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Balancing the Quantitative and Qualitative Aspects of Social Network Analysis to Study Complex Social Systems

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Social Network Analysis (SNA) can be used to investigate complex social systems. SNA is typically applied as a quantitative method, which has important limitations. First, quantitative methods are capable of capturing the form of relationships (e.g. strength and frequency), but they are less suitable for capturing the content of relationships (e.g. interests and motivations). Second, while complex social systems are highly dynamic, the representations that SNA creates of such systems are often static. These limitations can be overcome by balancing a quantitative approach to SNA with a qualitative approach. In the article two different approaches that seek this balance are demonstrated. The illustrations show that in this combination quantitative SNA is most useful for revealing system-level patterns, but that a deeper understanding of the mechanisms that produce these patterns is more easily achieved through the interpretation of qualitative data.

Keywords: Social network analysis, Complex systems, Dynamic Network analysis, Qualitative analysis

1. Introduction

Complex systems emerge through the interactions among their constituent elements (Gerrits, 2012). The concept of emergence points to the fact that these systems cannot be reduced to the properties of their constituent elements (Goldstein, 1999). Complex systems are also dynamic, meaning that their structures and elements change over time (Room, 2011). The investigation of complex social systems therefore requires methods that take into account their emergent and dynamic nature. Traditional reductionist methods of scientific inquiry are unsuitable in this regard, as they tend to isolate properties of systems and analyze them separately, thereby losing sight of the system as a whole (Clancy, Effken, & Pesut, 2008). Social network analysis (SNA) is capable of simultaneously taking into account higher-order system structures and their constituent elements (Knoke & Yang, 2008). What sets SNA apart from other approaches in the social sciences

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is its focus on relationships among actors instead of attributes of actors (cf. Abbott, 1988). These relationships constrain individual behavior, while at the same time they are continuously remolded by that behavior (Spreitzer & Yamasaki, 2004).

Over the last decades the use of SNA in the social sciences has grown exponentially (Borgatti, Mehra, Brass, & Labianca, 2009). This growing interest has resulted in major advances in the methods of SNA. Advances have been made primarily in quantitative methods such as the mathematical methods of mapping networks and measuring their properties (Coviello, 2005; Crossley, 2010; Edwards, 2010; Heath, Fuller, & Johnston, 2009). Quantitative methods of SNA can be used to study complex systems; they offer an efficient way to describe and analyze complex social structures (Edwards, 2010). However, quantitative methods also abstract a great deal from the actual complexity of social systems in two ways. First, although they are capable of capturing the form of relationships (intensity, frequency, or strength), they are largely blind to their content (interests, purposes, drives, and motivations) (Crossley, 2010; Edwards, 2010; Knoke & Yang, 2008). Second, with some exceptions, these quantitative methods are used to study static structures, and they largely neglect the changes that these structures undergo (Knoke & Yang, 2008; Scott, 2013; Wolbers, Groenewegen, Mollee, & Bím, 2013). This hampers understanding the mechanisms responsible for the emergence and development of complex social structures.

In this article we demonstrate how these limitations can be overcome by complementing quantitative methods of SNA with methods that are primarily qualitative and focus explicitly on network dynamics. We introduce two methodological approaches and demonstrate their value in the investigations of complex social systems with two case illustrations. The two approaches help to establish a stronger link between patterns at the system level and micro-level behavior, while at the same time explicitly taking into account the dynamic nature of social systems. Our approaches include quantitative methods through which broader system-level patterns and the changes in them are uncovered. These system-level patterns act as a starting point of a qualitative analysis to study how these patterns are linked to micro-level behavior, allowing us to uncover the mechanisms that are at the basis of the evolution of the social system.

The central research question of the article is: *What can qualitative and dynamic approaches to Social Network Analysis contribute to our understanding of the emergent and dynamic properties of complex social systems?* We start our article with a discussion of SNA as a method to study complex systems, focusing primarily on the value of qualitative and dynamic methods of SNA. We then offer a detailed discussion of two methods to overcome the limitations of quantitative SNA and we demonstrate their workings through case illustrations. The illustrations are followed by the conclusions in the final section.

2. Balancing Quantitative and Qualitative SNA

The primary conceptual starting point of this article is that complex social systems are emergent and dynamic. An understanding of the emergent nature of complex systems requires an investigation of micro-processes and their relations with macro structures

(Morçöl, 2014). These processes describe how the behaviors of individuals generate higher-order structures on the one hand, and how these higher-order structures affect individual behavior on the other hand (Morçöl, 2012b).

As Knoke and Yang (2008) point out, SNA offers conceptual and methodological tools to explicitly link micro-level behavior to macro-level structures; both micro-level entities (i.e., actors and their relationships) and the macro-level structures that they form (i.e., the networks of relationships among actors) are included in the representations of social networks. Although SNA factors in both the structure of social networks and the nature of interactions between actors (Jack, 2010), explanations for outcomes are sought almost exclusively in macro-level patterns (Kilduff & Tsai, 2003; Knoke & Yang, 2008). Measuring and representing these structural patterns has become the central objective in SNA, thereby neglecting the role of active individual actors in shaping the structures (Kilduff & Tsai, 2003). From a complexity perspective this is problematic, as micro-level behavior is understood to be at the basis of the emergence and development of social structures. Neglecting micro-level behavior will lead to oversimplified descriptions (Byrne & Callaghan, 2013) and hampers our understanding of complex social systems.

The emphasis on structural patterns in SNA applications has also led to the generation of static pictures of networks (Knoke & Yang, 2008; Scott, 2013; Wolbers et al., 2013). However, networks are not static; they change over time as actors intentionally and unintentionally change relational structures. Therefore, it is important to take into account the temporal dimensions of networks (Doreian & Stokman, 1997a, 1997b). However, collecting longitudinal network data can be very time consuming. In addition, commonly used methods of data collection, such as surveys and interviews, rely on the capacity of respondents to recollect interactions that have happened some time ago and could therefore be imprecise (Morçöl, 2012a). Nevertheless, there have been considerable developments in the collection of longitudinal data and the methods to analyze these data. Several studies have incorporated a temporal dimension in SNA. For instance, Powell, Koput, and Smith-Doerr (1996) and Powell, White, Koput, Smith, and Owen-Smith (2005) study the evolution of interorganizational collaboration in biotechnology and the life sciences by mapping contractual agreements between companies in these sectors. Ahuja (2000) performed a similar type of study for the chemical sector. Zaheer and Soda (2009) perform a longitudinal investigation of co-membership networks in the Italian TV production industry to study the origin of structural holes. Abbasi and Kapucu (2012) have looked at the dynamic changes of interorganizational response networks during Hurricane Charley.

Wolbers et al. (2013) provide a toolset to measure network dynamics. This toolset combines time slices, two-mode analysis and information pathways to specifically follow the flows of information during an emergency response. Other important work has been done by the Center for Computational Analysis of Social and Organizational Systems (CASOS) at Carnegie Mellon University. They have developed Dynamic Network Analysis (DNA), which offers a set of techniques and tools to investigate complex and dynamic sociotechnical systems (Carley, Diesner, Reminga, & Tsvetovat, 2007). One of the tools developed by CASOS, ORA, is a dynamic meta-network assessment and analysis tool which allows researchers to visualize and analyze networks over time in a user-friendly environment. Although these studies and tools help us to grasp the temporal dimension of networks, they are still mainly focused on macro-level patterns.

To analyze the evolution of networks other researchers have developed a relatively new set of methods, which can be grouped under the heading of Dynamic Social Network Analysis (DSNA). This approach usually entails the development of models that are tested through statistical analysis or simulations. Hypothesized rules of action by actors are then used in a simulation to generate patterns of network evolution, which are compared to actually observed patterns (Scott, 2013). A closely related approach is based on the use of Exponentional Random Graph (ERG) models, in which an empirically observed network is regarded as one possible outcome of some unknown social process (Frank & Strauss 1986; Robins, Pattison, Kalish, & Lusher, 2007a; Robins, Snijders, Wang, Handcock, & Pattison, 2007b). A stochastic model is developed of the social process that is assumed to have generated the network, and the parameters of the model are estimated. Typically, the aim of this approach is to assess whether certain structural characteristics occur more commonly in the observed network than would be expected by chance. A drawback of these approaches is that only a limited set of fairly general mechanisms (e.g. preferential attachment, homophily, transitivity) can be considered in the analysis. The question is whether such general mechanisms can truly account for the behavior that we encounter in complex social systems (Morçöl, 2012a).

Although a more qualitatively oriented approach does not allow for the same statistical rigor, it also holds some advantages. As Crossley (2010) points out, many different mechanisms are at play in complex systems and the interactions between mechanisms make it difficult to isolate specific mechanisms responsible for the observed outcomes. Because we cannot always know in advance which mechanisms account for the emergence and development of complex social systems, it may be necessary to rely on qualitative observations to understand how mechanisms manifest and operate in a specific context (Byrne & Callaghan, 2013; Crossley, 2010; Teisman & Gerrits, 2014). This can even lead to the discovery of new mechanisms (Crossley, 2010).

Also, the effects that these general system-level patterns have on micro-level behaviors can be different across cases. For example, two actors may have structurally equivalent positions in two different networks, but respond to the conditions raised by this position differently based on their specific beliefs, desires, and the opportunities. Thus, as a result of contextual differences general patterns are often accompanied by unique circumstances that invite different explanations across cases (Buijs, Eshuis, & Byrne, 2009; Teisman & Gerrits, 2014). By combining the quantitative aspects of SNA with qualitative observation and analysis it is possible to introduce contextual details that are otherwise lost in the abstractions that SNA makes (Crossley, 2010; Morçöl, 2012a; Morçöl, 2014).

In order to use SNA to its full potential in the investigation of complex social systems, a better balance needs to be sought between the quantitative and the qualitative aspects of SNA both in terms of data collection and analysis (Crossley, 2010; Edwards, 2010;

Kapucu, Hu, & Khosa 2014). In our view the two primary ways in which qualitative methods and techniques can complement a quantitative approach are:

1. By offering a more detailed account of the micro-level behavior from which system-level patterns emerge, thereby allowing the researcher to consider not only the form of relationships (intensity, frequency or strength), but also their content (interests, purposes, drives an motivations);
2. By taking into account the temporal dimension of the emergence and development of networks, without restricting attention to a limited set of mechanisms in advance. Thus, the discovery of new mechanisms is a possibility.

We emphasize the complementary nature of these additions because in our view quantitative methods and techniques are still most useful for capturing the higher-order structures of complex social systems. Qualitative methods and techniques tend to emphasize idiosyncrasies, and thereby run the risk of losing sight of the whole. We believe SNA to be at its strongest when qualitative and quantitative methods and techniques are combined (Edwards & Crossley, 2009).

In the next section we introduce and demonstrate two approaches that can be used to balance the quantitative and qualitative components of SNA[1]. In the first example a mixed-method approach is applied. Qualitative data are analyzed using both quantitative and qualitative methods. This makes it possible to adopt a multi-staged methodology in which quantitative SNA is a preliminary stage that informs qualitative research (or vice versa) (Edwards, 2010). This approach is applied to a case study on inter-organizational coordination in the Dutch Railway system.

In the second example the focus is primarily on using qualitative data to introduce a temporal dimension to the analysis of the network. The data that are at the basis of the study consist out of chronologically ordered, qualitative descriptions of interactions. Quantitative methods are used to abstract system-level patterns from the data, which are subsequently qualified by offering further interpretations based on the underlying data. The approach is demonstrated through an illustrative case study on the emergence and development of a collaborative process on sustainable cluster development in the Canal Zone of the Netherlands.

3. Exploring Two Approaches to Balance Quantitative and Qualitative SNA

3.1. Combining DNA with Sensemaking to Study Coordination in a Complex System

In the first case illustration we used a multi-staged approach in which a quantitative approach to Dynamic Network Analysis informs the qualitative analysis of sensemaking at the micro-level. Sensemaking is used as a lens to explain how the actors, in and through

[1] The two studies have been performed by the authors independently from each other, and they are brought together here purely for illustrative purposes.

interactions with each other, frame situations as a basis for (coordinated) action. In this particular case the organizations were confronted with the news that four double-switches and two rail tracks were deemed no longer fit for use. This was decided by the responsible track manager and track inspector, who also set the deadline at six o'clock in the evening for the switches and tracks to be taken out of service. The other organizations had roughly three hours to prepare for the operation. By the end of the study period, almost three hours after the involved organizations received the news, the process ended with the decision to stop all train movement during rush hour in one of the busiest parts of the Netherlands. The case study aims to reconstruct and explain the dynamics that led up to this decision. More specifically, the study focuses on the changes that occur in the information flows between the involved actors, and the micro-level dynamics underlying these changes.

We applied Dynamic Network Analysis to visualize and analyze the flows of information that followed the decision to take the switches and tracks out of service. We reconstructed the information flows from qualitative data. We obtained all available recordings of telephone conversations between actors involved in the process. These recordings offer rich and complete network data. We transcribed the recordings and then translated them into numerical data. This could be done quite easily as most of the files included information on the specific actors communicating and the time of communication. In addition, we used interviews and shift reports as additional data for the DNA as not all (telephone) conversations were recorded. Visualizing the flows of information, and how these changed over time allowed us to determine where the most striking changes in the structure of information flows occurred. The qualitative analysis aimed specifically at developing an understanding of these changes. Using sensemaking as a theoretical lens, we performed a qualitative analysis of the telephone conversations and interviews to study how the involved actors framed the situations with which they were confronted throughout the process, and how these frames informed the (coordinated) actions that they engaged in.

We created an edge list from the qualitative data, containing the sources and targets of information flows and the time of communication. Each row in an edge list represents a single tie in the network, and it is possible to attach variables (such as the time of occurrence) to the ties in separate columns (see table 1). It thus allows for the inclusion of information that cannot be included in, for example, an adjacency matrix. We split the entire process into time slices of thirty minutes, such that the interactions of a specific time interval can be visualized and analyzed (Wolbers et al., 2013). In addition, it allows us to show the development of the communication patterns over time. We also created a two-mode

Table 1
An example of an edge list

Nodetype	ID	Nodetype	ID2	Value	Time
Actor	Train Dispatcher	Actor	RIIB 1	1	yyyy-mm-dd hh:mm
Actor	WD 2 AM	Actor	WD 3 AM	1	yyyy-mm-dd hh:mm
Actor	WD 2 AM	Actor	WD RBI	1	yyyy-mm-dd hh:mm

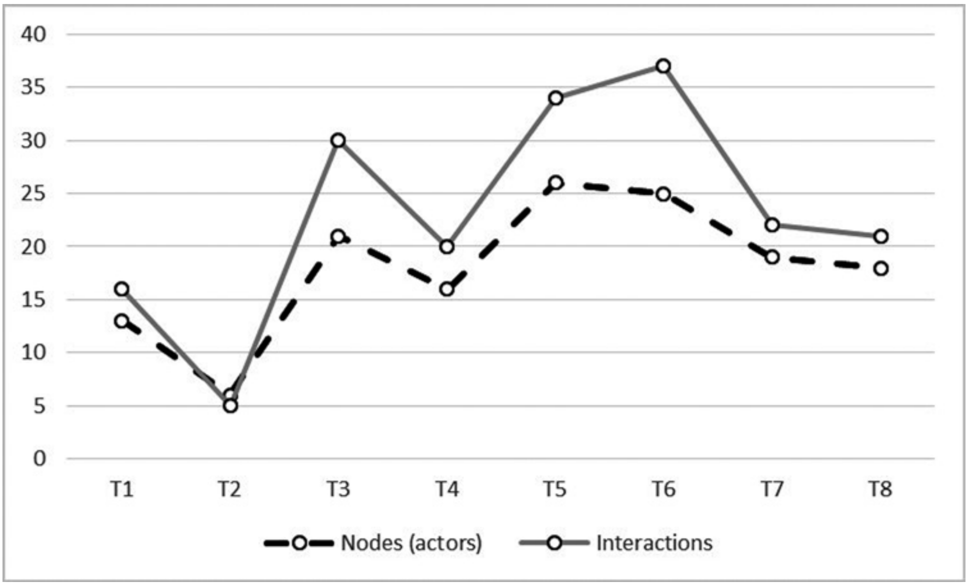

Figure 1. Number of actors and interactions throughout the process.

network[2] that shows which actors were involved in which time slice of the process. The two-mode network is recorded as an incidence matrix in which the presence (1) or absence (0) of actors in the different time slices is marked. We used two-mode variants of network centrality metrics to identify important actors (Faust, 1997). In this case we used fifteen minute time slices in order to get a more detailed picture of the network development. The software package ORA was used to visualize and analyze the dynamic network.

Figure 1 shows the number of actors involved and the instances of information sharing during each time slice. We identified a total of 205 instances of information sharing among 42 actors (or nodes). Each actor represents an individual performing a specific role in the process. The number of actors involved and the interactions increases with a peak in the number of interactions at time slice 6 (when the decision was made to stop the train service). There is however a dip in the number of actors and interactions at time slice 4. Perhaps even more remarkable is the spike in the number of actors and interactions between time slices 2 and 3. To explain this sudden increase between time slices 2 and 3 we have to take a look at the first time slice.

Figure 2 shows the network graph for the first time slice. From the network graph we can tell that the track manager (WD 2 AM) gave an early warning to the actors (RIIB 1) in the OCCR[3]. Given what we were told in various interviews, this is somewhat surprising, as most of our interviews consider the train dispatchers to be crucial for the process (they

[2] For detailed discussions on two-mode networks see chapter 8 in Borgatti and Everett (1997), Borgatti and Halgin (2011), Scott (2013), and Wasserman and Faust (1994)

[3] The OCCR is the national control room of the railway sector in which the infrastructure manager ProRail and the train operating companies monitor the railway traffic flows on the main corridors.

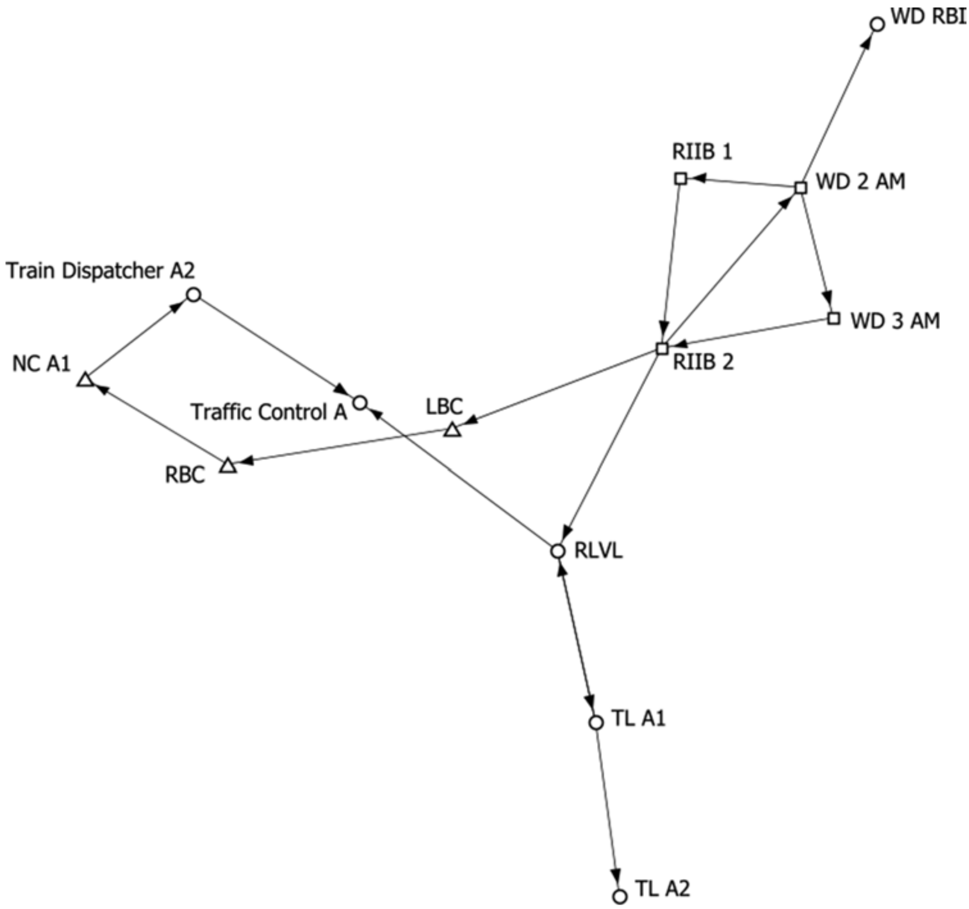

Figure 2. Network graph showing the interactions in the first half hour of the process.

control the switches and are responsible for safe railway operations), and should therefore be among the first to be informed by the track manager. However, the track manager assumed that the OCCR would coordinate the process and inform the train dispatchers and traffic controllers in the regional control centers[4]. He thus assumed to have informed the train dispatchers indirectly. The national traffic manager (RLVL) in the OCCR on the contrary, decided to wait for further details and didn't want to alarm the regional control centers just yet to avoid any unnecessary panic. As is illustrated in the time slice, the train dispatchers did receive some rumors on the decision to take the switches out of service from one of the train operating companies (LBC).

In the second time slice the actors in the OCCR discussed the additional information on the switches and tracks they received from the track manager. This new information

[4] In the regional control centers local railway traffic is monitored by regional traffic controllers and train movement is controlled by train dispatchers using switches and signaling.

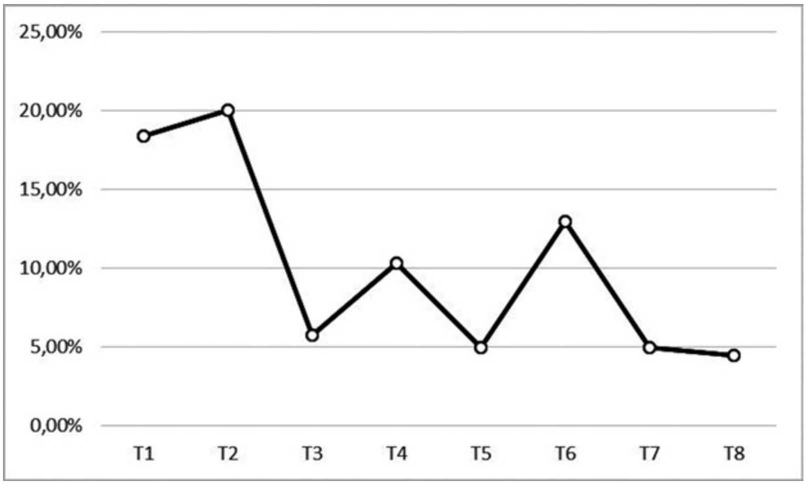

Figure 3: Betweenness centralization of the network over time.

however once again uncoordinatedly spread through the network and caused a chain of reactions. Train dispatchers and regional traffic controllers were approached by the train operating companies for confirmation on the information they had just received. However, the train dispatchers couldn't confirm these 'rumors', as they were still not *officially* notified about the situation. The regional control center therefore felt as if they were excluded from the process and blamed the RLVL for not following procedures. As a result communication became more conflictual than problem solving.

Our qualitative analysis also pointed out that the abrupt changes of the network gave respondents in the OCCR the feeling that no one was in control and that everyone held only small pieces of information. We made a quantitative assessment of this statement by looking at the centralization of the networks[5]. We calculated the betweenness centralization of the networks (figure 3) to assess the potential of an actor or small group of actors to control the flows of information. We normalized our measures to compensate for changes in the size of the network. Overall, the betweenness centralization remains low. This indicates that there wasn't a central actor or group of actors, but that information was dispersed throughout the different clusters and locations in the network. Thus, no one seemed to have been able to provide an overall direction to the flows of information. This resulted in much confusion among the different actors on the switches and tracks that had to be taken out of service, the reason behind this decision, and the procedure being followed.

The two-mode analysis does show that the RIIB and the RLVL show the highest consistency over time in terms of distributing information (table 2)[6]. The betweenness scores of actors can be seen as an indication for their potential to digest and distribute

[5] A network centralization measure indicates how tightly the network is organized around its most central nodes (Abbasi & Kapucu, 2012).

[6] Degree centrality of an actor indicates the percentage of time events the actor was actively communicating in. With betweenness centrality we looked at the presence of actors in unique time events.

Table 2
Actors overall degree and betweenness centrality in two-mode network

	Agent	Normalized Degree Centrality	Normalized Betweenness
1	RIIB 2	0.94	0.134
2	RLVL	0.75	0.076
3	Traffic Control A	0.75	0.054
4	Train Dispatcher A3	0.63	0.036
5	TL A2	0.56	0.032
6	LVL 1	0.56	0.026
7	Train Dispatcher A1	0.56	0.026
8	Traffic Control B1	0.56	0.023
9	WD 2 AM	0.50	0.031
10	SMC	0.50	0.020

information in other time periods and thus their importance in providing communication opportunities between actors (Wolbers et al., 2013). The analysis shows that the RIIB and the RLVL had the highest potential to offer these opportunities. The qualitative analysis shows that the RLVL and the RIIB framed the situation as a routine procedure and they therefore tried to restore normal practices, which explains the consistency of their activities. This involves making sure that the train dispatchers receive an official notification from a contractor, so they can take the lead in the process. Thus, although the RLVL and the RIIB had full details on the switches and tracks, they did not feel that they were in the position to provide the train dispatchers with this information, nor that they had the power to tell them to take the switches and tracks out of service.

As a result the important task of officially informing the train dispatchers was not taken up by anyone. The drop in the number of interactions during time slice 4 (figure 1) can be explained by the conflict of perceptions between the track team and the OCCR, as both were unaware of this situation and therefore focused on their own tasks. Around half past five the track team provided the train dispatchers with the exact details on the switches and tracks along with the deadline of six o'clock. The train dispatchers decided not to co-operate with the track inspector, as he is officially not an authority that can forbid them to stop using the switches and tracks if there isn't an immediate threat. In the perception of the train dispatchers cooperating would also give a wrong signal to the track inspector and would even pose a threat to their role during similar situations in the future. Instead they demanded confirmation from a contractor along with an official reference number. Yet, moments later, when a contractor also proved to lack the full details, the train dispatchers decided to stop all rail traffic, as they could no longer guarantee safe operations.

3.2. Reconstructing Networks from Event Sequences

In our second case illustration we used a methodological approach that starts with the reconstruction of social processes as sequences of discrete events (Boons, Spekkink, & Jiao 2014). The events represent theoretically relevant actions and interactions among actors.

	Event 1	Event 2	Event 3
Actor A	1	1	0
Actor B	1	0	0
Actor C	0	1	0
Actor D	0	1	1
Actor E	0	1	0
Actor F	0	0	1

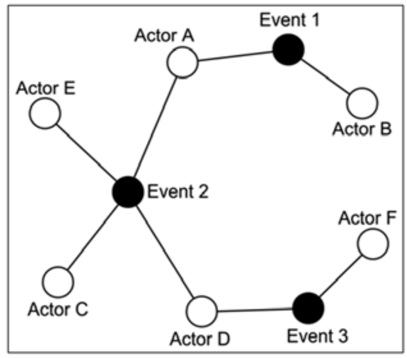

Figure 4. An incidence matrix (left) and its corresponding two-mode network (right).

The data on these actions and interactions are typically gathered from archival sources, including newspaper articles, documents produced by involved actors, as well as web pages. Information from these sources is then recorded as chronologically ordered incidents in an event sequence dataset (cf. Poole, Van de Ven, Dooley, & Holmes, 2000). The incidents are brief qualitative descriptions that include information on (1) the action or interaction performed, (2) the actors involved, (3) the date at which the action/interaction occurred, and (4) the source of the data. Some incidents may be grouped together if they can be understood to refer to the same event. In this respect, incidents can be understood as indicators of events (Abbott 1988, 1990). An event sequence dataset can be analyzed in different ways and each type of analysis requires further preparation of the data (Boons et al., 2014; Poole et al., 2000). To use the data as the basis for the analysis of network dynamics, we coded the actors that participate in the events. Once the data have been coded, the information retrieved can be represented in an incidence matrix that shows the affiliation of actors to events (see figure 4).

An incidence matrix can easily be converted into a valued adjacency matrix by multiplying it with a transposed version of itself. The adjacency matrix shows the direct relationships between actors, where the relationships represent the joint participation of actors in events (see figure 5)[7]. The more events that actors feature in together, the stronger the relationship will be, indicated by the value that is reported in the corresponding cell of the matrix. As figure 4 demonstrates, the incidence matrix can list the events in their chronological order. Thus, the information about the temporal order of the event data is maintained. This quality of the matrix can be exploited by dividing the matrix into different "frames," where each frame represents the network of actors at a different point in the process. By having these frames overlap with each other, the gradual changes that occur in the social network from one event to the next can be studied. For example, if we divide the matrix into frames of 30 events each, our first frame will contain events 1 to 30, our second frame will contain

[7] see Doreian (1979–1980) and Stadtfeld and Geyer-Schulz (2011)for similar approaches.

	Actor A	Actor B	Actor C	Actor D	Actor E	Actor F
Actor A	-	1	1	1	1	0
Actor B	1	-	0	0	0	0
Actor C	1	0	-	1	1	0
Actor D	1	0	1	-	1	1
Actor E	1	0	1	1	-	0
Actor F	0	0	0	1	0	-

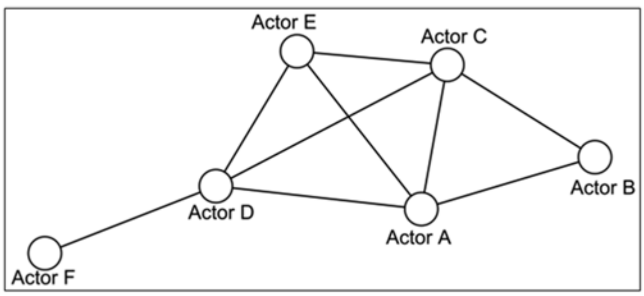

Figure 5. Adjacency matrix (top) and corresponding network graph (bottom). This matrix was created by multiplying the incidence matrix of figure 4 by a transposed version of itself.

events 2 to 31, our third frame will contain events 3 to 32, and so on. We can then convert each separate frame into an adjacency matrix, and make measurements on the resulting matrices that are relevant to SNA, thereby creating time series of SNA measures.

To illustrate this approach, we present a case study of the evolution of Biopark Terneuzen, a collaboration between governments, companies, and knowledge institutes that aims to develop a sustainable industrial cluster in the Canal Zone of the province of Zeeland in the Netherlands[8]. More specifically, companies in the cluster want to improve their environmental performance by exchanging by-products to replace their “normal” inputs, and by sharing utilities. The initiative also aims to strengthen the local economy by attracting new economic activities to the region. We reconstructed the collaborative process using the procedure described above. We excluded informal interactions from the study, as they leave too few traces behind to be reconstructed in a reliable way. In total, 220 events were reconstructed for the collaboration. We coded all events in the dataset to identify the actors involved in them (at the organizational level).

We produced several time series that represent changes in different SNA measures of the collaborative network (see figures 6 to 8). Producing and inspecting the time series is only the starting point of analysis. The time series offer a description of the evolution

[8] The initiative is described in more detail in Spekkink (2013) and Spekkink (2014).

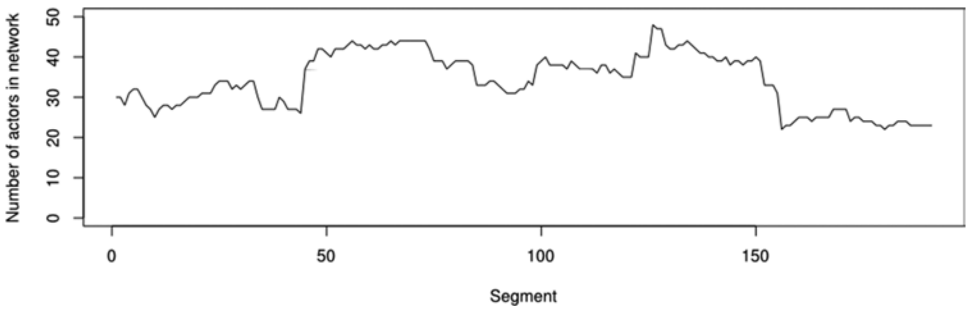

Figure 6. The size (number of actors) of the collaborative network over time.

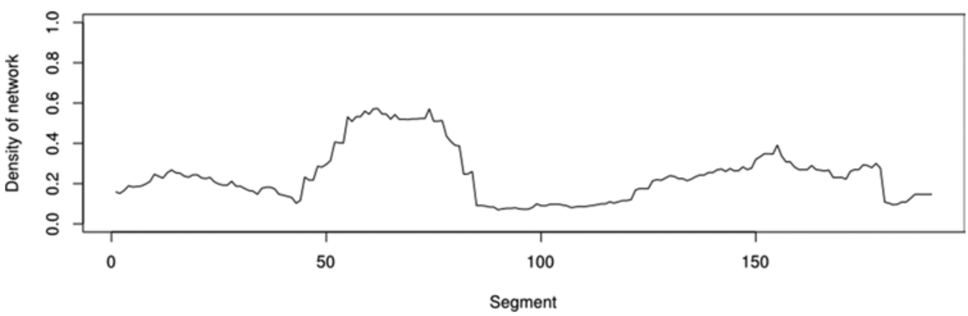

Figure 7. The density of the collaborative network over time.

of the collaborative network over time, but a visual inspection offers no information about the mechanisms that are at the basis of this evolution. To offer an interpretation of the network dynamics a qualitative analysis is performed of the underlying event data, using the qualitative descriptions of events to developing an understanding of the network dynamics visualized in the time series.

Figures 6 and 7 show the size and density of the collaborative network respectively. Both time series show a sudden increase in the size around segment 45. The increased size is maintained for quite some time (although there is a dip around segment 95), but the density of the network drops again relatively quickly. As multiple explanations for these patterns are possible (including correlations between the size and density of the network) we rely on our qualitative analysis of the underlying event data to develop an understanding of the mechanisms behind these patterns. Before the point where the size of the network and the network density suddenly increase the collaboration has not formally started yet, although several actors are already working on relevant projects more or less independently from each other. The sudden increase occurs when these actors are brought together for a formal process in which they discussed the benefits that could be achieved by combining their efforts; this marks the formal start of the Biopark Terneuzen initiative. The projects that the actors were working on independently before the start of the formal process are included in the new, overarching initiative.

The fact that a large number of actors is brought together from different projects (and therefore different actor constellations that are already present in the network) is reflected in the increased density of the network. New actors, primarily knowledge institutes, were also temporarily introduced into the network to provide additional support to the collaborative process, which leads to an increase of the number of actors involved in the network. A few meetings take place in which a rather large group of actors discuss the aims of the Biopark Terneuzen initiative and the studies of the knowledge institutes. After a few meetings, Biopark Terneuzen was officially launched with a public event. The decrease in the density of the network occurs briefly after this event. A closer inspection of the sequences of events reveal that the actors involved in the collaboration worked on the implementation of the vision for Biopark Terneuzen in parallel projects. The projects were carried out by small constellations of actors with only limited overlap, which explains why the density of the network is relatively low during the implementation phase.

In the later stages of the process density increases slightly, which coincides with a decrease in the number of actors involved in the network. At this point, some of the projects that are part of the collaboration have been successfully implemented, while others are abandoned. Some companies involved in the collaboration had anticipated on governmental support for the production of biofuels, but the national government ended up deciding otherwise in fear of the negative consequences that biofuel production might have for food production. One of the companies decided to cancel its plans for a biofuel factory. Another company had already constructed a biofuel factory and went bankrupt, which was also partly due to the bad economic circumstances at the time. At this stage, the activities are focused primarily on one project, which concerns the supply of CO_2 and residual heat from a fertilizer factory to several newly developed greenhouses. The realization of this exchange is one of the main successes of the Biopark Terneuzen collaboration. The shift in focus is reflected in the decrease in the size of the network, which in this case also accounts for the increase of density.

Figure 8 reveals that in the early stages of development the network is characterized by a relatively high degree of betweenness centralization, which indicates that there is a small number of actors that function as a bridge between different parts of the network. The pattern in figure 8 is almost entirely accounted for by position of three public actors that were involved in the process: the municipality of Terneuzen, the province of Zeeland, and the port authority Zeeland Seaports (the province being the most prominent). They obtained their high betweenness centrality through their involvement in various projects at the same time, largely due to their administrative responsibilities in these projects. They were thus in a good position to observe the commonalities that existed in the activities that were being carried out in the different projects, and to broker the relationships between the actors involved in the projects (cf. Burt, 2000, 2001). These three actors are also at the basis of the Biopark Terneuzen collaboration. Thus, in this case the mobilization for collaborative action was initiated by actors that had the best opportunity to do so, because of the special position that they took in their network. From the qualitative

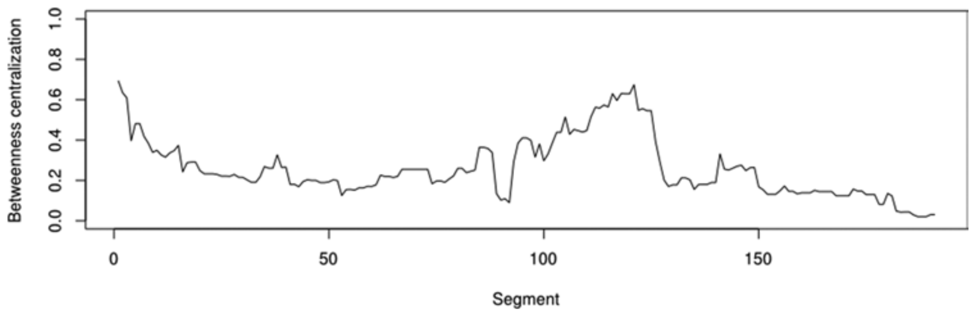

Figure 8. Betweenness centralization of the network over time.

data we know that these public actors brought the other actors together for a deliberative process in which the vision for Biopark Terneuzen was developed, which marked the start of the collaboration. In the literature on collaborative governance this mechanism is known as facilitative leadership (Ansell & Gash, 2008; Bryson, Crosby, & Stone, 2006; Emerson, Nabatchi, & Balogh, 2007; Vangen & Huxham, 2003).

Figure 8 reveals that the betweenness centralization of the network decreases as different members of the network are brought together for collaboration and start interacting with each other directly. Around frame 100 betweenness centralization increases again. Here too, the pattern is accounted for almost entirely by a position of relatively high betweenness centrality of the three public actors. This is the phase of the process where the vision for Biopark Terneuzen is implemented through several parallel projects. The public organizations are typically the only organizations that are involved in all these projects, and thus they again function as bridges between the groups of actors involved in the projects. Betweenness centralization decreases again near the end, as some projects are finished, while one project is abandoned. Despite the setbacks that the collaborating actors faced Biopark Terneuzen is still in progress.

4. Conclusion

In this article we have developed the argument that a balanced application of quantitative and qualitative SNA can contribute to a better understanding of the emergent and dynamic properties of complex social systems. We illustrated two approaches in balancing the quantitative methods of SNA with qualitative methods.

The case studies show that the quantitative methods of SNA offer important benefits when studying complex social systems. Quantitative analyses reveal system-level patterns that would remain obscure in a completely qualitative approach. For example, certain system-level patterns entail numerous indirect relationships between actors, such as the centrality of actors in communication flows and the bridging position of actors between different parts of the network. This is where the quantitative tools for SNA are superior. We however took a different approach than traditional quantitative methods of SNA, which solely look for effects of the network structure on observed behavior. We used the quantitative measurement of network structures and dynamics as useful starting points for a more in-depth, qualitative analysis of the mechanisms behind these system-level patterns.

As we discussed in section 2, there are other approaches that achieve similar results through statistical modeling and simulation. Although these approaches allow for more statistical rigor in the analysis, the type of mechanisms that can be considered through them are typically of a very general nature. Qualitative data and analysis can guide the interpretation of findings by offering a more vivid picture of the sequences of events that are at the basis of the observed system-level patterns, as has been shown in the second case. In addition, as the first case has shown, qualitative data and analysis can offer insight in the quality and meaning of ties for actors (Edwards, 2010). For instance, it showed that the actors in the OCCR did not use their central positions in the network to provide others with crucial information, because they did not believe that it was their role. Qualitative data and analysis therefore offer important contextual details to gain a good understanding of the observed system level patterns and contributes to a greater understanding of the changes in these patterns.

We believe that the combination of a quantitative and qualitative analysis does not only offer important value for those researchers who mainly apply traditional quantitative SNA. A mixed-method approach can also be beneficial for qualitative researchers, who are used to doing interviews and writing thick case descriptions. As has been shown in this article, SNA can be an interesting tool to structure these case descriptions, by abstracting and visualizing system-level patterns and by offering useful starting points for a more in-depth, qualitative analysis. In addition, visualizations of (changes in) networks of relationships can also serve as aid in the collection of additional qualitative data by discussing the visualizations with respondents. For example, actors in the Dutch Railway system declared that they were unaware of their relatively central position in the network and thus their potential to steer the process.

As Edwards (2010) notices, there is no one best way to integrate quantitative and qualitative methods in SNA. In this regard, we see our own approach as complementary to existing approaches in the SNA literature, and not as a replacement. Overall, both approaches introduced in this article helped us to improve our understanding of complex social systems by establishing a stronger link between micro-level patterns and emergent patterns at the system level without completely reducing one to the other. In addition, both approaches relatively easily deal with the highly dynamic nature of complex social systems, by making possible a relatively fine-grained reconstruction of the dynamics that have occurred.

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