Detecting and disrupting criminal networks
A data driven approach
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Chapter 2

Social Network Analysis applied to criminal Networks
Recent developments in Dutch law enforcement

Objective: This chapter examines the application of social network theory in Dutch law enforcement. Increasing amounts of information about habitual lawbreakers and criminal networks are collected under the paradigm of Intelligence-Led Policing. Combined with data gathered from open sources such as social media, such resources allow criminal analysts trained in social network analysis (SNA) at the Police Academy of The Netherlands to apply advanced network analysis methodology and crime scripting. The objective of this chapter is twofold: 1) to inform the reader about recent developments of the application of network analysis in controlling crime in the Netherlands; 2) To offer insight into the practical application of network analysis in law enforcement, specifically applied to effectively target criminal networks.

Method: A case study of the 'Blackbird' crime network, involved in the wholesale cultivation of cannabis is presented to illustrate the power of SNA when combined with crime script analysis. Using a mix of quantitative and qualitative analysis, the topology of the 86-strong Blackbird network is laid out and its substructures and key individuals exposed. In detailing the network’s social embeddedness, the importance of female actors for the flexibility and efficiency of the network structure is clarified and thereby for the continuity of criminal business.

Network data: N= 86 nodes

Results and Conclusion: Applying SNA is already helping criminal intelligence units of the Dutch police in identifying intelligence gaps and potential informants. Working in symbiosis, analysts and informant handlers develop a better understanding of strategic targeting and access points to relatively unknown criminal communities and markets. To be delivered in a timely way to be useful in ongoing criminal investigations, SNA products require even faster data processing. Also, when applied to dark networks SNA should be tailored to better take network dynamics into account, in particular regarding the adaptability to network disruption.
2.1 INTRODUCTION

Criminal networks can be defined as networks operating outside the boundaries of the law, for which network achievements come at the cost of other individuals, groups or societies (Milward & Raab, 2006; Morselli, 2009). Across the globe criminal networks have a significant impact on national defense and security. Criminal networks try to infiltrate legal businesses and governments, infecting economic branches with violence and corruption. Moreover, upcoming threats like cybercrime, child pornography, maritime piracy, match fixing, illegal logging and identity theft, cause substantial harm to society and require proactive interventions to target the criminal networks underlying them (Europol, 2011; UNODC, 2010).

Government and law enforcement agencies therefore seek ways to effectively disrupt criminal network structures, preferably at an early stage. Since criminal networks face a constant threat from government agencies as well as aggressive criminal competitors, network members tend to evade detection and intervention (Milward & Raab, 2006). This makes it difficult to assess and collect reliable criminal network data. Therefore criminal network structures remain largely unknown as compared to other types of empirical networks (Morselli et al., 2006; Xu et al., 2009; Lindelauf et al., 2009). Consequently, little empirical knowledge concerning the impact of different disruption strategies on criminal networks is available to policymakers and law enforcement agencies.

The Netherlands has a relatively long tradition in controlling and studying organized crime. Over the years different paradigms have shaped the way in which law enforcement strategies against organized crime were applied. In the late 1980s Dutch law enforcement agencies thought of criminal organizations as hierarchical structures, leading to prolonged and extensive investigations targeting the presumed ‘Capo di Tutti Capi’ at top of the pyramid. Only recently have criminologists acknowledged organized crime from a different perspective through the social network paradigm [Sparrow, 1991; Kleemans et al., 2002; Morselli et al., 2009; Spapens, 2010]. Gradually this paradigm is being adopted within the Dutch law enforcement intelligence community, now leading to innovative ideas about law enforcement strategies.

Two important opportunities for network analysis have contributed to this development. First the Dutch Police have invested in the process of Intelligence-Led Policing, leading to an increased focus on collecting information in the frontlines of law enforcement. Consequently, more detailed data about network members and their illicit activities now become available within different police databases. Secondly research shows that more and more information about criminal network members can be found in bright networks, e.g. within online communities (Décay-Hétu & Morselli, 2011; Dijkstra et al., 2012). Dutch
law enforcement agencies are experimenting with the retrieval of such open source intelligence for operational purposes.

The increased availability of data on criminal networks enables network analysis on two levels. First, it offers opportunities for scientific research in network analysis, aimed at revealing how these criminal networks operate and how they react following network disruption. These insights offer a better understanding for law enforcement decision makers in estimating the effectiveness of different criminal disruption strategies in general (e.g. Morselli & Petit, 2007; Bright & Delaney, 2013). Secondly, network analysis is becoming an important method within operational intelligence projects, leading to more strategic ways of targeting criminal networks. To stimulate this development, the Dutch Police Academy currently offers police analysts special training in Social Network Analysis (SNA), aimed at applying this additional analysis tool in both criminal investigations and strategic intelligence projects. Which lessons can be learned from this application of network analysis in crime control? What are the practical implications of applying network analysis in targeting criminal networks and strategic intelligence gathering? What does dynamical network analysis research tell us about the effectiveness of criminal network disruption? How does the network paradigm connect with law enforcement decision-making? These are the questions this chapter aims to address.

The aim of this chapter is thus twofold: First, to inform the reader about recent developments of the application of network analysis in controlling crime in the Netherlands. Secondly, to offer insight into the practical application of network analysis in law enforcement, specifically applied to effectively target criminal networks.

The remainder of this chapter is as follows: Section 2 describes the evolution of three different paradigms for organized crime, and how this shaped control strategies across time. Section 3 describes the results of a case study of SNA used to understand the structure and resilience of a cannabis cultivation network. Following the limitations and challenges of this case study, Section 4 describes the recent progress and developments within overcoming these challenges within the application of SNA in Dutch law enforcement. Section 5 ends of this chapter with an overall conclusion.

2.2 THREE PARADIGMS OF ORGANIZED CRIME

This Section discusses the evolution of three different paradigms of organized crime, as well as their impact on control strategies. This is illustrated by developments within Dutch law enforcement over the last 30 years.
Organized crime was first recognized as a relevant phenomenon for Dutch law enforcement in the mid-1980s, when narcotics traffickers were found to engage in worldwide smuggling operations connecting dozens of operators and making enormous profits (Klerks, 2000). When the first crime analysts began to draw up their reports on criminal gangs around 1988, they portrayed mostly hierarchical groups in which often dozens of criminals worked under a division of labor on (most often) the import and distribution of hashish, heroin and cocaine. Every group had a clearly identified leadership, and the strategy by which the police attempted to tackle them was mostly to intercept and confiscate drug shipments and arrest those involved. The idea was to build up pressure on a group's business, and thus force the supposed organizers in the background to expose themselves and show their hand. ‘Dismantling criminal structures’ and sentencing ringleaders to long prison sentences, so it was thought, would counter organized crime. This strategy resulted in major confiscations and some prison sentences of ten years, but it soon became clear that the intercept rate never reached more than about 20 percent of the estimated total drug markets.

In the early 1990s, while most academic researchers still shied away from studying organized crime, the police and public prosecutor's office began to understand the Dutch narcotics underworld through such metaphors as a ‘monkey rock’ or ‘octopus’: a more or less integrated and hierarchical criminal conglomerate in which markets were divided and coordinated through negotiations and occasional conflicts. This called for a ‘war on crime’, including drastic measures such as the deployment of criminal informants who were allowed to grow into a position where they would be able to provide incriminating information on the supposed premier league of criminal masterminds. Such ‘growing informants’ could not always be kept under control. One such resourceful informant was permitted by his police handlers to bring shipments of thousands of kilos of cannabis, hashish, ecstasy and cocaine on the market while customs authorities conveniently looked away. When this came to light in 1994, a traumatizing scandal erupted of which the shock waves are noticeable even today. A parliamentary inquiry followed, and by the year 2000 Dutch criminal investigation procedures had become as strict as anywhere in the world.

This hierarchical pyramid or bureaucracy model of organized crime, while appealing to enforcement practitioners and some journalists, has never attracted interest or support from Dutch academic researchers. Their interest was raised substantially however when, in the wake of the 'IRT affair', four of the leading Dutch criminologists were tasked with writing a thorough and comprehensive study of organized crime in The Netherlands. In 1996 their authoritative report changed the perception of organized crime. Criminal gangs and entrepreneurs were found to have gained footholds in several inner-city areas and branches such as prostitution and parts of the catering industry. There was however no
sinister master mind at work: most criminal markets were relatively open for competition, with varying sets of illegal entrepreneurs often profiting from lax or gullible branches of local government. Thus, organized crime became conceptualized as mostly entrepreneurial in nature, with fluid criminal groups working in clandestine logistical arrangements to overcome the challenges of serving illegal markets. Consequently, crime control strategies became more sophisticated with an explicit responsibility for administrative bodies to impose tighter controls on permits in vulnerable branches and city areas (Van de Bunt & Van der Schoot, 2003). Also, attempts were made to increase the financial investigative capacities of the police and more interventions were aimed at reducing criminal opportunity structures and controlling chokepoints in criminal business processes. Criminal ‘facilitators’ were targeted that bridge the gap between illegal entrepreneurs and their legitimate environment providing them with financial and logistical services, thus blocking money laundering channels and the acquisition of apparatuses for producing narcotics (Nelen & Lankhorst, 2008).

From the mid-1990s onwards, dozens of researchers in the Netherlands became involved in empirical studies of organized crime phenomena [Kleemans et al. 1998; 2002; Van de Bunt & Kleemans, 2007]. With the police now more open to outside scrutiny and public debate, it had become much easier for serious scholars and their students to gain access to police files. Many detailed and extensive studies appeared, allowing for a more knowledge-based crime control policy. Both the police and the justice department commissioned their own periodical crime monitors and threat reports and gradually, a mild consensus formed on the approximate size and shape of the organized crime problem (Kruisbergen et al 2013; Nationaal Dreigingsbeeld 2004; Korps landelijke politiediensten (2008); Boerman et al 2012; Staring et al (2005); Soudijn 2006; Spapens 2006; Spapens et al (2007); Zaitch 2002). Since around 2002 the social network approach to organized crime has become increasingly popular, initially among academic students of organized crime and through their teaching and involvement in crime control projects, also among a new generation of analysts and investigators. Where initially the concept of ‘criminal networks’ was amply defined, serving rather as an antithesis to the traditional paradigm of rigid hierarchical organizations, researchers like Klerks (2000, 2001), Kleemans (Kleemans et al. 2002) and Spapens (2006, 2010) advanced this to include the micro-level of networks (criminal groups or ‘collectives’) forming and operating in the context of criminal macro- and meso-networks. The macro network in theory is worldwide and connects all able and willing (potential) offenders through criminal relations. In practice this macro network clusters into smaller meso-networks, thus establishing criminal opportunity structures located in specific periods times and areas.
From the academic literature through teaching and intellectual osmosis, the social network model gradually began to permeate police reports. In 2005, the Board of Chiefs of Police brought out their strategic vision paper ‘Politie in ontwikkeling’ (Police in development) which contained concepts like the ‘nodal orientation’ inspired by the thinking of Manuel Castells ((Projectgroep Visie op de politiefunctie, Raad van Hoofdcommissarissen 2005). This nodal orientation implied that the police can only be effective in a network society if they organize surveillance and intervention capabilities on the ‘nodes’ through which streams of people, products, money and information flow such as airports, seaports, highway inter-changes and the Internet. A popular handbook on net-centric strategies in law enforcement, distributed for free among policymakers and practitioners, further helped to familiarize these audiences with networking concepts (Roobeek & Van der Helm 2010). Police researchers and analysts gradually became acquainted with more technical network applications through social network analysis courses given at the Police Academy and from internal reports such as Neve (2010), and they began to use them in their work. Currently, nearly one hundred law enforcement analysts have passed the Police Academy exams in SNA and an increasing number of them apply their SNA skills in either operational or strategic intelligence work. Some of them publish their experiences in articles and internal reports, such as Bosveld (2010) on the application of forensic SNA in cold case investigations, Visser (2013) on post-intervention re-adjustments in the modus operandi of a criminal network, and Van der Horst et al. (2013) on the time-saving application of SNA for targeting criminal youth gangs.

Current conceptualization of organized crime in the Netherlands centers on the notion of illegal entrepreneurship serving illegitimate markets including narcotics, human trafficking, stolen vehicles, illegal arms trade and irregular waste disposal. Holland being a trade and transit rather than a production economy, its mirroring illegal economy also has a predominant character of international trade with the important exception of producing marihuana and synthetic drugs. Four conceptual dimensions are now considered important in combating organized crime:

1. the criminal business processes and logistics (and the ways to disrupt them);
2. the physical infrastructures enabling illegal entrepreneurs to unobtrusively produce and ship their merchandise;
3. the social networks that spawn criminal cooperation and conflicts;
4. the financial streams that provide energy and motivation to the ‘underworld’, connect it with the ‘upperworld’ and allow investigators to link discrete organizers and their social entourage to the repellent crimes from which they profit (Verantwoording aanpak georganiseerde criminaliteit 2012, 2013).

All four of these dimensions profit from the tools and techniques of social network analysis, and the insights they can provide.
2.3 A CASE EXAMPLE: UNRAVELING THE BLACKBIRD NETWORK WITH SNA

The previous Section explained how network theory is getting increasing attention within both criminology and Dutch law enforcement agencies involved in organized crime control. The interest for this paradigm among intelligence analysts also influences the way some police commanders and public prosecutors in the Netherlands think about the current control strategies for organized crime. As described above, the development of a practical SNA training course for intelligence analysts at the Dutch Police Academy has stimulated this development and leads to a growing number of explorative case studies. Besides empirical knowledge of criminal network problems, these case studies offer great lessons for the operational application of SNA. In this Section one of these case studies is presented, specifically demonstrating the advantages, limitations and challenges of the practical implementation of SNA within Dutch law enforcement.

Description of Operation Blackbird and Research Questions

In the autumn of 2007 an investigation team within a regional police department in the Netherlands started criminal investigation Blackbird against a criminal group involved in organized cannabis cultivation. This operation was part of project Umbrella, the goal of which was to target a regionally active but extensive criminal network involved in multiple forms of organized crime, such as cannabis cultivation, ecstasy production, cocaine trade, extortion, violence and even first degree murder. The objective of operation Blackbird was twofold: (1) to target the core members (‘big fish’) of the criminal network that were specifically involved in organized cannabis cultivation; (2) to retrieve additional intelligence about criminal network members within the embedding criminal network. Operation Blackbird lasted for nine months in total, leading to the initial arrest of eleven suspects and a final conviction of the three presumed core members (the big fish) for involvement within a criminal organization.4 The operation was considered a success, because the first goal of catching the big fish was achieved.

However analysts and detectives working within project Umbrella soon retrieved signals that although the three important network members were convicted and detained, this didn’t stop the remainder of the criminal network to continue their cannabis cultivation activities. It showed that the cultivation network was highly resilient against network disruption and didn’t fall apart as implicitly expected at the start. Therefore public prosecutors and law enforcement managers evaluating the case asked themselves how the network’s

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4 Within Dutch Penal law, ‘participation within a criminal organization’ is an independent misdemeanor punishable under article 140 of the Dutch Penal Code.
resilience could be explained. An answer to this intelligence question might contribute to the adjustment of future law enforcement strategies.

A team of three analysts involved in the Social Network Analysis (SNA) training program at the Dutch Police Academy started a search for the answers using SNA methodology. The primary question of the analysis was twofold: what is the structure of the Blackbird network and how did it contribute to the observed resilience against law enforcement interventions? An implicit third question was: can SNA methodology help in targeting these criminal network structures more effectively from the start?

**Data Sources and Research Design**

As usual, the analysis process started with the identification of possible data sources and collection of data. In conventional SNA research, data are mostly collected by taking surveys from all members of the studied social network, including questions about the origin and nature of their mutual social relationships (Hanneman and Riddle, 2005). Unfortunately, most criminal network members don’t like to be asked questions about their criminal activities, nor are they easily approached to discuss their mutual criminal relationships (Van der Hulst, 2009). Therefore the first challenge in the criminal network analysis field is collecting substantive relational data with enough content to interpret the nature of mutual relationships. In general, most SNA practitioners within criminology therefore turn to criminal investigations as a main source of data. These investigations involve wiretap data, eyewitness and suspect statements and surveillance data over a certain period of time, containing valuable clues about the nature of social and criminal relationships, specific language used, ways of communication and participation in (criminal) activities of members in a criminal network (Klerks, 2001, Kleemans et al. 2002; Natarajan, 2006; Morselli, 2009).

**Data Collection**

Operation Blackbird was part of a larger operation Umbrella, covering multiple criminal investigations aiming at different criminal hotshots at the same time. Additional relational data about the Blackbird network members could therefore also be retrieved from four other operations during that same time period. This strengthened the validity of our observations, because every network representation based on criminal investigations data is biased to a certain extent toward its initial objectives (Morselli, 2009). Because these four operations had different objectives, this validity problem could be confined. Initial relational data were therefore retrieved from extensive wiretap data sets, eyewitness statements, suspect statements and surveillance data from these four investigations, to be combined into one dataset.
In addition to these primary data sources data from social media were also obtained. A quick scan within different Internet communities such as Facebook and Hyves, showed that several members of the Blackbird network were actively participating in these social network sites. These data contained additional relational information revealing other (social) relationships within the embedding Blackbird network.

**Data Processing**

The data where processed using different actor-by-actor matrices and graphs as described by Scott (2000) and Hanneman and Riddle (2005). In addition, we used the UCINET 6 and Netdraw software package (Borgatti, Everett and Freeman, 2002). One of the central research questions was to reveal features from the network structure that contribute to its resilience. Some detectives of the investigative team pointed already at the importance of family—and affective relationships for its social structure. Following this hypothesis, it was decided to distinguish between the following types of connection according to the type of relationship between actors, including:

1. Criminal ties
2. Kinship ties
3. Affective ties.

For every type of relationship another actor-by-actor matrix was processed, in order to compare the different networks at a later stage.

**Combing SNA with Crime Script Analysis**

In addition to exposing the criminal network structure through the social network analysis method, ‘crime script analysis’ adds insight into the individual positions of actors within a criminal network. Cornish (1994) was one of the pioneers describing criminal markets in terms of crime scripts. Following this method a crime script is a systematical blueprint of the different phases of a criminal business process, that each consist of different facets. The permutation (possible combinations to pass all phases) is an indicator of its flexibility. In other words, the more options (facets) built into the crime script to pass the different phases, the more resilient the crime script is against disruption. Sparrow (1991) already emphasized that this method could be very useful in intelligence analysis to identify actors with unique roles.

Bruinsma and Bernasco (2004) combined crime script analysis and social network analysis to describe the flexibility within the criminal markets of heroin trade, trafficking in women and car theft. They found some evidence that the structure of criminal networks was shaped according to the features of the criminal activities and illegal markets, for instance the

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possible legal and economic consequences of the specific criminal activities. Additionally, Morselli and Roy (2008) integrated crime scripting with Social Network Analysis methodology in labeling different actors within a criminal network according to their involvement in the different phases and facets of the crime script of organized car theft. They identified the importance of brokers between the different roles in the crime script. According to Sparrow (1991) these actors have low ‘substitutability’ and are therefore interesting targets for network disruption, because this means that most of the criminal network depends on just a few actors for a successful outcome of the criminal business process. Sparrow (1991) emphasizes that disruption of actors with specific skills might have major consequences for the criminal network, as compared to actors involved in more general tasks or roles. Crime script analysis is therefore an essential additive to contemporary social network analysis methods in the criminal intelligence toolkit.

In accordance with the previous studies, crime script analysis was also used to unravel the structure of the Blackbird network. One of the selection criteria for actors to be included into the Blackbird network is involvement in organized cannabis cultivation business. Cannabis cultivation is a complex and delicate criminal business, involving many roles and tasks. Based on observations in the data and studies by Morselli (2001), Spapens et al. (2007) and Emmet and Broers (2009), the configuration of the crime script of organized cannabis cultivation was retrieved (see Figure 2.1).

Figure 2.1 Crime script of cannabis cultivation (Emmet and Broers, 2009; Morselli, 2001; Spapens et al. 2007)

To integrate the crime script analysis in the social network analysis framework an actor-by-variable matrix was used to assess the participation of each actor in the different phases of the cannabis cultivation business process (See Table 2.1). In this way tasks or roles

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6 Unfortunately a fully detailed description of the different phases and facets of the organized cannabis cultivation process is out of scope of this chapter. For a more detailed description see Spapens et al. (2007) or Potter et al. (2008)
could be identified that are thinly populated within the overall network structure. Actors representing these roles might be difficult to substitute (Sparrow, 1991).

Table 2.1: Example of integrating crime script analysis within an actor by variable matrix

<table>
<thead>
<tr>
<th>Arranging location</th>
<th>Building plantation</th>
<th>Taking care of plants</th>
<th>Harvesting</th>
<th>Storage processing</th>
<th>Distribution</th>
<th>Etc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
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<tr>
<td>0</td>
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<td>0</td>
</tr>
</tbody>
</table>

**Consideration About Data Validity**

All data-sources (wiretaps, statements, reports) were scored on these variables by the three analysts at the same time. This required intensive discussion of interpretations of language used by the actors in their communication. As a form of counterstrategy the actors within the Blackbird network often used coded language when referring to (specific) illegal activities, accomplices or locations, which would be susceptible to multiple interpretations (Klerks, 2001; Morselli, 2009). This constituted a major risk to data validity, as conversations between actors had to be interpreted in a similar way by all three analysts. To ensure this consistency, fifty wiretap conversations were scored by all three analysts separately and checked on differences in interpretation. This check was often repeated.

Sometimes coded language was easily overlooked. In some conversations the actors talked about ‘getting a cup of coffee’ for example. In the context of conversations later on in time, it was found that this was code language for ordering specific cannabis growth necessities. Therefore, processed conversations had to be rechecked in order to preserve data validity. In addition to coded language the use of nicknames made it difficult to identify individual actors. In the end it seemed two presumed different actors were actually one and the same individual. Fortunately, this could be corrected afterwards within the actor-by-actor matrix by merging the two identities. To keep track of such changes and make these considerations transparent, every decision was noted in a log file.

**The Boundary Specification Problem**

After all raw network data were processed into the different matrices, the question arose which actors to include or exclude from the analysis (Sparrow, 1991; Coles, 2001; Krebs, 2002; Van der Hulst, 2009). This ‘boundary specification problem’ might affect the structure and scope of the criminal network. Therefore, selection criteria for boundary specification have to be set prior to the analysis process (Scott, 2000: 54). These selection
criteria might be based on theory or practical considerations derived from the principal research questions.

Police reports and wiretap data on the Blackbird network showed that actors were involved in more than one criminal activity. Some actors combined cannabis trade with the production of synthetic drugs and firearms trade. Our analysis was focused on actors from the Blackbird network involved in organized cannabis cultivation. Therefore, the decision was made to apply the criteria of ‘involvement in cannabis cultivation’ for inclusion or exclusion from the final dataset. This meant that actors involved in one or more facets of cannabis cultivation process were included, leading to a network consisting of 88 identified actors. As two actors were recognized as isolates, the final network representation consisted of 86 actors in total. This was the starting point for answering the intelligence questions.

**Quantitative Analysis of the Blackbird Network**

For simple networks network visualizations are often useful for analyzing the features of network structure. However, for bigger networks these visualizations soon resemble plates of spaghetti, in which individual positioning is difficult to identify with the naked eye. To overcome this problem, the SNA toolbox contains numerous algorithms that can be used to calculate individual actor features within the densest of networks. SNA practitioners, like some intelligence analysts, are often confronted with the dilemma of which algorithms to use to answer a specific research question. Choosing the right algorithms for a specific research question requires a high level of understanding of all possibilities and their implications. In order to decide which SNA algorithms are suitable for answering the research questions Roberts and Everton (2011) introduce an analytical framework that divides network structure into three levels:

1. System level
2. Subgroup level
3. Individual level

Within SNA methodology distinctive measures are associated with these different levels of network structure. This classification gives SNA practitioners a good reference for choosing the right algorithms to use. Roberts and Everton (2011) point out that in order to fully understand network structure it’s essential to understand all three levels. Baker and Faulkner (1993), Robins (2009) and Morselli (2009) all emphasize that features of individual positioning and subgroups within illegal networks can only be interpreted properly, if the overall network topology is understood in the first place. Robins (2009) even points specifically at the symbioses of individual psychological features and properties of network topology. These practitioners call for an integrated analysis of the different levels of criminal network structure, to understand the way these criminal networks operate. Elaborating from these considerations, this same analytical framework was used to unravel the structure of the
Blackbird network in relation to its network resilience. In this next Section the results of this quantitative analysis are described.7

**Blackbird Network Topology**

SNA offers many measures to analyze network topology. According to Hanneman and Riddle (2005) and Everton (2011), the five most important measures for network topology are: centralization, density, average degree, average path length and network diameter. Table 2.2 shows the results of applying these algorithms on the overall Blackbird Network (N = 86).

<table>
<thead>
<tr>
<th>Measures of network topology</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degree Centralization</td>
<td>58.50%</td>
</tr>
<tr>
<td>Betweenness Centralization</td>
<td>41.47%</td>
</tr>
<tr>
<td>Density</td>
<td>0.07</td>
</tr>
<tr>
<td>Average degree</td>
<td>6.44</td>
</tr>
<tr>
<td>Average path length</td>
<td>2.25</td>
</tr>
<tr>
<td>Network diameter</td>
<td>5</td>
</tr>
</tbody>
</table>

In SNA terms, a degree centralization of 58.49 % and betweenness centralization of 41.47 % indicate that the network gravitates around a few central actors who have relatively more direct connections in the network than the rest of the network. It means that there is a distinction between a core and periphery in the network. This implies that peripheral actors depend on a few central actors for their information and resources flowing through the network. According to network theory this gives the central actors a powerful and influential position in the network (Hanneman and Riddle, 2005).

The third important metric for unraveling network topology is density. This metric is defined as the total number of ties within a network divided by the total possible number of ties, which means that network density measures range from 0 to 1. Density gives insight in the speed at which information diffuses among the actors and the extent to which the actors in general have high levels of social capital (many connections) (Everton, 2011; Hanneman and Riddle, 2005). Density within the Blackbird network is relatively low (0.0663). In network theory this means that information doesn’t spread effectively through the network. This again emphasizes that there are actors who depend on other actors for their information about network activity and are therefore not that well connected.

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7 A full description and explanation of all possible SNA measures would go beyond the scope of this chapter. For an extensive overview of these measures, see Hanneman and Riddle (2004).
This interpretation is further underpinned by the results for average degree centrality. This algorithm represents the average number of direct connections of actors in the network. A high score for average degree means that actors are very well connected. Actors in the Blackbird network have an average of 6.44 direct connections. The total network consists of 86 actors. This means in theory that every actor can have a maximum of 85 \((N - 1)\) connections. In this sense 6.44 average direct connections per actor is quite low.

Finally, the average path length and network diameter were calculated. Average path length is calculated by finding the shortest path between all pairs of nodes, adding them up, and then dividing by the total number of pairs. This shows, on average, the number of steps it takes to get from one actor within the network to another. Network diameter is equal to the longest of all the calculated shortest paths in a network. Table 2.2 shows that actors in the Blackbird network can reach each other in an average of 2.2 steps with the longest distance between two actors in the network being 5 steps apart.

In sum, analysis of network topology showed the network is centralized (58 %), but that it has a rather low density (0.066) and average degree (6.44). This means that the network gravitates around (a few) central actors and that there are less connections throughout the network. However, the average distance between actors in the network (2.2) indicates information flows fast, meaning that most information and resources has to pass through the central actors to become available to other actors within the network. This suggests that a substantial part of the Blackbird network is dependent on these central actors for their information and resources. A further understanding of these mathematical results follows from the sociogram of Figure 2.2. It reveals that a high number of single link actors form a “loose” periphery, that is connected by a just few actors with the dense core of the network.
Substructures Within the Blackbird Network

In the previous Section we analyzed the network as a whole. In fact this was a top-down approach to unravel its structure. In this Section we will analyze the Blackbird network from a bottom up approach, as we seek for substructures that keep the network together. SNA methodology covers many different measures for identifying substructures of groups within a social network (Hanneman and Riddle, 2005). Here we apply two of the most common algorithms for identifying substructures: K-core analysis and clique analysis.

The K-cores metric uses degree centrality to identify clusters of actors that are tightly connected. This approach doesn’t pay attention to the degree of individual actors in the network but to the degree of all actors within a cluster (Evans, 2011). A cluster is called a K-core, for which K indicates the minimum degree of each actor within the cluster. This means a 3-core cluster contains all actors that have three or more ties to other actors.

The results of the K-cores analysis of the Blackbird network are shown in Figure 2.3a, b. Figure 2.3a shows that the network gravitates around a highly connected 6-Core, represented as the red actors in the graph. Figure 2.3b zooms in on this core, representing the 6-Core (in red), 5-Core (in blue and red combined) and 4 Core (in green, blue and red combined). The 6-core sub-network consists of 17 actors in total. Calculation of the

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8 See Hanneman and Riddle (2005) for a complete overview of all possible algorithms to identify subgroups.
topological measures of the core network of 3b, reveals that density is higher (0.3) then for the overall network and diameter is shorter (2.0) (Table 2.3). This supports the hypothesis that the network is highly centralized around and gravitates around a tightly knit core.

Figure 2.3 The K-core distribution is visualized as part of the total network (2.3a). Secondly its core structure is visualized in 2.3b, depicting different K-core levels: 6-Core (red nodes), 5-Core (red and blue nodes combined) and 4-Core (red, blue and green nodes combined)
Table 2.3: Topological features of the core of the Blackbird network

<table>
<thead>
<tr>
<th>Measures of network core (minimum of 4-6 connections)</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degree centralization</td>
<td>34.0 %</td>
</tr>
<tr>
<td>Betweenness centralization</td>
<td>22.4 %</td>
</tr>
<tr>
<td>Density</td>
<td>0.31</td>
</tr>
<tr>
<td>Average degree</td>
<td>10.9</td>
</tr>
<tr>
<td>Average path length</td>
<td>1.7</td>
</tr>
<tr>
<td>Network diameter</td>
<td>2.0</td>
</tr>
</tbody>
</table>

Within SNA every measure has its own approach. Therefore, it’s essential to combine different measures in order to draw any conclusions about network structure (Evans, 2011). Based on the results for the K-Core analysis, another important method to identify subgroups in the overall network is clique analysis. In essence, a clique is a sub-set of a network in which the actors are more closely and intensely tied to one another than they are to other members of the network. In a clique all nodes are connected to every other node (Hanneman and Riddle, 2005). Clique analysis offers a second “bottom up” approach to understanding network structure. It focuses attention on how solidarity and connection of large social structures can be built up out of small and tight components (Hanneman and Riddle, 2005). The result for the clique analysis of the Blackbird network are depicted in Figure 2.4a, b. Figure 2.4a shows the number of cliques in relation to its members. Clique analysis thus confirms that the Blackbird network is built up out of a total of 64 tightly knit coalitions (cliques). It also shows that some actors are part of many different cliques (actor 1, 2, 3). Although there are many cliques identified within the Blackbird network, they tend to stay small in size. Figure 2.4b shows the biggest clique identified (N = 8) as part of the total network (N = 86).

In sum, the K-Core analysis shows that the Blackbird network is built around a tightly connected core of actors. This might be an explanation for its network resilience. Hence, when actors 1, 2 and 3 were arrested the rest of its core members were mutually well-connected to prolong the cannabis production process. Furthermore the clique analysis shows that the Blackbird network is built up out of numerous small coalitions (cliques) within both its core and its periphery. In theory this adds more flexibility to the network’s structure and strengthens the chance that ties between the core members and (essential) peripheral actors become restored. In short, the particular structure identified offers resilience against network disruption. If one coalition falls apart due to arrests, there is a great chance that remaining actors can fall back on other coalitions and reestablish the lines of production.
Figure 2.4 Results for clique analysis of the Blackbird network with a Biggest clique b Involvement of actors (red circle) in the identified cliques (blue square)
**Individual Positioning Within the Blackbird Network**

The previous Section offered one explanation for the network’s flexibility against disruption caused by the criminal investigation. In order to find additional evidence for this hypothesis, we need to zoom in on the individual level of the network. Networks consist of individuals that have different influence and power within the network. Understanding individual actors’ properties in terms of influence and power is important for understanding overall network structure. One of the most significant measures related to influence and power is actor centrality (Hanneman and Riddle, 2005). There are many different measures to estimate centrality. The most commonly used centrality measures are listed and explained in Table 2.4.

<table>
<thead>
<tr>
<th>Table 2.4</th>
<th>Common measures to estimate centrality (Hanneman and Riddle, 2005)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degree centrality:</td>
<td>Number of direct contacts that an actor has</td>
</tr>
<tr>
<td>Bonacich Power</td>
<td>The extent to which an actor is connected to other actors that score high in degree centrality</td>
</tr>
<tr>
<td>Closeness centrality</td>
<td>Indicates how close each actor is to all others</td>
</tr>
<tr>
<td>Betweenness centrality</td>
<td>The number of paths that connect pairs of nodes that pass through a given node</td>
</tr>
</tbody>
</table>

Table 2.5 shows all scores for the top 15 actors on these centrality measures. Not surprisingly these different measures for centrality reveal that actor 1 and 2 are in highly central positions within the network. Although they might have a lot of influence within the network, the relatively low scores for Bonacich Power (32 %) reveal that they might in fact not be all that powerful in network terms. Bonacich (1991) argued that being connected to others that are not well connected makes someone powerful, since such actors are dependent on you—whereas well-connected actors are not. So according to Bonacich an actor’s power in networks depends not solely on their own connections, but mostly on the connections of their direct neighbors.

We can explain this further by looking at the graph of Figure 2.4a representing the size of the nodes according to the scores for degree centrality. Although actor 1 and 2 score high on degree centrality, a representative part of their direct neighbors within the core of the network, are well-connected themselves. This means that these neighbors aren’t solely dependent on actor 1 and actor 2 for their resources or information. According to network theory this reduces the power that actor 1 and 2 have over the core members, as they are self-sufficient for their resources and information. However, Figure 2.2 reveals that the actors in the periphery of the network are often dependent on actor 1 or 2 for their

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9 For a full description of these measures see Hanneman and Riddle (2005).
participation in the cannabis cultivation process. This might give actors 1 and 2 a strategic advantage and an opportunity to apply power to these peripheral actors.

<table>
<thead>
<tr>
<th>Actor</th>
<th>Degree</th>
<th>Bonacich Power</th>
<th>Closeness</th>
<th>Betweenness</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>55</td>
<td>32.3</td>
<td>73.9</td>
<td>0.444</td>
</tr>
<tr>
<td>1</td>
<td>53</td>
<td>31.8</td>
<td>70.8</td>
<td>0.388</td>
</tr>
<tr>
<td>3</td>
<td>36</td>
<td>20.4</td>
<td>57.4</td>
<td>0.132</td>
</tr>
<tr>
<td>14</td>
<td>23</td>
<td>21.9</td>
<td>56.3</td>
<td>0.018</td>
</tr>
<tr>
<td>8</td>
<td>21</td>
<td>20.4</td>
<td>55.9</td>
<td>0.019</td>
</tr>
<tr>
<td>7</td>
<td>20</td>
<td>18.3</td>
<td>55.3</td>
<td>0.034</td>
</tr>
<tr>
<td>10</td>
<td>13</td>
<td>15.7</td>
<td>52.5</td>
<td>0.005</td>
</tr>
<tr>
<td>19</td>
<td>13</td>
<td>15.2</td>
<td>52.1</td>
<td>0.002</td>
</tr>
<tr>
<td>31</td>
<td>13</td>
<td>14.4</td>
<td>51.8</td>
<td>0.006</td>
</tr>
<tr>
<td>20</td>
<td>12</td>
<td>13.6</td>
<td>51.8</td>
<td>0.005</td>
</tr>
<tr>
<td>9</td>
<td>12</td>
<td>13.5</td>
<td>51.5</td>
<td>0.008</td>
</tr>
<tr>
<td>24</td>
<td>11</td>
<td>13.5</td>
<td>51.5</td>
<td>0.002</td>
</tr>
<tr>
<td>36</td>
<td>11</td>
<td>12.8</td>
<td>51.2</td>
<td>0.002</td>
</tr>
<tr>
<td>4</td>
<td>11</td>
<td>10.2</td>
<td>50.6</td>
<td>0.056</td>
</tr>
<tr>
<td>13</td>
<td>11</td>
<td>10.0</td>
<td>51.2</td>
<td>0.007</td>
</tr>
</tbody>
</table>

More evidence for this assumption can be found in the individual scores for betweenness centrality (Table 2.5). The size of the nodes in Figure 2.5b represents the score on betweenness centrality. It reveals that actor 1, 2 and 3 score high on betweenness as opposed to the remainder of the network. The graph indicates they form a bridge between the network’s periphery and core. According to network theory, betweenness centrality is associated with strategic advantage. Burt (1992) offers a theoretical framework for understanding this phenomenon and found that having quick access to information offers some actors abilities to fill positions that allow them to seize rewarding opportunities. The entrepreneurial opportunity that follows from the position of ‘bridge’ between two separated parties is called a structural hole. According to Burt (1992), actors with the capacity to enrich their personal network with a proportionally higher set of structural holes may come to control other actors in the network. Morselli (2001) specifically studied brokerage positioning in criminal networks of career criminal Howard Marks in the international cannabis trade. Morselli found that the key to Marks’s successful criminal career was that he structurally stayed in between different criminal groups. This brokerage position contributed to his reputation and strategic advantage in the worldwide criminal macro network.
In accordance with Burt (1992) theoretical framework, brokerage positioning within the Blackbird network was analyzed. First, the results of betweenness centrality analysis reveal that actors 1, 2 and 3 score high on potential brokerage positions. In addition, structural
hole analysis reveals that actors 7, 8, 9 and 14 often occupy a structural hole position. As these specific actors were left out of the scope of the investigation and final arrests, this could be an additional explanation for the observed network resilience after intervention. These results might offer another explanation for network resilience. Hence, this analysis reveals that the structural holes that are left behind by the arrested actors 1, 2 and 3 could with a non-zero probability be occupied by actors 7, 8, 9 and 14.

In sum, analysis of the individual positions within the Blackbird network, revealed that the network is built around two highly connected actors. Betweenness centrality (Table 2.5) shows that these actors are also important hubs for the flow of information and resources throughout the network. Figure 2.5b shows that this brokerage role connects the ‘loose’ periphery with the tight core of the Blackbird network, making actors 1 and 2 influential actors. However, the results for the Bonacich power analysis (Table 2.5) reveals that their power might be reduced, because they are connected to well-connected others. Figure 2.5a shows that these well-connected others (high degree) are part of the network core (N = 32). This can be acknowledged by the structural hole analysis, which revealed that actors 7, 8, 9 and 14 are often in structural holes position themselves. Referring to network resilience this means these actors might play an important role in network recovery, in case actor 1, 2 and 3 become arrested.

The aim of this analysis was to unravel the structure of the Blackbird network and how it managed to continue with cannabis cultivation after law enforcement interventions. To search for the answers, we used quantitative social network analysis to unravel the Blackbird network structure on three levels: network topology, substructures and individual positioning. Through analysis on all network levels, different network properties could be identified that might have contributed to the observed network resilience against a major enforcement intervention. Although this gives us some answers, it also leaves us with a lot of additional questions: What causes this network to be highly centralized? How can the high level of redundancy within the core of the network be explained, compared to the non-redundant periphery? What are the characteristics of the central actors and their ‘independent’ well-connected neighbors? Answers to these question are essential for making any meaningful recommendation for law enforcement tactics. This is the point where mathematical methods and qualitative methods of social network analysis converge. The next Section describes how qualitative features of the Blackbird network can place the observed Blackbird network structure into a different perspective.

**Qualitative Analysis of the Blackbird Network**

Many SNA scholars have emphasized the importance of integrating individual characteristics within the study of criminal networks (e.g. (e.g. Carley et al., 2002; Morselli, 2009,
Robins, 2008; Varese, 2012). Although quantitative methods offer us direction of interesting network features, qualitative methods are essential for placing these results in the right context or even revealing other aspects of network structure that cannot be calculated. As described above, detectives who worked many hours on the Blackbird investigation, pointed in the direction of an embedding social structure of kinship and affective relationships as an important explanation for the observed flexibility within the criminal network structure. Based on this hypothesis kinship and affective relationships were scored in different matrices in addition to all observed criminal relationships. The graph of Figure 2.6 shows the results for combining these different networks matrices.

As in the previous graphs, criminal relationships are visualized by gray lines. More interesting in this graph is the way in which the network structures of affective ties (red lines) and family ties (green lines) are intertwined in the core of the criminal network. Another interesting feature in relation to this network's structure is revealed by visualizing male (blue nodes) and female (pink nodes) actors. Figure 2.6 shows, that women are an essential part of the core, suggesting they might hold influential and powerful positions within the Blackbird network. Additional evidence for this hypothesis was already found.
in the quantitative results on individual centrality measures (Table 2.5), for which five of the most central actors are female. But how do these women end up in these influential positions in the network? The answer can be found in the social network in which the criminal activities were embedded.

**The Social Embeddedness of the Blackbird Network**

Figure 2.7a displays this embedded social network of combined affective (red lines) and kinship (green lines). It reveals that actor 2 is most important for introducing women in the network. Evidence for this is found in many wiretap conversations over the six-month time period and in statements made by some of these women after the final arrests. These police reports show that actor 2 was a skilled networker who applied his organizational skills not only in his criminal environment but also in his social life, as he managed to maintain affective relationships with different women at the same time. Furthermore it shows that as these women were introduced into the network by actor 2 over time, they became accepted within the tight social core surrounding actor 1 and 2. Some women even started new love affairs within this social network, after their relationship with actor 2 had ended. An important factor in this respect, deriving from the surveillance reports and wiretap data, is that all activities within this social structure seem to gravitate around a small geographic infrastructure of cafés, hangouts and restaurants.

Furthermore, as these women became members of this social core, they became connected to other women in the network (see Figure 2.7b). Various wiretap conversations and surveillance reports show that besides their progressing influence in the social network, most women were introduced to the illegal activities of cannabis cultivation. The development of trust seemed to play an important role in this. Different suspect statements reveal that as these women proved themselves to be reliable and loyal members of the embedding social network, they were allowed to participate in criminal activities. Moreover, newly-introduced women began to establish mutual criminal relationships between themselves. Figure 2.7b presents the criminal relationships observed between female actors.
Figure 2.7  a) Visualization of the embedded social network of combined affective (red lines) and kinship (green lines). Red nodes correspond to females and blue nodes correspond to males in the Blackbird network. b) Criminal relationships between females after they had entered the embedded social network.
Although some of the women played important roles in coordinating different phases of the cannabis cultivation process, they were ignored as serious suspects in the Blackbird operation. These findings are consistent with a study of Kleemans and Van de Bunt (1999) on the ‘social embeddedness’ of organized crime. Based on their analysis of 40 cases of organized crime, they found that women were not only important for maintaining and establishing contacts between different parts of the criminal network, but were in some cases in charge of a whole criminal association. They concluded that the importance and influence of women in terms of social embeddedness in organized crime is often a blind spot in law enforcement control strategies.

In addition to these affective relationships, another important part of the embedding structure of the Blackbird network was formed by kinship ties, as indicated by green lines in Figures 2.6 and 2.7a. These graphs show that Kinship ties play an important role for the observed redundancy within the network’s core. In addition, based on quantitative measures for network positioning, it was already concluded that actor 14 is an influential actor often positioned on a ‘structural hole’ position within the network. In fact, qualitative analysis shows that actor 2 is his father. These findings support the idea that actor 14 might have inherited his father’s criminal achievements (and possibly reputation) and therefore his social and criminal capital. This observed generational heritage in criminal career opportunities, is consistent with observations made by Spapens (2010) based on his study of criminal ecstasy networks operating in the south of the Netherlands.

The importance of social ties for criminal network development was first addressed by Granovetter (1983). He introduced the theoretical concept of ‘the strength of weak ties’. According to Granovetter strong ties are important for illegal as well as legal transactions, because trust is built between like-minded actors. Especially within the hostile and uncertain environment of organized crime, strong ties of family, friendship and even love often offer a necessary fundament of trust. Different studies show that trust in criminal networks is often found in an embedded network of social ties (Hagan and McCarthy, 1995; Kleemans and Van de Bunt, 1999; Klerks, 2000; Morselli, 2001; 2009; Spapens, 2010). This is in accordance with our findings in the Blackbird network. The tight core of this network is formed not only through criminal relationships, but more importantly through affective and family relationships. Additional empirical evidence is found in the analysis of a high number of wiretap conversations between core members. Most conversations concern a mixture of social and criminal activities. In general it can be concluded that strong ties of affective and kinship ties form an important framework of trust, from which criminal activities in the Blackbird network originated.
Granovetter (1983) also emphasizes the importance of weak ties for expanding business opportunities. Weak ties are connections between people who are not intimate or close. In these relations mutual trust is not easily attained. But precisely because of this, these ties are not redundant and are therefore essential for access to new resources and information. Weak ties can therefore offer new opportunities, especially within an illegal enterprise (Kleemans and Van de Bunt, 1999; Klerks, 2000, Morselli, 2001).

Besides strong ties, the Blackbird network also consists of a high number of weak ties. The introduction of women in the Blackbird network is an example of this ‘strength of weak ties’ principle. In the beginning they are recognized as weak ties, but as the number of connections with the redundant core increases over time, these actors become trusted and serious participants in the criminal activities. Another example of this mechanism within the Blackbird network is the difference in observed redundancy between the core of the network and the embedding periphery. Most actors in the periphery of the Blackbird network are connected with the core of the network through a single tie with actors 1, 2 or 3 (Figure 2.5b). These connections are in fact non-redundant, but part of the network because of their direct involvement within the cannabis cultivation process. Qualitative analysis of these weak ties in the Blackbird network reveals that most of these actors are not ‘isolated’ freelancers, but often representatives or even brokers between the Blackbird network and other criminal networks that are connected with actor 2 for expanding their criminal business.

For instance, based on additional content analysis of wiretap data, it was recognized that actor 87 is an important representative of a foreign mafia organization and an important buyer of cannabis from actor 2 from the Blackbird network. Besides his criminal relationship with actor 2, he also had a short love affair with female actor 26 (Figure 2.5a). Female 26 seemed to have had an intimate relationship with actor 2 in the past. Although the investigative data doesn’t allow drawing a timeline of the initiation of these criminal and affective relationships, it’s evident that this social connection played an important role in the initiation of an export route of cannabis from the Blackbird network to Italy. The weak ties between the Blackbird network and the Italian Mafia network that offered new opportunities for the Blackbird network to market their illegal product, developed into a stronger tie over time due to social embeddedness. Based on these findings it can be concluded that the social embeddedness observed within the Blackbird network structure offers another explanation of its flexibility and resilience against disruption.

The ‘Division of Labor’ Within the Blackbird Network

In the beginning of this chapter the application of crime script analysis was explained to identify unique roles in the cannabis cultivation process. In Figure 2.8 the actor-by-variable
matrix of involvement in cannabis cultivation is visualized. Every link represents the involvement of an actor in a specific phase of the cannabis cultivation process. Actors of which role specific information was missing were left out in the final representation. However, even without the missing data this visualization shows a highly redundant division of labor, in which every task is covered by multiple participants. Based on crime scripting analysis, it was assumed that actors responsible for ‘manipulation of electricity supply’ would be thinly populated within the network, because of the specific skills and knowledge needed to complete this task. Figure 2.8 on the contrary shows that this ‘specialized’ task is covered by no less than five actors within the network. Qualitative analysis of the wiretap conversations reveals that these specific skills were learned in the network by actors through experience. This is a form of differential association described in classic studies of learning criminal networks (Sutherland, 1937; Hagan and McCarthy, 1995). In this way the network could efficiently replace these actors in case of arrest or other external interventions from its own redundant core network.

In addition, Figure 2.8 also reveals that the most central actors 1 and 2 are involved in many specific tasks themselves instead of delegating from a distance. On the one hand, this gives them a lot of control over the criminal business process, but on the other hand it increases their visibility and therefore their vulnerability. This could probably be one of the
explanations for their final arrests, which raises the question: might there be an external ‘supervisor’ from the periphery who was missed in this investigation? Unfortunately, answers to this question are out of the scope of the dataset.

Another interesting aspect of this division of labor is the position of women within the criminal process. Figure 2.8 shows that most females are involved in simple tasks, such as ‘harvesting’ and ‘helping with the installation’ of the plantation. The specific task of harvesting requires that these women were working together in a small and closed room for several hours. Qualitative analysis of the surveillance-, wiretap- data and eyewitness statements reveals that this was one of the reasons these women developed mutual social and criminal connections. Moreover it seemed that females 3 and 8 were also involved in tasks of coordination and leadership within the whole network. This is also observed within the ‘women network’ of Figure 2.7b, in which these females occupy a central position. Although female 3 got arrested in the end, female 8 might have played an important role in network recovery and reestablishing the division of labor within the whole process.

These findings for ‘division of labor’ are in line with research associated with the tradeoff between efficiency and security that is revealed within previous research (Erickson, 1973; Baker and Faulker, 1993; Morselli et al, 2006; Lindelauf, 2009). On the one hand illicit networks try to keep their illegal activities concealed from the government or criminal competitors. This means that direct communication between co-conspirators concerning illegal activities needs to be restricted to a minimum. On the other hand, risks have to be taken in times of action, often demanding highly efficient communication and trust among its participants (Erickson, 1981; Morselli, Giguère and Petit, 2006). This tradeoff shapes the way illicit networks are structured. For instance, criminal networks demanding high levels of action and therefore efficiency are often characterized by high levels of redundancy. Terrorist networks on the contrary often demand just one successful action to reach its network objectives. These network structures are therefore characterized by high levels of non-redundancy and compartmentalization in different cells (Krebs, 2001; Morselli and Petit, 2007). Terrorist networks use this strategy to decrease the risk of becoming detected by the arrest or detection of a single actor. Criminal networks also try to build in security, but as times-to-task are much shorter efficiency often predominates.

Analysis of the Blackbird network according to this theoretical framework reveals that a certain level of compartmentalization can be found in its network structure. Hence, there seems to be a clear separation between the network’s core and periphery, which might offer some security to core members if peripheral actors become arrested. However, the crime script analysis in combination with SNA reveals that tasks are divided in a highly redundant way, which is typical for ‘action-minded’ criminal networks (e.g. Morselli and
Petit, 2008). On the one hand this gives the network the advantage of flexibility in replacing actors after arrests or seizures, which is also observed in our analysis of the Blackbird network. On the other hand, this increases the risk for exposing the network as a whole if a single actor gets arrested. Hence, due to the high level of redundancy, chances are substantial that a single arrested actor is directly connected to the central actors 1 and 2. This increases the risk of exposing these important actors, for instance by tracking previous telephone calls. Apparently the low level of security within their network structure is exactly what ultimately caused the arrest of actors 1 and 2.

Conclusion
By combining quantitative and qualitative methods of SNA, the structure of the Blackbird network was unraveled. Quantitative analysis revealed that its overall network structure gravitates around a few central actors. These actors form a redundant core that is connected with a non-redundant periphery by just a few highly connected actors. These actors occupy strategic positions, but because they are connected to well-connected others their positions are not irreplaceable. Qualitative analysis reveals that the core of the criminal network is embedded in family and affective relationships. Women and children play an important role in this embedded and criminal network, as they add to overall network redundancy and fulfill coordinating tasks that become specifically important after their husbands and fathers become arrested. Crime script analysis revealed that this redundancy is also translated to the division of labor, for which all tasks can be fulfilled by multiple actors. In part this offers an explanation for the observed flexibility and resilience against disruption. On the other hand, it has been shown that this redundancy increases network visibility and offered opportunities for arrests. However, it can be concluded that these control strategies were ineffective, as the process of cannabis cultivation continued due to the flexibility and efficiency that is built into its network structure. Based on these conclusions it could be recommended in search for effective control strategies in the future to take notice of the active and important participation of women and direct relatives in the organization of criminal activities.

Discussion
As described in the beginning, this case example demonstrates how the application of Social Network Analysis (SNA) could be of value in understanding the effects of current control strategies and creating and adjusting future strategies aimed at these complex criminal network problems. This case study also demonstrates that applying SNA on criminal networks demands a twofold approach, integrating quantitative and qualitative methods. As was demonstrated in this case study, this is essential in understanding not only the answers to the ‘what’ questions, but also the important ‘why’ questions. For instance, an additional qualitative interpretation was crucial to understanding why women
occupied central positions in the core of the network. Answers to these ‘why-questions’ are therefore the key to really understanding the ‘covert’ mechanisms associated with criminal networks and for the translation of such insights into concise recommendations for law enforcement control strategies. This case-study therefore shows that the application of quantitative and qualitative methods of SNA together with crime script analysis constitutes a powerful tool for agencies confronted with criminal network problems. However, in addition to such advantages, the case study also revealed some important limitations.

First, practitioners should realize that the final representation of the criminal network is to a large extent a product of the boundary specification criterion and available data (Krebs, 2002; Morselli, 2009; Sparrow, 1999; Van der Hulst, 2009;). For instance, we observed based on qualitative analysis, that some ‘isolated’ actors in the periphery that were selected for their involvement in the cannabis cultivation process, were in fact representatives of other criminal groups. This emphasizes the fact that our observed Blackbird network is in fact part of a bigger macro-network (Spapens, 2010). Another important point to address is missing data. Our observations are solely based on investigative data. This naturally filters the data collection process and therefore the network representation to a certain degree according to the initial goal of the investigation (Morselli, 2009). This becomes especially important when interpreting the results from quantitative measures, such as centrality and individual positioning. The fact that actors occupy strategic positions in the local setting of the Blackbird network, doesn’t necessarily mean that they are powerful or influential in general. Placing quantitative results in a qualitative context is therefore crucial when using this method. The challenge for the practical application of SNA would therefore be to combine different sources of relational data, for instance intelligence data, street cop data, arrest records and ‘online’ data. Every source has its own filter through which we observe ‘reality’. Combining ‘filters’ might increase the reliability of the final network representation.

Secondly, one of the critical success factors within intelligence-led-policing is timely intelligence products. Time in this context is related to law enforcement demanding swift decision-making. Decision makers in law enforcement settings therefore want fast, reliable and concise advice (Ratcliffe, 2008). Social network analysis on the contrary is a time-consuming exercise. As shown in this case example, data have to be collected and processed in a structured way. Additionally, results need to be interpreted in the right context. The application of SNA within an operational law enforcement environment might therefore become problematic. The final results might only come available too little too late. The challenge for the practical application of SNA within organized crime control is therefore to find a way of processing data in a faster way.
Thirdly, like any social network, criminal networks aren’t static but dynamic (Carley et al., 2002). The structure of the network as well as its activities is ever-changing. Our case study focuses on the network configuration before the final arrests. This offers unique insights into the properties of network structure that explains its flexibility, but it doesn’t offer us insight in the way the network really adapted to the arrests. The challenge for the practical application of SNA in organized crime control would therefore be to find ways of observing these network dynamics and the network’s adaptability to network disruption.

These are tough challenges that are not easy to translate into practice. However, in the Netherlands these challenges are slowly becoming reality. In the next Section the progress and developments in the Dutch Police in answering these challenges will be discussed.

2.4 SNA AND RECENT DEVELOPMENTS IN DUTCH LAW ENFORCEMENT

As described above, this case study is one of the recent experimental examples of the practical application of SNA in current Dutch law enforcement. However, the issues and challenges that were addressed are no novelty, as they were already recognized before by Sparrow (1991). It can therefore be concluded that the implementation of SNA within the operational law enforcement environment is a major challenge, as two decades after Sparrow introduced and addressed these issues they are still topical in Dutch law enforcement. Yet this isn’t a lost cause, as there are promising developments that might help to translate network theory into SNA practice: the increasing availability of data on criminal cooperation and advances in SNA methods from computational science.

ILP and the Increasing Availability of Criminal Network Data

One of the important challenges for the practical application of SNA within criminal intelligence that Sparrow (1991) identified is creating an automated data-management system for parallel processing technologies in which different databases can be linked together in a structured way. Klerks (2001) was confronted with this challenge in his SNA-based study of Dutch criminal networks involved in international drugs smuggling. The initial coded data within the police databases turned out to be unreliable for SNA practice. For instance, specific persons were registered multiple times. The data had to be recoded all over again, requiring a lot of time and effort.

One reason for these data validity problems in Dutch police databases is that information gathering and processing aren’t always recognized as one of the primary tasks of law enforcement officers in the frontlines of police work. This often results in poor quality of data, especially about the more circumstantial features of observed criminal cooperation.
and communication which are important for SNA. For instance, within the Blackbird operation ‘social’ conversations between women in the network were labeled ‘irrelevant’ by detectives, but SNA of the Blackbird network revealed that these conversations specifically emphasized the importance of these women as ‘mediators’ in case of internal conflict. Therefore, the practical application of SNA within law enforcement in general depends for an important part on the ‘information-mindedness’ of police officers and detectives.

Still, compared to 10 years ago the general information quality and quantity in Dutch law enforcement shows progress. One reason is the introduction of the concept ‘intelligence led policing’ (ILP), which increased the general awareness of specific intelligence tasks involving daily police work (Ratcliff, 2008). This has resulted in the introduction of specified intelligence tasks during police surveillance, aimed at retrieving information from the direct observation and registration of ‘local heroes’ or ‘hot spots’ (e.g. bars, restaurants) associated with local organized crime. In practice, this has led to the recognition of ties between high profile criminals that weren’t observed before. Information collection is therefore increasingly recognized within Dutch law enforcement as a primary task of regular police work. It also helps that the 25 regional police forces in Holland were merged into one National Police in January 2013, facilitating the implementation of shared doctrine, ICT, and decision-making.

Another important development associated with the introduction of ILP is an increased awareness of the importance of powerful ICT tools for ‘user-friendly’ data processing in criminal investigations. Although data quality in general is still a concern, these tools are already showing increased uniformity and quality in data processing. These developments are still in their infancy, but they are promising for the effective application of SNA in the law enforcement environment. A more specific aspect of this development is the effective use of human intelligence (HUMINT) and social media intelligence (SOCMINT) for proactive law enforcement intelligence purposes. These developments will be discussed in the next Section.

**Human Intelligence**

Every regional police unit in the Netherlands maintains a Criminal Intelligence Unit (CIU). These CIU’s are specifically tasked with retrieving ‘human intelligence’ from criminal informants and have primarily been focused on assisting ongoing criminal investigations with supporting evidence. More recently, it is recognized that the CIU’s are also important for delivering proactive intelligence products aimed at discovering strategic trends in illegal criminal markets and the translation of such trends in effective operational targeting of subjects at the start of investigative operations. The growing symbiosis between analysts and handlers in the criminal intelligence process has strengthened this development. This
leads to a more goal-oriented intelligence collection process. For many years the search for criminal informants has been rather opportunistic, often the result of sudden opportunities following arrests in criminal investigations or conflicts between known criminal rivals. Although this remains a fruitful tactic for recruiting motivated informants, it mostly leads to more information on already familiar actors and well-known criminal markets. The biggest challenge for CIU’s is therefore to find potential informants in criminal networks or criminal topics that are still relatively unknown to the police, for instance cybercrime networks or human trafficking rings.

Following these considerations, SNA is increasingly recognized as an important method for intelligence analysts in profiling such potential informants and identifying opportunities for approaching them. For instance, SNA helps to identify criminal brokers within criminal networks that might function as potential ‘points of access’ to relatively unknown criminal communities and –markets. It needs no further explanation that these brokers might be high-potential sources of criminal intelligence. In this way SNA stimulates strategic thinking about proactively shaping intelligence positions according to novel trends in the criminal environment, as opposed to the traditional opportunistic selection of informants based on ongoing operations. Moreover, as this increases the validity and reliability of human intelligence databases, this offers chances for a more concise application of SNA with the aim of targeting criminal networks effectively.

**Social Media Intelligence**

A second development that offers improved opportunities for SNA in law enforcement is the increasing usage of open source intelligence in Dutch law enforcement. A growing number of studies reveal that Internet communities such as Facebook, Twitter and Google are not only used by criminals for ordinary social reasons, but also for expanding their criminal markets or even threatening criminal rivals (Décary-Hétu and Morselli, 2011; Decker and Pyrooz, 2009). Social Media Intelligence (SOCMINT) is therefore recognized as an indispensable source of operational intelligence about criminal network structures (Omand, Bartlett and Miller, 2012).

In practice, social media intelligence offers an opportunity to peek behind the social network structures embedding the criminal cooperation. For instance, it was found that some members of the Blackbird network shared the same hobby: sport fishing. Combining police information with the pictures they posted on social media posing with their fishing trophies, some new (criminal) ties in the criminal network could be revealed that had not been observed before. SOCMINT therefore offers a different perspective on underlying social network structures, often unknown to law enforcement. Still, the application of SOCMINT is associated with some difficulties. First, it takes some time to adjust legisla-
tion for the use of intelligence to encompass such exponentially expanding technological developments. This problem leads to tension between public goods of security on the one hand and citizens rights to the rule of law, liberty and privacy on the other (Omand et al. 2012). Secondly, Intelligence analysts are confronted with big data, which is near-impossible to analyze using traditional SNA analysis methods. Therefore, computational methods are essential in addition to traditional SNA for mining these big sources of data for relevant information, which will be demonstrated in chapter 5.

Validation of the results of these data mining methods on the Internet needs to be achieved by comparing them with other criminal intelligence sources and placing it in the context of the specific characteristics of the target (criminal) subgroup and social media platform. By using this data and knowledge to ‘train’ these computational models, validity and reliability of the results will increase over time.

Towards a ‘Real-time’ SNA Approach to Organized Crime

Following these previous considerations, it can be concluded that HUMINT and SOCMINT are in themselves important pieces for constructing the criminal network representation. However, this intelligence puzzle cannot be completed based on these data sources alone. Moreover, as criminal networks are dynamic in nature the developments within criminal networks following from these data-sources need to be monitored continuously. In Dutch law enforcement, these considerations have lead to a ‘real-time’ SNA approach for analyzing criminal networks. In essence, this approach consists of the structural integration and analysis of multiple data sources into one relational database. This method offers the opportunity of assessing ‘missing data’ in the criminal network representation (Morselli, 2009). This leads to the identification of ‘intelligence gaps’, which can be translated into topical intelligence collection plans (McDowell, 2009). For instance, an identified social tie between two known criminals that is identified based on SOCMINT can be translated into concise intelligence questions for criminal informants from a HUMINT approach to assess the nature of this relationship. Although verifying information in this way is already part of everyday police work, continuously and structurally combining multiple sources in the context of previously collected intelligence aimed at identifying criminal networks, is not always a matter of course. Because new information is continuously interpreted in the light of previous developments in the criminal environment, opportunities for identifying recent change in such networks arise. Identifying these changes is an important part of effectively targeting criminal networks at a certain point in time. However, it needs no further explanation that continuously monitoring different information sources by hand would be very time-consuming. Powerful ICT tools are therefore essential to this approach, because different data sources with varying data formats have to be integrated and merged
automatically into one relational database. State of the art database analysis tools, such as IBM’s i2 iBase, offer these ICT solutions with integrated visualization and SNA applications.

This approach has some important advantages for the application of SNA in law enforcement:

1. Data from different data sources can easily be validated with other data sources, leading to a more strategic approach for data collection.
2. Because data is collected and processed in an ongoing and automated process in a structured format suitable for SNA methodology, time is saved for actual SNA practice and making recommendations. This results in timely intelligence products that find the connection with the time-dependent decision-making cycle that characterizes operational law enforcement management.
3. Because new data are continuously analyzed, changes in criminal networks or criminal markets can be identified. The flexibility offered by this approach is important for recognizing chances for effective interventions at a certain point in time and offers the possibility to analyze criminal networks as dynamic structures instead of static snapshots.

**Combining Computational Methods with SNA**

Besides the application in retrieving relevant data from social media, computational methods are increasingly important for understanding the complex dynamics of criminal networks. Appreciating these dynamics may have major consequences for the way we think about the effectiveness of control strategies aimed at criminal networks. SNA scholars agree however that capturing network dynamics is one of the most difficult challenges in criminal network research (e.g. Morselli, 2009; Sparrow, 1991; Xu et al, 2004). The limited number of studies on this topic identifies four methods for capturing network dynamics: descriptive, statistical, simulation and visualization methods (Doreian 1997; Xu et al., 2004). Descriptive methods are focused on structural changes in social networks by comparing structural properties across time. These structural changes are associated with changes in nodes, links or groups within the network. The statistical approach is not only focused on structural changes but also involves an evaluation of the reasons for such changes, for instance the effect of gender for preference in social bonding. Simulation methods rely on multi-agent technology, for which actors are modeled as agents making decisions based on specific criteria. These criteria are translated into algorithms. Visualization methods aim at comparing network maps at certain points in time through visual inspection (Doreian, 1997; Xu et al. 2004).

An example of the application of descriptive and visualization method was recently presented by Bright and Delaney (2013). These authors studied the evolution of a drug
trafficking network and found that participants change their specific role in the crime script based on needs, as opposed to simply recruiting replacements to fill those needs. Secondly, they found that these changes have a direct impact on the centrality of single actors in the network. Bright and Delaney (2013) emphasize that law enforcement needs to respond flexibly to these changes in network composition. However, one of the important limitations of this study was that the observed changes in the network could be artifacts of intelligence collection methods.

Capturing network dynamics with simulation modeling is less sensitive to this type of bias, as network behavior is not empirically observed but simulated with multi-agent technology. This method offers the opportunity to perform “what-if” scenarios to study how social networks adapt to different external shocks (Xu et al., 2004). A computer simulation methodology applied to a large criminal network (N=29,345 nodes) will be presented in chapter 4.

Although study presented in chapter 4 aims to understand these criminal network dynamics in general, this multi-disciplinary method might have direct relevance to the operational law enforcement environment. As these models can be ‘trained’ and adjusted over time by the increased availability of empirical criminal network data, this approach might become a powerful method for pro-actively experimenting with “what-if” scenarios and strategically thinking about intervening effects on live criminal networks. Secondly, these models might contribute to the identification of ‘telltales’ often hidden in the data, which might function as an early warning for upcoming criminal activity, travel movements, unusual financial transactions or changes in criminal network structures. These early warnings might be translated into proactive, well-timed and specifically targeted control strategies. Combining SNA and practical law enforcement knowledge with simulation methods and the increased availability of data may therefore become an integral part of proactive organized crime control in the near future.

2.5 CONCLUSION

The aim of this chapter is to inform about recent developments of the application of network analysis in controlling crime in the Netherlands. It offers insight into the practical application of network analysis in Dutch law enforcement, specifically applied to effectively targeting criminal networks. Based on the developments described in the chapter, some conclusions can be drawn about the practical implementation of SNA: (1) It can be concluded that SNA is a useful method for unraveling the structure of criminal networks. It offers renewed understanding of hidden social structures that might be of direct relevance
to strategic planning within organized crime control. (2) The strength of SNA within law enforcement becomes most evident if quantitative and qualitative methods are combined. This places the quantitative results in the necessary context. (3) The biggest limitations of traditional SNA methodology (as applied in the case study) are that it’s time consuming, static and often too little too late in the eyes of law enforcement decision makers. (4) Due to an increasing ‘information mindedness’ within Dutch law enforcement in general and availability of advanced ICT applications, new opportunities arise for a data driven approach to SNA in law enforcement. This makes it possible to combine multiple data-sources, which can be connected and integrated automatically. (5) The progress with this approach is strengthened by strategic planning in the field of human intelligence (HUMINT) and social media intelligence (SOCMINT) gathering. The ultimate goal of this approach is to establish a ‘real-time’ intelligence position on organized crime, from which topical changes in criminal network structures, compositions and activities can be monitored and identified. This offers timely opportunities for proactive control strategies. (6) Simulation methods from computational science might play an important role in understanding these complex criminal network dynamics in the near future. Not exclusively in contribution to the field of science, but also towards operational organized crime control.

In resemblance with the fluidity observed in such criminal network structures, these developments show that the practical application of SNA in Dutch law enforcement is not at all static. Moreover, as the net-centric doctrine of organizing law enforcement cooperation between various agencies and partners becomes more accepted and implemented, flexible criminal networks and law enforcement networks begin to show increasing similarities. While government agencies will always be restrained by legal requirements and subject to budget restrictions, they appear to become somewhat more attuned to the fluid and opportunistic tactics of illicit entrepreneurs. Aided by advanced analytical methods such as SNA, they may become increasingly effective in tackling vital elements of the criminal machinery.

For the near future, law enforcement organizations will at least formally continue to resemble the geometric hierarchy that every civil servant knows as the line-and-block chart, while criminal entrepreneurs will operate in the fluid, random and seemingly chaotic environment that we have come to conceptualize as networks. It is not hard to comprehend that agile and flexible entities unrestricted by laws will often succeed in outsmarting rigid and policy-obese government agencies, even though the latter have the law on their side. Social network analysis provides the guardians of society with a better understanding of the mechanics of criminal networks. As they gradually learn to appreciate some of the benefits of networking, law enforcement and intelligence organizations may become more effective at their core business of safeguarding society.
This chapter demonstrates the application of SNA in Dutch Law Enforcement and its additive value following the in-depth case example of the Blackbird network. In order to fully understand SNA's opportunities and limitations however, we need to look further its application across the different types of criminal networks and within the different settings that are typical for Law Enforcement practice (e.g. youth gangs, organized crime, fraud schemes). The next chapter therefore provides an empirical overview of recent SNA case studies applied to different criminal network problems in Dutch law enforcement. Based on the structural aggregated analysis of these case studies (N=39) we elaborate on the feasibility and potential of SNA as part of a data-driven approach to the study, detection and disruption of criminal networks.
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