A Dynamic Network Analysis of rail disruption management

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ABSTRACT

Railway systems experience disruptions on a daily basis. We test the use of Dynamic Network Analysis as a methodological tool in order to investigate the communication patterns during the dynamic process of disruption management. The tool was applied to a simulated case of a catenary failure in the Dutch railway system. DNA provides a systematic overview of the communication patterns and tasks associated with the disruption management process. Key actors were identified and the overall structure of the network analyzed. The dynamic component to our network analysis revealed that information is being shared within disconnected parts of the network during the first few minutes, without those parts having a direct link to the source of the information. These findings show that employing only static analysis of networks obscures the real dynamics of information sharing during railway disruptions and potential coordination problems. DNA therefore can be an important method and tool to reveal issues that need to be resolved.

2.1 INTRODUCTION

The Dutch railway network is the busiest of Europe in terms of passenger kilometers per kilometer of railway track (Ramaekers et al., 2009). Accommodating all the different train services on the relatively small rail network makes it difficult to run according to schedule and delays can easily have knock-on-effects causing problems to spread to other parts of the network. This makes the Dutch railway system highly vulnerable to disruptions, i.e. an event or a series of events that leads to substantial deviations from planned operations (Nielsen, 2011). Nevertheless, the overall performance of the railway system in terms of punctuality has been good in the previous years. However, as the winter seasons often demonstrate: when things go wrong they tend to go wrong on a large-scale, leading to loss of control and long recovery phases.

These major disruptions lead to dissatisfaction among travelers, extra expenses, and revenue losses. In response, train operating companies (TOCs), infrastructure provider ProRail, and the Dutch government have sought ways to improve operational performance. As the possibilities to expand the infrastructure capacity are limited, due to financial and environmental constraints, most of these resources have been aimed at reducing the system's vulnerability, i.e. increasing its robustness to absorb shocks and to improve its capacity to recover from disruptions. Simplification of the infrastructure (unbundling of nodes, reducing the number of switches), time table and logistics is considered to contribute to the robustness of the system (Ministerie van Infrastructuur en Milieu, 2011). One major vulnerability is the coordination between the different parties involved in managing disruptions (Ministerie van Infrastructuur en Milieu, 2011). This process has become so complex that that it is considered unsuitable to anticipate and recover from disturbances (ibid.). A possible solution would be to reduce the number of actors involved and to introduce stricter procedures in an attempt to bring down the diversity in possible behavioral responses (Sutcliffe & Vogus, 2003). While this may help in coping with most of the common disruptions, research shows that optimization of existing systems has a limited impact, there is a trade-off between optimization and brittleness in the face of novel events and uncertainties (cf. Csete & Doyle, 2002; Hoffman & Woods, 2011; Woods & Branlat, 2011a).

We understand the railway system as being a complex socio-technical system (cf. Comfort, 2005; Walker et al., 2008) that consists of several social subsystems, each with particular goals, perceptions, tasks and resources. These geographically separated subsystems have to coordinate their activities during a disruption in order to return to the original operational plan as quickly as possible (Bharosa, Lee, & Janssen, 2010). Coordination relies on effective communication in such complex systems (Faraj & Xiao, 2006; Gittell, 2011; Ren et al., 2008). While most policies and research focus on reducing this complexity, fewer (empirical) studies have focused on understanding and harnessing the complexity of disruption management. A comprehensive overview of who does what during a disruption and of how information is being shared between actors in the Dutch railway system is therefore still missing.

In this article we want to propose and demonstrate a method with which such a comprehensive understanding of the complex communication patterns during disruption management can be mapped and analyzed. Visualizing and analyzing network structures can reveal properties of the operation of the railway system that might not be obvious from standards operating procedures (Houghton et al., 2006). Naturally, that requires collecting, structuring and analyzing a considerable amount of data. We propose Dynamic Network Analysis (DNA) as a promising method and tool for such an endeavor because it allows capturing the irregular flows of information during a disruption, in contrast to the more static tools of traditional social network analysis. However, to our knowledge DNA (or even SNA) has not been applied to studies on railway disruptions. These considerations lead to us to the following research question: How can DNA help to investigate coordination between the geographically distributed teams involved in the management of a railway disruption? We will use an example of a failing catenary to demonstrate the various aspects of DNA.

We will first discuss the properties that make disruption management so complex and the need for DNA (section 2.2). Next, DNA will be presented (section 2.3), followed by the research methodology (section 2.4). A short overview of how disruptions are managed in the Dutch railway system is provided in section 2.5. The results of applying DNA to the catenary failure are presented in section 2.6 followed by a discussion (section 2.7), and the conclusions (section 2.8).

2.2 THE COMPLEXITY OF MANAGING RAILWAY DISRUPTIONS

There is a growing interest among theorist in conditions that influence organizations to reliably manage large and complex technical systems (cf. Hollnagel et al., 2011; La Porte, 1994; Leveson, Dulac, Marais, & Carroll, 2009; Perrow, 1999; Rochlin et al., 1987; Weick, Sutcliffe, & Obstfeld, 2008). A breakdown of the services that such systems provide can cause very serious problems to the economy and society (De Bruijne & Van Eeten, 2007). Consequently, protecting these systems against failures, or making sure that they can be rapidly restored, has become an important objective. Paradoxically, while there is a growing demand for high-reliable services, we have witnessed the dismantling of the organizations operating these systems (Schulman, Roe, Eeten, & Bruijne, 2004). Under the influence of restructuring policies, the provision of reliable services has shifted from a primarily intra-organizational task to an inter-organizational challenge (De Bruijne & Van Eeten, 2007).

These now multi-layered networked systems, such as the one this chapter focuses on, have to deal with dispersed authority, information asymmetry and consist of organizations with diverging goals and specialized tasks, which may be mutually conflicting (Branlat & Woods, 2010; De Bruijne, 2006; Ren et al., 2008; Woods & Branlat, 2010). Providing reliable services therefore requires multiple teams who are separated by organizational and geographical boundaries, to align their goals and activities. However, as De Bruijne (2006) notes, a thorough understanding of how *networks* of organizations operate and coordinate their actions to reliably operate complex technological systems is still lacking.

The volatility and complexity of the networked system means that operators will increasingly have to deal with unexpected conditions. In these cases they cannot always rely on predefined protocols or contingency plans. Schulman et al. (2004) & De Bruijne & Van Eeten (2007) point to the increasing importance of flexible response capabilities to maintain reliable services in complex networked systems. This means that operations move from long-term planning to real-time operations, with a central role for dispatchers and operators, who need to make constant adjustments to the planned operations.

Adaptation in networked systems however has it challenges. Each disruption is somehow unique and how it propagates is difficult to predict (Törnquist, 2007). A disruption is a developing situation where the knowledge of the state of the system only gradually becomes available (Nielsen, 2011). This means that adaptation is done under pressure in a dynamic environment, which affects the solution options available (Kohl et al., 2007; Nielsen, 2011). There is a considerable tension between fast decision-making and gathering the right information to make an informed decision. Decision-making therefore takes place under conditions of uncertainty, stress and imperfect information, which is also spread among the different organizations (Grabowski & Roberts, 1997).

Besides, there is the complication of subsystems being *simultaneously* autonomous and interdependent (Grabowski & Roberts, 1999). Subsystems operate independently of other subsystems. However, they do this in the context of networks of interdependencies with other subsystems and cross-scale interactions, which will have implications at the system level (Branlat & Woods, 2010). The thirteen traffic control centres of ProRail are a prime example of this. As each control centre has its own bounded geographical area for which it is responsible, traffic controllers will make decisions based on local information. However, most trains cross several control areas, so decisions made by one traffic controller will impact train traffic in another area. Each individual action may affect the ability of others to manage the system reliably (De Bruijne, 2006).

In addition, given the many subsystems and the complex relations between these interacting subsystems (Perrow, 1984; 1999), local failures can easily cascade and reinforce through the system, e.g. local problems in one control area can be amplified unintentionally by the traffic controller in the next area, thereby creating a cascade of failures and corrective measures (Nederlandse Spoorwegen et al., 2012). This explains the non-linear effect where two or more small disturbances can lead to a system breakdown, such as often occur during winter seasons, when initial disturbances are aggravated because the complex interactions and ambiguous couplings reinforce the non-linear relationship between local actions and the systemic whole (Leveson et al., 2009).

The uncertainty, time pressure and the interdependence of activities during a disruption increases the need for coordination and thus the exchange of up-to-date information between the different actors in order to return to normal operation as soon as possible (Faraj & Xiao, 2006; Ren et al., 2008). However, sharing information in complex and dynamic situations has proven to be difficult (cf. Bharosa et al., 2010; Faraj & Xiao, 2006; Kapucu, 2006). These difficulties are reinforced by the poor communications endemic to those across organizational boundaries and between distributed teams (Pidgeon & O'Leary, 2000). Distributed teams are known for having difficulties in sharing information evenly, accurately, and when needed (Hinds & McGrath, 2006).

It is necessary to understand how actors connect and share information during a disruption. As Ren et al. (2008) mention, most research focuses on the processes from the point of view of one focal actor or a co-located group to understand information exchange. Only a few studies have taken the whole network as their unit of analysis (cf. Hossain & Kuti, 2010; Provan, Fish, & Sydow, 2007; Provan & Kenis, 2008). Following Hinds & McGrath (2006) and Hosain & Kuti (2010), we believe that the whole network needs to be studied in order to gain insights into how the communication structure affects its capacity to coordinate. We will introduce Dynamic Network Analysis as a method that allows such an analysis of the network. Not only does it enhance our understanding of the communication patterns and interdependencies of the network, but it also shows its dynamics during the process of disruption management.

2.3 DYNAMIC NETWORK ANALYSIS

Dynamic Network Analysis or DNA, is rooted in Social Network Analysis or SNA. SNA was developed to highlight and analyze formal and informal relationships. It helps to collect and analyze data from multiple interacting individuals or organizations (Provan, Veazie, Staten, & Teufel-Shone, 2005). SNA focuses on relationships between actors instead of the attributes of individuals. As such, it emphasizes the importance of relationships for the exchange of resources like information (Wasserman & Faust, 1994). It is these patterns of relationships (linkages) between actors (nodes) that affect the kind of information that is being exchanged, between whom and to what extent (Haythornthwaite, 1996). The patterns of information flows through time and space can then be quantitatively analyzed. To this aim, several metrics have been developed for both the node level and the network level (Kim, Choi, Yan, & Dooley, 2011). Using these metrics makes it possible to quantitatively assess how the general network structure and the positioning of each organization within the network influence the information that is conveyed through the network (Provan et al., 2007).

Traditionally, SNA work is a strongly quantitative method focused on small, bounded networks, with a focus on one type of relation and a single type of node (Carley, 2005). DNA varies from SNA in that it can handle large dynamic, multi-mode, multi-link networks with varying levels of uncertainty (Carley, 2003). Multi-mode means that the socio-technical systems being analyzed can consist of a plurality of node types, such as people, organizations, resources and tasks. Any two nodes can have various types of connections; DNA is therefore well-suited to analyze the multi-link relations of socio-technical system (Carley, Diesner, Reminga, & Tsvetovat, 2007). Such systems can be represented by these many different networks, e.g. a social network (actor by actor) or a task network (actor by task). The collection of these networks is referred to as a meta-matrix (Tsvetovat & Carley, 2004). The added value of a 'network of networks' approach has also been acknowledged by others (cf. Salmon et al., 2011). The meta-matrix framework represents the network of relations connecting node entities (see Table 2.1). It is used to analyze the properties of the socio-technical system and its interactive complexity.

Table 2.1 The meta-matrix framework

	People	**Task**
People	Social network Who talks to whom?	Assignment network Who is assigned to which task?
Task		Dependencies Which tasks are related to which?

Source: Carley and Remminga, 2004 (edited by authors)

Another important attribute of DNA is that it is able to deal with longitudinal data series. As the previous sections have shown, disruption management is a dynamic process. Here, networks are not static but continuously changing through interactions among its nodes (Knoke & Yang, 2008). What is needed is an understanding of how information flows are structured and how these structures change over time (Wolbers, Groenewegen, Mollee, & Bím, 2013). This makes traditional SNA less suitable to model communication during disruption management as it only provides one static snapshot (Effken et al., 2011). We can add time stamps to the data and groups these to create time slices (Wolbers et al., 2013). Time slices show the frequencies of information exchange in the network as it develops over time. The flow of information can then be analyzed by comparing these time slices.

2.4 DATA COLLECTION AND STRUCTURING

Gathering complete network data for inter-organizational networks is challenging (Hossain & Kuti, 2010). Obtaining real-time data on the response network to a disruption requires several knowledgeable researchers, to be at different locations in the network at the right moment. Disruptions also occur unpredictably, so gathering real-time data can be quite time consuming and costly. ProRail has therefore utilized value stream mapping to determine what happens from the moment a train driver notices a damaged catenary, until a contingency plan is implemented. With the help of a complete team of representatives involved in the process a map was created, using pen and paper, showing every step as it happens in reality. The process was broken down in to specific tasks and the flows of information were included in the map[5]. Creating the value stream map took several days for which a safe environment was created, so participants would feel free to provide as much detail as possible. ProRail gave us the permission to use the data from this value stream map for our DNA.

The data was converted into an edge list. 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. Every edge represents an actor x actor (who shares information with whom?), actor x task (who does what task?) or task x task (how are tasks related?) tie. Since the actor x actor ties represent the flow of information between actors, the edges are directed and valued, meaning that the information flows in a certain direction and that there might be multiple interactions between two actors. We have chosen to focus our analysis on the actors who check and implement the contingency plan. Consequently, the tasks related to the repair of the catenary and those on providing travel information are not included. The edge list was then imported into ORA[6]. ORA generated series of reports that contain multiple metrics, both on a node- and whole network level (Carley et al., 2007; Carley & Pfeffer, 2012).

Given the properties of disruption management in the Netherlands, we are interested in the *centrality* of actors. Centrality is fundamental to node-level metrics and reflects the relative importance of individual nodes (Kim et al., 2011). It is used to capture the flow of information in a network and estimate potential levels of coordination (Hossain, Wu, & Chung, 2006). Freeman (1979) identified three distinct facets of network centrality: degree, betweenness and closeness, with each of these measures having different implications for coordination. The three measures are conceptually operationalized in in Table 2.2.

Degree centrality allows us to measure the activity in communication of every node. Nodes that process and distribute a high amount of information feature a high in- and out-degree centrality. By combining the degree centrality of nodes with the actor by task

5 ProRail initiated the so-called ‘Lean Transformatie’ program as a concerted effort to improve its operational performance and (as a result) to improve its customer relations. The mapping of a catenary failure was part of this program and aimed to identify the number and quality of interactions following when staff develops a solution to such a failure. A better understanding of these interactions should then be used to implement a Kaizen-like way of working.

6 ORA is a dynamic meta-network assessment and analysis tool developed by CASOS at Carnegie Mellon University, Pittsburg (PA). This user-friendly software tool allows researchers to visualize and analyze networks over time.

Table 2.2 Node-level metrics and their conceptual definition

Node-level metrics	**Measurement**	**Conceptual definition**
Degree centrality	Measures the number of direct ties a given node has. The larger the number of direct ties an actor has the higher its degree centrality. In directed networks (networks that show the direction of information flowing), a distinction can be made between in-degree (information flowing to a node) and out-degree centrality (information flowing from the node).	The more central an actor is, the more potential it has for activity in communication (Mullen et al., 1991).
Betweenness centrality	Measures the extent to which a particular node lies in between the other nodes of the network	The more central an actor is, the more control or capacity it has to interrupt information flowing through the network. Betweenness reveals bottlenecks and structural weak points in information flows (Hossain & Kuti, 2010), but also influential nodes that can coordinate group processes (Mullen et al., 1991; Hossain et al., 2006)
Closeness centrality	Measures the sum of distances from one node to all others, so closeness refers to the extent a node is close to all other nodes in the network.	The more central an actor is the more independence the actor has and the easier it can distribute messages in a minimal amount of time (Mullen, Johnson, & Salas, 1991).

relationships, we can get an indication on the workload of every node. Betweenness centrality shows which nodes will most likely have to pass along information for information to traverse disparate parts of the network. These nodes can become weak points in the process when they (unknowingly) distort information or are no longer able to process it. Finally, with closeness centrality we can assess whether the nodes that distribute the most information can actually do this within the least amount of time, given their position in the network.

Network level metrics are used in order to define the overall structure of the network. For these measures we turn to the work of Stanton et al. (2012) & Walker (2009), who showed that the following network-level metrics can be used to define a network of organizations: network density (distribution of information), diameter (patterns of interaction), and centralization (allocation of decision rights). Table 2.3 shows the conceptual definition of these three measures. Density measures how fragmented (or sparse) the network is, i.e. what the influence is of the indirect communication on the distribution of information through the network. The diameter of the network measures the maximum number of steps needed to travel from one node to another. Information will need to traverse a lot of actors in fragmented networks. Centralization calculates whether the network is centralized or decentralized.

Table 2.3 Network-level metrics and their conceptual definition

Network-level metrics	Measurement	Conceptual definition
Network density	Measures the actual number of ties as a ratio to the maximum number of ties possible, ranging from 0 (no nodes are connected) to 1 (every node is connected to every other node).	Density measures how well connected a network is. This gives information about the rate of flow of information among nodes (Chung & Hossain, 2009). The denser a network is, the broader the dissemination of information will be possible, since there are more direct pathways between sender and receiver (Stanton et al., 2012).
Network diameter	Measures the largest number of nodes that have to be traversed when traveling from one node to another.	The higher the diameter of the network the more actors there are on the lines of communication (Stanton et al., 2012). Networks with a high diameter will need more steps to distribute information.
Network centralization	Measures the extent to which the overall connectedness is organized around particular nodes in a network.	Network centralization and network density are complementary. Whereas density is concerned with the cohesiveness of the network, centralization reflects distribution of power or control across the network (Kim et al., 2011). Highly centralized networks have a few influential nodes, while in decentralized networks power is more distributed.

2.5 DISRUPTION MANAGEMENT IN THE DUTCH RAILWAY SYSTEM

It is essential to first give a brief overview of the nature of disruption management in the Dutch railway system in order to understand its complexity before discussing the analysis. Until the mid-1990s, NS used to manage the railway traffic. This unit was then split-off from the commercial passenger services into ProRail. ProRail controls and monitors all the train movements and its traffic controllers assign paths to all TOCs. During disruptions, these traffic controllers have to manage the overtaking, re-routing, short turning, or canceling of trains (Jespersen-Groth et al., 2009).

There are several companies that offer passenger and cargo services. NS is by far the largest provider of passenger services and operates all main railway lines. During a disruption the TOCs will have to guarantee that rolling stock is available and that crew schedules are adjusted. Infrastructure, rolling stock and train crew are highly interrelated in practice, which presents a complex puzzle that needs to be solved in a coordinated manner. Given the dominant position of NS and the historical bond between ProRail and NS, we will focus on how these two companies manage disruptions.

Besides the organizational divide between ProRail and NS, there is also a divide between the national level, and the regional level (Figure 2.1). ProRail has thirteen regional traffic control centres that are responsible for the railway traffic in specified geographical areas. Regional traffic controllers monitor the railway traffic in the designated areas and optimize traffic flows. In addition, train dispatchers are responsible for securing safe railway opera-

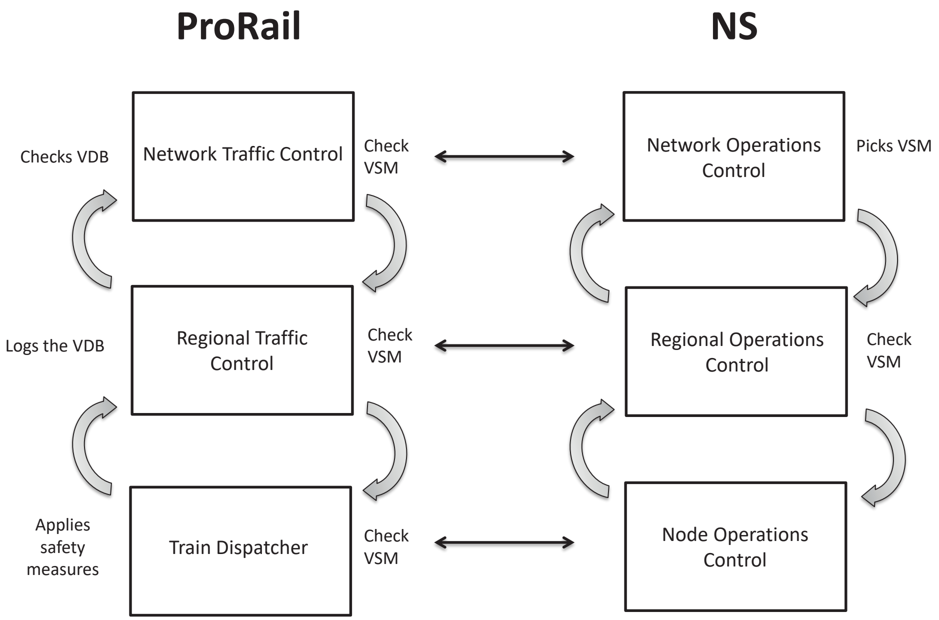

Figure 2.1 Communication flows during a disruption between ProRail and NS

tions on the sections assigned to them. Train dispatchers control the train traffic through switches and signals. This is mostly an automated process. Similarly, NS has five regional control centres where the railway traffic is monitored and where crew and rolling stock are managed. Coordinators have been assigned to important nodes (mostly large stations) to manage the shunting process and to inform employees on the platforms. Not only do these regional centres of ProRail and NS monitor *different* geographical areas, but this is also done from *different* locations or rooms. This means that information on the availability of infrastructure and rolling stock & crew has to be shared by phone or data links.

In 2010, ProRail and NS established a joint Operational Control Centre Rail (OCCR). The OCCR is to serve as a boundary spanning platform that should encourage mutual communication, coordination and learning in order to reduce recovery time during disruptions. In the OCCR ProRail and NS monitor the railway traffic on a national level and intervene when necessary. For instance, network traffic controllers can overrule decisions made by regional traffic controllers, if the decisions made by these regional traffic controllers are conflicting. As such, the management of disruptions is done by two different organizations and each organization has its subsystems that have different responsibilities both in terms of tasks and geographical areas. The OCCR is meant to overcome some of the organizational divides.

We will now have a closer look at the process of disruption management as designed by ProRail and NS. In most cases, train drivers are the first who are confronted with a disruption. They will have to inform the train dispatcher about the situation, who will apply the necessary safety measures. The train dispatcher will then alarm other actors according to a decision tree. Next, the train dispatcher and the regional traffic controller (RTC) assess the impact of the disruption on the traffic and decide to what extent services can continue on the affected section. The RTC will then log the decision concerning the new distribution of the capacity (VDB), which is then checked by the network traffic controller (NTC) to see if the chosen distribution does not conflict on a national level. The network operations controller (NOC) of NS will then select a contingency plan (VSM). These are predefined plans for the most common disruptions. The NTC can adjust these contingency plans within the limitations set by the RTC in the VDB. Implementation of the VSM is done at the regional level, where it first has to be checked in terms of feasibility, e.g. whether train drivers are available to operate trains.

Defining, checking and implementing a contingency plan during disruptions leads to considerable information flows through the system as is illustrated by Figure 2.1. It shows there is a vertical two-way flow of information within both of the organizations (left column ProRail, right column NS), as well as horizontal flows of information between the different subsystems of ProRail and NS, as indicated by the black arrows. Diagonal communication has been reduced to a minimum in order to avoid misunderstandings. So, each division of ProRail should only communicate with its counterpart of NS in terms of geographical responsibility.

2.6 USING DNA TO ANALYZE AND VISUALIZE A CATENARY FAILURE

The network shown in Figure 2.2 features all the actors (red round nodes) involved in the management of the disrupted catenary, i.e. the process leading up to the implementation of the contingency plan, and the tasks (blue triangular nodes) that these actors need to perform in this process (see appendix for the full name of the abbreviations). The dotted lines indicate task by task relationships. A first observation concerns the large number of actors that are involved in the process, something that is not surprising given the situation in the Dutch railway system. Besides the actors mentioned in Figure 2.1, there are numerous others that perform specific tasks (24 actors and 35 tasks), which results in a complex network of interdependent actors and tasks. The graph also shows that there is an asymmetrical distribution of the tasks and communication activity among the nodes.

Table 2.4 shows the centrality measures applied to the nodes in the network. The nodes with an asterisk have a higher than normal value, meaning the value is more than one standard deviation above the mean. Since this is a directed graph we calculated both the indegree (number of ties directed to the node) and outdegree (the number of outgoing ties of a node). The links have been inverted (1/w) when measuring betweenness and closeness centrality to take into account the valued data. This was necessary because ORA treats

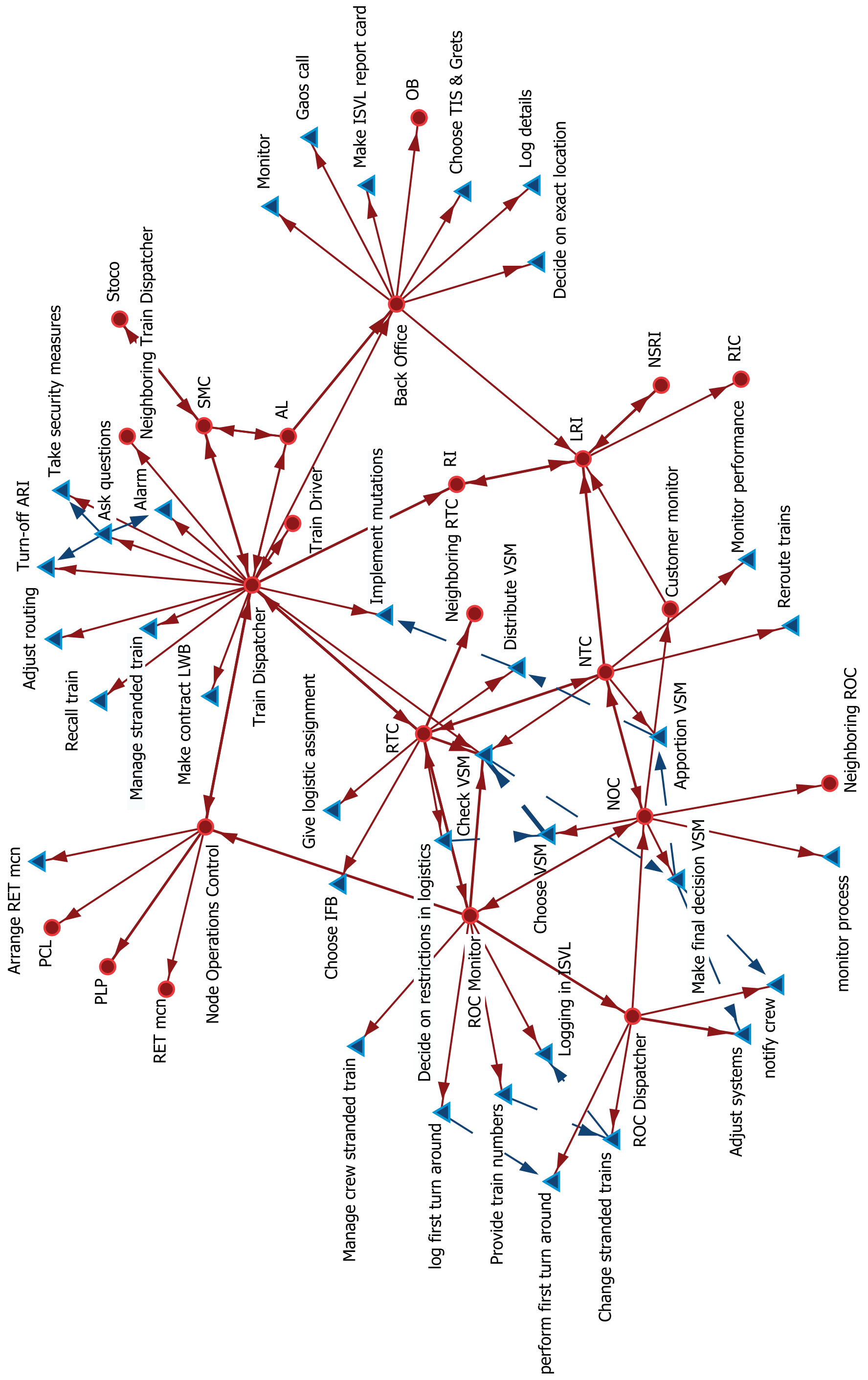

Figure 2.2 Overview of the overall network of actors and tasks during the management of damaged catenary.

Table 2.4 The most central nodes based on degree, closeness and betweenness centrality measures

	Total degree centrality	Indegree centrality	Outdegree centrality	Closeness centrality	Betweenness centrality
1	Train Dispatcher (20)*	LRI (8)*	Train Dispatcher (12)*	Train Dispatcher (0,236)*	Train Dispatcher (0,259)*
2	RTC (15)*	Train Dispatcher (8)*	RTC (9)*	RTC (0.241)*	RTC (0,156)*
3	LRI (12)*	RTC (6)*	Node Operations Control (7)*	ROC Monitor (0,211)*	ROC Monitor (0,116)*
4	Node Operations Control (11)*	SMC (5)*	ROC Monitor (7)*	Node Operations Control (0,206)*	NOC (0,079)
5	ROC Monitor (11)*	NTC (4)	NOC (5)	SMC (0,204)*	Node Operations Control (0,079)

line weight as distance while we treat it as the number of interaction between nodes. Tie strength therefore indicates a possibility of information to pass along. By inverting the links we can keep the interpretation of line weights as similarity information.

The train dispatcher has the highest centrality score for all measures, except for that of indegree centrality, followed by the regional traffic controller. The train dispatcher (total degree score 20) is the actor that communicates most frequently with other actors. The large number of outgoing ties of the train dispatcher illustrates its central role in distributing the information in the network. The high closeness centrality score supports this role, as the central position of the train dispatcher makes it possible to distribute the information within the least amount of time. The high betweenness centrality score of the train dispatcher shows that the train dispatcher acts as a hub in transmitting information between disparate parts of the network. These findings confirm the specialized role of the train dispatcher in disruption management as he or she is solely responsible for safe railway operations.

Table 2.5 shows the scores for the whole network measures. Density assesses the interdependency of actors. The diagram shows that there is no diagonal communication between the actors, exactly as was designed in order to avoid miscommunication. This also influences the rate of flow of information, as in more sparse networks there will be less communication linkages. Because there are often no direct ties between nodes, multiple steps are necessary for information to flow through the network. The network is indeed sparse (density 0.08) indicating that the actual number of ties are a low percentage of the potential maximum number of ties. The diameter score of 13 shows that there are many nodes on the line of communication between the two most separated nodes, given the theoretically maximum diameter of 23 (number of nodes minus 1).

Table 2.5 The results of the network-level metrics

Network-level metrics	Results
Network density	0,08
Network diameter	13
Centralization, Indegree	0,078
Centralization, Outdegree	0,139
Centralization, Betweenness	0,242
Centralization, Closeness	0,373

The centrality scores indicate how tight the network is organized around the most central node, the train dispatcher. The degree centralization scores are relatively low so there isn't a particular node dominant in the network, i.e. the network is loosely coupled with information distribution (out-degree) being more dominated by a few nodes than information receiving (in-degree). The betweenness centralization is a bit higher, but there isn't a dominant node that controls the flow of information. Closeness has the highest centralization score. Still the overall accessibility of information is moderately low.

We have visualized and described the whole network and the role of specific nodes within. However, the importance of a node in a network cannot be determined without reference to the dynamic patterns of communication during the different phases of the disruption management process (Borgatti, 2005; Wolbers et al., 2013), as described in section 2.3. Therefore we have created six time slices to see how the network develops over time and how the position of nodes changes (see Figures 2.3 to 2.8).

The first time slice shows the train driver alarming the train dispatcher about the damaged catenary. The train dispatcher subsequently applies the safety measures. At this initial stage, it is crucial that the train dispatcher collects accurate and detailed information about the situation from the train driver because other actors will use this information for their decisions and actions. It is therefore remarkable to see three isolated networks during time slice 1. It highlights actors acting without having a direct link to the train dispatcher (their official source of information). This is the result of the co-location of the RTC, the travel informant (RI) and the train dispatcher, which makes it possible for them to overhear the phone call of the train dispatcher with the train driver. So without having the full details on the situation, the RI and the RTC already start making preparations. After the official notification by the train dispatcher, information is quickly exchanged throughout the network in order to determine the consequences of the damaged catenary and to work towards the contingency plan (time slices 2 to 4). The network becomes fragmented again, when the plan for the disruption has been defined and checked and actors focus on their own specific task in the implementation phase. Apparently, this can be done in isolation from the other actors (time slices 5 and 6).

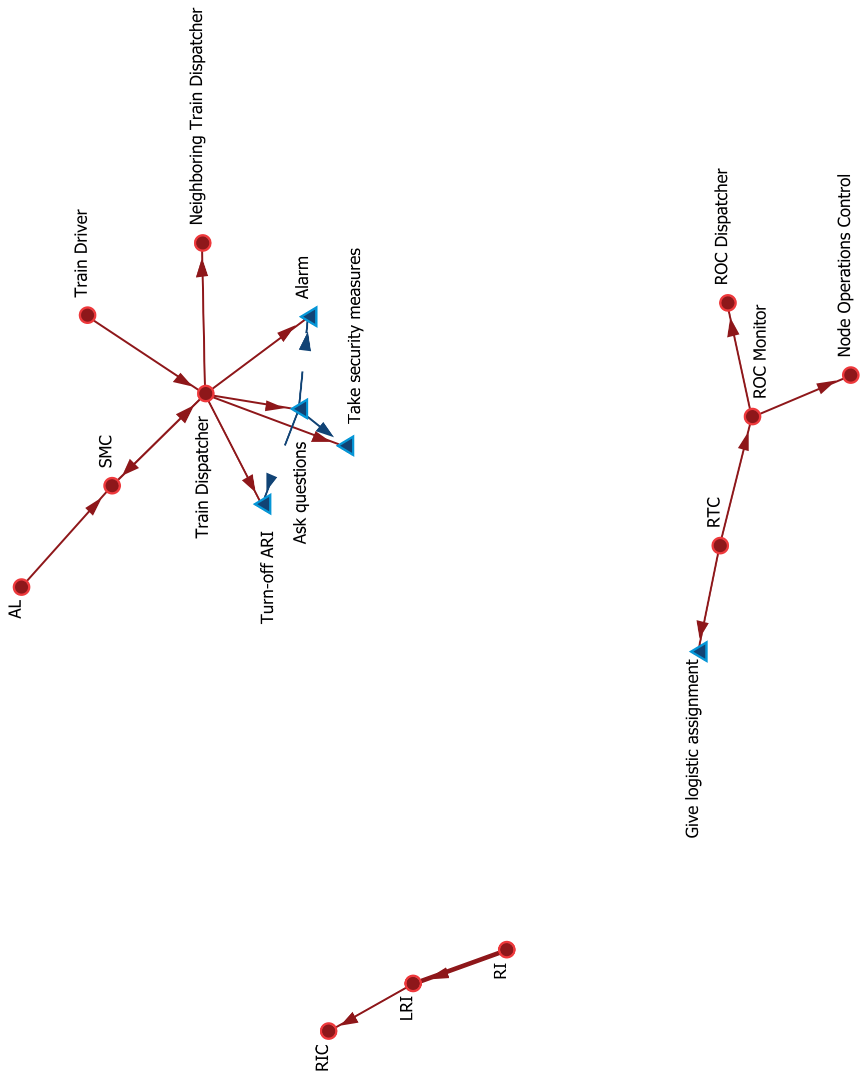

Figure 2.3 Time slice 1

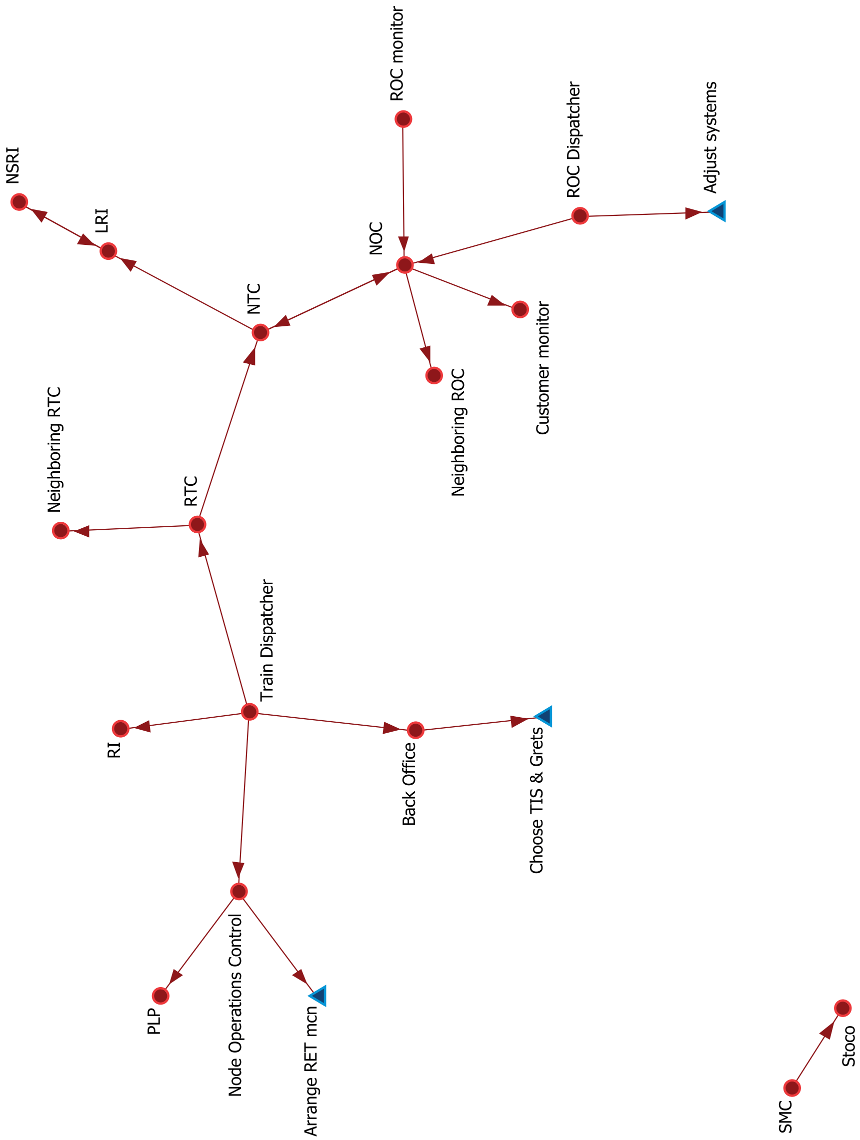

Figure 2.4 Time slice 2

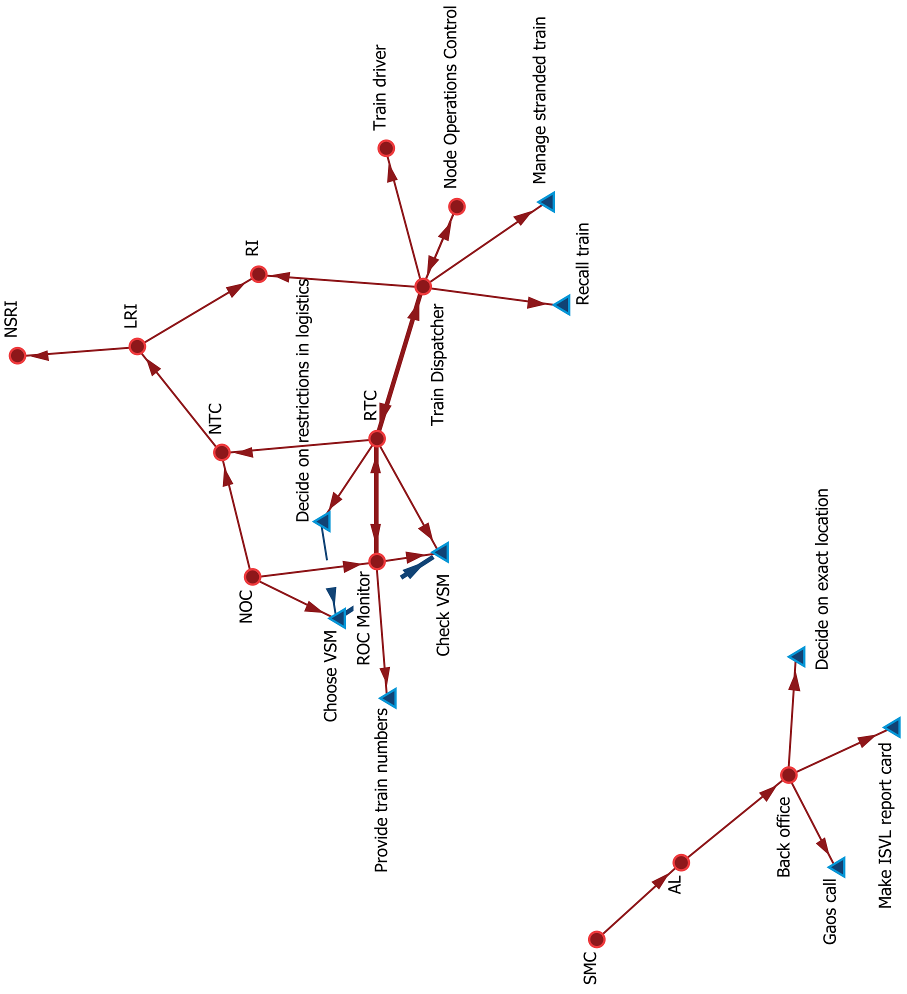

Figure 2.5 Time slice 3

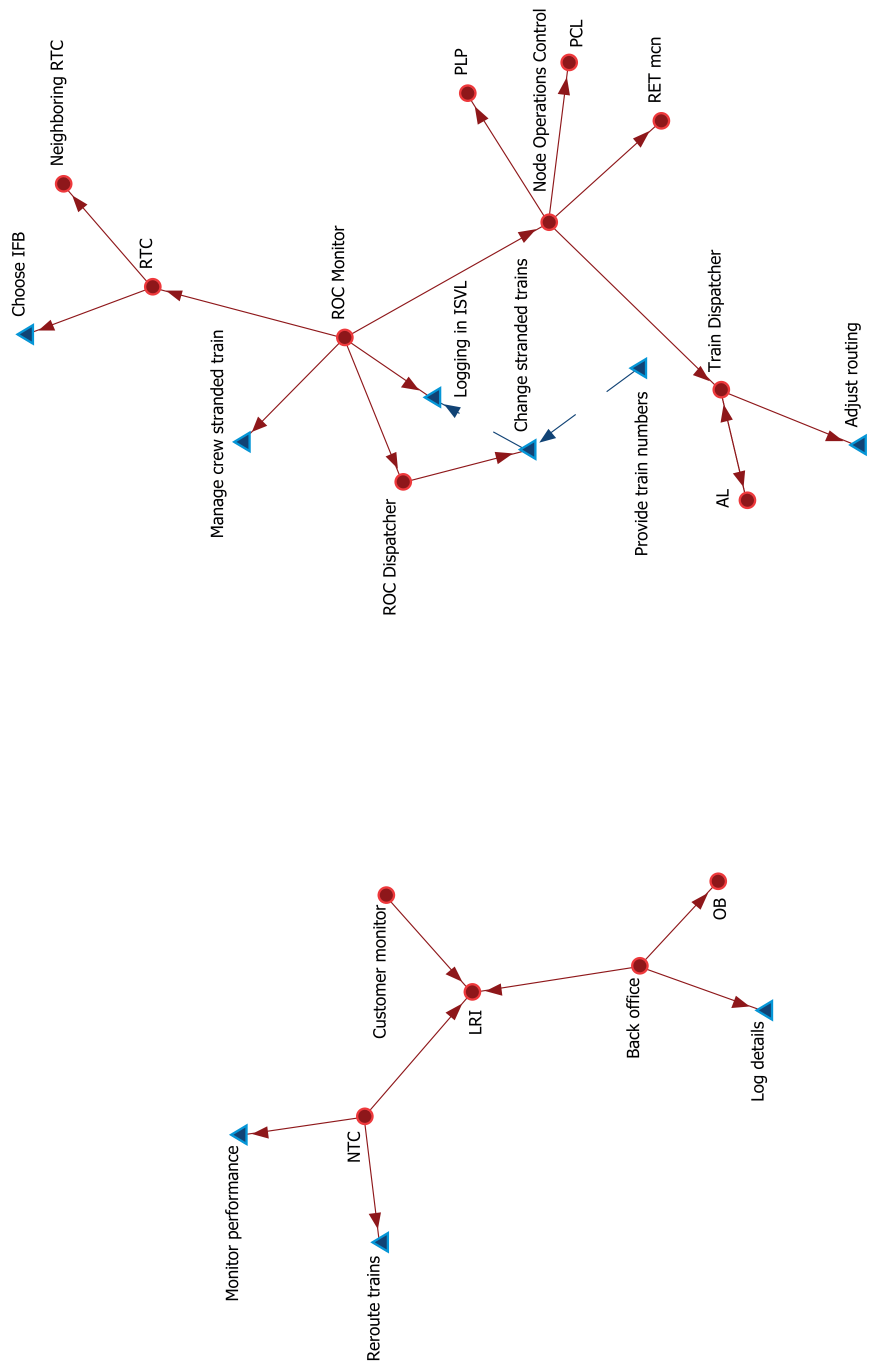

Figure 2.6 Time slice 4

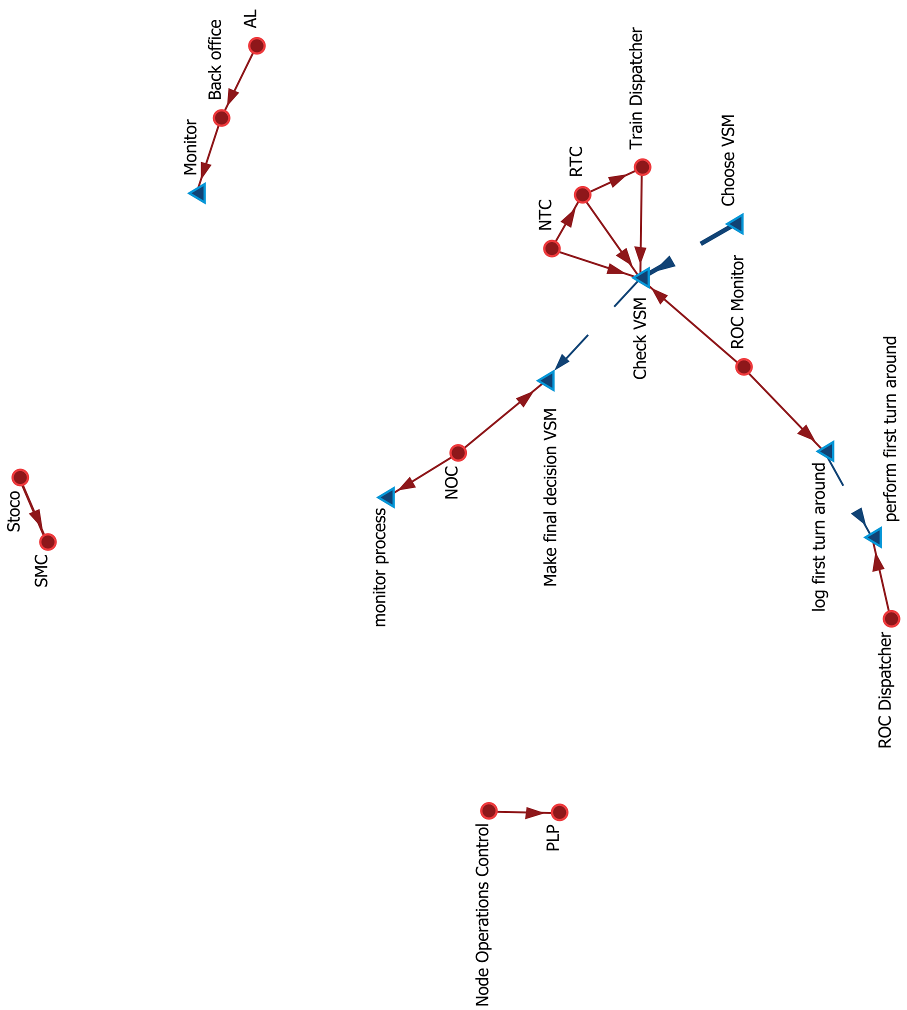

Figure 2.7 Time slice 5

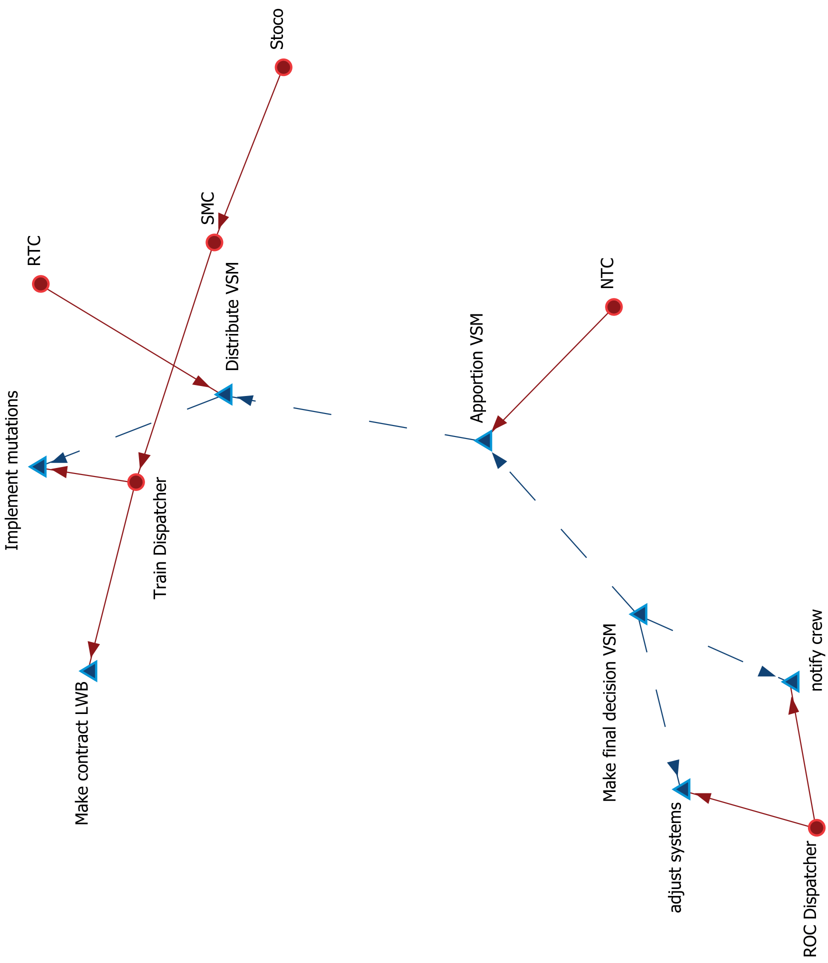

Figure 2.8 Time slice 6

Table 2.6 shows the most central actor for each time slice in terms of degree-centrality and betweenness-centrality. Closeness centrality is not calculated as in most time slices the networks are disconnected, rendering closeness centrality problematic to calculate (Borgatti, Everett, & Johnson, 2013). There is a high correlation between both measures, but both show that the most central actor varies considerably in each time slice. This confirms the decentralized and fragmented nature of the network. The various (disconnected) sub-networks act rather autonomously in managing the disruption, without there being a central core (Wolbers et al., 2013).

Table 2.6 Most central actors per time slice

Time	Nodes (Actors)	Nodes (Tasks)	Ties (Actor x Actor)	Total degree centraltity	Betweenness centrality
T1	12	5	10	Train Dispatcher	Train Dispatcher
T2	17	3	17	NOC	NOC/NTC
T3	13	9	16	RTC/ Train Dispatcher	RTC/ Train Dispatcher
T4	15	9	14	Node Operations Control	Node Operations Control
T5	12	7	5	RTC, SMC, Stoco	RTC
T6	6	7	2	SMC	SMC

2.7 DISCUSSION

Three centrality measures (degree, betweenness and closeness) were used to assess the role of the actors in the disruption management process. For all measures, except indegree, the train dispatcher and RTC were the highest in centrality. This shows their importance in the processing and distribution of information. However, this important role is simultaneously a potential weak point in the flow of information. Given their hub functions, it is crucial that the train dispatcher and the RTC provide others with timely and accurate information. However sharing the right information can be difficult when confronted with an information-overload under high workload. Especially the train dispatcher can become a bottleneck instead of an efficient hub, because the train dispatcher also has the most tasks assigned to him or her (10).

The first priority of a train dispatcher during the first minutes of a disruption is to take all necessary safety measures and, secondly, to provide the other actors with detailed information about the situation. During a severe disruption the workload of a train dispatcher influences its capacities to share information. In such situations they are often no longer able to rely on the automated traffic control system and thus have to solve the situation manually. It then becomes very challenging to perform an efficient control of the traffic (Kauppi, Wikström, Sandblad, & Andersson, 2006). The high workload in terms of manual control and oral communication makes it difficult to keep the other actors up-to-date on the situation in order to create a shared understanding, in particular in a dynamic situation that requires constant adjustments. As Comfort et al. (2004) explain, when the information requirements for coordination increases, the cognitive capacity of human decision-makers to process the expanding amounts of information decreases. Under high workloads, actors are confronted with an information-overload in which it is difficult to determine what should be shared. Consequently actors limit themselves to their formal tasks and important but non-formalized information is no longer properly communicated (Bharosa et al., 2010; Steenhuisen, 2009; Sutcliffe & Vogus, 2003). With components stretched to their performance limits, the system's overall control of the situation can collapse abruptly (Branlat & Woods, 2010; Woods & Branlat, 2011a).

Another interesting finding, related to the previous one, is the low centrality scores for the actors in the OCCR (NTC and NOC). Closeness centrality can also be seen as indicating the independence of nodes. Nodes with a high closeness centrality can act autonomously and navigate freely across the network to access information in a timely manner (Kim et al., 2011). As a centralized monitoring centre we would expect the OCCR to be within close reach of the other actors in the network. The low closeness centrality scores (NTC, 0.170; NOC, 0.161) show that this is not the case, which means that the OCCR is heavily dependent on the information it receives from the regional control and operating centres. The actors in the OCCR often need to actively collect the information from the regional centres. This can turn the OCCR in a bottleneck in the decision-making process when considerable exchanges of information are required and channels for this exchange are difficult to maintain (Branlat & Woods, 2010). An often heard complaint is that the OCCR makes decisions based on outdated information of local situations. The low centrality scores of the NTC and NOC in this particular case might however also have to do with the nature of this (small-scale) disruption.

In addition, we calculated the density, diameter and centralization in order to define the overall network structure. The low density score and high diameter of the network show that it is relatively loosely coupled. As there are often no direct ties between nodes, information will have to pass along many actors before reaching the intended recipient and actors will therefore have limited access to information. Given the large amount of nodes on the line of communication there is a high chance that information gets distorted, as errors typically accumulate in retellings. In addition the network might prove less efficient than a dense communication structure, as information might not reach actors in time. It is however difficult to decide upon the right amount of integration of a network, as more ties between nodes will also lead to a higher complexity and thus higher coordination needs (Carroll & Burton, 2000). For instance, Hinds & McGrath (2006), found that dense communication between distributed teams was associated with more coordination problems, while hierarchy of communication led to smoother coordination.

Finally, the time slices revealed that information is being shared within disconnected parts of the network during the first few minutes, without those parts having a direct link to the source of the information. We know from our observations that operators frequently make decisions based on experience. They anticipate that a situation will unfold itself according to earlier experiences and already start to manage the disruption without having full knowledge on the situation. This ties in with the tension between fast-decision making and gathering the complete information to make an informed decision mentioned before. Inevitably, decisions based on incomplete information could also lead to ineffective or counterproductive solutions (Quaglietta, Corman, & Goverde, 2013).

2.8 CONCLUSIONS

We set out to test the utility of Dynamic Network Analysis (DNA) as a network tool in order to investigate the communication patterns during the management of a disruption in the Dutch railway system and how this structure might influence coordination. The Dutch railway system is a networked system in which several organizations and teams, separated by geographic and organizational boundaries, manage disruptions. It is therefore important to understand how these actors connect and share information during a disruption. DNA makes it possible to capture the irregular flows of information during a disruption. The tool was applied to a simulated case of a catenary failure to visualize and analyze the network of interdependent actors and tasks over time.

Our research question was: how can DNA help to investigate coordination between the geographically distributed teams involved in the management of a railway disruption? DNA as a method seems to perform well in describing and structuring the complex information flows during disruption management. Even the first, still static, overview of the overall network has given a systematic overview of the communication patterns and tasks during the development of a solution for the catenary failure. Key actors could be defined using the centrality values and the overall structure was described using network-level measures. This revealed the central roles of the train dispatcher and regional traffic controller, and the decentralized structure of the network along with the long lines of communication.

The dynamic nature of disruption management is captured through the time slices. The network changes shape over time and to understand this change requires such time slices. The analysis showed that there is a considerable variation in the centrality of actors per time slice. For instance, the train dispatcher is mostly active communicating in the first minutes of the disruption (T1 and T3). The time slices also showed the emergent character of the network. In the first time slices the network quickly becomes highly connected as information on the disruption is shared between the different teams, but the network quickly becomes more fragmented as actors return to their own specific task. Time slices revealed that information is being shared within disconnected parts of the network during the first few minutes, without those parts having a direct link to the source of the information. These dynamics do not appear in the static image of the network with which we started. However, it forms an essential link between the different parts of the network. This aspect confirms Wolbers et al. (2013) finding that employing only static analysis of networks obscures the real dynamics of communication and potential coordination problems. DNA therefore makes it possible to discover issues that can be resolved (cf. Hossain & Kuti, 2010).

For the sake of a fair evaluation, we should also point to a limitation of DNA such as we encountered during the case analysis. While DNA allowed us to structure the information flows, we were unable to say anything about the content of the information that flows through the ties, or how actors respond to this information because it would be difficult to incorporate this in analysis and it would require an enormous amount of data. DNA reduces the ties between actors to being either present or absent, which in our case means information is flowing between actors or not. It is possible to classify the ties between actors by adding an attribute, i.e. information quality, but this mainly makes a contribution in terms of visualization and not for the analysis. For a comprehensive analysis of such disruptions, it would be necessary to combine a DNA with a qualitative analysis (Crossley, 2010).

Naturally, there are limitations on the data we used for this analysis and how the data was collected. The process mapping was focused on the first phase, directly after the catenary failure, and not on the return to the normal state after the disruption. We therefore cannot relate the findings from the network analysis to the performance of the network in terms of coordination outcomes. Secondly, process mapping might not give an exact representation of how actors behave during real-time operations, although it can be observed that actors have indicated that they deviate from procedures. Process mapping however makes it possible to create a detailed representation of the process and the information flows, which is supported by the whole team of representatives. Finally, the chosen case shows quite some resemblance with the standard operating procedures. Although many actors are involved, the case is relatively low in complexity. As such, solving it requires a great of deal of routine tasks. It can be expected that non-standardized disruptions force actors to deviate from their routines and procedures, which will most likely result in different network structures and information flows.

Given these considerations, we recommend applying DNA to larger and more complex disruptions and to combine DNA with qualitative data such as records of telephone conversations, when attempting to understand how and with what results actors in the railway network coordinate their activities to get the system back to a normal state. Of course, DNA could be used in other networked infrastructures to make operations visible and to identify coordination issues.