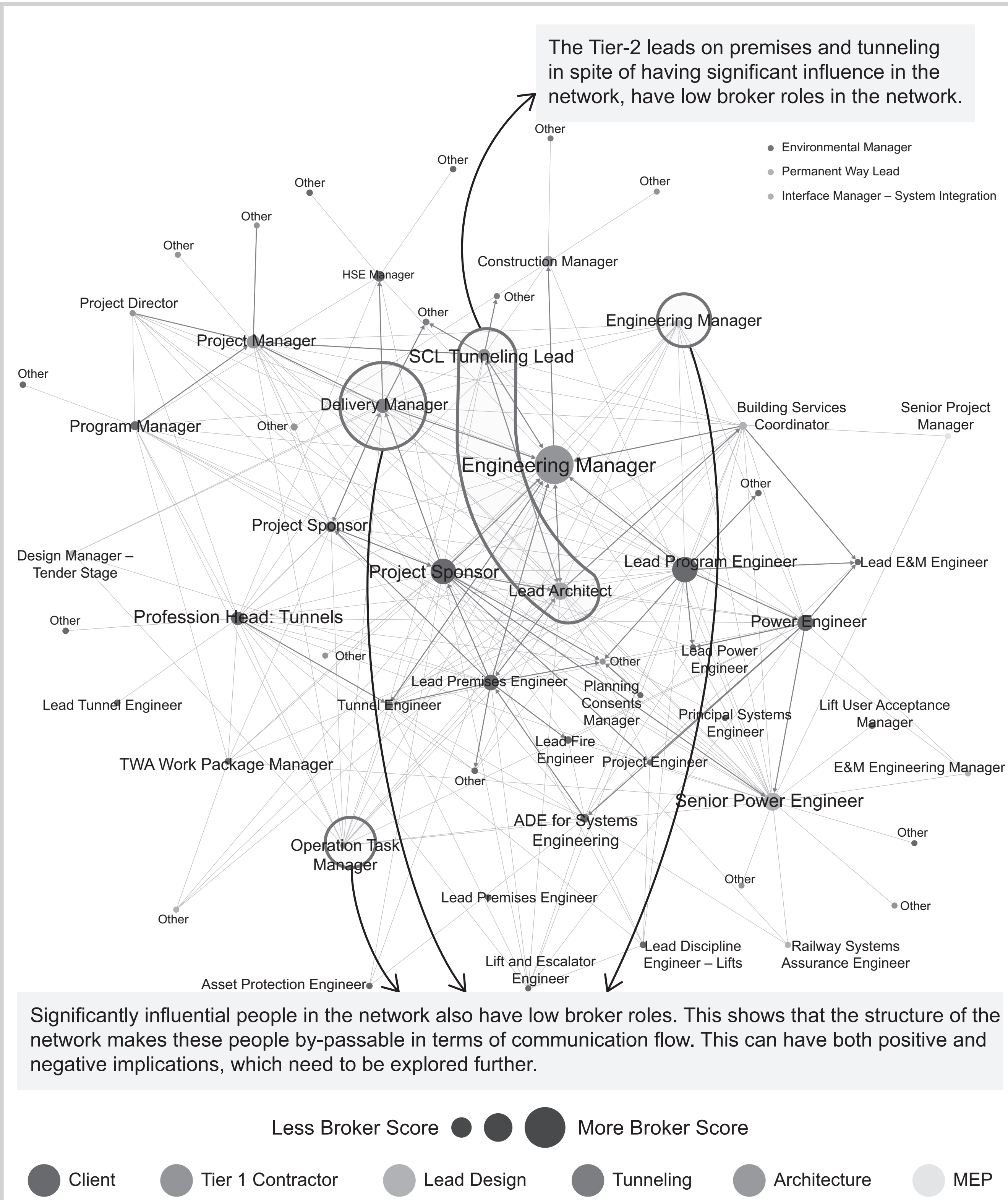

Figure 6: Brokerage potential of actors within the information-exchange network. (A larger format, full-color version of this figure is available for viewing at https://www.ucl.ac.uk/bartlett/construction/sites/bartlett/files/pmj-networks-figures-3-6.pdf)

our observed self-organized network topology?

In order to interpret the functional significance of the identified topology, it is important to understand the factors that such networks are optimizing. The function of the network that we studied was mainly to deliver the design with minimum delay and rework while dealing with iterative communication in the resolution of the design-development issues. The functioning of the self-organized network was optimized in terms of swift communication by certain network characteristics identified in our study and other studies of real-world self-organized networks (Wagner & Fell, 2001; Albert, Jeong, & Barabási, 1999; Watts & Strogatz, 1998; Newman, 2001a, 2001b; Braha & Bar-Yam, 2004) such as short, average path lengths and dense "functional" community structures exhibiting small-world properties. This small-world topology facilitated rapid communication across the whole network through short path lengths and dense clusters that encompass internally most of the interactions required with minimum cross-cluster ties. The network also exhibits high centralization with few actors with much higher connectivity than other actors. This could be the result of new team members joining the design-development issue-resolution network preferentially attaching themselves (Albert & Barabási, 2002); or directing their communication toward those well-connected actors, in our case actors from the engineering disciplines as well as the project sponsor. High centralization also indicates that individual actors' power considerably varies across the network and that positional advantages are somewhat unequally distributed (Hanneman & Riddle, 2005). The role played by those prominent coordinating actors is important in establishing and maintaining connections that are critical for the flow of communication. It is clear, hence, that self-organizing networks in complex infrastructure projects exhibit significant similarity to the topological scaling properties found in other large-scale interaction systems, particularly robustness and error-tolerance while being vulnerable to the removal of those well-connected actors.

We contend that identifying the above structural characteristics may offer insight into how the network's function and topology may affect each other. We particularly argue that mutual adjustment in communication will take place in an environment with sufficient local autonomy in decision-making processes on information transfer and communication in relation to the project objectives. This, coupled with shared goals and joint understanding, will allow the functionally dictated self-organizing network structure, or topology, to spontaneously emerge. This is particularly important for project managers. Following Donaldson's (2001) contingency view of organizations, we propose that social-network topology can be optimized by capable and autonomous actors (Mahmud, 2009) to improve the functioning of the self-organizing network and increase its overall performance.

In addition, the study demonstrates the usefulness of SNA in facilitating a better understanding of self-organizing processes in large-infrastructure projects. A study of network density can provide a measure of the intensity in which information and problem solving occur. Density may also reflect 'iterativeness' (Luhmann, 1986), a function of technical and organizational complexity. Identifying community structure aids in underlining the "functional" community not procured through formal contractual agreements. In particular, we identified three distinct subgroups in design activity in a large complex engineering project: "Doing," "Decision making," and "Designing." It is evident that these three sub-functions of design are not procured, facilitated, or managed at the time of the study. We recommend that the *functions* of these communities are to be identified by the communities' members themselves, once the research team has analyzed the data and presented it back to the network actors. We also recommend that these communities, and others yet to be identified, should be sponsored and facilitated through a range of network-based interventions to ensure their evolution (Prokopenko, 2014). We also proposed an extension to Pryke's (2012) measures of tie strength in the project environment. A model utilizing frequency and six measures of quality was developed and a correlation analysis supported this combination of frequency and quality. Future studies could benefit from adopting these measures for a more precise representation of the communication ties among project actors. Actor centrality provides a measure of prominence of an actor in a given network. Degree centrality would be suitable to establish whether an actor involved in communication is appropriately connected. Eigenvector centrality will help those managing projects to identify actors who are performing a governance role—and we would consider the appropriateness to the project function in question. Finally, betweenness centrality identifies those providing brokerage—those individuals who "know who to call" and are performing coordination and problem-solving activities. Such powerful actors are the networks' 'weak' points and are vulnerable to removal from the network through, for example, absence, sickness, dismissal, or resignation. Their removal can result in difficulties to achievements of the project objectives (McCulloh et al., 2013).

Finally, we demonstrate that the use of purely quantitative analysis, although commonplace in mainstream SNA studies, is not the ideal approach in the application of SNA to the study of projects. We have combined statistical analysis with more qualitative judgments based upon graphical materials and we interpreted this material by working closely with the project–actor respondents. This can provide valuable information to project managers. In particular, it may expose dysfunctions in the project network, such as, for example, long path lengths increasing the distance between key actors, reducing their reachability, or the presence of actors with high potential to fragment the network or block the spread of ideas and information. Identifying such network dysfunctions will allow for the development of network-based interventions to design team structures that facilitate successful collaboration.

Conclusion

There is a growing interest in the study of the informal and emergent characteristics of large-infrastructure projects (Müller & Martinsuo, 2015; Zhang et al., 2015), thus extending the focus of research from the economic attributes of projects and organizational effectiveness (e.g., strategy, culture, and operations) to examining the social and relational dimensions in projects at the micro level of individuals (Rooke et al., 2009). This is mainly driven by the multidisciplinary and people-intensive nature of the construction industry in which informal conversations and interpersonal communication is paramount for "getting the work done," knowledge transfer, and facilitating collaborative problem solving and decision making (Emmitt & Gorse, 2003).

Adopting a complexity theory approach, the contribution this article makes is to extend the concept of self-organization to the management of large-infrastructure projects. Most importantly, the findings underline the need for management scholars to recognize management patterns not procured through contracts, a bottom-up approach that emerges from the iterative communication of project actors working together to realize joint-project goals. This is in contrast to the top-down hierarchical and contractually prescribed structure that is not self-organizing. The study employed the literature of social networks to argue the need to acknowledge the power of the self-organized project-delivery network relationships as a form of governance in complex, transient project organizations complementing or acting as a substitute to the formal hierarchical and contractual structures (Bechky, 2006; Di Vincenzo & Mascia, 2012).

For project management practitioners, the study has yielded a number of important implications. Specifically, there is an urgent need for adequate managerial understanding of self-organization in large infrastructure projects. Project managers need to concede that self-organizing networks 'cannot be managed'—they are self-induced changes in organization that grow largely from joint and serendipitous efforts by project actors through pursuing shared goals and mutual understanding, with no external order being imposed. Self-organizing communities evolve in response to individual actors' autonomy and motivation to seek and disseminate information, and in this way to discharge their contractually prescribed project roles. In contrast to the Newtonian view of management, which views leaders as maintainers of the state of equilibrium, complexity theory sees management as fundamentally a social function with the manager's role being the facilitator of the self-organization process (Mahmoud, 2009). The role of project managers is, hence, to cultivate the adaptive and self-organizing capacity of the project network, which ultimately enables the task, or project function, to substantially determine the organization form, in other words, the network topology. This is achieved by appointing project actors with the appropriate capabilities and ensuring their commitment to a clear set of project goals. Local autonomy should then be facilitated through lower levels of managerial control and through rules such as, 'seek forgiveness not permission' (Mahmud, 2009), which may encourage project actors' independent judgment and entrepreneurial spirit in resolving issues creatively. The strengthening of informal relationships among project members can also cultivate supportive communication, reduce defensive communication, and allow for better alignment in interpretation and enduring personal relationships (Emmitt & Gorse, 2009). It is also notable that the communities are formed around actors of high influence (eigenvector centrality) who act as leaders of these clusters. The management team could endeavor to replicate similar structures through measures such as co-location, encouraging personal relationships, and assigning enablers or facilitators to identified themes. The organization of tasks and resources could also be done while keeping these communities in mind.

A number of important limitations need to be considered. First, given the limitation of our single case study approach, more case study observations are needed to enable the generalization of findings. In addition, our study took a cross-sectional approach to the case study at a particular point of its development; however, project networks are dynamic and continuously evolving, and future studies should investigate the dynamics of large infrastructure project networks longitudinally. Future research could also examine the appropriateness of the self-organizing structure to the functioning of the project by conducting a longitudinal network study that investigates changes in project performance over time (as the network changes), or alternatively compare the performance of several projects with different structures. Furthermore, we observed that project team members often cluster in small, densely connected problem-solving groups that are sparsely connected to other parts of the network. Future research may identify the capabilities and value systems, for example, open communication and interpersonal trust (Mahmud, 2009), shaping the formation of such clusters and contributing to a deeper understanding of the self-organizing mechanisms of large-infrastructure project networks.

We consider this research as a first step in examining the nature of self-organizing networks in the delivery of large-infrastructure projects, with the hope of stimulating interest and laying the foundations for future enquiry in this important research area in project management.

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Stephen Pryke is Professor of Supply Chain and Project Networks in the School of Construction and Project Management at University College London, United Kingdom. Stephen is a Fellow of the Royal Institution of Chartered Surveyors and Director of the Centre for Organisational Network Analysis at UCL. His research deals with relationships and networks in the field of construction projects. Stephen published five books and a large number of journal articles in these areas annd has recently finished a two-year research project with Transport for London, using SNA to identify the self-organizing aspects for a large, complex infrastructure engineering project. He can be contacted at s.pryke@ucl.ac.uk

Dr. Sulafa Badi is Associate Professor of Management and Organisational Behaviour at the British University in Dubai (BUiD), United Arab Emirates, and honorary Senior Research Fellow at the Bartlett School of Construction and Project Management, University College London (UCL), United Kingdom. Sulafa started her career as an architect before joining academia and holds a PhD in Project Management from UCL. Sulafa's specific research interests at present lie in the areas of sustainability, innovation, and project-based networks. Her work has examined a variety of contexts, including complex infrastructure projects, supply networks, small and medium-sized enterprises (SMEs), and community stakeholders. She has presented work at a number of international conferences, including the European Academy of Management (EURAM), International Research Network on Organizing by Projects (IRNOP), and the International Network of Social Network Analysis (INSNA). Recent articles written by Sulafa have appeared in *Construction Management and Economics, Industrial Marketing Management, Built Environment Project and Asset Management,* and the *International Journal of Managing Projects in Business*. She can be contacted at sulafa.badi@buid.ac.ae.

Huda Almadhoob is a PhD researcher in the Bartlett School of Construction and Project Management (CPM) at University College London, England. Prior to this, she worked as a lecturer in the Architectural Department at the University of Bahrain after finishing her MSc. degree in Project and Enterprise Management (with distinction) from CPM. Currently she is working on her PhD research project to establish a new theoretical framework for managing large construction projects, grounded in complexity theory with reference to social network theory and its analytical techniques. Her main research interests involve organizational behaviors, supply chain management, and the application of social network analysis in the study of construction project networks. She can be contacted at huda.almadhoob.11@ucl.ac.uk

Balamurugan Soundararaj is a PhD researcher in the Department of Geography at University College London. Prior to this, he was a research associate with the Bartlett School of Construction and Project Management, University College London, working on the Knowledge Transfer Partnership between UCL, Transport for London and Innovate UK (formerly the Technology Strategy Board) in evaluating, designing, and implementing collaborative teams for complex infrastructure projects through organizational network analysis. The project was part of the ongoing attempt to bring both industry and academia to create a 'network' based theory and practice in project management that can be used by managers of large, complex infrastructure projects to ensure efficient design of the organizational structure. He can be contacted at s.bala@ucl.ac.uk

Simon Addyman is both a practicing project manager in the construction industry and a PhD candidate at University College London. He started his career in property refurbishment before moving overseas to work on World Bank and United Nations construction programs in development and humanitarian relief in West Africa and Yugoslavia. He has spent the last 15 years with Transport for London, the last five years as program manager for the redevelopment of London Undergrounds' Bank Station Capacity Upgrade project, a large civil engineering and tunneling infrastructure project. Simon earned a distinction in his MSc in Construction Project Management from Heriot-Watt University, Edinburgh, Scotland in 1999. He became a Certificated Project Manager in 2008 with the UK's Association for Project Management (APM) and, in 2013, was awarded APM's Project Professional of the Year Award for his work in implementing a novel procurement methodology on the Bank Station Capacity Upgrade project. He also currently holds the position of Chairman of the APM's Research Advisory Group. Simon was the industrial partner for the Knowledge Transfer Partnership between TfL and UCL, looking at social networks in infrastructure projects. His PhD and research interests are in the (re)creation of organizational routines in temporary organizations. He can be contacted at simon.addyman.13@ucl.ac.uk