# ENRICHING KNOWLEDGE NETWORKS – CONSIDERING SYNERGIES BETWEEN SOCIAL NETWORK ANALYSIS, COMMUNITIES OF PRACTICE AND KNOWLEDGE MAPS

by

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**THESIS**

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*I would like to dedicate this thesis to:*

*Professor Adeline du Toit, who inspired me to conduct this research. It was a thought-provoking journey. Thank you for your support and your perseverance even through difficult times. Words cannot express my appreciation.*

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*Willem and Willa Davel, my adoring parents. Without your support and encouragement I would never have been able to accomplish this.*

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# Abstract

The constructive management of existing knowledge and the access to and development of new knowledge has become essential to organisations. Since tacit knowledge can often not be captured or documented, knowledge is often created and shared through social interaction within organisations. Relationships are thus fundamental to knowledge creation and knowledge transfer and the various forms of social networks existing within organisations play a primary role in leveraging these relationships. This study followed the socialisation philosophy as reflected in the works of Nonaka and Takeuchi (1995) and Hansen et al. (1999), where the creation and sharing of knowledge occurs primarily by way of social interaction between individuals. The said interaction typically occurs within informal networks, also known as knowledge networks (Helms & Buijsrogge 2006).

In recent times there has been a growing awareness of social network analysis (SNA) as an instrument to plot knowledge and expertise as well as to confirm the character of connections in informal networks (Cross et al. 2004; Chan & Liebowitz 2006; Müller-Prothmann 2006; Murale & Raju 2013; Cooke & Hall 2013; D'Errico et al. 2014). In line with the aforementioned studies, this study intended to investigate how the integration of networking into KM can produce significant advantages for organisations.

This research intended to outline a method for organisations to strengthen their social capital by analysing, shaping and reinforcing their knowledge networks, thereby enhancing the manner in which they share and create knowledge. Subsequently the main research problem of this study was to investigate how knowledge networks can be improved as a result of synergies between SNA, CoPs and knowledge maps. The researcher attempted to illustrate via this question that cultivating synergies between SNA, CoPs and knowledge maps will enable organisations to produce stronger knowledge networks and ultimately increase their social capital.

In order to execute this study, the researcher developed a process map with the aim of demonstrating exactly how knowledge networks could be advanced as a result of synergies between SNA, CoPs and knowledge maps. This process map - which answers the "how" in this question - is presented as the new contribution that this study makes towards any organisation wanting to reinforce knowledge networks. It is anticipated that this research will enable organisations to enrich their knowledge

networks and expand their social capital by building on the process map that was developed and implemented in this study.

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# List of Abbreviations

| Abbreviation | Definition |
|---|---|
| BI | Business Intelligence |
| CC | Commodity Control |
| CoPs | Communities of Practice |
| DAM | Data Analytics and Mining |
| ERGMs | Exponential Random Graph Models |
| ETL | Extract, Transform, Load |
| GIS | Geographical Information Systems |
| KM | Knowledge Management |
| KNA | Knowledge Network Analysis |
| ONA | Organisational Network Analysis |
| Q&A NETWORKS | Question and Answer Networks |
| QM | Queue Management |
| RIS | Regional Innovation Systems |
| SMC | Service Manager Cases |
| SNA | Social Network Analysis |
| SR | Single Registration |

# CHAPTER 1

***"Coming together is a beginning; keeping together is progress; working together is success."***

**- Henry Ford**

# 1 INTRODUCTION

Knowledge and innovation have become widely recognised as strategic resources that enhance the competitive advantage of organisations (Magnier-Watanabe *et al.* 2011; Itzkin 2000). As Dougherty (1995) points out, an organisation's competitive advantage is predominantly rooted in the intangible, tacit knowledge of its employees and these capabilities do not exist separate from those who acquired them. This notion is confirmed by Zhang *et al.* (2009) who mention that when tacit knowledge is actively obtained, created and shared within organisations, there is a higher likelihood of creating an enduring competitive advantage. In the modern day knowledge economy the ability to manage knowledge has thus become imperative as the creation and distribution of knowledge has become vital to organisations' competitiveness (Dalkir 2011:2).

Wiig (2000:3) accentuates the fact that knowledge management (KM) involves a wide range of disciplines. As a result of this multi-disciplinary nature several KM approaches and models, depicting the KM cycle, have materialised (Davenport & Prusak 1998). According to Alqahtani *et al.* (2012:143-144), four of the most popular KM models include:

- the Karl Wiig KM model (1993) that stresses the belief that in order for knowledge to be useful and valuable, it has to be organised;
- Nonaka and Takeuchi's (1995) SECI model that categorises the KM process in relation to socialisation, internalisation, externalisation and a combination of practices;
- the KM model identified by Davenport and Prusak (1998) defining the KM process as generating, codifying and transferring knowledge; and
- Alavi and Leidner's (2001) KM model that associates KM process with the creation, storage and retrieval, transfer and application of knowledge.

Song and Lee (2007) distinguish between two general KM approaches namely technological and non-technological approaches. *Technological approaches* to KM, also known as a techno-centric approach, uses information and communication technology to capture, codify, store, disseminate and reuse knowledge within organisations. Conversely, the *non-technological approach* is much more people centred and focuses more on managerial, social and cultural techniques to manage organisational knowledge.

Since large amounts of tacit knowledge cannot really be captured or documented, knowledge is often created and shared through social interaction between people (Nonaka & Takeuchi 1995:8, 57, 60, 72, 85). Weick and Westley (1996) and Araujo (1998) confirm that new knowledge as well as competencies can be indirectly generated and shared via dialogue and networking activities. These interpersonal relationships form patterns which are labelled social innovation capital or social capital (McElroy 2002:30).

Research indicates that relationships are critical to knowledge creation and knowledge transfer (Levin & Cross 2004:1477) and that the various forms of social networks that exist within organisations contribute fundamentally to the dissemination thereof (Murale & Raju 2013). This notion is underlined by Thomas (cited in van den Berg & Snyman 2003), who observes that *"… it is in communities that individuals develop the capacity to create, refine, share and eventually apply knowledge."* Allee (2000:5) adds to this by affirming that when knowledge work is at stake, *"… people require conversation, experimentation, and shared experiences with other people who do what they do …"* and that one cannot separate knowledge from *"… communities that create it, use it, and transform it."* It is thus important that organisations encourage the formation of communities in order to promote knowledge sharing and learning.

In the words of Dalkir (2011:2): *"An organisation in the Knowledge Age is one that learns, remembers, and acts based on the best available information, knowledge, and know-how."* Amidon (2002) supports this perspective by maintaining that innovation and knowledge creation depend considerably on existing knowledge networks within organisations, and by what means these networks consider or inhibit diverse knowledge domains from being connected in new and meaningful ways.

This study aims to join the non-technological KM approach, more specifically the socialisation school of thought, as reflected in the works of Hansen *et al.* (1999) and Nonaka and Takeuchi (1995), where the creation and sharing of knowledge occurs primarily by means of social interaction between individuals. The said interaction usually occurs through informal networks, also known as *knowledge networks* (Helms & Buijsrogge 2006).

Social network analysis (SNA) provides a logical approach to discover, review and verify knowledge sharing processes within these networks (Müller-Prothmann

2007:219). Of late there has been growing awareness regarding SNA as an instrument to plot knowledge and expertise as well as to confirm the character of connections in informal networks (Cross *et al.* 2004; Chan & Liebowitz 2006; Müller-Prothmann 2006; Murale & Raju 2013; Cooke & Hall 2013; D'Errico *et al.* 2014). While these works focus primarily on connections between SNA and CoPs; or relations between SNA and knowledge maps, this study intends to present a process map aiming to enhance organisational social capital by strengthening the synergies that exist between SNA, CoPs and knowledge maps.

## 1.1 THE NATURE OF THE RESEARCH PROBLEM

Since its appearance in the 1930s, SNA has grown into a practice that offers visual and statistical elements to analyse the attributes of individuals and their relationships (Scott 1988:109-110). Like KM, SNA has been employed in a variety of disciplines. The importance of SNA as an instrument that can be applied to examine the social- and knowledge networks within organisations is underscored by Badaracco (1991:13-14) who points out that *"…in an age of rapidly proliferating knowledge, the central domain is a social network that absorbs, creates, transforms, buys, sells, and communicates knowledge. Its stronghold is the knowledge embedded in a dense web of social, economic, contractual, and administrative relationships."*

Seufert *et al.* (1999) maintain that organisations are progressively transforming from well-defined, manageable structures into interwoven network structures with blurred boundaries. As a result it is important to recognise that the creation and transfer of knowledge is increasingly taking place within a network environment as opposed to within traditional organisational boundaries. In short, network relations and the proficiency to manage networks have developed into significant drivers of a new way of conducting business.

This study intends to investigate how the integration of networking into KM can produce significant advantages for organisations. The aim of the research is to examine a process or methodology that can have an effect on the interactions between SNA, CoPs and knowledge maps concerning knowledge networks. This research aspires to outline a method for organisations to strengthen their social capital by analysing, shaping and reinforcing their knowledge networks, thereby enhancing the manner in which they share and create knowledge. Consequently, the main research problem of the study was to investigate:

How can synergies between SNA, CoPs and knowledge maps reinforce knowledge networks?

The researcher endeavoured to illustrate via this question that cultivating synergies between SNA, CoPs and knowledge maps will enable organisations to produce stronger knowledge networks and ultimately increase their social capital. The method or process map - which answers the "how" in this question - is presented as the new contribution that this study makes towards any organisation wanting to reinforce knowledge networks.

## 1.2 RESEARCH OBJECTIVES

In order to resolve the said problem, the following sub-problems were addressed:

1.2.1 Establish the level of interaction with the actual experts in knowledge networks by linking key network positions with the experts pinpointed in knowledge maps.

1.2.2 Determine whether any correlation exists between the levels of CoP participation and network positions held by individuals.

1.2.3 Investigate how the establishment of CoPs and the distribution of knowledge maps could influence knowledge network structures, specifically in terms of cohesion, cut-points and hubs.

1.2.4 Examine in what way CoPs can influence network connectivity considering whole-network assessments.

The effect of interactions between SNA, CoPs and knowledge maps on knowledge networks were determined by concentrating on the aforementioned sub-problems. The methodology applied to influence the effect of interactions was designed, analysed and documented to present a potential contribution towards formalising a process map that can be used to improve synergies towards:

- better sharing and creation of knowledge; and
- analysing, shaping and reinforcing knowledge networks.

## 1.3 RESEARCH APPROACH

Goddard and Melville (2001:1) emphasise that research revolves around knowledge discovery and creation and that good research is *"... systematic in that it is planned, organised and has a specific goal."*

Considering that studies pertaining to knowledge embedded in existing social networks are somewhat new (***Section 1.4***), the researcher pursued a pragmatic paradigm as both qualitative and quantitative research methodologies were applied. Accordingly the researcher followed an abduction approach and designed the research as a cross-sectional study with a simple mixed method approach, namely *explanatory sequential mixed methods* (these research methodological choices are discussed in detail in ***Chapter 4***).

A cross-sectional, mixed methods research approach was thus followed to demonstrate the influence SNA, CoPs and knowledge maps could have on knowledge networks.

Data collection was conducted via questionnaires (considering information regarding knowledge maps as well as SNAs); in-depth, semi-structured group interviews as well as indirect unobtrusive measures, in this case computer based data logging.

Research was conducted in three phases. During the preparation phase the research sample population was identified, buy-in was obtained, research instruments were developed and information was collected considering which subject matters employees within the division should be proficient in.

In the next phase knowledge maps (based on proficiency and experience in terms of years) regarding predefined subject domains were constructed and revised based on management input. Thereafter a SNA with a KM approach (KNA) was performed. Subsequently four different online CoPs were constructed and members in the division were invited to participate. During this time the results of the knowledge maps were also communicated. Two months after the CoPs came into existence, a follow-up SNA was conducted, involving only members who joined the respective CoPs.

In the final phase, five types of networks, namely: *knowledge*, *recurrence*, *access*, *level of engagement* and *trust*, were constructed. In addition, four separate knowledge networks (based on the subject matters that employees were most interested in) were assembled. All of the aforementioned networks were constructed at two points in time after which the results of the different cases were compared. Knowledge maps were assessed according to visual network maps based on degree centrality scores (***Section 5.2.1***). CoP commitment and participation levels were linked to positions individuals occupied within knowledge networks. Cliques, cut-points and hubs within the respective knowledge networks were compared to illustrate the effect CoPs and knowledge maps had on knowledge network structures. Finally a whole-network assessment comparison was conducted to reveal the effect CoPs could have on connectivity in knowledge networks and knowledge relationship networks.

## 1.4 VALUE OF THE RESEARCH

A vast number of KM methods and KM tools are being recommended to advance the management of knowledge within organisations. Heisig (2009:4) managed to collect a total of 160 KM frameworks from science, practice, associations and standardisation bodies around the world while *The European Guide to Good Practice in Knowledge Management* (2004) alone, registered approximately 90 KM methods and KM tools. While many of these tools have by now reached a plateau of productivity (i.e. best practices) some tools are still at phases of enlightenment (i.e. virtual teams), inflated expectations (i.e. real-time collaboration) or technology triggers (i.e. corporate blogging) (Rao, 2005:61). Even so, as far as the researcher could establish, very little research, that examines interrelationships of different KM tools and the potential synergies among them, has been published. Furthermore, as stated by Filieri (2010:x), research has indicated a rising interest in SNA as a tool for mapping knowledge and capabilities as well as to record the nature of relationships within informal networks. Murale and Raju (2014:51-52) also mention that a literature gap exists regarding knowledge rooted in existing human networks. The chosen topic is thus very relevant to organisational practice and therefore requires academic scrutiny and research as a result.

Associating knowledge maps (in terms of expertise) with CoP participation and knowledge network positions will enable organisations to integrate underlying expertise as well as to confirm that the correct sources are being approached for information. Moreover, productive CoPs require a variety of members such as brokers, thought leaders and managers and KNA can assist in pinpointing contenders for these types of roles (McInerney & Koenig 2011:60). The value of this study lies in the methodology that was designed and tested in this case and which is presented as a process map in ***Chapter 6***. It is envisaged that this process map will offer organisations an approach to analyse the synergies between SNA, CoPs and knowledge maps to help evaluate, shape and reinforce its knowledge networks and ultimately strengthen their social capital.

## 1.5 THESIS OUTLINE

This chapter offers the basis for this study. It presents the research problem, clarifies the research objectives, defines the research approach and considers the significance of the research.

The literature review is presented in ***Chapters 2*** and ***3***. It discusses the connection between social capital and KM and offers an overview of the difference between knowledge networks, social networks, KNA and SNA.

***Chapter 4*** deals with the research methodology applied in order to conduct this study. Information regarding data collection, together with the nature, type and size of the population selected for this research is also discussed in this chapter.

The results of the research are presented and deliberated in ***Chapter 5*** with the main findings being emphasised at the end.

***Chapter 6*** concludes this study by reiterating the principal discoveries of the research and incorporating these into fundamental problem statements. It also discusses the value and recommendations of the findings, suggesting areas for future research.

# CHAPTER 2

*"The most useful information is rarely that which flows down the formal chain of command in an organisation, or that which can be inferred from price signals. Rather, it is that which is obtained from someone you have dealt with in the past and found to be reliable."*

**- Walter W. Powell**

# 2 LINKING SOCIAL CAPITAL AND KNOWLEDGE MANAGEMENT

Knowledge networks are becoming increasingly important in the modern-day interconnected world we live in (Pugh & Prusak 2013:79). This chapter aims to accentuate the connection that exists between social capital and KM in order to highlight the importance of knowledge networks within organisations. To begin with this chapter defines the terms 'social capital' and 'knowledge management'. Thereafter different social network structures for explicit, tacit and potential knowledge are discussed, followed by a debate around the relationship between social capital and KM.

## 2.1 EXPLAINING SOCIAL CAPITAL

Alguezaui and Filieri (2010:892) identify Judson Hanifan as the first person to formally articulate the concept *social capital* in 1916. They also point out that even though contemporary literature on social capital recognizes authors such as Jane Jacobs and Glen Loury's works as the antecedents of the modern concept of social capital, these authors never presented a detailed analysis of the concept. On the other hand the term *social capital* can be fundamentally attributed to the works of Bourdieu (1985), Coleman (1988) and Putnam (1993, 1995, 2000).

As a result of functional and ideological reasons, social capital exhibits rather diverse definitions. According to Claridge (2004), these definitions fluctuate primarily depending on whether their focus is *"…(1) on the relations an actor maintains with other actors, (2) the structure of relations among actors within a collectivity, or (3) both types of linkages"*. In essence, social capital deals with the belief that *"… social relationships have value."* (Putnam 2000:18).

According to the literature, two general views regarding social capital exist (Bakker *et al*. 2006:595). One perspective declares mere social relations to be social capital, where the size of one's social capital is measured by the number of ties one maintains. Burt (1992) describes social capital as *"know-who"* and maintains it is about *"… everyone you now know, everyone you knew and everyone who knows you even though you do not know them."* In addition, Smedlund (2008:65) maintains that social capital can be seen as *"a collective good"* located in the relations between people rather than in the people themselves.

There exist arguments that social ties can only be converted into social capital if they *"… assist an actor in the attainment of a particular goal"* (Gabbay & Leenders 2003).

Hamre and Vidgen (2008) support this argument by asserting that social capital revolves around an individual's relationships, the resources available via those connections and the competence of the individual to gain value from such relationships.

The fundamental aspect of social capital reflects the need for individuals to connect with others in order to look for resources that they do not have at their own disposal (Lesser & Prusak 1999). Thus, in order to possess social capital, one has to be connected to others, and it is those others, who are the actual source of one's advantage (Portes 1998:7).

Nahapiet and Ghosal (1998) maintain that social capital has three dimensions namely: *structural* (signifying network ties and relationships, as well as the ease with which one can join and integrate into a network), *cognitive* (referring to a shared language and history) and *relational* (implying trust and norms, as well as responsibilities within a network). These dimensions enhance the enthusiasm and ability of organisations to exchange and transfer knowledge, therefore increasing their intellectual capital (Widén-Wulff & Ginman 2004:449; Järvenpää & Immonen 2004:4-5). This perception is supported by Anklam and Salonen's (2013) argument that *"collaboration itself is one of the most powerful mechanisms for building social capital."*

One can thus contend that although social capital is located in the connections between people within a social network, it is essentially concerned with the value that is created as a result of these relations.

## 2.2 DEFINING KNOWLEDGE MANAGEMENT

The concept KM formally entered popular usage in the late 1980s and exploded in popularity in the late 1990s and early 2000s, becoming one of the leading buzzwords of the time (Frost 2014). However, philosophers and metaphysicians have been making use of similar practices for decades (e.g., Descartes, Goethe, Hume and Kant to name but a few) (Sutton, 2007b:29).

Although he never actually used the term KM, in 1938 Wells expressed his vision of a *World Brain* that would sanction the intellectual configuration of the sum total of our collective knowledge. This *World Brain* would represent *"..a universal organization and clarification of knowledge and ideas."* (Wells 1938, xvi). Practically fifty years later the term KM was formally used for the first time by Donald Marchand (1985) and Karl Wiig (who coined the concept in 1986) respectively (Dalkir 2011:19).

Dalkir (2011:7) calls attention to the fact that one of the few areas of agreement in the KM domain is that it is highly multidisciplinary. Intellectually KM has many origins incorporating philosophical thinking; specific interests regarding expertise in the workplace; and educator and business leader perceptions (Wiig 2000:3). Significant contributions regarding the evolution of KM have also been made by management theorists such as Drucker (1999), Senge (1990), Nonaka (1991; 1995; 2009), Takeuchi (1995), and Stewart (1991). O'Dell and Grayson (1998) draw attention to the philosopher Michael Polanyi's work that served as the foundation of Nonaka's much acclaimed KM theories.

Sutton (2007a:1) points out, that although there are many descriptions of KM today, explaining the concept remains a challenge since it lacks *"… a single, comprehensive definition, an authoritative body of knowledge, proven theories, and a generalized conceptual framework"*. This can be mainly attributed to a lack of consensus regarding what the term knowledge really entails, together with the fact that many KM contributors have roots in diverse disciplines, which further lead to different perceptions of what the term actually means (Frost 2014).

***Table 2.1*** provides a high-level overview of these different definitions.

**Table 2.1: Diverse definitions of Knowledge Management**

| Viewpoint | Definition |
|---|---|
| Business Perspective | ▫ *"Knowledge management is a collaborative and integrated approach to the creation, capture, organization, access, and use of an enterprise ' s intellectual assets"* ( Grey 1996).<br>▫ *"Knowledge management is the process by which we manage human [centred] assets . . . the function of knowledge management is to guard and grow knowledge owned by individuals, and where possible, transfer the asset into a form where it can be more readily shared by other employees in the company" (Brooking 1999:154)*<br>▫ *"The tools, techniques, and strategies to retain, analyse, organize, improve, and share business expertise"* (Groff & Jones 2003).<br>▫ *"...the exploitation and development of knowledge assets of an organi[s]ation with a view to furthering the organi[s]ation's objectives. This knowledge [includes explicit, documented] and tacit, subjective knowledge and entails all the processes associated with the identification, sharing and creation of knowledge"* (Davenport & Prusak).<br>▫ *"Knowledge management is a discipline that promotes an integrated approach to identifying, capturing, evaluating, retrieving, and sharing all of an enterprise's information assets. These assets may include databases, documents, policies, procedures, and previously un-captured expertise and experience in individual workers"* (Gartner Group). |
| Intellectual (knowledge asset) Perspective | ▫ *"...leveraging intellectual assets to enhance organi[s]ational performance"* (Stankosky 2008). |
| Cognitive Science Perspective | ▫ *"Knowledge - the insights, understandings, and practical know-how that we all possess - is the fundamental resource that allows us to function intelligently. Over time, considerable knowledge is also transformed to other manifestations - such as books, technology, practices, and traditions - within organi[s]ations of all kinds and in society in general. These transformations result in cumulated expertise and, when used appropriately, increased effectiveness. Knowledge is one, if not THE, principal factor that makes personal, organi[s]ational, and societal intelligent behavior possible"* (Wiig 1993). |
| Library and Information Science Perspective (School 1) | ▫ *"KM is predominantly seen as information management by another name"* (Davenport & Cronin 2000). |
| Library and Information Science Perspective (School 2) | ▫ *"....understanding the organi[s]ation's information flows and implementing organi[s]ational learning practices which make explicit key aspects of its knowledge base. It is about enhancing the use of organi[s]ational knowledge through sound practices of information management and organi[s]ational learning"* (Broadbent 1997). |
| Process-Technology Perspective | ▫ *"Knowledge management is the concept under which information is turned into actionable knowledge and made available effortlessly in a usable form to the people who can apply it"* (Patel & Harty, 1998).<br>▫ *"The tools, techniques, and strategies to retain, analy[s]e, organi[s]e, improve, and share business expertise"* (Groff & Jones 2003).<br>▫ *"A capability to create; enhance; and share intellectual capital across the organi[s]ation...a shorthand covering all the things that must be put into place, for example, processes, systems, culture, and roles to build and enhance this capability"* (Lank 1997). |

*(Adapted from Dalkir 2011:5-7, Koenig 2012 and Kumar & Agrawal, 2011)*

From the above definitions one can thus conclude that KM is an astonishing combination of strategies, tools, and techniques with many different outlooks. The description could thus vary depending on what one sets out to achieve. The researcher opted to align this study with the process technology perspective of KM as defined by Patel and Harty (1998), Groff and Jones (2003) and Lank (1997).

## 2.3 KNOWLEDGE AND SOCIAL NETWORK STRUCTURES

The value of knowledge within organisations has been well documented and is often regarded as one of its core assets (van Reijsen *et al.* 2014:1). It is however important to note that different types of knowledge exist.

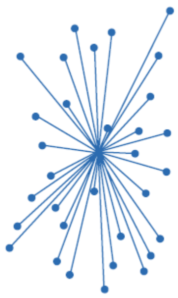
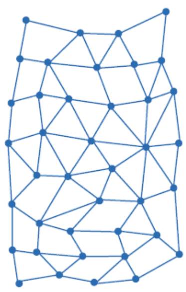
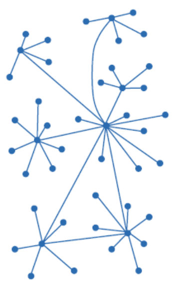
Most KM academics classify knowledge as either *explicit* or *tacit* (Nonaka 1991:92; Ponelis & Fairer-Wessels 1998:113). Explicit knowledge is regarded as systematic and can be formally articulated, easily shared and transmitted (Nonaka 1991:92), whereas tacit knowledge is highly personal and based on values and experience. It is difficult to transmit and therefore rarely documented. Tacit knowledge has a very important cognitive dimension and is regarded as the key to creating new knowledge (Nonaka 1991:92; Despres & Chauvel 2000:60). In addition, Scharmer (2001:138, 142) and Smedlund (2008:63) identify another type of knowledge they refer to as *potential* knowledge. They maintain that potential knowledge can be either tacit or explicit and refers to knowledge of which the value for an organisation has not yet been revealed (not-yet-embodied knowing). Smedlund (2009:79-80) describes potential knowledge as *"… the total amount of knowledge someone has in contrast to the 'actual' knowledge someone uses in his work."*

Knowledge assets are frequently based on the experience and expertise of an organisation's employees (Smedlund 2008:66) and in order to remain competitive it is vital for organisations to be able to make use thereof (Zack 1999:45). Ghaznavi *et al.* (2014:279) point out that access to this cutting-edge knowledge and specialised know-how can be gained by using social capital. According to social capital literature social capital resides in the connections between people within a social network and is primarily concerned with the value that is created owing to these relations. Social networks can thus be regarded as vital sources of social capital. This belief is supported by Kianto and Waajakoski (2010) who maintain that knowledge is considered a *"socially constructed and shared resource"*, with the primary interest being *"social relationships and interaction"* and that the emphasis is on *"the* *characteristics of the social relationships connecting the actors and social capital embedded in them."*

Organisations can therefore gain the maximum value from its knowledge assets by leveraging social network structures.

According to studies by Barabási (2002) centralised, distributed and decentralised social network structures are ideal environments for explicit, tacit and potential knowledge respectively (***Table 2.2***).

**Table 2.2: Social network structures for explicit, tacit and potential knowledge**

| Knowledge Type | Social Network Structure | Beliefs \| Norms \| Trust | Functioning Mechanisms |
|---|---|---|---|
| EXPLICIT | <br>Centralised | <u>BELIEFS</u><br>▫ High quality and discipline<br>▫ Future-oriented stories<br><u>NORMS</u><br>▫ Clear defined, explicit rules<br><u>TRUST</u><br>▫ Trust in hierarchy<br>▫ Follow agreements faithfully | ▫ The focal node in the network manages the knowledge flow.<br>▫ Knowledge flows hierarchically from the top down and from the bottom to the top.<br>▫ There are no knowledge exchange links between subordinates. |
| TACIT | <br>Distributed | <u>BELIEFS</u><br>▫ Lifelong learning and potential growth<br><u>NORMS</u><br>▫ Reciprocity - everybody contributes<br>▫ Unwritten rules<br><u>TRUST</u><br>▫ Augmented, dense trust and durable relationships<br>▫ Enables risk and adaptation | ▫ No specific actor manages the flow of knowledge.<br>▫ Knowledge flows horizontally from one actor to another.<br>▫ Each actor has knowledge links to a few other actors. |
| POTENTIAL | <br>Decentralised | <u>BELIEFS</u><br>▫ Need for innovation<br>▫ Rewarding innovativeness<br><u>NORMS</u><br>▫ Acceptance of mistakes<br>▫ No punishment for failure - freedom to try and err<br><u>TRUST</u><br>▫ Fast trust<br>▫ Thin and fragile<br>▫ Short-term affairs | ▫ Hubs in the knowledge network control the flow of knowledge and intermediate between different groups.<br>▫ Some actors are more connected than others. |

*(Adapted from Smedlund 2008:69-70, 72 and Smedlund 2009:84)*

A *centralised social network structure* revolves around a key actor with dyadic, strong links to others, but the others are not linked to one another. The key actor manages the flows of knowledge with disconnected others (Smedlund 2009:83). Within these networks knowledge is predominantly documented, explicit knowledge. Centralised social network structures are supported by distinct rules, beliefs in high quality and trust in organisational hierarchy (Smedlund 2008:71-72).

In a *distributed social network structure*, each actor is firmly connected to a few others in the network, with no weak links or structural holes. These network structures do not have brokers, as relationships are distributed evenly and each actor has knowledge links to a few other actors (Smedlund 2009:83). According to Smedlund (2008:70-71), these network structures are best applied to situations where tacit knowledge (experience-based) is shared in a trustworthy and stable atmosphere. A distributed social network structure is upheld by the norms of reciprocity, beliefs in constant learning and personal growth, and augmented trust.

In contrast to distributed network structures, a *decentralised network structure* has many structural holes and weak ties. These networks are built on *"individuals as hubs of knowledge"* who collect and exchange knowledge from different sources (Smedlund 2009:83). These networks change frequently and relationships are often short. Smedlund (2008:71-72) points out that in a decentralised network structure knowledge is still very much evolving, potential and in a *"not-as-yet invented form."*

There is a fundamental amount of literature highlighting important relationships between knowledge and networks including works by Inkpen and Tsang (2005), Reagans and McEvily (2003), McFadyen and Cannella (2004) and Borgatti and Cross (2003). Hansen (1999:85-86) for example, maintains that strong ties stimulate the transfer of complex knowledge while weak ties promote the transfer of simple knowledge.

Network structures impact on how knowledge flows within organisations. Subsequently, since organisations require all types of knowledge (explicit, tacit and potential) to create and maintain a competitive edge, they need to implement specific network structures to promote specific types of knowledge.

## 2.4 ADVANCING KM THROUGH SOCIAL CAPITAL

The importance of social capital for KM has been debated by several authors including Swan *et al* (1999), Zack (1999), Miles *et al* (1998), Lesser and Prusak (1999), Liebowitz (2005), Hoffman *et al*. (2005), Inkpen and Tsang (2005), McElroy *et al*. (2006), Smedlund (2008) and Manning (2010), to name a few. It has also been hypothesised that social capital can increase an organisation's KM capability as it has the capacity to influence KM in various ways (Hoffman *et al*. 2005:98).

### 2.4.1 The influence of social capital on KM processes

Inkpen and Tsang (2005:151) emphasise two levels of social capital that are often interconnected. *Individual social capital* originates from an individual's network of relationships and constitutes a private good while *organisational social capital* stems from an organisation's network of relationships and is made up of a public good. Social capital as a public good enables members of an organisation to "… *tap into the resources derived from the organisation's network of relationships without necessarily having participated in the development of those relationships."* (Kostova & Roth 2003).

Knowledge exists primarily in tacit form and has to be shared in order to become valuable to organisations (Nonaka 1994). Since it is important for organisations to preserve and enhance their competitive edge regarding the knowledge they possess, they need to create opportunities to facilitate the creation of knowledge in order for members to learn something new (Järvenpää & Immonen 2004:6).

Kogut and Zander (1993:265) regard organisations as social communities who specialise in the creation and internal transfer of knowledge. They also claim that social capital can enhance the capturing, codification and transfer of knowledge. Corresponding with this argument, Daud and Yusoff (2010:140) identify social capital as the most intricate component of intellectual capital as it depends on the combination of knowledge and experience of various parties to create new knowledge. A vast amount of knowledge thus exists in social interactions.

However, one can hardly compel people to participate in knowledge creation and knowledge sharing processes. Since knowledge is often considered as a source of competitive advantage, a high level of motivation would thus be required for individuals to share their knowledge (Aslam *et al*. 2013:30).

Social capital is essential for the meaningful sharing and transfer of knowledge since effective relationships eliminate distrust, fear and frustration from the knowledge creation process. (von Krogh 1998:143). Aslam *et al.* (2013:30) support this statement when they contend that *"… it requires a platform, culture and certain amount of trust between individuals of a collective to induce them to share their knowledge."*

Daud and Yusoff (2010:149-150) maintain that the level of social capital increases as relationships become more established. Nahapiet and Ghoshal (1998:252-256) also claim that social capital can have a positive effect on the knowledge sharing and knowledge creation environments within organisations. Similarly Abidin *et al* (2015), demonstrated that social capital has a direct and meaningful effect on an organisation's ability to manage knowledge. Apart from facilitating the development of collective intellectual capital, social capital can also enhance knowledge capture, knowledge codification, and knowledge sharing.

In brief, social capital directly impacts on the effective implementation of all KM processes.

### 2.4.2 Social capital encourages participation

The claim by Hoffman *et al.* (2005:98), that social capital promotes cooperative behaviour is supported by Bakker *et al.* (2006:594-602), who assert that team membership has the biggest influence on the density of knowledge sharing relationships.

Participation within organisations can be promoted through informal social interaction and vice versa (Rodríguez-Pose & von Berlepsch 2014). Members within a community rely on social resources (e.g. a common identity, familiarity, trust and a level of shared language and context) to provide value to themselves and their organisations. These resources become evident in a number of ways, such as locating experts within an organisation faster and reducing the costs associated with the authentication of expertise. Such activities assist organisations in managing its knowledge resources more effectively (Lesser & Prusak 1999). This statement is supported by Reagans and McEvily (2003:240) who suggest that *"… social cohesion around a relationship affects the willingness and motivation of individuals to invest time, energy, and effort in sharing knowledge with others."* Inkpen and Tsang (2005:151, 154-156) reinforce this argument by asserting that networks make knowledge available to organisations owing to recurring and lasting relationships between members.

One can thus state that social capital produces trusting relationships that in turn promote knowledge sharing.

### 2.4.3 Discovering knowledge via network relationships

Social capital has been posited an essential element in providing access to resources through network ties (Hoffman *et al.* 2005:98). However, network ties only translate into social capital if they support an actor to accomplish specific goals (Bakker *et al.* 2006:595).

Several academics such as Adler and Kwon (2002), Nahapiet and Ghoshal (1998) and Anand *et al.* (2002) have debated that one of the most significant direct benefits of social capital, is the access to new sources of knowledge. Members within networks are exposed to potentially valuable knowledge via various network ties between and within organisations (Inkpen & Tsang 2005:154). This is supported by Powell's (1990:304) observation that *"… the most useful information is rarely that which flows down the formal chain of command in an organisation, or that which can be inferred from price signals. Rather, it is that which is obtained from someone you have dealt with in the past and found to be reliable."*

Network ties have different attributes and can fluctuate in terms of their frequency of interaction, emotional closeness and types of pursuits (Ünlüsoy *et al.* 2014:226). Järvenpää and Immonen (2004:3) stress that network structures are determined by the nature of business relations and that network ties are either strong (embodied in frequent interaction, reciprocal relationships and self-disclosure) or weak (where interaction is sporadic, negligible or incidental) (Haythornthwaite & de Laat 2010:185).

According to Hansen (1999:84-88), the strength of a relationship will influence the ease with which knowledge is shared. It is easier to obtain knowledge from strong ties, since they can be reached swiftly and they usually have more motivation to be of assistance than weak ties (Granovetter 1982:113). Singh (2000) points out that the number of strong ties an individual can have is limited due to maintenance costs and time requirements. In contrast, individuals can have many weak ties as these ties require little upkeep and time investment. Even though these ties are called *'weak'*, they play a very important role in making unique knowledge available, as weak ties can connect individuals with knowledge that is not available via strong ties. This belief is supported by Granovetter (1982:110) who maintains that within a social network, information is much more likely to be disseminated via weak ties than through strong ties. Hagel *et al*. (2010:23) also emphasise the value of weak ties when they state: *"The edges of our social networks represent the weak ties that connect us to people who can provide us with access to new insights, experiences, and capabilities that provoke us to improve our own game."*

Schrader (1991) discovered that the choice whether to share knowledge or not was often influenced by the length of time a source had known the recipient. Moreover personal or professional contact affects dependability, recurrence affects reciprocity and interaction in terms of team work or co-location affects obligation (Ensign 2009:149).

Although strong ties are regarded significant as they are usually readily accessible and prepared to share knowledge, weak ties also have a very important function as they connect individuals with information from remote parts of their social network. One can thus state that as a result of both strong and weak relationships, members within organisations will discover new knowledge.

## 2.5 SUMMARY

This chapter underscored the profound relationship that exists between social capital and KM practices. A literature investigation revealed that although social capital stems from bonds between individuals within a social network, it is fundamentally concerned with the value that is created as a result of these relations. Consequently social networks can be deemed a vital source of social capital.

It also revealed that since network structures influence knowledge flows within organisations, particular network structures (centralised, distributed or decentralised) should be used to support specific types of knowledge (explicit, tacit or potential). Organisations can thus benefit from its knowledge assets by leveraging its social network structures.

Finally it was ascertained that social capital can enhance an organisation's KM proficiency in many respects. Apart from fostering trusting affiliations (thereby encouraging knowledge sharing) and discovering knowledge via network relationships, social capital impacts on the successful implementation of all KM processes.

# CHAPTER 3

***"In today's highly connected world, we are learning to trust in the 'wisdom of crowds', to learn together with others and to look to our peers for shared experiences."***

**- Geoff Parcell**

# 3 SOCIAL NETWORKS VS KNOWLEDGE NETWORKS

A substantial amount of an individual's *information environment* comprises the relationships he or she can exploit for diverse information and knowledge needs (Cross *et al*. 2001:100-101). Social networks promote both professional and social collaboration between individuals and enhance the creation, exchange and transformation of knowledge (Jones 2001:1; Pathak *et al*. 2006:1).

Cross *et al*. (2001:101) elaborate on this contention when they declare: *"As we move further into an economy where collaboration and innovation are increasingly central to organisational effectiveness, we must pay more attention to the sets of relationships that people rely on to accomplish their work."*

This chapter intends to differentiate between social networks and knowledge networks as well as SNA and KNA. An overview of SNA metrics used in this study is presented, as well as a summary of the most important roles of individual members within a network. Furthermore the value of SNA, from a KM perspective, is addressed whilst focusing on knowledge maps and CoPs.

## 3.1 SOCIAL NETWORKS AT A GLANCE

### 3.1.1 Social networks

Social networks have been described as *"… a finite set or sets of actors and the relation or relations defined on them"* (Wasserman & Faust 1994:20). In short, social networks reflect communication, collaboration and loose acquaintances in networked communities (Reinhardt *et al*. 2009:1). This interpretation is supported by Hanneman and Riddle's (2005) notion that a social network consists of a group of actors (nodes) that may have relationships (ties) with each other.

Haythornthwaite and de Laat (2010:184-185) contend that these actors could refer to individuals, organisations, communities or other groups and that they could be tied by one or many relations. These relationships form the foundation of social networks and may range from distant to intimate, sporadic to recurring, elective to mandatory, one-way to reciprocal. Depending on the nature of the relationship, ties are described as being either weak or strong. Strong ties typically involve high levels of trust, reciprocity and a high frequency; while weak ties often span boundaries and can potentially be a source of new ideas (Meehan *et al*. 2012:3).

According to Nelson and Hsu (2011:1470-1478) social networks contain two principal elements namely: *transactional content* and *configuration*. Transactional content refers to the type of relationship that exists between actors, while configuration focuses on the shape (structure) of the network and the actor's position therein.

Conversely, Dong *et al* (2016) maintain that the notion of *structural homophily*, the underlying assumption that *"more common friends means a higher probability to connect"*, is not necessarily valid as it does not account for the diverse ways in which people may be connected, a phenomenon known as *structural diversity*.

Social networks are fundamentally informal and influence the speed and efficiency with which knowledge is created and disseminated within organisations (Murale & Raju 2014:56; Nelson & Hsu 2011:1470-1478).

A social network thus refers to an informal body consisting of a set of actors (e.g. individuals or groups) and the relationships between them. These relationships can be weak or strong; similar or diverse; and has an effect on the creation and distribution of knowledge among its members.

### 3.1.2 Social network analysis

While some of the philosophies surrounding network analysis dates back to the ancient Greeks, the main development of the field commenced in the 1930's with Harvard sociologists, Manchester anthropologists, and the Gestalt theory (predominantly associated with Wolfgang Köhler) (Scott 2000). Subsequently three main ideologies developed namely: sociometric analysis (graph theory); interpersonal relations and the establishment of cliques; and finally the structure of communal relations. By the 1960s SNA was integrated into an intricate but coherent framework and at present it is applied to analyse social structures and their otherwise hidden relationships. SNA is still advancing and with the computing age it is about to realise its full potential (Richards & Higgins 2001).

Otte and Rousseau (2002) maintain that SNA is a research approach that enables researchers to quantify the configuration of relations among a set of actors. With relational data being the focus of investigations, *"…the relationships between actors become the first priority, and individual properties are only secondary"*. They also draw attention to the two main types of SNA namely the *ego network analysis* where the network of one person is analysed; and the *global network analysis* which tries to find all relations between participants in a network.

In its broadest sense, SNA has been described as a practice that *"…(1) conceptualises social structure as a network with ties connecting members and channelling resources, (2) focuses on the characteristics of ties rather than on the characteristics of the individual members, and (3) views communities as 'personal communities', that is, as networks of individual relations that people foster, maintain, and use in the course of their daily lives"* (Wetherell *et al*. 1994:645).

Krebs (2006) provides a more concise definition when describing SNA as *"… the mapping and measuring of relationships and flows between people, groups, organisations, computers or other information/knowledge processing entities. The nodes in the network are the people and groups, while the links show relationships or flows between the nodes"*. Ehrlich and Carboni (2005) support this belief in stating that a SNA explores the structure of social relationships within a group in order to reveal the informal connections between people. In addition, these networks can be analysed visually as well as quantitatively (Hanneman & Riddle 2005).

Serrat (2009:2) compares SNA to an "*organisational x-ray"*, asserting that it detects relationships that are not normally visible. SNA deems relationships significant, and maps and evaluates both formal and informal connections in order to obtain an understanding of what assists or hampers knowledge flow within cooperating divisions. SNA diagrams indicate the importance of each node, the volume of connectedness and the strength of the relationships among nodes (Euerby & Burns 2013:10).

According to Mertens *et al*. (2013:3), SNA employed within an organisation is occasionally referred to as organisational network analysis (ONA). In such an instance, the emphasis is placed on "… *identifying key networks within organisational boundaries, understanding the structure of personal and group relationships within these networks, and using this understanding to make a difference to business performance."*

Although SNA originally emerged in the sociology domain (Helms & van Reijsen 2008) it has since been used across many other disciplines (Liebowitz 2005:78). With mathematical graph theory at the heart of SNA, it has become a multidisciplinary method and just like KM it can be applied in many domains (Otte & Rousseau 2002:450).

SNA offers organisations the means to identify strategically positioned (central) individuals within a network, whose relationships are vital for accessing knowledge and information and who can influence others in adopting innovations (Cross *et al.* 2002:6). By concentrating on these strategic points, managers can ensure faster dissemination of information, collaboration among the correct individuals as well as the timeous guidance of strategic expertise. Subsequently, well-managed networks are integral to performance, learning and innovation (Hamre & Vidgen 2008).

SNAs can therefore be regarded as visual and mathematical tools and techniques that are utilised to identify and analyse relationship patterns among actors within a network. It can be implemented in order to help organisations develop their strategic decisions, promote innovation and to advance the flow of information and knowledge for example.

### 3.1.3 SNA metrics

SNA metrics are applied to measure network properties (Tubaro 2012). It assists in understanding information flow patterns and by studying the ties between team members (Benhiba & Abdou Janati-Idrissi 2013:92). SNA metrics can identify hidden influencers, bottlenecks and leverage points (Mohr 2015).

In social networks, where actors are linked by means of one or several relationships, SNA provides structural measurements:

- to describe the network as a whole; and
- to provide information on the participation of each actor in the network (Martinez *et al.* 2003:360).

There exists a very diverse set of metrics that depicts the structure of networks (Benhiba & Abdou Janati-Idrissi 2013:92). ***Table 3.1*** offers an overview of conventional SNA metrics.

**Table 3.1: Fundamental SNA metrics**

| WHOLE-NETWORK ASSESSMENT | |
|---|---|
| SNA Metric | Significance |
| Network size | ▫ The count of the number of members/nodes within a network.<br>▫ Indicates how big or small the network is. |
| Network reachability | ▫ The accessibility of points of the network based on a notion of 'path'.<br>▫ The degree to which any member of a network can reach other members within the network. |
| Network centralisation | ▫ The degree to which relationships in a network revolve around one or a few central network members.<br>▫ High network centrality implies that knowledge flows within a network depend on a few single nodes and the removal of these nodes may distort the knowledge flows. |
| Network density | ▫ The proportion of direct ties in a network relative to the total number of possible ties.<br>▫ Measures the health and effectiveness of a network. |
| NETWORK STRUCTURE | |
| SNA Metric | Significance |
| Cliques<br>(clusters of expertise) | ▫ The maximum number of actors (but at least three), who all have ties present among themselves - the geodesic distance is 1 for everyone (i.e. everyone is directly related).<br>▫ Actors are more closely and intensely tied to one another than they are to other members of the network, with many direct and reciprocated ties.<br>▫ Cliques tend to indicate stronger relationships, similarity in information and resources available, more constraints, but also more support.<br>▫ Cliques can be instrumental in influencing attitudes and behaviours both positively and negatively. |
| Bottlenecks<br>(cut-points) | ▫ Bottlenecks can be obstacles to knowledge sharing within a network as too many links can lead to inefficiency of knowledge exchange.<br>▫ Either plays a central role to maintain information or power advantage, or people whose jobs have grown too big. |
| Hubs | ▫ Nodes with high degree- and betweenness centrality.<br>▫ A network centralised around a well-connected hub can fail rapidly if that hub is disabled or removed. |
| PROMINENCE (Prestige & Centrality)<br>*(Indicate the social power of a node based on how well they 'connect' the network.)* | |
| SNA Metric | Significance |
| Betweenness centrality | ▫ Helps to identify knowledge brokers and gatekeepers within a network.<br>▫ A node with high betweenness has significant influence over what information and knowledge flows in the network and what does not.<br>▫ Without this node, some nodes could be cut off from the flow of information and knowledge in the network. |
| Closeness centrality | ▫ Nodes with high closeness centrality access all the nodes in the network faster than everyone else, i.e. they have the shortest path to everyone else in the network.<br>▫ They have the best visibility into what is happening in the network.<br>▫ Reflects the ability to access information through the grapevine of network members. |
| Degree centrality | ▫ Reveals who in the network has the most direct connections.<br>▫ Indicates expertise and power of network members.<br>▫ The node with the highest number of direct connections is the most active node (person) in the network.<br>▫ Plays the 'connector/hub role' in the network.<br>▫ In-degree is a count of the number of ties directed to the node and out-degree is |

| | |
|---|---|
| | the number of ties that the node directs to others. When ties are associated with some positive aspects such as friendship or collaboration, in-degree is often interpreted as a form of popularity (prestige), and out-degree as extroversion. |
| Eigenvector centrality | ▫ Measures the importance of a specific node in a network.<br>▫ Assesses how connected an entity is and how much direct influence it might have over other connected entities in the network. |
| DISTANCE | |
| SNA Metric | Significance |
| Maximum flow | ▫ Measures the number of different pathways, regardless of the length of the pathway between any two actors. |
| Geodesic distances | ▫ Calculates the number of relations in the shortest possible walk from one actor to another, i.e. the shortest path between any two nodes. |
| Diameter | ▫ The largest geodesic distance between nodes in a connected network. |
| Average path length | ▫ Measures, on average, the number of steps it takes to get from one member of the network to another. To be precise, the average of all geodesic distances on the graph. |
| CONNECTIVITY | |
| SNA Metric | Significance |
| Point connectivity | ▫ Calculates the number of nodes that would have to be removed in order for one actor to no longer be able to reach another.<br>▫ If there are many different pathways that connect two actors, they have high 'point connectivity' in the sense that there are multiple ways for a signal to reach one another. |
| Reciprocity | ▫ The extent to which two actors reciprocate one another's interactions.<br>▫ The higher the incidence of reciprocal ties; the stronger the relationship; and the healthier the network. |
| Tie strength | ▫ Defined by the linear combination of time, emotional intensity, intimacy and reciprocity.<br>▫ Strong ties are associated with homophily, propinquity and transitivity, while weak ties are associated with bridges. |

*(Benhiba & Abdou Janati-Idrissi 2013:94-95; Cooke & Hall 2013:11; Hanneman & Riddle 2005; Krebs 2006:15-16; Mohr 2014; Müller-Prothmann 2007:225-227; Pandia & Bihari 2014:186-189 and Wasserman & Faust 1994:167-202, 254)*

### *3.1.3.1 Whole network analysis*

Cooke and Hall (2013:11) list *size*, *density*, *reachability* and *centralisation* as some of the most commonly measured network features.

Size plays a very important part regarding the structure of social relations due to the limited resources and capacities actors have considering the development and upholding of relationships (Hanneman & Riddle 2005). In addition, Scarbrough *et al.* (2014) emphasise the value of network size considering the exchange of knowledge and information by revealing that *"… the more knowledge contacts a person has relationships with, the greater the chance that one of them has the resource he or she needs."*

Network density can be described as *"… the total number of ties divided by the total number of possible ties*" (Hanneman & Riddle 2005). Müller-Prothmann (2007:225) points out that network density is significant for knowledge community building within and between organisations as it defines the overall relationship between network members. In addition to this, Coulon (2005:8) points out that network centralisation and network density are important complementary measures, since density indicates the general level of connectedness within a network, whilst centralisation focuses on the extent to which this connectedness is organised around principal nodes.

Network reachability refers to *"the accessibility of points of the network based on a notion of path*" (Cooke & Hall 2013:11). In other words, an actor is reachable if there is a path between the actor and other actors. Coulon (2005:9) goes even further and maintains that apart from being reachable, networks are regarded as efficient when actors can instantly reach a large number of other actors through a relatively small number of ties. Efficiency is measured by calculating the number of non-redundant contacts and the average number of ties an *ego* (also known as an individual actor) has to cross in order to reach any *alters* (people in the network that an individual actor interacts with). This number is known as the *average path length*. The shorter the average path length in relation to the network size, the more efficient the network.

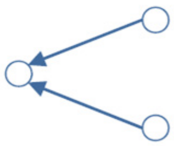
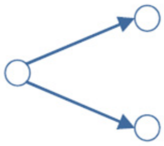
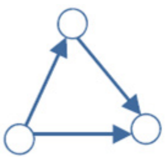
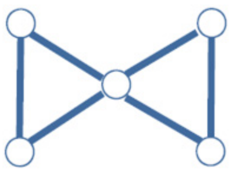
Hanneman and Riddle (2005) describe network centralisation as *"… the global centrality of a network.*" Network centralisation calculates the degree to which relationships in a network are focused around one or a few central network members. High network centrality indicates that knowledge flows within a network depend on a few single nodes and that removing these nodes would distort knowledge movements.

#### *3.1.3.2 Network structure analysis*

It is important to point out that there exist different approaches pertaining to network structure analysis. Kim *et al.* (2016:23) draw attention to Exponential Random Graph Models (ERGMs), a somewhat new analytical approach to examine multiple interdependent social processes involved in network formation. ERGMs can provide additional insights in terms of how network structures form. In general ERGM analysis assesses tie formation at network level; unravel possible cross-dependencies as well as evolving network structures and other outcomes that cannot be addressed via conventional approaches, which concentrate mainly on dyadic relationships.

ERGMs are commonly expressed through two questions: *How do perceived network structures develop?* and *Which underlying social processes triggered the materialisation of the observed structures?* Kim *et al.* (2016:24-25) elaborated on these questions by exploiting a set of structural effects that may arise independent of firm or dyad characteristics, namely: reciprocity, popularity, activity, triad closure and brokerage. ***Table 3.2*** below offers an overview of each of these network attributes.

**Table 3.2: Network structures and associated endogenous processes**

| Social Network Structure | Associated Endogenous Processes | Description |
|---|---|---|
|  | RECIPROCITY | ▫ The most basic, yet one of the most important tendencies in social relations.<br>▫ It describes tie formation as *returning the favour* by reciprocating an earlier interaction with a network actor. |
|  | POPULARITY | ▫ Depicts the process by which already-popular actors may become even more popular<br>▫ In-degree centrality. |
|  | ACTIVITY | ▫ Actors who are very active in seeking new network connections. |
|  | TRIAD CLOSURE | ▫ The formation of ties between any set of three actors.<br>▫ Reveal that two actors are prone to form a tie if they are each tied to a separate common actor, creating a triangle connecting all three actors.<br>▫ Typified by reduced individuality, less individual power, and mediated conflict suggesting that those individuals who form part of this type of group are more restricted and less autonomous than individuals in isolated dyadic relationships.<br>▫ *A friend of my friend is also my friend.* |
|  | BROKERAGE | ▫ Brokerage occurs as an actor serves as the link between other actors who are not otherwise linked.<br>▫ As relationships depend on external persons for knowledge transfer, they are subjected to a loss of information given that the intermediary might not be deeply acquainted with the domains associated with the other actors. |

*(Adapted from Kim et al. 2016:25 and Hollenbeck & Jamieson 2015:374-377)*

Another approach to network structure analysis has been initiated by Stuck *et al.* (2016) who linked network theoretical concepts and insights to the well-known classification of Regional Innovation Systems (RIS) types by Cooke (2004). This approach emphasise on three well-known network structures namely: *small-world type networks*, *core-periphery type networks* and *gatekeepers*.

The notion behind *small-world type network structures* dates back to Milgram (1967), whilst Watts & Strogatz (1998), and Barabási & Albert (1999) made substantial contributions to the formalisation of this phenomenon. Stuck *et al.* (2016) maintain that a small-world network is characterised by a high amount of *clustering,* signifying the frequent presence of at least three nodes that are entirely linked, also known as *cliques*. As these cliques tend to be connected by just a few links, only a few nodes are considered to have a high centrality value whereas many have low centrality values. Small-world networks largely support the efficient distribution of knowledge within the network. With a substantial number of structural holes in these networks, they also provide sufficient potential for the creation of new knowledge (Cowan & Jonard 2004). In addition, nodes that link cliques hold prominent broker positions (high betweenness centrality), these networks are characterised by a strong power hierarchy (Ravasz & Barabási 2003).

According to Borgatti and Everett (1999), a network has a core-periphery structure if its nodes can be partitioned into two sets: the core and the periphery. Nodes within the core have strong links among themselves whilst the peripheral nodes are sparsely interlinked. In addition, peripheral nodes are frequently either isolates or weakly linked to the core nodes. Stuck *et al.* (2016) observes that *"If networks qualify as core-periphery networks their nodes are in a hierarchical order with those belonging to the core being more powerful and influential than nodes in the periphery."*

Considering Stuck *et al.*'s (2016) approach*, gatekeepers* are considered central actors within a regional network who additionally link the regional to extra-regional networks. It is the task of these gatekeepers to ensure that knowledge from outside the region is accessible, which they assist to diffuse within the region. Given that they broker these knowledge flows to an extent, they possess key positions within regional knowledge networks (Graf 2011).

According to Müller-Prothmann (2007:225), three rudimentary types of network structures are central in terms of knowledge sharing processes namely: *cohesion* (clusters of expertise), *cut-points* (bottlenecks) and *hubs*.

*Cohesion* is a primary network structure which contributes to the creation of knowledge and is revealed by the existence of *cliques*[1]. Kyk asb wat met jou voetnota hieronder geword het, net een lyn is sigbaar. Cliques or clusters of expertise emerge due to dense connections between sub-sets of network members (Müller-Prothmann 2007:225). As a result cliques drive the process of knowledge creation based on their strong intra-responsiveness relations (Aviv *et al.* 2003:5).

According to Liebowitz (2006:83) *cut-points* or *bottlenecks* indicate a network that would become separated into isolated networks should a node be removed. Similarly, Müller-Prothmann (2007:225) describes *cut-points* as network members that are critical in holding components of the network together and are therefore also referred to as *bridges*. Cut-points are thus key nodes that offer the only connection between different parts of a network.

Müller-Prothmann (2007:225) describes *hubs* as network members who are important in various clusters. These nodes have a high degree and betweenness centrality (Krebs 2006) and are thus enablers of effective knowledge transfer since they can effectively connect different sub-groups of the network. Due to the significant influence hubs have on network efficiency, they can thus be described as the individuals in a network with the most influence.

Considering that interactive network RIS implies a large number of interacting actors in absolute as well as in relative terms (Stuck *et al.* 2016) and that ERGMs are predominantly applied to cross-sectional data, the researcher opted to make use of Müller-Prothmann's network structure classification when comparing network structures before and after KM interventions.

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[1] In addition to the description provided in *Table 3.1*, a clique can be described as a sub-set of a network where actors are more closely joined to one another than they are to other members of the network. Cliques are connected with many direct and reciprocated ties and the geodesic distance is one for everyone. Formally, a clique is the maximum number of actors - but at least three - with all possible ties present among themselves (Hanneman & Riddle 2005).

#### *3.1.3.3 SNA metrics: prominence*

SNA metrics calculate exactly how prominent or outstanding each actor is within a network. An actor is regarded as prominent if his or her ties render him or her particularly visible to the other actors in the network. However, as it is not evident from the number of ties alone whether an actor is important or not, Knoke and Burt (1983) identified two types of visibility, namely *prestige* and *centrality*.

According to Daniel (2009:67) prestige can be regarded as a more sophisticated measure of prominence than centrality, since prestige measures of prominence apply only to directed graphs. Wasserman and Faust (1994:199) emphasise the significance of three types of prestige measurements namely: *degree*, *proximity* and *status*.

*Degree prestige* is similar to degree centrality, but it only considers an actor's incoming ties. High degree prestige indicates that an actor has been chosen or approached by many other actors (Coenen 2003:137). Degree prestige or in-degree centrality typically indicates popularity, admiration or leadership (De & Dehuri 2014:132).

*Proximity prestige* measures closeness by using distances to, rather than distances from, each actor in a directed graph. It considers the set of all network actors who can reach a specific actor, directly as well as indirectly (Wilson & Banzhaf 2009:3259).

*Status prestige* is based on the supposition that an actor's rank is a function of the ranks of the actors who connect with him or her (Wasserman & Faust 1994:206). An actor that is chosen by many highly-ranked others obtains thus a higher position of prestige than someone who is the target of only lowly-ranked actors.

Everton (2013:206-208) regards centrality as the most insightful metric among all the existing SNA metrics and asserts that all measures of centrality available to researchers are based on Freeman's general classification of centrality namely *degree,*[2] *closeness* and *betweenness*.

[2] *Eigenvector centrality* is regarded a degree-like measure, akin to degree centrality, as it counts the number of ties of each actor. The only difference is that it weights the score by the centrality of the actors to whom someone is connected.

A central actor can thus be regarded as someone with many ties to others (*degree centrality*); someone with many ties to highly central actors (*eigenvector centrality*); someone who is close (in terms of distance) to other actors in the network (*closeness centrality*); or someone who is positioned on the shortest path between numerous pairs of actors in a network (*betweenness centrality*) (Everton 2013:207).

Degree centrality points to expertise and power of network members by calculating the incoming and outgoing connections of network members. As far as non-symmetric data is concerned, incoming connections (in-degree) reveal an actor's popularity. In a knowledge and information context, individuals with many such ties are regarded as especially prominent or having high levels of expertise. Out-degree refers to the number of outgoing connections of a network member. Actors who have a high out-degree are believed to be remarkably influential within their network (Müller-Prothmann 2007:226). Consequently one can employ the in-degree centrality value to identify experts or authorities, i.e. knowledgeable individuals within a specific knowledge domain.

Schröpfer *et al*. (2013:31) affirm that knowledge consumers hold a high out-degree as well as a very low in-degree centrality value. This means that they turn to others for information, yet they themselves are hardly ever approached for information, i.e. they 'consume' rather than transfer knowledge. It could also imply that other network members do not perceive them to possess any expert knowledge on a specific subject; hence they never approach them in this regard.

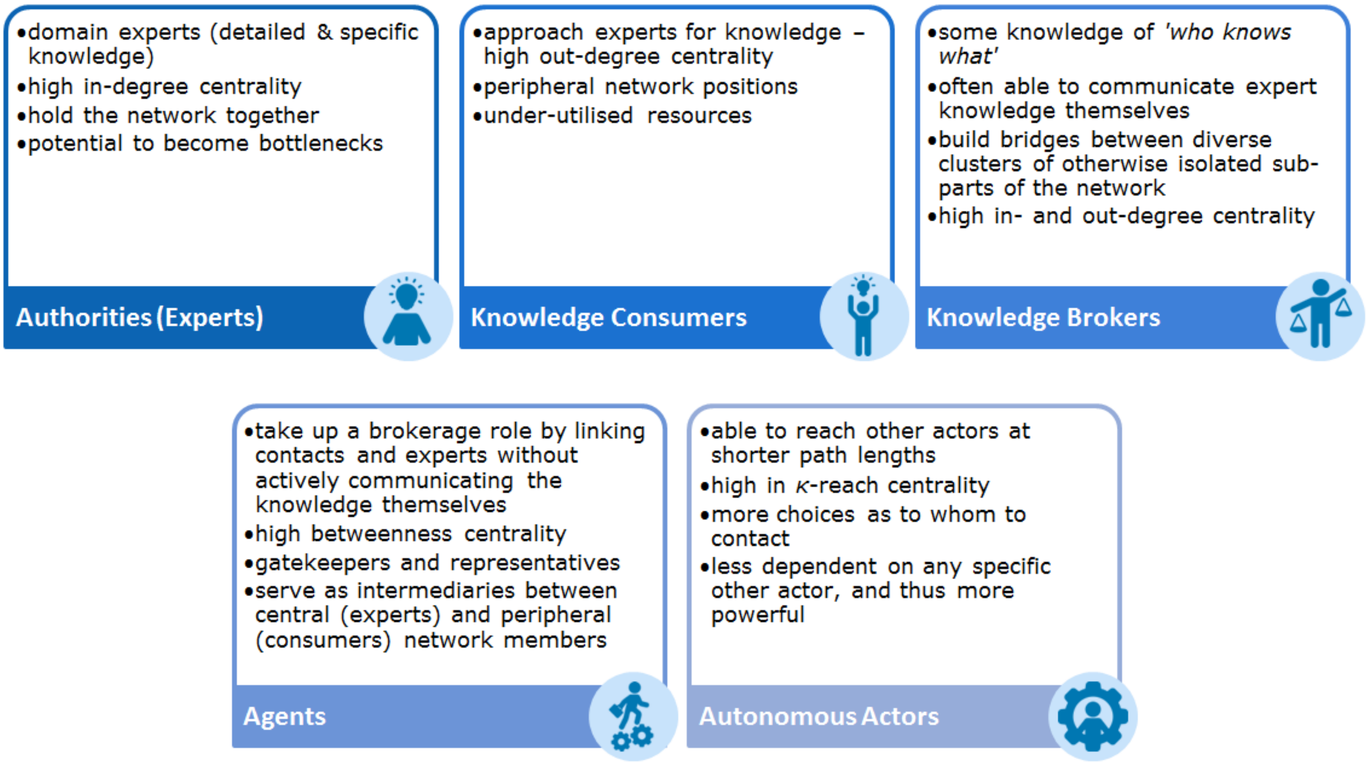
In addition, actors with a combination of a high in- and out-degree value can be regarded as knowledge brokers. These network members receive knowledge and pass it on, acting as an expert on some occasions and as a consumer in other instances (Schröpfer *et al*. 2013:31).

Müller-Prothmann (2007:226) affirms that closeness centrality reveals the level of integration (or isolation) of networks. Closeness centrality incorporates indirect ties when measuring the reachability of network members. It concentrates on the distance of an actor to all other actors in the network. The higher someone scores on closeness, the greater their independence as they can readily reach other members easily (and vice versa). The reverse applies to low closeness centrality which signifies higher individual member dependence on other members of the network.

However, Borgatti *et al.* (2013:177-178) point out that closeness centrality is not well suited when analysing directed data and recommend that $\kappa$-reach centrality be considered instead. They maintain that when deliberating directed data, *out* $\kappa$-reach centrality is defined as the proportion of actors that a specific actor can reach in $\kappa$-steps or less. In contrast, *in* $\kappa$-reach centrality refers to the proportion of actors who can reach a given actor in $\kappa$-steps or less. In line with the aforementioned statement, Hanneman and Riddle (2005) indicate that actors who are able to reach other actors by using shorter path lengths have more advanced positions. Actors with more ties have better opportunities since they have choices as to whom they prefer to contact. This independence makes them less dependent on any specific other actor and thus more powerful.

Betweenness centrality assesses an actor's position on the geodesic paths between other members of a network (Müller-Prothmann 2007:226). According to Izquierdo and Hanneman (2006:27), the notion behind betweenness centrality is that by being in between actors, you are powerful as you may be able to control the flow of information between these actors. Betweenness centrality therefore assists in detecting agents (gatekeepers) within a network.

Based on the above centrality measures, Müller-Prothmann (2007:228) identifies four fundamental roles that individuals within networks play as far as knowledge sharing is concerned, namely as *experts*, *knowledge brokers*, *agents* and *knowledge consumers*. When taking Borgatti *et al.* (2013:177-178) and Hanneman and Riddle's (2005) perspectives regarding *reach* into consideration, another dimension, namely the autonomy of actors, can also be considered. ***Figure 3.1*** below summarises these different roles.




*(Borgatti et al., 2013:177-178; Walker, 2013; Müller-Prothmann, 2007:228; Hanneman & Riddle; 2005 and Cross et al., 2004)*

**Figure 3.1: Fundamental roles for individual network members considering knowledge sharing**

SNA can be a great instrument for assessing networks (Müller-Prothmann 2007:221-222). However, in Mohr's (2014) words, *"Metrics only get you started."* It is vital that one does not simply jump to conclusions based on SNA results, but that one validates the results by observing and investigating what is really happening in a network. For example, someone might score very low on *out-degree centrality* simply because that person is a big introvert or has been recently appointed.

## 3.2 REVIEWING KNOWLEDGE NETWORKS

There exist important differences between work groups, teams, CoPs, and knowledge networks (Allee 2000:10). Nonetheless, the essential element in all these groupings remains the concept of *practices*, where groups share, acquire, and create their knowledge and in so doing develop their own identity (Verburg & Andriessen 2011:36).

### 3.2.1 Knowledge networks

If social networks disclose *"who knows whom"*, knowledge networks disclose *"who knows what"* (Jones 2001:3). As Cross *et al.* (2002:2) put it, *"… who you know has a significant impact on what you come to know."*

Helms *et al.* (2010:53) maintain that due to the tacit nature of knowledge, knowledge sharing often takes place within an organisation's informal networks through social interaction and that these types of informal networks can be termed *knowledge networks*.

According to Du Preez *et al.* (2005), knowledge networks imply a number of actors and resources, where the relationships between them bring about knowledge capturing, knowledge transfer and knowledge creation for the purpose of creating value. Du Preez elaborates further on this notion by maintaining that *"… integrated knowledge networks span all domains, communities, and trust relationships with the goal of fostering sustainable innovation that will continue to promote the competitiveness of its users."*

Although a knowledge network has the same composition as a social network, knowledge networks are as a rule more complex and dynamic. Knowledge networks aim to facilitate the flow and sharing of knowledge as well as to create new knowledge and to ensure the application thereof (Denner 2012:14-15). Knowledge networks also refer to groups of actors with a common interest known as a '*knowledge area'*. Helms (2007) contends that *"… within the knowledge network people exchange knowledge with each other related to the knowledge area …,"* and that it is the knowledge area that connects actors and spans organisational boundaries.

Verburg and Andriessen (2011:41-42) differentiate between four ideal[3] types of knowledge sharing networks, namely: *informal networks*; *question and answer networks; strategic networks* and *online strategic* networks. The main attributes of these archetype networks are summarised in ***Table 3.3*** below.

[3] In practice one may find networks with characteristics of more than one type or networks that oscillate between types (Verburg and Andriessen (2011:41).

**Table 3.3: Ideal types of knowledge sharing networks**

| Type of Knowledge Sharing Network | Characteristics |
|---|---|
| Informal Networks | ▫ Groups of employees with a shared field of interest, often closely related to their work, having considerable interaction and a corporate culture involving shared concepts, ideas and stories.<br>▫ Main purpose of network members is to learn from each other (the transfer of this shared knowledge to the organisation is less important)<br>▫ This type of knowledge networks is usually not very formalised, are either small or have a small core and a larger circle of peripheral members and participation is spontaneous.<br>▫ A very active coordinator or core group and adequate ICT support are generally required to ensure success of these networks. |
| Question and Answer Networks | ▫ Networks with low to intermediate proximity and low levels of institutionalisation.<br>▫ These networks comprise employees who exchange (via a company intranet) questions and answers concerning the solution of practical problems.<br>▫ While these networks may be rather large, they still display some form of group identity, based on commonality in function and organisation.<br>▫ Thrive without many success conditions, besides minimal commitment of members and good internet connections. |
| Strategic Networks | ▫ Established groups of experts whose activities are focused on organisational learning.<br>▫ These groups are highly supported with resources and participants are expected to perform for the company and to develop best practices.<br>▫ These networks generally consist of a limited number of experts, without a periphery of lurkers, as membership is generally not open.<br>▫ Members of these networks tend to be organisationally and geographically widely distributed. Nonetheless some members may have much interaction in face-to-face meetings. |
| Online Strategic Networks | ▫ Although relatively well-established, these networks display low levels of proximity among its members, particularly because of their exclusive communication via electronic means which complicates interaction, coordination, and cohesion forming. |

*(Adapted from Verburg and Andriessen, 2011:41-42)*

Knowledge networks differ from social networks in that they accentuate joint value creation by its members–shifting from information sharing to knowledge creation; it reinforces its members' innovation and communication skills; it implements strategies in order to engage decision makers more directly (Creech 2001:5). Moreover, the exchange of information and knowledge as transactional content is emphasised in knowledge networks (Müller-Prothmann 2006:150).

Hence, knowledge networks could be described as social networks from a KM perspective. These networks form with the purpose to collect and implement knowledge– mainly via knowledge creation and knowledge sharing processes–in order to create value.

### 3.2.2 Knowledge network analysis

Of late the importance of socialisation within KM has been accentuated. Helms *et al.* (2010:55-56) consider the application of SNA to study knowledge networks, especially learning networks such as KNA. KNA can thus be considered an extension of SNA (Helms & Buijsrogge 2006) as SNA provides a systematic method to pinpoint, study and verify processes of knowledge sharing in social networks (Müller-Prothmann 2007:219).

KNA helps to disclose what facilitates or hampers knowledge flows, who knows whom and who shares what information and knowledge with whom (Al-Hashem & Shaqrah 2012:2). It also enables one to observe different types of knowledge networks based on the type of knowledge exchange, e.g. *obtaining advice* vs. *learning* (Helms *et al.* 2010:55).

KNA can thus be described as a SNA with a KM approach. It explores social networks beyond a regular information-flow angle and focuses on what actors know, whether they have access to one another and most importantly, whether learning takes place and new knowledge is created.

## 3.3 THE IMPORTANCE OF SNA FROM A KM PERSPECTIVE

Cohen and Prusak (2001) state that *"… knowledge flows along existing pathways in organisations. If we want to understand how to improve the flow of knowledge, we need to understand those pathways."*

According to Allee (2000:3), technology happens to be the easy component of supporting knowledge creation and sharing, while the actual difficult part is the human element. An important result of any SNA is thus uncovering who connects, communicates and collaborates with whom (Roberts 2014:1).

SNA is regarded as a very effective tool for analysing knowledge sharing within networks (Müller-Prothmann 2007:222), considering that it unveils relationships that either support or obstruct the creation and transfer of knowledge (Cross *et al.* 2002). It also assists in pinpointing experts, key information brokers as well as bottlenecks and provides a detailed analytical foundation for examining informal communities and networks (Müller-Prothmann 2011).

Since a SNA uncovers the availability and distribution of knowledge within networks, it could be used to: enhance the growth of organisational knowledge; identify and develop core skills; create opportunities to better communication; and to discover and support CoPs (Müller-Prothmann 2007:222).

For the purpose of this study the potential value of a SNA is highlighted in terms of knowledge maps and CoPs as is discussed in the sections that follow.

### 3.3.1 Building knowledge maps

Grey (1999) describes a knowledge map as a *"… navigation aid to explicit information and tacit knowledge, showing the importance and the relationships between knowledge stores and dynamics. The knowledge map portrays the sources, flows, constraints and sinks of knowledge within an organisation."* It is, however, imperative to note that knowledge maps point to knowledge, but do not possess it. As Davenport and Prusak (1998) put it: *"Knowledge maps are guides and not repositories."*

Knowledge maps thus assist to document and portray existing knowledge resources in a structured manner. According to Eppler (2001) there are five types of knowledge maps that can be used to manage organisational knowledge, namely: knowledge-sources, -assets, -structures, -applications and -development stages.

Knowledge maps aim to record the location of explicit as well as implicit knowledge. Chan and Liebowitz (2006:21) affirm that a key advantage of knowledge maps is to increase the visibility of knowledge sources and as a result facilitate and accelerate the process of locating relevant expertise within an organisation. Moreover, knowledge maps tend to save search time; pinpoint *islands of expertise* and locate effective CoPs (Grey 1999).

A knowledge map can therefore be described as a tool that indicates what knowledge resides where, therefore enabling organisations to construct visual directories of available experts, knowledge-databases, -structures and -applications.

Knowledge maps themselves do not present a systematic way to measure the efficiency of knowledge flows. SNA techniques can be applied in building as well as analysing knowledge maps (Chan & Liebowitz 2006:20).

In this study, knowledge maps were constructed in order to pinpoint expertise. Thereafter SNA was conducted with the intention of determining whether the actual experts were contacted and to what extent.

### 3.3.2 Social networks and CoPs

As a phenomenon, CoPs have been around for decades but the term itself was only coined in 1991 by Jean Lave and Etienne Wenger (Hildreth & Kimble 2004:ix). Lave and Wenger (1991) perceived the acquisition of knowledge as a social activity where people participate in collective learning at different levels, subject to their level of authority in the group. Since then many studies have been done to examine CoPs and their characteristics.

CoPs are groups of people that are connected through shared skills and within these communities learning occur as a derivative of working together (Amin & Cohendet 2004:76). CoPs can thus be viewed as *"… groups of people who share a passion about a topic, and who deepen their knowledge and expertise in this area by interacting on an ongoing basis"* (Wenger *et al.* 2002:4).

Brown and Gray (1995:78) describe CoPs as *"… peers in the execution of real work"*. Bonds are formed by a common sense of purpose and a desire to discover members' knowledge. These communities are defined by knowledge rather than duties and their life cycles depend on the sustained value as opposed to project deadlines (Allee 2000:5).

Wenger (2011:1-2) maintains that in order to be regarded a CoP, three fundamental elements need to be present: a *domain* (shared area of interest), a *community* (members that participate in joint activities and discussions, cultivating relationships enabling them to learn from each other) and a *practice* (shared collection of resources). A CoP can form naturally based on members' shared interest in a specific area or it can be established with the purpose of gaining knowledge related to their area of interest. Members are given an opportunity to develop themselves personally and professionally by sharing information and experiences within the community (Lave & Wenger 1991:98).

Those interested in social learning processes often seek to understand what distinguishes a CoP from other types of groups or networks. Wenger *et al.* (2011:10) emphasise the social learning elements in CoPs by revealing that *"… [the establishment of a community] creates a social space in which participants can discover and further a learning partnership related to a common domain. This partnership can be formal or informal and its intention can be explicit or tacit. The key* *characteristic is the blending of individual and collective learning in the development of a shared practice.”*

Nickols (2003:3) points out that CoPs can be self-organising or sponsored. Similarly CoP roles can be either spontaneous or formalised. ***Table 3.4*** offers an overview of these roles.

**Table 3.4: Roles and responsibilities within CoPs**

| Behaviours | |
|---|---|
| **Position** | **Activities** |
| Connectors | ▫ Know many others.<br>▫ *“Their ability to span many different worlds is a function of something intrinsic to their personality, some combination of curiosity, self-confidence, sociability and energy”* (Gladwell 2000:49). |
| Mavens | ▫ Connect others with information.<br>▫ Collect information and want to tell other people about it. |
| Salesmen | ▫ Reach out to the unconvinced and persuade them to accept or try something new. |
| Members | |
| **Position** | **Activities** |
| Sparkers (debate triggers) | ▫ Identify gaps and needs for new approaches; ask questions, plays devil’s advocate and point out shortfalls and inconsistencies.<br>▫ First to identify issues that needs to be resolved. |
| Synthesizers | ▫ Help to give meaning to the community.<br>▫ Set the context, provide background information and outline successes or failures. |
| Sole contributors | ▫ Contribute their own arguments and do not actively try to persuade anyone to accept their opinion.<br>▫ State their case and typically end their participation for the time being. |
| Witnesses | ▫ Support a position with their 'vote of confidence' based on their own experience. |
| Champions | ▫ Most actively involved member(s) of the community.<br>▫ Keen interest in the success of the community and taking on a leadership role. |
| Community members | ▫ Interact with each other, sharing information, insights and experiences, participating in discussions and raising issues and concerns regarding common needs and requirements.<br>▫ Primary responsibility is to participate actively, to learn and to share their learning. |
| Subject matter experts | ▫ Serve as important resources for others.<br>▫ Often need to be encouraged to participate. |
| Lurkers | ▫ *'Seen but not heard'.*<br>▫ Visit the community on a regular basis but their participation is limited to viewing the contributions.<br>▫ Look for and use content, information, and connections. |
| Active lurkers | ▫ Same as lurkers but transmit and promote content and information to others outside the network. |

| Supporting Roles | |
|---|---|
| Position | Activities |
| Core team members | ▫ Contribute to the effective and efficient achievement of the CoP's purpose<br>▫ May take the lead on specific activities. |
| Facilitators | ▫ Responsible for clarifying communications, drawing out the reticent, ensuring that dissenting points of view are heard and understood, posing questions to further discussion and keeping discussions on topic—all subject to the will of the group. |
| Sponsors | ▫ Communicate organisational support for a sponsored community.<br>▫ May help remove barriers that obstruct community progress (e.g., time, funding and other re-sources).<br>▫ Instrumental in establishing the mission and expected outcomes for the community. |
| Technicians | ▫ Maintain and develop the online platform itself for it to remain modern and easy to use. |

*(Davidove 2010; Nickols 2003:4; Saint-Onge & Wallace 2003:42-44)*

Although roles and responsibilities will differ depending on the CoP type, the diverse levels of participation available will remain the same regardless. All CoPs will have *core members*, members with *unique expertise* (Hearn & White 2009:3), *active participants*, *occasional participants* and *lurkers*, who, even if they do not actively participate, may follow discussion threads closely and be privately active in communicating what they read/learn with others (Tarmizi 2008:17).

Allee (2000:6-7) indicates that CoPs materialise *"…in the social space between project teams and knowledge networks."* Moreover knowledge cannot be separated from the communities where it is created used and altered, given that in all types of knowledge work, people need to discuss, to research and to share experiences with their peers.

According to Tzagarakis *et al.* (2009:126) CoPs are regarded as one of the most efficient approaches to promote *collective intelligence* also known as *organisational memory*. Adding to this, Schenkel *et al.* (2001) maintain that *"… every CoP consists of one (or many) social networks, but not every social network forms a CoP."* Social networks thus serve as a potential base for CoPs.

Hence, SNA not only contributes to the examination of relationships and information flows between people in CoPs, but it can also help to discover and improve existing CoPs and to establish new CoPs (Cross *et al.* 2006: 37-38).

The term CoPs can thus be described as groups of people (either self-organised or sponsored) with a shared concern or passion for something, who become more skilled in this regard through frequent interaction. These people learn from each other as they share their knowledge and experiences with the group. The longevity of such a community will depend on its sustained value.

## 3.4 MEASURING KNOWLEDGE RELATIONSHIPS

It is often expected of knowledge workers to solve complicated problems within a short time frame. They consequently need to be able to correctly interpret the problem, devise a suitable solution and convince others of the appropriateness of their recommended course of action. Cross *et al.* (2004:3) maintain that as a result of this dynamic problem-solving process, informal networks as opposed to databases, remain vital to knowledge transfer, the dissemination of innovations and the creation of knowledge that can be applied to a particular situation.

SNA presumes that relationships are important and depicts connections or ties between people. The mere presence of a network tie implies that a relationship exists. These ties can be strong or weak, direct or indirect and one-way or reciprocal. Within a SNA, a tie can reveal if someone likes, trusts, reports to, communicates with, or obtains information from another (Ehrlich & Carboni 2005:6-7).

Hollenbeck and Jamieson (2015: 370-374) maintain that SNA enables organisations to identify which employees are most skilled in developing sound, trusting relationships, a vital success factor both within and between teams. Similarly, with regards to knowledge networks, organisations should understand which employees control information distribution and who links otherwise disconnected subgroups (brokerage roles). Organisational norms and beliefs are often transferred as tacit knowledge via relational ties (Nonaka & von Krogh, 2009). Should new employees fail to integrate, they also stand a chance not to adapt to the organisation's culture, which could isolate them further and impact negatively on their performance.

Cross *et al.* (2001; 2002) recognises five key attributes (summarised in ***Table 3.5***) namely: meta-knowledge of employees, access to colleagues, the frequency and intensity of interaction and amount of trust, as critical for relationships to be effective in terms of the creation, sharing and implementation of knowledge.

**Table 3.5: Relational characteristics that promote the creation, sharing and implementation of knowledge**

| Relational Dimension | Objective(s) | Impact on knowledge creation & sharing |
|---|---|---|
| KNOWLEDGE (Knowing what someone knows) | ▫ Raise awareness of *'who knows what'* and *'who is working on what'* within an organisation. | ▫ Knowing what someone else knows (even if initially inaccurate, but adjusted over time) is a precursor to approach a specific person when faced with a problem or opportunity.<br>▫ Before approaching someone, one must have at least some perception of their expertise. |
| RECURRANCE (How often people interact) | ▫ Measure how often network members interact with each other and assess the strength of relationships.<br>▫ Filter out relations that occur infrequently since these relations are not considered to take place structurally. | ▫ Mature relations are more intense and are based on the intensity and frequency of interactions. |
| ACCESS (Gaining timely access to a person's knowledge) | ▫ Understand who is able to reach whom within a sufficient time frame.<br>▫ Consider the extent to which people have access to each other's knowledge.<br>▫ Improve *speed of access/responsiveness* to knowledge sharing. | ▫ Knowing who is knowledgeable is only useful if one can gain access to their knowledge in time.<br>▫ Access is profoundly influenced by the closeness of one's relationship as well as physical proximity, organisational design and collaborative technologies available. |
| ENGAGEMENT (Problem solving through cognitive engagement) | ▫ Communication that actively engages people.<br>▫ Enhanced performance.<br>▫ Increased awareness of skills and knowledge of co-workers.<br>▫ Improve the effectiveness with which people learn from one another. | ▫ People who are supportive in learning interactions People who are supportive in learning interactions actively assist others in thinking through the problems they are trying to solve.<br>▫ People who attempt to understand someone's need for information, after which they actively shape their answer (knowledge), are more helpful in terms of knowledge creation.<br>▫ Instead of dumping information, these people first attempt to understand the problem as experienced by the seeker and fashion their knowledge to the problem at hand. |
| TRUST (Learning from a safe relationship) | ▫ Allow trusting affiliations to develop over time.<br>▫ Encouraging people to voice riskier ideas will result in more creative solutions. | ▫ When a person asks for information, they could become vulnerable since *'seeking help could imply incompetence or dependence'.*<br>▫ Relationships that are trustworthy are often most effective for learning purposes as trust reduces defensive behaviours that could potentially hamper learning.<br>▫ The ability to admit a knowledge deficiency often results in creativity and learning. |

*(Cross et al. 2001:105-116 & Cross et al. 2002:7-8 and 12)*

Based on the aforementioned attributes one can thus concur that KNAs can assist in determining:

- who the (perceived) domain experts within a network are;
- how often these experts are contacted;
- whose knowledge can be accessed by whom in a timely manner;
- what level of problem solving relationships exist within networks; and
- in which relationships network members feel comfortable enough to voice their opinions to create new knowledge.

## 3.5 CULTURE, KM AND SOCIAL NETWORKS

The term *corporate culture* is very comprehensive and far-reaching. Deem *et al*. (2015) draws attention to the fact that there are over 164 definitions of corporate culture in academic literature. They also point out that the definition most often cited, can be ascribed to Schein (1992): *"A pattern of shared basic assumptions that the group learned as it solved its problems of external adaptation and internal integration, that had worked well enough to be considered valid, and therefore, to be taught to new members as the correct way to perceive, think and feel in relation to those problems."* Schneider (2000) offers a more straightforward explanation by describing corporate culture as the character or personality of an organisation, in short *"…the way things are done in an organisation."*

Research pertaining to the main reasons why KM does not succeed in organisations, theorise that corporate culture is the principal obstacle to success (Bart 2000; Park *et al*. 2004). This can be attributed to the notion that culture affects the knowledge-related behaviours of individuals, teams and organisational units within organisations. Though knowledge is transferred through informal social interactions of *"person-to-person channels"* (Yi, 2009:69), it is ultimately culture that determines *"…which knowledge is appropriate to share, with whom, and when."* (Shahabinia cited in Mojibi *et al*. 2015:282).

Hollenbeck and Jamieson (2015:381-2) accentuate the connections that exist between social networks and corporate cultures: Organisations that are in touch with its social network will be more proficient in identifying sources of undesirable influence and in taking appropriate action should an unsuitable culture (or sub culture) start to develop. Likewise organisations wishing to foster a positive culture will know which actors will be best suited to help distribute messages, and will recognise which areas in the organisation are potentially isolated and in need of special attention.

SNA can also be applied to evaluate corporate culture. Elfenbein and Zenger (2014) conclude that the establishment of trusting interpersonal relationships is an important feature of employee development. As a result, by networking with more experienced members in an organisation, new employees are not only able to increase their skills, but are also afforded opportunities to obtain a better perception of organisational values and beliefs. Once organisations comprehend who networks with whom and who is excluded from social development opportunities, they will be able to assist with relationship development where it is most called (Hollenbeck & Jamieson 2015:381-2).

There is thus an important link between knowledge transfer, social networks and corporate culture. Corporate culture determines which knowledge will be shared, with whom, and when. Social networks can be applied to influence corporate culture as well as to connect new employees with more experienced ones and to ensure that they appreciate and adopt the culture of the organisation.

## 3.6 SUMMARY

This chapter formulated a distinction between social networks and knowledge networks along with SNA and KNA. To summarise, knowledge networks differ from social networks in that they are more intricate and dynamic and are predominantly concerned with groups of actors who have a mutual interest, known as a knowledge area. Consequently knowledge networks could be labelled *social networks with a KM perspective*.

A SNA *per se* is concerned with the application of visual and mathematical tools and techniques to identify and analyse relationship patterns among actors within a network. A KNA though, can be explained as a SNA with a KM approach. KNA analyses social networks beyond a regular information-flow angle as it focuses on what actors know; whether they have access to one another and most importantly; whether learning takes place and new knowledge is created.

Both KNA and SNA make use of the same metrics in order to interpret relationships in an impartial manner. These metrics provide structural measurements to define the network as a whole and to offer information on the involvement of each actor in the network. In view of the fact that network structures can be described using a very diverse set of metrics, the metrics discussed (***Table 3.1***) in this chapter were limited to:

- a whole-network review;
- the network structure (cliques, bottlenecks and hubs);
- prominence (prestige and centrality);
- distance (maximum flow, geodesic distances and average path length); and
- connectivity (point connectivity, reciprocity and tie strength).

Supplementing the aforementioned, this chapter also summarised the four fundamental roles performed by individuals regarding knowledge sharing (as identified by Müller-Prothmann 2007:228), namely *experts*, *knowledge brokers*, *agents* and *knowledge consumers*.

The potential usefulness of a SNA was revealed in terms of knowledge maps as well as CoPs. A knowledge map is often regarded as a tool that reveals *which knowledge resides where*. Therefore, studying knowledge maps in conjunction with a SNA will enable organisations to determine whether the real experts are being contacted and to what extent.

Moreover, it was emphasised that social networks can serve as a foundation for CoPs as the term CoP refers to groups of people with a shared concern or passion for what they do, who become more proficient in this regard due to frequent interaction. Subsequently SNA can be applied to detect and adjust existing CoPs as well as to establish new CoPs.

This chapter also presented five attributes (adopted from Cross *et al*. 2001:105-108 and Cross *et al*. 2004) namely *knowledge*, *recurrence*, *access*, *engagement* and *trust* to consider when measuring the effectiveness of relationships insofar as the creation, sharing and implementation of knowledge is concerned. To end with, a brief description of the relationship between KM, social networks and corporate culture was provided.

# CHAPTER 4

*"Only theory can turn a heap of facts into a tower of knowledge."*

**- Andreas Wagner**

# 4 RESEARCH METHODOLOGY

Theory, methodology and empirical phenomena form the three cornerstones of research (Dubois & Gibbert 2010:129). This chapter aims to address the research methodologies and approaches followed in the study. It outlines the research design and describes the data collection and analysis methods.

As shown in ***Chapter 1 (Section 1.1*** and ***1.4***), not much has been published considering research pertaining to the interrelationships of different KM tools and the underlying synergies among them. Being rather explanatory, the researcher aimed to design and test a methodology to examine how synergies between SNA, CoPs and knowledge maps could influence knowledge networks. The research design pursued could thus be best described as abductive reasoning based on a pragmatic, social network paradigm.

## 4.1 FRAMING THE RESEARCH PARADIGM

The social network paradigm is rapidly achieving acclaim in the social and behavioural sciences as the theoretical foundation for studying social structures (LeCompte & Schensul 2010:73-75). Since its beginnings in the 1930s, SNA has emerged as a major paradigm for social theory and research. Owing to key methodological developments in the 1970s and early 1980s, the range of applications using SNA has grown remarkably. Rather than analysing individual behaviours, attitudes and beliefs, SNA concentrates on how social entities interrelate and how these interactions constitute a framework that can be examined in its own right (Wasserman & Galaskiewicz 1994:5-7).

Freeman (2004) maintains that SNA has four distinct characteristics. SNA:

- is inspired by a structural perception that actors are linked by ties;
- is grounded in systemic, empirical data;
- leans severely on graphic imagery; and
- relies on the application of mathematical and/or computational models.

Furthermore Müller-Prothmann (2007:221-222) claims that the social network paradigm and SNA tactics are widely accepted as a potential approach to analyse, evaluate and influence communication within networks.

SNA thus offers techniques and metrics that can be used to identify, visualise and analyse knowledge networks within and between groups.

Johnson *et al.* (2007:113, 125) contend that pragmatism is the primary philosophy of mixed research as it offers both the epistemological justification and logic for mixing approaches and methods. Pragmatism acknowledges that there exist singular and multiple realities that are open to empirical analysis and takes a stance to resolve *real world* challenges. As a result pragmatism does not restrict the researcher with mental and practical constraints imposed by the *"forced choice dichotomy between post positivism and constructivism"* (Creswell & Plano Clark 2011:20-28).

Moreover pragmatists maintain an *"anti-representational"* interpretation of knowledge" contending that rather than providing an "accurate account of how things are in themselves", research should be useful, to *"aim at utility for us"* (Rorty 1999:xxvi). In essence pragmatism implies that the principal issue is whether the research has assisted in determining what the researcher wants to know (Hanson 2008:109).

The philosophical paradigm of this research could thus be considered a pragmatic, social network epitome.

## 4.2 RESEARCH DESIGN

As studies pertaining to knowledge rooted in existing social networks are fairly new, this study was based on a pragmatic paradigm. Correspondingly the researcher made use of abduction and designed the research as a cross-sectional study following a simple mixed method approach namely *explanatory sequential mixed methods*.

In explanatory mixed methods design, qualitative data is gathered after quantitative data (Creswell & Plano Clark 2011), hence data for both the knowledge maps and the SNAs were collected and analysed prior to a follow-up of qualitative data collection and evaluation. This strategy was applied to confirm that the qualitative data *"...refined, extended or explained"* the results obtained from the quantitative data (Cresswell 2012:542). ***Figure 4.1*** delineates the explanatory mixed methods design of this study.

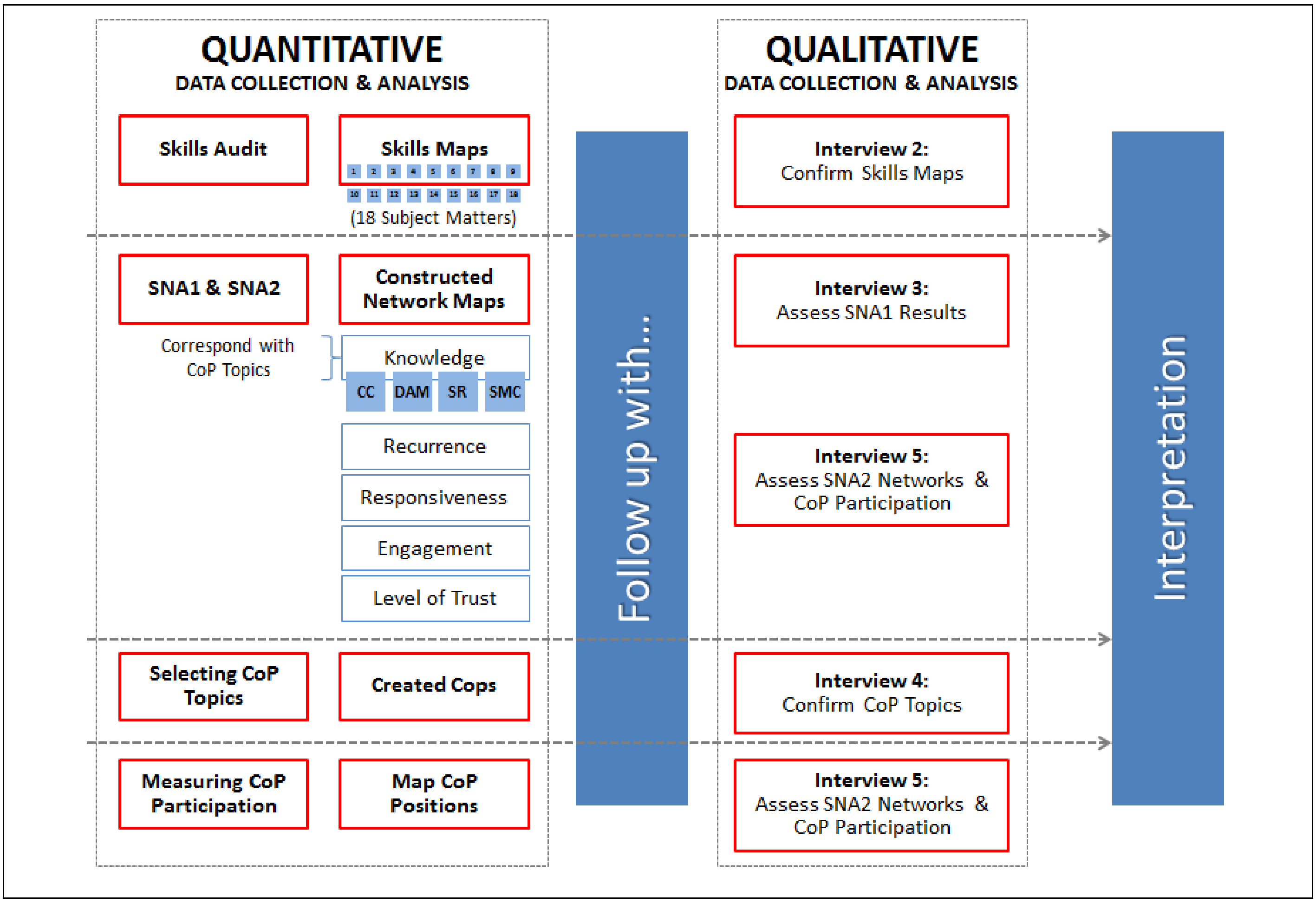



**Figure 4.1: Explanatory mixed methods design of this study**

The first interview of this study (***Appendix 3***) was conducted in order to identify the key subject matters members in this division were concerned with; and to determine whether there existed key individuals outside the specific business area that members were supposed to engage with in order to better their knowledge in the identified subject matters. Next a skills audit was conducted and 18 skills maps were constructed. The correctness of the results of these skills maps were discussed during ***Interview 2*** (***Appendix 3***), after which the researcher revised the skills maps where necessary. ***Interview 3*** (***Appendix 3***), enabled the researcher to put some of the SNA results into context and to confirm if the results in general, were a true reflection of the relationships between and within the respective sub-divisions. Divisional members were asked to participate in a quick poll in order to determine which of the identified subject matters appealed to them most. These outcomes were discussed in ***Interview 4*** (***Appendix 3***), during which the CoP topics were confirmed. Finally the results of both the second SNA as well as the CoP participation were discussed during ***Interview 5*** (***Appendix 3***), enabling the researcher once again to verify if the overall results were a true reflection of the relationships between and within the respective sub-divisions and to put some of the specific SNA outcomes into context.

Considering that this explanatory mixed methods design is applied within one organisation, the disadvantages and associated biases of cases study research can be applicable in this case. According to Bromley (1986:1 23), all case study research commences with a desire to obtain a comprehensive understanding of a single or small number of cases set in a real-world context. Case studies are thus relevant when the research addresses either a descriptive question (*what has happened?*) or an explanatory question (*how or why did something happen?*).

Yin (2014:15) maintains that a case study approach is especially relevant when conducting research within organisations with the intent to study systems, individuals, programmes or events. He stresses that although case studies are frequently qualitative; it can also incorporate the quantitative paradigm and can be based on *"any mix of quantitative and qualitative evidence"*.

Merrian (1998) asserts that case studies assist in the discovery of new meaning, increase prior knowledge or substantiate what is already known. Moreover, in a definition postulated by Woodside (2010), case study research is depicted as *"… an inquiry that focuses on describing, understanding, predicting and/or controlling the individual (i.e. process, animal, person, household, organi[s]ation, group, industry, culture, or nationality)."* Adding to this, Woodside (2010) contends that the primary objective of case study research is deep understanding and in order to achieve deep understanding, the implementation of multiple research methods within multiple time periods is recommended.

In this study, the impact that SNA, CoPs and knowledge maps could have on the respective knowledge networks was studied. Comparisons were made between the four respective knowledge networks as well as between the networks constructed pertaining to *recurrence*, *access*, *level of engagement* and *trust*, before and after the knowledge maps were communicated and formal CoPs were implemented. By comparing these knowledge networks at two specific points in time, the researcher was able to detect changes in the characteristics of the knowledge networks at both network and individual levels.

### 4.2.1 Foundation Theories to SNA

SNA, also termed *structural analysis*, is not a formal theory, but rather a comprehensive approach to examine social structures. While traditional individualistic social theory and data analysis regard the characteristics of actors as the main priority, SNA consider relationships between actors as the primary concern, followed by individual characteristics. Although SNA studies focus on relational data, it is important to point out that individual attributes as well as relational links are required to fully understand these social occurrences (Otte & Rousseau 2002:441-442).

Fredericks and Durland (2005:15) maintain that SNA stem from three main and parallel influences commencing in the 1930s, namely: *sociometric analysis*, which used *graph theory* methods; the Harvard analysis, a *mathematical approach* taken up first by Kurt Lewin which laid the foundation for the analysis of social networks and introduced the notion of cliques; and a stimulus prompted by the Manchester anthropologists who looked *at the structure of community relations* in villages. In the 1960s and 1970s these influences were integrated and contemporary SNA was established (Kilduff & Tsai 2003).

Of the German Gestalt theorists in psychology that came to work in the United States in the 1930s, Jacob Moreno was the most remarkable. Moreno, who examined how an individual's actions were influenced by his or her group relations, was credited with formulating the *sociogram*[4] as a way to portray social relationships. In the 1950s, Dorwin Cartwright and Frank Harary extended Moreno's work and connected the sociogram to mathematical formulas to create graph theory (Harary *et al.* 1965). In early graph theory, lines started to have value, indicating the direction of relationships (Fredericks & Durland 2005:16), permitting the group structure to be analysed while simultaneously considering each individual's position. This initiated the concept of asymmetry and balance in network theory and analysis (Kilduff & Tsai 2003).

[4] The sociogram is a diagram in spatial geometry practice, where individuals are represented as nodes and relationships as the lines that connect these nodes. The sociogram offers thus a visual representation of the social structure that is examined and explains specific elements of the relationships that constitute the structure (Fredericks & Durland 2005:16).

The studies of the mathematicians and graph theorists were mostly founded on complicated and intricate algorithms. Due to the complexity and laborious nature of the calculations, applications were demanding and time-consuming and mostly performed on small groups. With the expansion of computer-based analysis techniques in the 1970s, attention to the development of network analysis reappeared in the works of Bonanich (1972), Freeman (1979), Burt (1982) and Breiger (1988) (Fredericks & Durland 2005:17).

In addressing the debate with reference to whether SNA is a theoretical field unto itself or simply an assortment of practices used in the study of social relations, Fredericks and Durland (2005:17) indicate that as a rule, prominent researchers in the field work in one of three categories, namely: *graph network theory or social psychology (balance and social comparison theory)*; *an assortment of ideas such as heterophily and structural holes that originated from within the field of SNA itself*; and *the application of network approaches in other subject areas such as contingency theory, population ecology, institutionalism, and resource dependency theory*.

SNA is a research approach that offers empirical tools to study relationships among social entities and the patterns and implications of these relationships (Luo & Hsu 2009:921; Wasserman & Faust 1994). Network approaches explicitly challenge the difference between deduction and induction and emphasise the importance of relationships. It accentuates the joint influence of structure and social relationships and enables the visualisation and quantitative description of social ties between actors in a network (Kolleck 2013:1).

According to Monge (1987) a SNA approach presents several benefits to researchers, especially as far as units of analysis, levels of analysis, aggregation, disaggregation and cross-level influences are concerned. The strength of SNA thus lies in its ability to make sense of social traits that cannot be sufficiently explained by collecting data on individual conduct or attributes. For example, network theories can be tested at all levels of aggregation namely: dyads, triads, sub-groups and groups (Wasserman & Faust 1994:22).

In addition to this, Marsden and Lin (1982) maintain that a SNA approach is particularly valuable:

- when addressing complexities associated with efforts to assimilate several levels of analysis;

- in grasping how social structure forms around individual action;
- in determining how social structure limits individual and collective action; and
- in clarifying how attitudes and activities are controlled by the social context in which encounters take place.

Wellman and Berkowitz (1988:4) define network analysis as *"… neither a method nor a metaphor, but a fundamental intellectual tool for the study of social structures"* and regard relations as *"… the basic units of social structure."*

Since these connections can be measured, modelled and visualised, this approach could appear very mathematical. It does not mean that a SNA is simply a quantitative research technique, for a great deal of significance can be found in the analysis of the quality of relations that exist between nodes (Scott 2000:3-5).

Similarly, Svihla (2009:43) describes SNA as a combination between graph theory and matrix algebra which presents portrayals that *"… preserve the complexity of interaction, yet also provides variables summarising characteristics of the group."*

SNA techniques enable one to uncover attributes such as the nature of relations within a network, the extent and/or intensity of the interactions, the type of structural patterns in a network and whether and how relations develop over time.

According to Krätke (2010:86) network analysis provides useful *macroscopic* mapping of existing links within a given territory and quantitative measures of network properties that allow the comparative analysis of different regions or sub-sectors.

Quantitative analysis involves the application of graph theory to reveal certain structural properties of the networks, while qualitative analysis implicates the analysis of a graphical depiction of a network (Helms 2007:6).

In this study network analysis was applied to both the quantitative and qualitative analysis of knowledge networks.

The SNA approach followed examined existing knowledge networks at two specific points in time[5] *('before' and 'after' knowledge maps were communicated and formal*

[5] SNA data collection was carried out in August 2015 and again four months later in early December 2015.

*CoPs were implemented)* in order to illustrate comparative differences and similarities regarding knowledge roles and knowledge relationships. A multiplex network study design[6] within four unique knowledge networks among the same set of nodes was implemented.

### 4.2.2 Triangulation

Lather (1986:67) maintains that triangulation is critical in establishing data trustworthiness and that for data to be credible, it is vital for the research design to pursue counter patterns as well as convergences.

Triangulation involves using diverse data collection techniques in a study to produce a deeper understanding and to increase belief in the subsequent findings. It provides insight into the reliability of findings and helps to prevent overgeneralisation (Bryman 2004:1142; Dwyer 2013:370). Two types of triangulation were used in this study, namely *data triangulation,* (collecting data at different points in time) and *methodological triangulation*, (using more than one method to gather data) (Denzin 1970).

The methods of data collection which were used in this study to triangulate findings included SNA surveys to construct a *before* and *after* snapshot of knowledge networks at two specific points in time, questionnaires to audit (map) network members' skills, as well as group interviews.

In this study, the design process comprised three main phases. See ***Figure 4.2***

[6] An extension of the whole-network data structure where a sub-set of actors is defined within the boundaries of the study (Robins 2015:69-70).

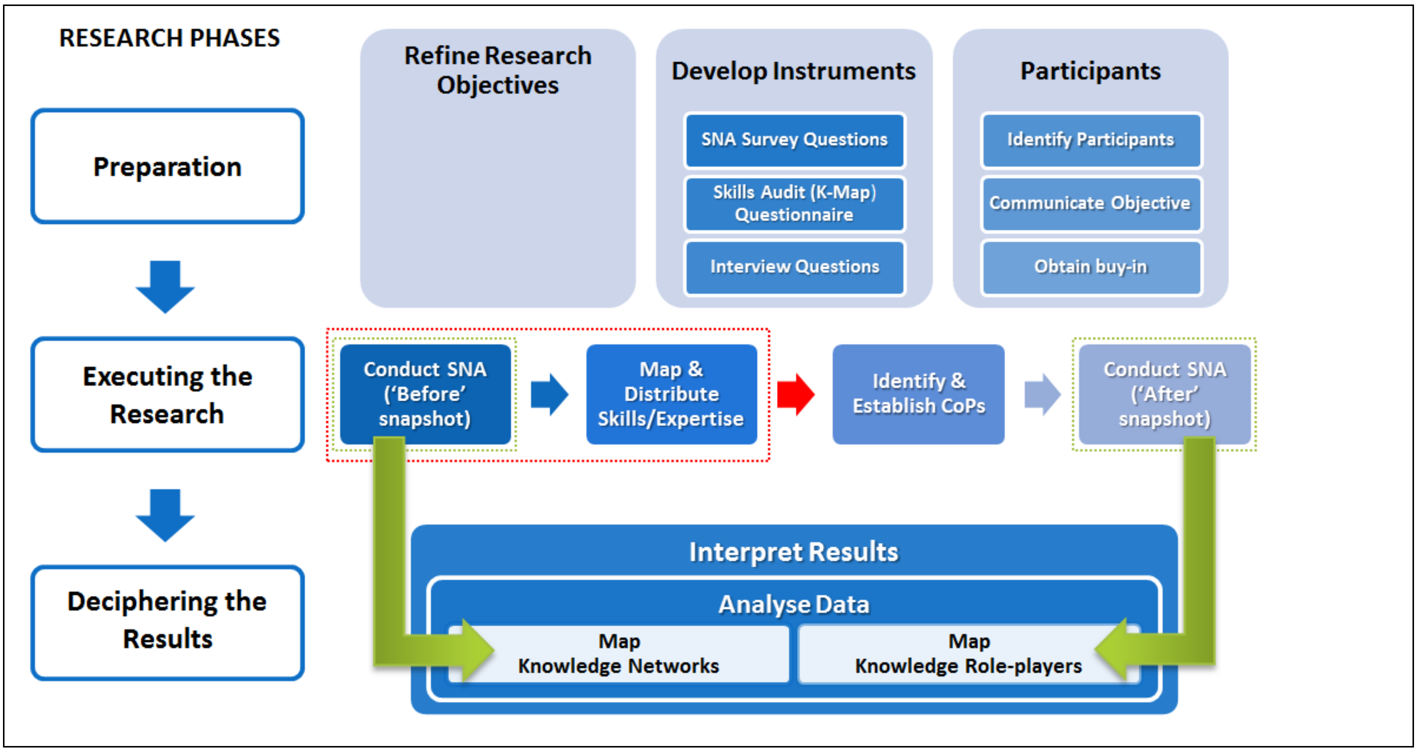



**Figure 4.2: Process design**

In preparation for this study, the scope of analysis was clearly defined. Subsequently instruments were developed in order to collect information to conduct the study. These instruments included developing a survey to perform a SNA at two different points in time (***Appendix 1***), designing a questionnaire to map the skills and expertise (***Appendix 2***) of the participants and compiling a few guided queries[7] for group interviews (***Appendix 3***), permitting interviewees to better express their opinions and ideas (Esterberg 2002:87), should the need arise. Finally all members to participate in this study were identified – in this case, members of a specific business unit. All participants were provided with background information about the goal of the study and its importance, in order to ensure that they take it seriously and participate correctly. In order to obtain a high response rate for the surveys, managers of the respective sub-divisions also motivated the identified actors to participate.

[7] The interview guide followed a logical order and was limited to a few neutral questions. This enabled the researcher to pursue interesting allegations and allowed participants to supply more detail where needed (Greeff 2002:302-3).

In the next phase, a SNA with a KM approach was conducted. This served as the *before* snapshot of the research. This SNA enabled the researcher to plot five different types of relationships namely:

- maps indicating who contacts whom regarding specific *subject matters*;
- the frequency of the interaction that took place;
- *how accessible* colleagues' knowledge was (i.e. how responsive contacted professionals were to requests for information);
- to what extent people were willing to engage in assisting their colleagues in solving work-related problems; and
- how *comfortable* employees felt to share their ideas in the workplace with one another.

Hereafter knowledge (skills) maps that identified knowledge experts in specific areas were constructed and distributed among the participants. Based on the outcome of the first SNA and the knowledge maps and with the agreement of interviewees, four online CoPs were launched. Interaction in these CoPs was closely monitored[8] and two months after the respective CoPs were established, a second SNA (with exactly the same survey questions[9] and participants as before[10]) was conducted in order to create an 'after' snapshot.

In the final phase, the results of the two SNAs were compared in order to achieve the research objectives.

## 4.3 CLARIFYING RESEARCH OBJECTIVES

According to research regarding the influence of SNA on CoPs, SNA assists in identifying the correct people to participate in a CoP (Hamre & Vidgen 2008). It was also revealed that a SNA can assist a community in moving from an *ad hoc*, informal group to a value producing network (Cross *et al.* 2004). Moreover Al-Hashem and Shaqrah (2012:2) maintain that social networks underpin CoPs and that poor social networks will most likely produce poor CoPs.

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[8] The effectiveness of the CoPs was monitored based on participation–the number of members and the number of contributions/conversations.
[9] In the second SNA only the four subject matters pertaining to the identified CoPs were included in the 'knowledge' dimension as opposed to the 18 subject matters covered during the first SNA.
[10] Only the members who participated in the respective CoPs were requested to complete the second SNA although all members' names were available for selection regarding the knowledge dimension.

In studies regarding SNAs and knowledge maps, Norman and Huerta (2006) investigated the influence of knowledge maps on knowledge transfer behaviour of people who work together. Conversely Liebowitz (2005) investigated how SNA could be applied to develop knowledge maps and concluded that well-developed knowledge maps assist to pinpoint expertise, connect new members and increase organisational learning.

Based on the relevance of the aforementioned studies, the aim of this research was to examine the interrelationships between SNA, CoPs and knowledge maps pertaining to knowledge networks within a business unit of a South African parastatal.

Subsequently, the main research problem of this study was to determine:

How can synergies between SNA, CoPs and knowledge maps reinforce knowledge networks?

In order to resolve the said problem, the following research objectives were addressed:

- *Objective 1* - Establish the level of interaction with the actual experts in knowledge networks by linking key network positions with the experts pinpointed in knowledge maps.
- *Objective 2* - Determine whether any correlation exists between the levels of CoP participation and network positions held by individuals.
- *Objective 3* - Investigate how the establishment of CoPs and the distribution of knowledge maps could influence knowledge network structures, specifically in terms of cohesion, cut-points and hubs.
- *Objective 4* - Examine in what way CoPs can influence network connectivity considering whole-network assessments.

## 4.4 SAMPLE DESIGN

Research was conducted within a prominent parastatal which has to continuously consider how it enhances its internal resources in order to effectively execute its mandate. Prior to conducting this study, authorisation was requested from the parastatal to collect data from employees in a specific business unit. Approval was granted on condition that the identities of the participants as well as the parastatal remain confidential and that access to the results was made available to the parastatal. Confidentiality was guaranteed to all participants and participation was voluntary. ***Appendix 4*** presents a copy of the informed consent letter that was completed and signed by all participants. The researcher also obtained a letter of authorisation from the parastatal and ethical clearance was granted by the university.

It is important to note that the participants could not remain absolutely anonymous, due to some of the constraints associated with collecting data through SNA. In addition their identities had to be made known to the respective managers in order to: confirm their level of expertise as well as to put identified occurrences regarding the first SNA, into context during group interviews.

Martinez *et al*. (2003:361) maintain that in order to perform a SNA, one has to define the set of networks and relationships to which the study is to be applied. Consequently a purposive strategy was followed to explore the synergies that exist between knowledge networks, CoPs and knowledge maps.

Research participants were intentionally sampled for their specific affiliations (Esterberg 2002:93) regarding the sharing and creation of knowledge. Emphasis was placed on the knowledge element of SNA and as a consequence four different knowledge networks were constructed and assessed. Four additional relationships were also outlined, namely frequency of interaction, responsiveness, level of interaction (engagement) and trust. The latter four networks were essentially constructed to monitor changes regarding a whole-network analysis.

Handcock and Gile (2010:7) remark that in most network samples the unit of sampling is usually the actor (or node), while the unit of analysis is the relationship between two nodes (dyad). Populations studied through SNA may vary from small groups of people to huge networks consisting of millions of actors. Boundaries are determined by empirical conditions and available resources to observe network actors and their relationships (Müller-Prothmann 2007:222).

According to Norman and Huerta (2006:9) a SNA is optimised when a total population sample is achieved, particularly in cases where networks are small and specialised. In this study the researcher aspired to analyse a total population sample within a specific business unit of the parastatal. This business unit contained four sub-divisions consisting of 49 employees. Although each sub-division operated in its own area[11] of responsibility the majority of these employees were primarily occupied with coding. As a consequence some of their skills and expertise overlapped. Although the researcher knew some of the participants before conducting the study, they never worked together. This sample was specifically selected based on their shared affiliations in terms of their daily tasks. ***Section 4.8.3.1*** addresses the potential bias pertaining to SNA metrics concerning the organisational relationship between the researcher and the research sample, in more detail.

Since the respective managers of the sub-divisions were not able to identify potential participants outside their respective areas, a whole-network approach was followed in this study.

Forty-seven of the 49 network members from the respective sub-divisions participated in the skills survey as well as in the first SNA. Of the network members who did not participate, one had been seconded to a different division and another went on maternity leave at the time of the study. Another member went on maternity leave before the CoPs had been formed and had not returned by the time the second SNA was conducted. An additional two members were assigned to other divisions during the execution of the first SNA.

Twelve network members were not interested in joining any of the CoPs. Four members who did join the online CoPs never revisited the communities mainly due to time constraints. In order not to potentially distort the results of the research, these members were not considered as part of the CoPs.

In order to be able to compare apples with apples, networks that were compared, were only constructed based on information provided by participating members. As a consequence, members who did not want to join any of the CoPs were not asked to participate in the second SNA and did not form part of the final sample population. In total, 17 network members were eventually removed from the comparative analysis. ***Table 4.1***.provides more details of the participant sample. As far as the knowledge dimension was concerned, names of members who did not participate in the SNAs,

[11] Areas varied between *production support*, *systems testing*, *building big end-solutions*, *systems analysis* and *integrating environments*.

were still available for selection by participating members. As a result the knowledge networks constructed were asymmetric.[12]

A 100% response rate was achieved during the first and the second SNAs. It is essential to underscore once again that only members who joined the CoPs were asked to also participate in the second SNA. As a result, when comparing data between the first and second SNA, only relations between members who participated in both SNAs were considered for analysis. An overview of the number of participants is offered in ***Table 4.1***.

**Table 4.1: Overview of participant sample**

| | Participants per Subdivision | | | | |
|---|---|---|---|---|---|
| | Sub-division 1 | Sub-division 2 | Sub-division 3 | Sub-division 4 | TOTAL |
| Skills Audit | 15 | 8 | 13 | 11 | 47 |
| SNA 1 | 15 | 8 | 13 | 11 | 47 |
| Joined CoPs | 9 | 6 | 8 | 7 | 30 |
| SNA 2 | 9 | 6 | 8 | 7 | 30 |

The network members identified were initially associated with a total of 18 different subject matters, which were obtained from group interviews. These subject matters were reduced to four, based on:

- *a quick poll* during which network members had to indicate which of the predefined subject matters they were most interested in;
- group interviews with the managers of each sub-division;
- the results of the skills audit; as well as
- the outcome of the first SNA.

As a result the following CoPs were established[13]:

[12] Asymmetric networks occur when one person indicates a relationship with another, without the choice being reciprocated.
[13] The target organisation which provided the context for this research is so prominent in its industry that any further role description of the research subject matters would reveal its identity and breach confidentiality agreements.

- *Commodity Control (CC)* – a community that comprised 21 members and aimed to establish opportunities to learn about the distinctive CC processes.
- *Data Analytics and Mining* (DAM) – a community consisting of 22 members who were concerned with DAM, a technical capacity aimed at deriving business insights and value from data. This community intended to enlighten members on how DAM differs from Data Warehousing and Business Intelligence as well as what tools and techniques are used.
- *Single Registration (SR)* – a community focused on a system that is used to manage customer registrations and which stores customer master data. Nineteen members joined this community.
- *Service Manager Cases (SMC)* – a community containing 20 members who were involved with a system used in-house to track various actions employees need to perform in support of customer enquiries and collections.

CoP membership varied. While some members only felt qualified to join one CoP, others were inclined to become a member of all four CoPs. ***Appendix 5*** offers an overview of the membership and level of participation of each online CoP.

## 4.5 DATA COLLECTION METHODS AND INSTRUMENTS

The researcher aimed to adhere to Goddard and Melville's (2001:46-47) criteria of good questionnaires, ensuring that questions were objective, appropriate, relevant, unambiguous and understandable. All questionnaires utilised in this study were pretested to a small sample to determine the need for any amendments in order to ensure reliability.

The following techniques were implemented in order to assemble data for the purposes of this study.

### 4.5.1 Semi-structured group interviews

Semi-structured group interviews assisted in discovering information that might not have been thought of as relevant by the researcher, but was considered important by participants (Gill *et al*. 2008). Saunders *et al.* (2009:345-6) claim that although group interviews can produce highly productive dialogue, reported consensus could be in reality, *"a view that nobody wholly endorses and nobody disagrees with"* due to some participants dominating the interview whilst others may withdraw from the conversation resulting in some participants publically supporting the views of others, whilst disagreeing in private. Nonetheless the presence of multiple participants permits a range of perspectives to transpire and allow the group to respond to these opinions. This approach allows participants to reflect on opinions by other group members and to contest one another's opinions.

Group interviews were chosen since they allowed the researcher to explain or explore concepts by observing the intersubjective experiences (agreements and disagreements) between the participants (van Harmelen *et al.* 2001:26). This proved especially useful when interpreting the SNA results regarding the network roles allocated to individuals, as well as for identifying the subject matter experts.

Semi-structured interview guides were compiled and conversations were conducted roughly within the boundaries of these guidelines. A short explanation of what was expected of them was provided to interviewees at least two days before each interview to enable participants to reflect on the questions and to prepare their answers. This approach enabled participants to do some preparation beforehand and assisted them in recalling information relevant to the research focus.

In this study the groups that were interviewed consisted of the four managers of the respective sub-divisions of the business area. These four managers were considered to be the ideal candidates for the group interviews based on their expertise in their respective areas as well as their knowledge and understanding of the interaction between the employees who reported to them. Managers were responsible for supervising between eight and 15 employees which could explain their intimate knowledge regarding the collaboration that took place within their respective sub-divisions. Group interviews were conducted during the various phases[14] of the research.

These interviews assisted to:

- determine the most important subject matters on which knowledge and information should be shared among employees in the business area;

[14] In Preparation: Determine most important subject matters employees in the business area should converse on and identify individuals outside the business area that should be participating in the SNA.
During the Research Project: Discuss the outcomes of the first SNA (*before* snapshot) and agree on 1) the CoPs that should be established and 2) the individuals who should form part of the CoPs.
Towards the End of the Research Project: Discuss the outcomes of the second SNA (*after* snapshot).

- determine whether there were key individuals outside their business area, whom employees might (or should) be working with regarding the identified subject matters;
- confirm who the real experts per identified subject matter were;
- identify the subject matters of the CoPs that needed to be established; and
- put SNA results into context, as background information is often essential to draw the right conclusions from the findings (Helms 2007:18).

In total there were five group interviews. The first interview took place at the inception of this research and aimed to identify the sample population as well as the subject matters of the knowledge networks. The second interview was conducted after the results of the skills audit were consolidated in order to confirm its accuracy. Once the results of the first SNA were consolidated and network maps were assembled, a third group interview were conducted in order to assess these results and to put the outcomes of the first SNA into perspective. After a quick poll determining the subject matters participants were most interested in, a fourth group interview took place during which four CoP subject matters were confirmed. Finally a fifth interview was conducted after consolidating the results of the second SNA and constructing the respective network maps, in order to reflect upon these outcomes.

***Appendix 3*** provides an overview of these interviews, the reasoning behind the questions posed as well as the results obtained. It is important to point out that focus-group interviews were only conducted with the managers of the four sub-divisions that were studied. The motive for this was partly due to the fact that as confidentiality was guaranteed to all participants, the results of the SNAs could not be dispersed wider than these four managers. In addition these interviews were also used for the triangulation of data.

### 4.5.2 Online questionnaires

The sample population was requested to participate in three independent online questionnaires. One questionnaire was presented as a self-assessment survey, aiming to determine who the experts were on predefined subject matters. The second questionnaire was in the form of a SNA survey. Exactly the same SNA survey was repeated four months later, with the exception that the subject matters were reduced from 18 to four and only members who had participated in both the CoPs and the first SNA were asked to participate.

#### *4.5.2.1 Skills audit questionnaire*

As far as the skills audit questionnaire is concerned, participants were requested to do a self-assessment after which the results were confirmed with the respective managers. Data was collected electronically via an Excel spreadsheet that participants had to complete after which it was consolidated by the researcher.

The aim of the skills audit was mainly to pinpoint experts, but also to identify individuals who could potentially be interested in participating in a variety of CoPs. Consequently the researcher developed a skills audit questionnaire (***Appendix 2***) measuring:

- a participant's *proficiency* regarding the subject area; and
- how much *experience* a participant had in the subject.

Answers to the questions were based on a five-point Likert scale. The questionnaire was complete, but short in order to gain as much information as possible without wasting the respondents' time.

#### *4.5.2.2 Divisional Social Network Analysis*

In most cases, SNA as a KM tool uses questionnaires for data collection (Müller-Prothmann 2007:223). It is important to take into account that questionnaires do present artificiality and that findings depend heavily on the presumed validity of self-reports (Carrington *et al*. 2005:10). In order to address the aforementioned, interviews were conducted with the four respective managers in order to verify the outcomes and to place the results in context.

The SNA questionnaires (***Appendix 1***) collected information on five distinct types of relationships and apart from the knowledge dimension, the intensity of each relationship was measured by asking participants to 'type' the intensity of their relationships according to Likert scale items. The questionnaire focused on collecting data about the connections between people. Relationships investigated included:

- knowledge domain;
- frequency of interaction;
- responsiveness (access) to knowledge and information;
- engagement; and
- an element of trust.

By collecting the above information it was possible to determine which participants belonged to which networks and to what extent.

In this study, exactly the same SNA (apart from the number of subject matters and active participants) was repeated two months after the respective CoPs were established and four months after the first SNA was conducted. In both instances a two week time frame was allowed for participants to take part in the SNA questionnaire. The reason for this was based upon Müller-Prothmann's (2006:170) observation that a too short time period might result in a low participation rate, whilst a too long time period might distort the picture due to the process character of networks.

The researcher asked a small group of the sample population to review the questionnaire questions before distributing it among the respondents. In order to avoid misunderstanding and to increase buy-in from participants, the researcher also communicated the aim of the study to each participant and the respective managers encouraged their subordinates to participate. The questionnaire itself was explained in an email accompanying the questionnaire.

All surveys were conducted online. Not only was it easier to distribute the survey in digital format, but it also facilitated the process of integrating the survey results into UCINet.[15]

A whole-network study[16] was conducted, thus a list of actors (identified participants) was recorded before data collection began (Carrington *et al*. 2005:11). The survey instrument incorporated this list, allowing respondents to recognise rather than recall their relationships. Binary judgment response formats allowed respondents to indicate what type of knowledge relationships they had with each actor on the list as well as the strength of these relationships.

Furthermore, the questionnaire was conducted from the perspective of the person who initiated contact. Hence, the respondent only had to indicate whom he contacted for

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[15] UCINet is a Windows software package used for the analysis of social network data. It offers instruments to analyse 1-mode or 2-mode data (Borgatti *et al.* 1999).
[16] A whole-network study typically records a list of actors before data collection commences (Marsden 2005:10).

knowledge and information. The respondent did not have to indicate who approached him for knowledge and information, as this data became automatically available once everybody had completed the survey.

In order to reduce the amount of time that a respondent required to complete the survey, contextual data such as the respondent's name and sub-division was prepopulated.

### 4.5.3 Indirect unobtrusive measures

Unobtrusive research refers to data collection methods that do not impose on the subjects under study. It is presumed that this measurement can decrease the biases resulting from the intrusion of the researcher or the measurement instrument. Indirect unobtrusive measures ensue naturally *"…where the researcher is able to collect data without the respondent being aware of it"* (Trochim *et al.* 2016:65). One way to conduct indirect unobtrusive data collection is via automated data collection, where computer logs are used in evaluating human-computer interaction. Data is thus gathered indirectly from people based on their actions on a computer (Lazar *et al.* 2010:15).

Four online CoPs were created based on the results of the skills audit, the outcome of the first conducted SNA as well as inputs from the group interviews. The respective CoPs were created in SharePoint Server 2013 and automated data on these CoPs were collected over a period of two months. Automated data collection methods focus on studying data that computers collect unobtrusively (Lazar *et al.* 2010:129) and the researcher was thus able to collect this data without disturbing the respondents.

In SharePoint Server 2013, Community Sites provide a forum for members to contribute information and to ask for assistance from other members. *"Community Sites provide a computing solution for users to collaborate around questions, problems, interests, suggestions, opinions, and so on. Through feedback, in the form of replies, members gain access to valuable information from which they can further narrow the most useful responses via the number of members who like a reply and which reply is marked as the best reply. These actions provide incentives for members of the community to participate and build a reputation within the community. Over time, users who have provided the most positive contributions to the community become top contributors and earn trust from other members"* (Technet Library 2013).

Automated data was collected on each participant per community regarding:

- *participation* (general contributions | questions asked | replies/comments); and
- *reputation* (content liked).

## 4.6 CAPTURING AND EDITING DATA

Save for the group interviews with the respective managers, data was captured automatically via online questionnaires and automated computer logs. The group interviews were essentially treated as mini workshops, where the managers involved reached consensus which ultimately allowed the researcher to record:

- the main subjects of interest;
- the professed subject matter experts;
- the CoPs to be designed; as well as
- the context of the respective SNA results.

All online questionnaires were conducted in Excel. To safeguard anonymity, when presenting the results, participant names were replaced by numbers i.e. ID1 to ID49. Collected data was consolidated and data relating to the skills audit was analysed in Excel itself.

By conducting a SNA, it was possible to determine which participants belonged to which networks and to what extent. This was done by creating a series of data matrices which indicated whether relationships existed between participants and to what extent. These matrices were then all converted from Excel to UCINet datasets.

In UCINet all data are ultimately stored and depicted as collections of matrices (Borgatti *et al*. 2002). Consequently the researcher had to manually transform collected network data into matrices to produce UCINet datasets in which network analysis could be conducted. Similarly, all contextual survey data (such as the respondent's function and sub-division) were converted to an adjacency matrix and an attribute table.

## 4.7 DATA ANALYSIS

Order, structure and meaning were given to the collected data through the process of data analysis. By making use of triangulation,[17] more secure results were ensured and unusual phenomena were revealed (de Vos 2002:339, 342).

Data analysis took place alongside data collection, aiming to cultivate new investigation possibilities and to allow for questions to be refined (Pope *et al*. 2000:114-116). For example the results of the self-assessment which was aimed at locating subject matter experts, were communicated to the managers in order to verify the likelihood thereof.

After each SNA survey was finalised, the collected data was transferred to SNA tools[18] to be analysed.

### 4.7.1 Measures of network properties applied in the analysis

SNA enables one to calculate indexes and depict diagrams that describe and illustrate individual and collective relations of a network. In this study, knowledge networks (signifying different knowledge relationships) were constructed from the collected empirical data.

Network data was analysed using UCINet 6 and visually portrayed via Netdraw which permitted the visualisation of graphs (sociograms) of participants' relations in two dimensions.

There are numerous options against which networks can be measured. However, one can differentiate between measuring the overall properties of a network and measuring individual positions of certain actors or groups of actors within a network (Wasserman & Faust 2004). In addition, Owen-Smith and Powell (2004:19) emphasise the advantages of simplicity when conducting network analysis.

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[17] Conducting research from different angles, making use of multiple data collection methods and research strategies (Neuman 1997:50-51) in order to guarantee the validity of research findings.
[18] In this study, UCINet and Netdraw were applied to conduct the SNA. Data imported into UCINet can be visually observed via sociograms as well as statistically across various metrics (Springer & de Steiguer 2011).

Subsequently the investigation of the results of the SNAs conducted in this study was based on three diverse analytical levels, as identified by Müller-Prothmann (2007:225), namely:

- analysis of individual positions;
- analysis of clusters and components; and
- analysis of the *whole network*.

The first two sets of measures relate to dynamics, while the last suite is concerned with structure. In this study the first two assessments were applied to the four respective *knowledge networks*, whilst the *recurrence-*, *responsiveness-*, *engagement-* and *trust networks* were added to the whole-network analysis.

#### 4.7.1.1 Analysis of individual positions

Once the respective SNAs were conducted, the corresponding positions of actors were ascertained and compared according to the following centrality measures: *degree-*, *betweenness-* and *κ-reach* centrality. This was done in order to classify participants according to the four essential roles that individuals within networks perform pertaining to knowledge sharing (Müller-Prothmann 2007:228) namely: *experts*, *knowledge brokers*, *agents* and *knowledge consumers*.

Categorising individuals according to the aforementioned roles prompted some thought as to the reasons behind these positions, which in turn led to discussions with managers to contextualise the outcomes.

#### 4.7.1.2 Analysis of the network structure

Müller-Prothmann (2007:225) points out that as far as knowledge sharing processes are concerned, literature exposes three elementary types of network structures namely: *cohesion* (clusters of expertise), *cut-points* (bottlenecks) and *hubs*. The aforementioned configurations were evaluated and compared during the course of this study.

#### 4.7.1.3 Analysis of the whole network

Whole-network analysis refers to the *'evolving or changing structure of the network itself'* (Coulon 2005:5). In terms of the whole-network review, the following metrics were measured and compared before and after the implementation of the CoPs:

- network size;

- density;
- distance/reachability; and
- centralisation.

### 4.7.2 Skills audit analysis

In order to confirm the experts per subject area with the respective managers, two skills maps (of which one indicated proficiency and the other experience in terms of years) were created based on the results of the skills audit. Once the managers agreed on the actual experts per subject area, a skills map was created for each examined subject area. Since only four online CoPs were constructed, only the corresponding four skills maps are discussed for the purpose of this study, (***Appendix 6***). Subsequently the experts per subject area were communicated to the division. This was done in a formal way during which the subject matter experts were revealed via an email to all network members.

### 4.7.3 CoP analysis

In this study it was deemed necessary to evaluate the established CoPs in order to assess its effectiveness as a KM tool.

Community platforms *per se* contain a variety of simple metrics that can be used for evaluation purposes (Connected Educators 2011:3). While analysing the established CoPs, emphasis was placed on quantitative as well as qualitative measurements. As active CoP participation was rather limited, it was possible to consider every contribution and to put it into context (***Appendix 5***).

## 4.8 SHORTCOMINGS AND LIMITATIONS

This section summarise specific assumptions, limitations and delimitations the author experienced while conducting this research.

### 4.8.1 Assumptions

Hoppe and Reinelt (2010:617) maintain that it is challenging to collect network data and point out that utilising standard survey tools to collect network data for large networks is rather impractical. Although the sizes of the networks investigated varied between 47 and 19[19] actors, the researcher anticipated that it was already big enough to have an impact on the reachability metric.[20]

### 4.8.2 Limitations

To complicate matters, just after the first SNA was conducted, it was announced that the organisation was to undergo severe restructuring. As a consequence some members, who initially indicated that they would be willing to participate in this study, did not want to be involved any longer. This could also explain the subdued participation in the online CoPs. The fact that not all members who participated in the first SNA were willing to join any of the CoPs or to take part in the second SNA could be regarded as a limitation. Ideally one would prefer to compare the same data with all the same participants. Especially since not all experts participated in the second SNA, one could not measure whether experts were contacted more readily or not, or even if interaction between experts specifically had improved or not.

Initially the researcher aimed to conduct the second SNA after six months of CoP participation. This interval was reduced due to two reasons. On the one hand it was anticipated that the planned restructuring would start to take place rather soon (although at the time no one knew exact dates or which divisions would be affected first). This caused considerable uncertainty within the business area. On the other hand the CoPs were initiated in the beginning of October. With December and early January traditionally a time when many employees take their annual leave, the researcher was apprehensive that the CoPs could lose momentum and that employees being away for some time would skew the results of the second SNA. As a consequence the second SNA was conducted in the first week of December, before employees started to go on leave.

Another limitation could be attributed to the fact that the network elements pertaining to frequency, responsiveness, engagement and trust were handled as a whole and not per knowledge dimension. For example, one could not establish if the

[19] 47 divisional members participated in the first SNA, 30 members participated in the second SNA and the smallest CoP consisted of 19 members.
[20] According to Wasserman and Faust (1994) reachability is strongly related to size - reachability graphs associated with large structures will generally be complete.

frequency of interaction changed within the CC network as opposed to within the DAM network.

Although there are studies on SNA and physical proximity, this research did not intend to include a study on the effect of the physical closeness of network members. In this study physical proximity was only referred to in setting the scene as depicted in ***Figure 5.1***. In addition, while the researcher admits that culture plays a significant role in collaboration and the sharing of information and knowledge within organisations, this study did not intend to analyse the role of culture.

#### 4.8.3 Delimitations

It becomes challenging to use questionnaires for network evaluations that take place over a period of time, partially because it becomes difficult to manage name changes (e.g. when someone gets married and change their maiden name), which might lead to misinterpretation by the actor's extended network of contacts who has not necessarily kept track of the actor's change in status (Hoppe & Reinelt 2010:617). Another reason is because people might leave the network during the reviewed period. In this case, two members were not available to participate in the first SNA,[21] another went on maternity leave after the first SNA, but before the respective CoPs were established and another two, one being an expert, were seconded to two other divisions during the execution of the first SNA.

An additional constraint was that SharePoint audit trials could not be activated as it was considered to be too expensive by the organisation's IT division. Consequently one could neither monitor how many contributions were actually read, nor who had indicated whether they liked a specific contribution. As a consequence CoP participation could only be monitored in terms of actual input.

Some accuracy may also have been lost in terms of the frequency of interaction; responsiveness; engagement and trust networks, considering that these networks were defined by questions relating to member relations as a whole as opposed to relationships within a specific knowledge domain, i.e. the level of engagement within

[21] One member was seconded to another division and another went on maternity leave before information regarding the first SNA was collected.

the whole network was mapped as opposed to the level of engagement within each of the four knowledge domains: CC, DAM, SR and SMC.

#### *4.8.3.1 Addressing biases*

Bias is a huge obstacle for researchers in achieving credibility and accuracy. It has been argued that research in social studies is much more prone to bias and less objective, than studies in natural sciences for example (OECD 2001:14), since processing numbers and statistics is not as prone to bias as dealing with qualitative facts. The researcher aspired to achieve empathic neutrality in the conduct of this research by attempting to avoid evident, conscious or systematic bias and to be as neutral as possible considering the gathering, interpretation and presentation of data. According to Saunders *et al.* (2009) pragmatism offers a foundation for practical research by assimilating different perspectives which assist to explain the data interpretation process in research. In this study the researcher adopted a philosophical stance of pragmatism which draws heavily on abductive reasoning.

The sample selection was without bias. A whole-network approach was followed as the respective managers of the sub-divisions could not identify possible participants outside their respective areas employees needed to engage with regarding the identified subject matters.

Although Mohr (2014) maintains that SNA metrics provide an unbiased way to interpret relationships, like other forms of analysis, SNA itself is not entirely free from biases. However the biases in a SNA study can be *"…explicitly stated and subjected to sensitivity analysis"* (Polites & Watson 2009:595, 599). Concerns pertaining to biases pertaining to this SNA study included informant bias and sampling bias.

In view of the fact that SNA studies are primarily based on perceptual data, the findings could be to some extent the result of the subjective bias of respondents. However, as Cross *et al.* (2002:7) point out, in opting whether or not to pursue someone for information, one need to have at least some awareness of the relevance of that person's knowledge, skills and abilities concerning the question at hand. *"Although this perception might be wrong or biased by a variety of factors, it is still the basis for deciding to whom to turn for information or advice on a given problem."*

It is important to note that although SNA portrays a network, it does not uncover the underlying influences, context or history of the members contributing to the perceptions of prestige or knowledge flows within the network (Behrend & Erwee 2009:111). Informant bias can be described as inaccurate recall. Biased informants perceive themselves as central, tend to overlook less prominent network members and wrongly recall major actors within a network (Knoke & Yang 2008:33-36). Group interviews were thus conducted with the managers of each sub-division in order to collect in-depth, qualitative information so as to confirm the outcomes and to put the results into context. In order to minimise the possible loss of confidentiality, the researcher did not venture to open the group to other participants than the four managers of the respective sub-divisions. As a consequence the researcher could not confirm with other participants whether they agreed with what was mapped in the SNAs and had to rely on the feedback obtained from the group interviews. Even so the researcher anticipated that the group interviews would assist in upholding vigilance against bias by allowing for different perspectives and insights.

Anderson (2010:1) maintains that qualitative research is frequently criticised as *"…biased, small scale, anecdotal, and/or lacking rigor.."* but points out that if this type of research is executed correctly it is *"…unbiased, in depth, valid, reliable, credible and rigorous."* In this study, the researcher made use of a mixed methods approach by explicitly combining qualitative as well as quantitative elements. In order to substantiate the validity as well as the reliability of the study the researcher implemented measures such as triangulation, respondent validation, and qualitative software (UCINet and Netdraw). Potential researcher bias was therefore eliminated due to the inclusion of respondent validation, where respondents were invited to correct and clarify analysed data sets shared with them.

Despite efforts made to ensure validity, there was an element of sampling bias due to nonresponse. Sampling bias occurs as a result of nonresponse results from missing elements that should have been included in the sample but were not (Lavrakas 2008). In this study, the nonresponse was as a result of refusal. The SNA comparison could not be performed on the original population seeing that some members declined to participate in the CoPs and the second SNA. As a consequence, in order to allow the researcher to compare the same sample population before and after the implementation of the KM initiatives, members who refrained from participating in any of the established CoPs, and the second SNA, were disregarded when comparing the networks.

***Table 4.2*** below summarises how biases have been accounted for in terms of the *researcher*, the *respondents* as well as the *instruments* used to collect information in this study.

**Table 4.2: Accounting for biases**

| Concern | Measurements assumed |
|---|---|
| Researcher | ▪ Philosophical stance - the researcher adopted a pragmatic approach focusing on abductive reasoning whereby diverse perceptions were integrated to clarify the data interpretation process (Saunders *et al.* 2009). Moreover the researcher had no preconceived position to the results while conducting this study. |
| Respondents | ▪ Sample selection – sample was chosen based on a whole network approach as managers could not identify individuals outside the business unit employees had to engage with to better their knowledge regarding the identified subject matters.<br>▪ Informant bias – group interviews served to verify research outcomes and to put the results into context. Bias was addressed by allowing for different perspectives and insights.<br>▪ Sampling bias – as some members decided not to participate in the CoPs, and the second SNA, the researcher opted to exclude these members when comparing the different cases before and after implementing the KM interventions. |
| Instruments | ▪ Piloting – all online questionnaires were piloted on a small sample to establish any modifications required in order to ensure reliability.<br>▪ Question and articulation bias – the researcher provided details regarding what was to be discussed prior to each group interview. In addition questions were thoroughly clarified and the researcher applied active listening and mirroring techniques by referring to what interviewees had reported (Fisher 1993:430-436).<br>▪ Methodological triangulation - to enhance, augment and clarify the validity as well as the reliability of this study the researcher implemented instruments such as triangulation, respondent validation, and qualitative software. |

The limitations and demarcations of this research should be addressed in future and follow-up research. To overcome these limitations, it is suggested that instead of focusing on a single business area within a single organisation, future research should preferably include research across different business areas and diverse organisations to expose a more comprehensive representation of the research objectives. Such research could also serve in testing the proposed research process map developed in this study in numerous alternative cases and settings.

## 4.9 SUMMARY

This chapter offered an overview of the research selections that were pursued to determine the potential influence of CoPs and knowledge maps on the respective knowledge networks.

The study was based on qualitative as well as quantitative research. A combination of in-depth empirical ethnographic research and network analysis techniques were employed.

The study itself was conducted in three phases, namely:

- a *preparation* phase;
- an *execution of the research* phase; and
- a *deciphering of results* phase.

During the preparation phase the scope of the analysis was refined and instruments were developed to collect the information needed to conduct the study. These instruments comprised a questionnaire to perform a SNA at two different points in time, a questionnaire collecting information regarding the skills and expertise of the participants and a few guided queries for group interviews, permitting interviewees to better express their opinions and ideas. Participants were identified and informed of the objective of the study in order to obtain buy-in.

In the next phase information was collected pertaining to participants' skills and experience and a SNA was conducted in order to construct five different knowledge networks (*knowledge*, *recurrence*, *responsiveness*, *engagement* and *trust*). Subsequently the knowledge networks were analysed and the results of the skills audit were mapped. In order to put these results into perspective and to confirm the validity thereof, interviews were held with the respective managers. Based on the outcome of these interviews, four online CoPs were constructed. CoP collaboration was observed meticulously and two months after the implementation of the respective CoPs, a second SNA (with exactly the same survey questions and participants as before), was conducted, once again constructing five distinct knowledge networks. Yet again the knowledge networks were analysed and the results were discussed with the respective managers.

In the last phase, the results of the two SNAs (five types of networks at two different points in time) were compared in order to determine how the interrelationship between SNA, CoPs and knowledge maps could benefit knowledge networks. As a final point this chapter also offers a summary of particular assumptions, limitations and delimitations the author was subjected to while performing this research.

# CHAPTER 5

*"When a truth is necessary, the reason for it can be found by analysis."*

**- Gottfried Leibniz**

# 5 COMPARATIVE RESEARCH ANALYSIS

This chapter presents the discoveries made regarding the interaction between four sub-divisions across four knowledge networks. Apart from the knowledge dimension, network elements pertaining to frequency, responsiveness, engagement and trust are also touched on.

Research results are presented to correspond with the research objectives defined in ***Section 1.2***. The results of the skills maps are compared with degree centrality rankings in the respective knowledge networks followed by an assessment between actual CoP participation and key positions held by network members. Hereafter cliques, cut-points and hubs in the four knowledge networks are portrayed, both before and after the implementation of the respective CoPs and the distribution of the skills map. Finally the effect of the CoPs and the circulation of the skills map on five different network features are reviewed in terms of network size, density, reachability and centralisation.

## 5.1 CONTEXTUALISING THE SAMPLE POPULATION

Whilst collecting information to conduct this study, two individuals were initially excluded – one was on maternity leave and the other was seconded to another division. Another individual went on maternity leave before the respective online CoPs were created and had not returned by the time the second SNA was conducted. An additional two members were assigned to other divisions during the execution of the first SNA.

Moreover, 12 network members did not join any of the established online CoPs whilst four members did join, but never accessed any CoP after signing up[22]. Apart from time concerns, this reluctance to participate could have been prompted by an announcement that the organisation was to undergo major restructuring within the months to come.

[22] Members, who joined online CoPs but never accessed the CoPs thereafter, were handled as if they had not joined the CoPs.

The participation of the sample population had a direct influence on the manner in which the data was eventually analysed. ***Table 5.1*** provides an overview of how the data collected was ultimately used.

**Table 5.1: Summary of which data was collected, who contributed and how the collected data was applied**

| Data collected | Contributors | Data applied in order to: |
|---|---|---|
| Skills audit | ▫ All network members except one on maternity leave and one that was seconded. | ▫ assess whether the experts (as identified during the skills audit) are contacted for information as per SNA 1 |
| SNA 1 | ▫ All network members except one on maternity leave and one that was seconded. Network members did have the option to indicate relationships with members who did not participate in the first SNA.[23] | ▫ assess whether the experts (as identified during the skills audit) are contacted for information as per SNA 1.<br>▫ plot CoP participation and SNA 1 positions. |
| Communities of practice | ▫ Network members who opted to join respective online CoPs. | ▫ compare CoP participation and SNA 1 positions. |
| SNA 2 *(knowledge dimension)* | ▫ Network members who participated in the respective online CoPs. Network members did have the option to indicate relationships with members who did not partake in the second SNA.[24] | ▫ compare the structure of the four[25] knowledge networks before and after establishing CoPs and communicating skills maps. |
| SNA 2 *(recurrence, responsiveness, engagement and trust dimensions)* | ▫ Network members who joined the online CoPs. | ▫ compare the network connectivity of the four networks that were constructed (frequency, responsiveness, engagement and trust) before and after distributing skills maps and implementing the respective CoPs. |

### 5.1.1 Physical proximity of actors

Cross *et al.* (2002:7-8) maintain that apart from the nature of one's relationship, gaining timely access to someone's knowledge is also *"...profoundly influenced by ...physical proximity, organisational design and collaborative technologies available."* ***Figure 5.1*** below provides an office diagram of the individuals involved in the study. Actors depicted in red, took part in the skills audit, both SNAs and were members of

[23] Members who were either seconded to another division or on maternity leave.
[24] Members who did not participate in the CoPs were not asked to participate in the second SNA.
[25] Four knowledge networks were constructed based on the CoPs that were created namely: Commodity Control; Data Analysis and Mining; Single Registration and Service Manager Cases.

some (or even all) of the established CoPs. Actors depicted in blue, only participated in the skills audit and the first SNA. Two actors have been seconded to other divisions which were situated in two separate buildings (***Section 4.8.3***). Although the researcher did not have a work relationship per se, with any of the individuals that participated in this study, she had the opportunity to observe their physical interaction.

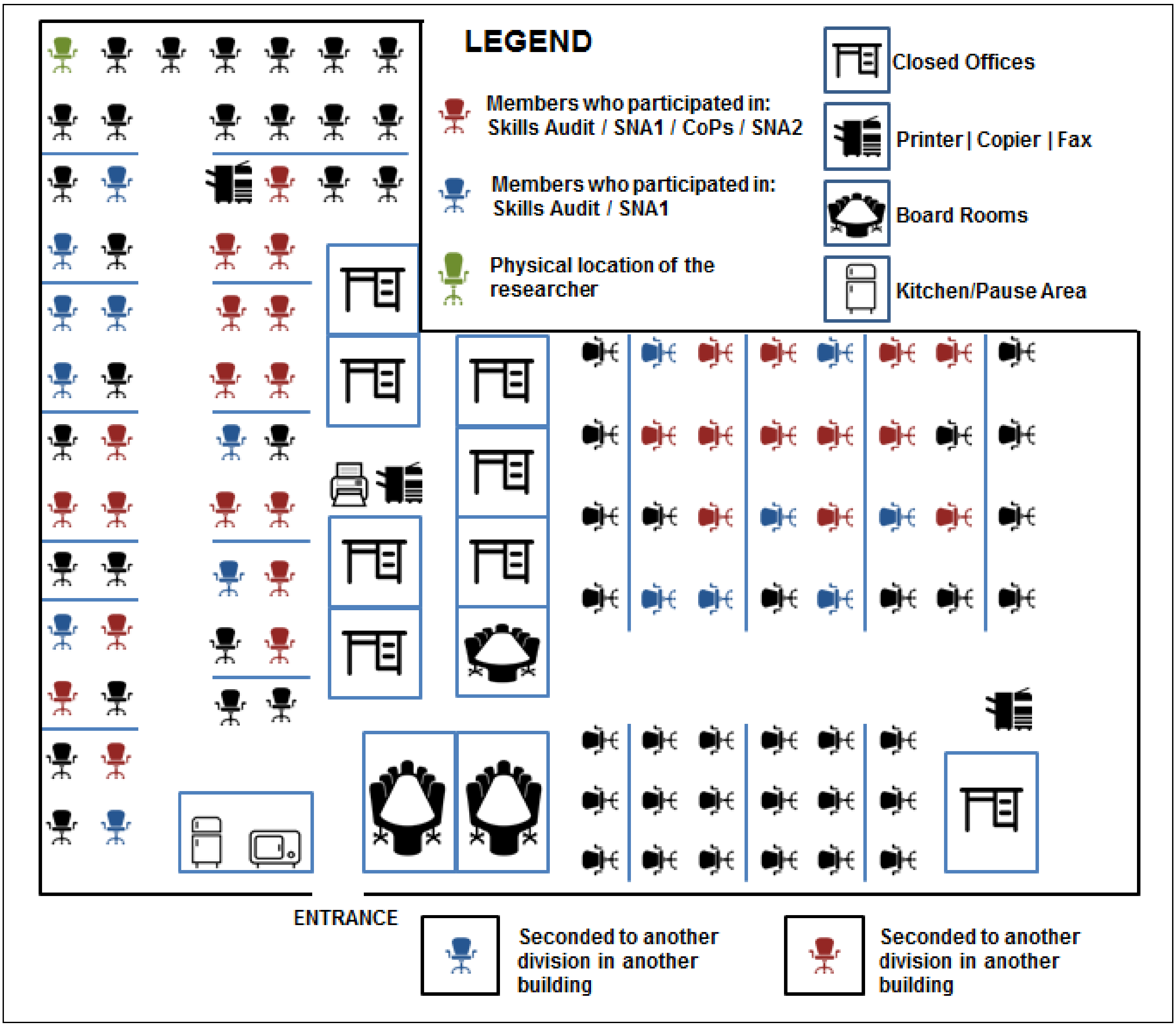


**Figure 5.1: Office diagram of individuals involved in this study**

## 5.2 PRESENTING THE RESULTS

### 5.2.1 Skills maps vs knowledge networks

At the outset of this study individuals were requested to evaluate themselves in terms of how skilled[26] they were regarding the 18 predefined subject matters. These results were then validated with the respective managers.

Subsequently, in order to ascertain whether experts and highly skilled individuals were actually approached by other network members for specialist information, knowledge networks[27] were constructed for each of these 18 predefined subject matters.

The expertise and power of each network's members were determined by calculating their respective incoming and outgoing connections (degree centrality[28]). Hence, in this study the in-degree rating represented the number of people who asked an actor for advice regarding a predefined topic, while the out-degree value signified how many people an actor approached for information regarding the topic in question. This was done in order to be able to compare the experts and highly skilled members identified during the skills audit with the knowledge authorities within the corresponding networks.

The respective knowledge networks are illustrated below (***Figures 5.2*** to ***5.13***) in terms of:

- in-degree centrality;
- out-degree centrality; as well as
- a condensed view regarding knowledge relations among experts and highly skilled members only.

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[26] Participants rated themselves in terms of their level of proficiency as well as the numbers of years of experience they had in the particular field.
[27] Based on the four online CoPs constructed, only the four corresponding skills maps and knowledge networks are discussed for the purpose of this study.
[28] Müller-Prothmann (2007:226) points out that from a knowledge and information perspective, individuals with many incoming (in-degree) ties are considered as especially prominent or to have high levels of expertise.

In order to understand these networks it is essential to explain some underlying elements:

- *Arrows* indicate the direction of interaction.
- *Grey lines indicate* one-directional relationships, while *orange lines* indicate reciprocal interactions.
- Different *node colours* have been used to distinguish between the respective network members:
    - *pink nodes* = *experts* as per the skills audit
    - *green nodes* = *highly skilled* as per the skills audit
    - *blue nodes* = network members
    - *yellow nodes* = members who did not participate in the SNA – but who were still available for selection by those who did participate
    - *black nodes* = network (isolates)
- The *node size* increased depending on Freeman's[29] *in-degree-* and *out-degree centrality*[30] respectively. This means that in the case of in-degree centrality, the more members approached a specific node, the bigger that node would be. Similarly, regarding out-degree centrality, the more members a specific node contacted for information, the bigger that particular node became.

[29] Linton Freeman (one of the authors of UCINet) developed basic measures of the centrality of actors based on their degree and the overall centralization of graphs (Hanneman & Riddle 2005).

[30] Degree centrality describes the number of links incident upon a node. In directed networks (where ties have direction) two distinct measures of degree centrality are defined, namely in-degree and out-degree. In-degree is a count of the number of ties directed to the node while out-degree is the number of ties that the node directs to others. When ties are associated to positive aspects such as collaboration, in-degree is often interpreted as a form of esteem and out-degree as sociability (Hanneman & Riddle 2005).

#### *5.2.1.1 Commodity Control network*

Two isolates, ID1 and ID25, were identified while compiling the CC network. This meant that 47 of the division's 49 members formed part of this network. As per the skills audit, the CC network incorporated nine highly skilled members and no experts.

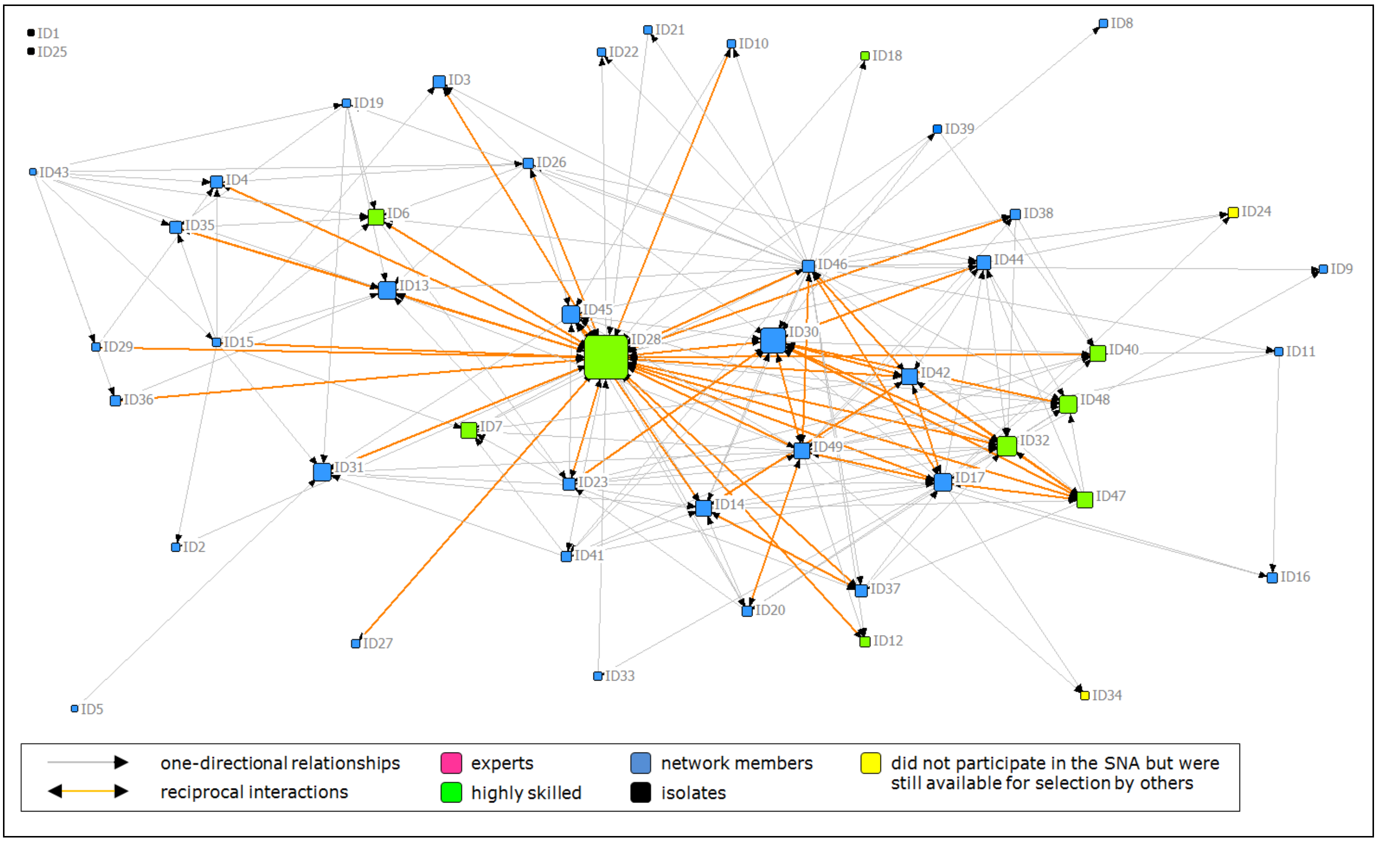


**Figure 5.2: CC network regarding in-degree centrality**

According to the skills audit, ID40 was regarded as one of the most skilled members regarding CC in terms of years of experience as well as proficiency (***Appendix 6***), followed by ID18 and ID28. When examining who were contacted by most other network members for CC information (***Figure 5.2***), the following new incidents were detected:

- Seven of the highly skilled members were approached to an extent where they could be considered knowledge authorities while ID18 and ID12, who were both regarded as highly skilled (as per the skills audit), turned out to be mere peripheral players.
- Eight network members, including two line managers (ID13 and ID30), who were neither experts nor highly skilled, according to the skills audit, scored high

regarding in-degree centrality and were thus viewed as experts by their colleagues.

- As per the knowledge audit ID40, ID28 and ID18 were regarded as the most proficient members of the division regarding CC. However, ID40 was approached by only 17% of the network and ID18 by a mere 0.02%. ID28 was contacted by most (64%) of the network for information with non-expert and line manager ID30 next in line being contacted by 32%.
- The network member contacted second most for CC information (ID30) was not regarded as an expert or even highly skilled. This could be attributed to the fact that ID30 was a line manager.

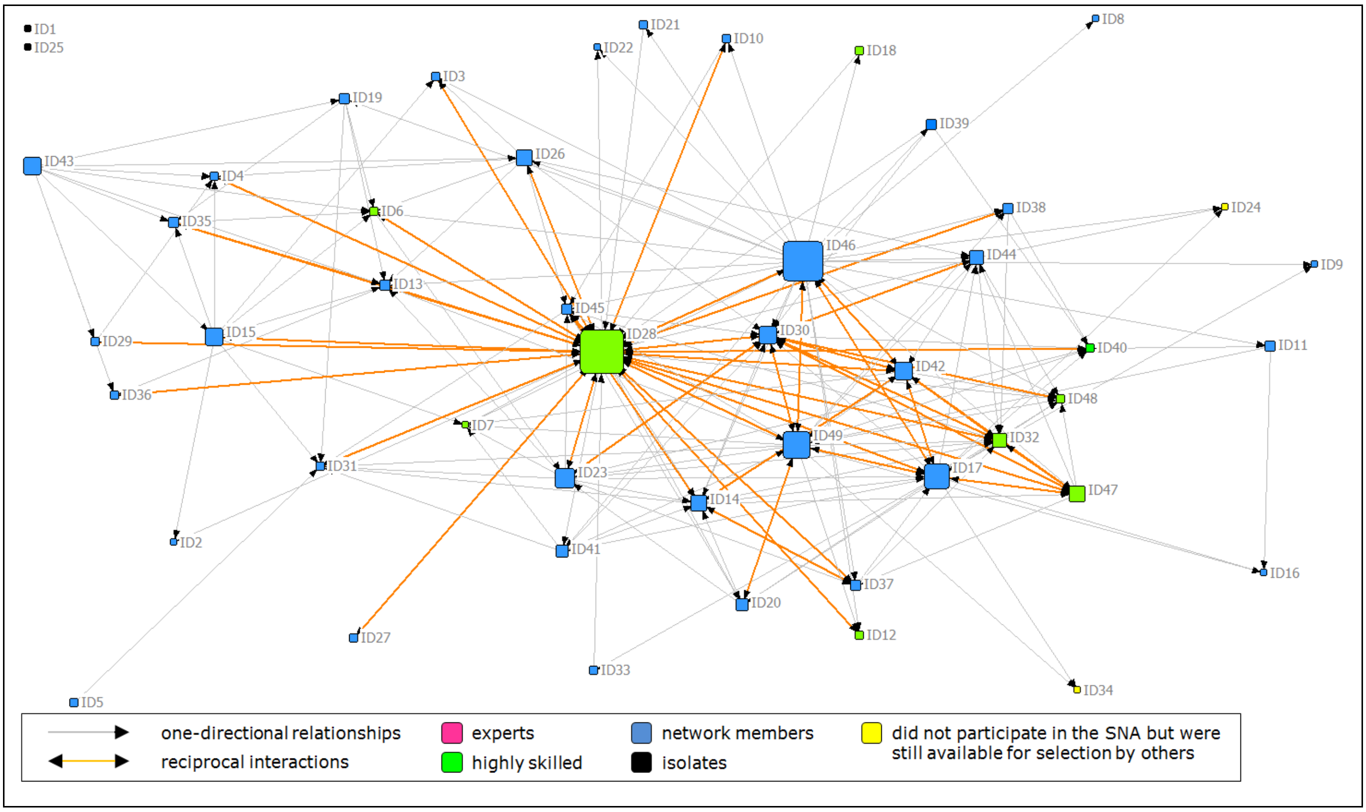


**Figure 5.3: CC network considering out-degree centrality**

When considering which members approached most others for information relating to CC, the following observations were made based on ***Figure 5.3***:

- Apart from being contacted by most members for CC-related information (highest in-degree ranking), ID28 also connected with most network members regarding CC. This could explain ID28's high reciprocity rate in this knowledge network.
- Except for ID28, it was mostly non-experts who approached their colleagues for CC information (out-degree centrality).

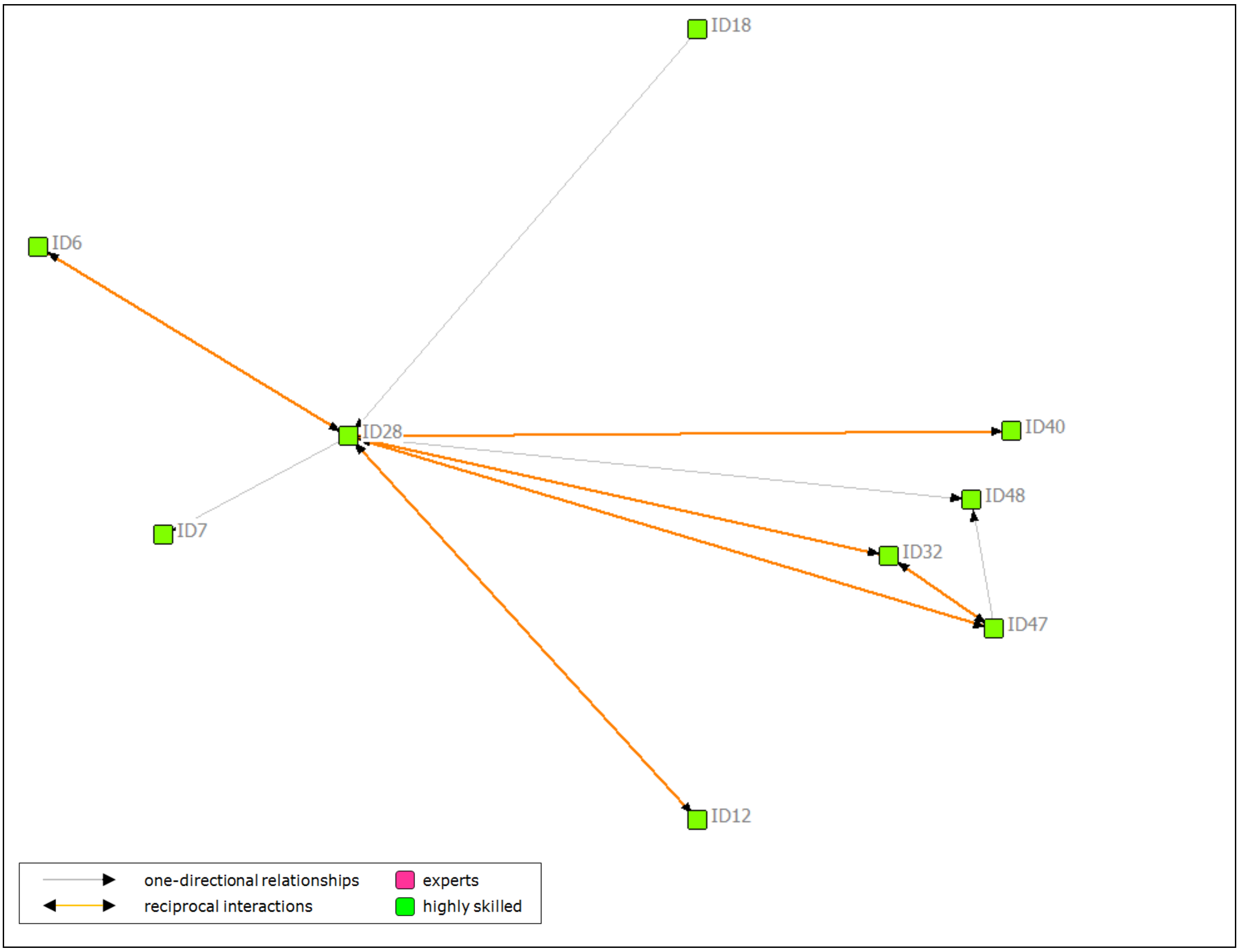


**Figure 5.4: CC network concerning experts and highly skilled members only**

The following was observed when taking the relations between all highly skilled CC members into consideration:

- Once again the prominence of ID28 was highlighted (***Figure 5.4***). Not only were most of this member's ties reciprocal, but it also became clear that as far as the 'highly-skilled' network members were concerned, ID28 played a very important brokerage role in connecting the highly skilled members.

#### *5.2.1.2 Data Analysis and Mining network*

With six isolates, the DAM network was the smallest of the four networks studied, comprising only 43 divisional members. As per the skills audit, this network comprised six experts and nine highly skilled members. ID5, a recognised expert, did not form part of the DAM network. This isolation could have been due to the fact that ID5 was relatively newly appointed and people were not necessarily aware of his skills.

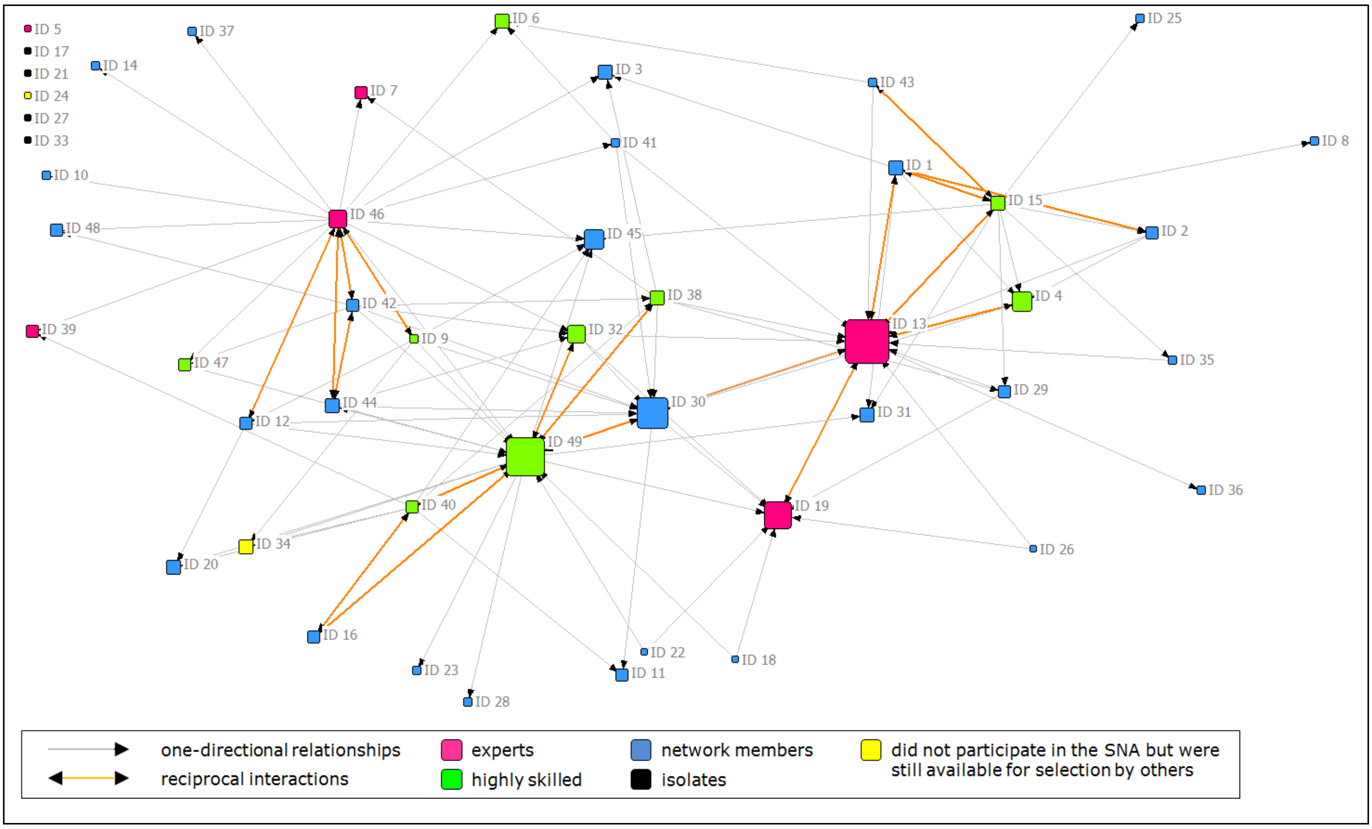


**Figure 5.5: DAM network regarding in-degree centrality**

While considering the members mostly approached for information (highest in-degree centrality) and by studying ***Figure 5.5*** above, it became apparent that:

- Only two experts (ID13 and ID19) and two highly skilled members (ID49 and ID4) operated as knowledge authorities within the DAM network. Some highly skilled members (ID6, ID40 and ID47) and experts (ID7 and ID39) appeared on the network periphery, with expert ID5 being completely isolated. This isolation could be attributed to the fact that he was a newcomer to the division.
- Expert ID13 was contacted by most members (33%) in the DAM network followed by highly skilled ID49 (at 28%).
- Non-experts ID30 (a line manager) and ID45 also scored high regarding in-degree centrality.

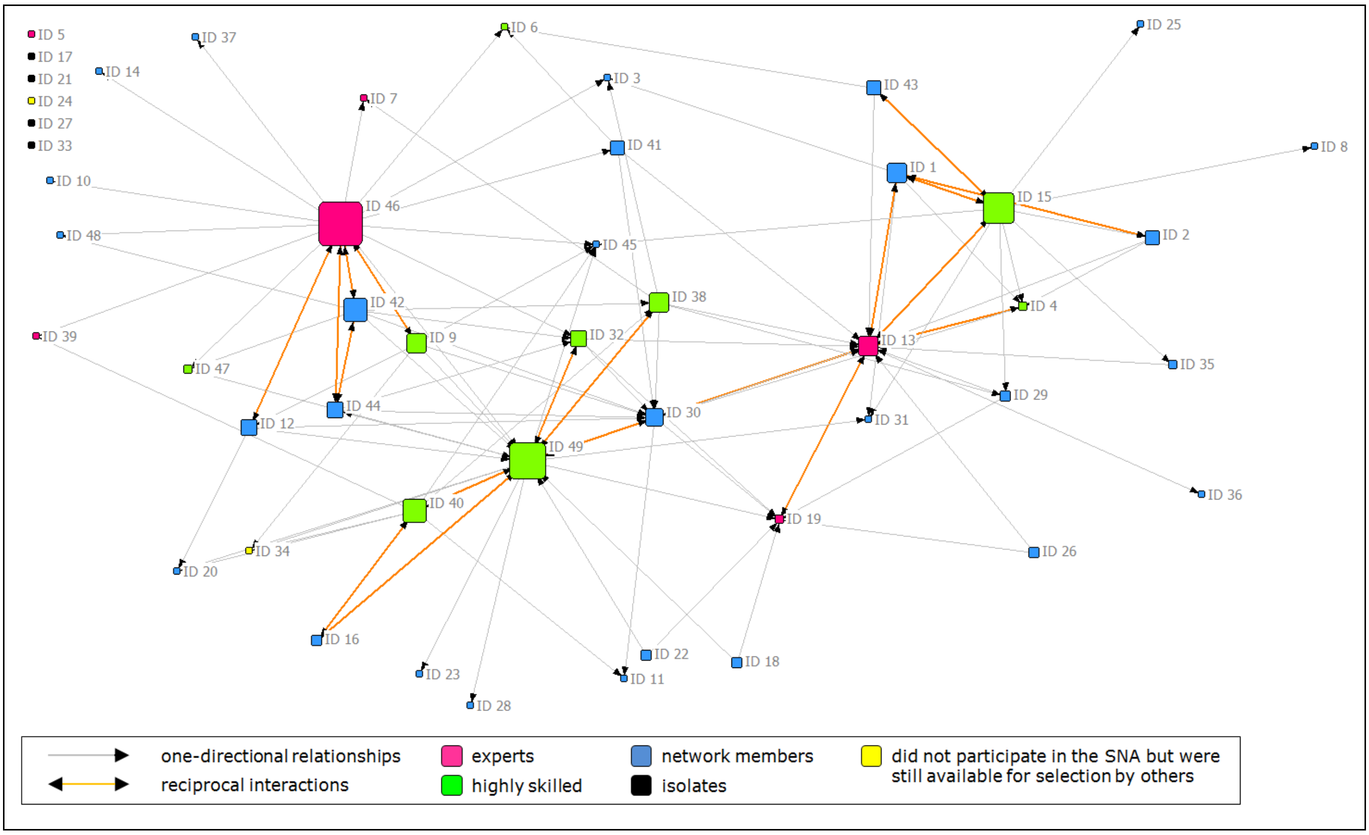


**Figure 5.6: DAM network regarding out-degree centrality**

Reflecting on which DAM network members approached most others for information (***Figure 5.6***) the following was observed:

- Two experts (ID46 and ID13) and five highly skilled members (ID49, ID15, ID40, ID9 and ID38) were among the top out-degree centrality positions, suggesting that (apart from ID1 and ID42), as far as the DAM network was concerned, it was mostly the highly skilled network members who were contacting their colleagues for information.
- Although expert ID46 had the highest out-degree centrality, there was no direct relationship regarding DAM information between experts ID46 and ID13, who ranked highest regarding in-degree centrality.

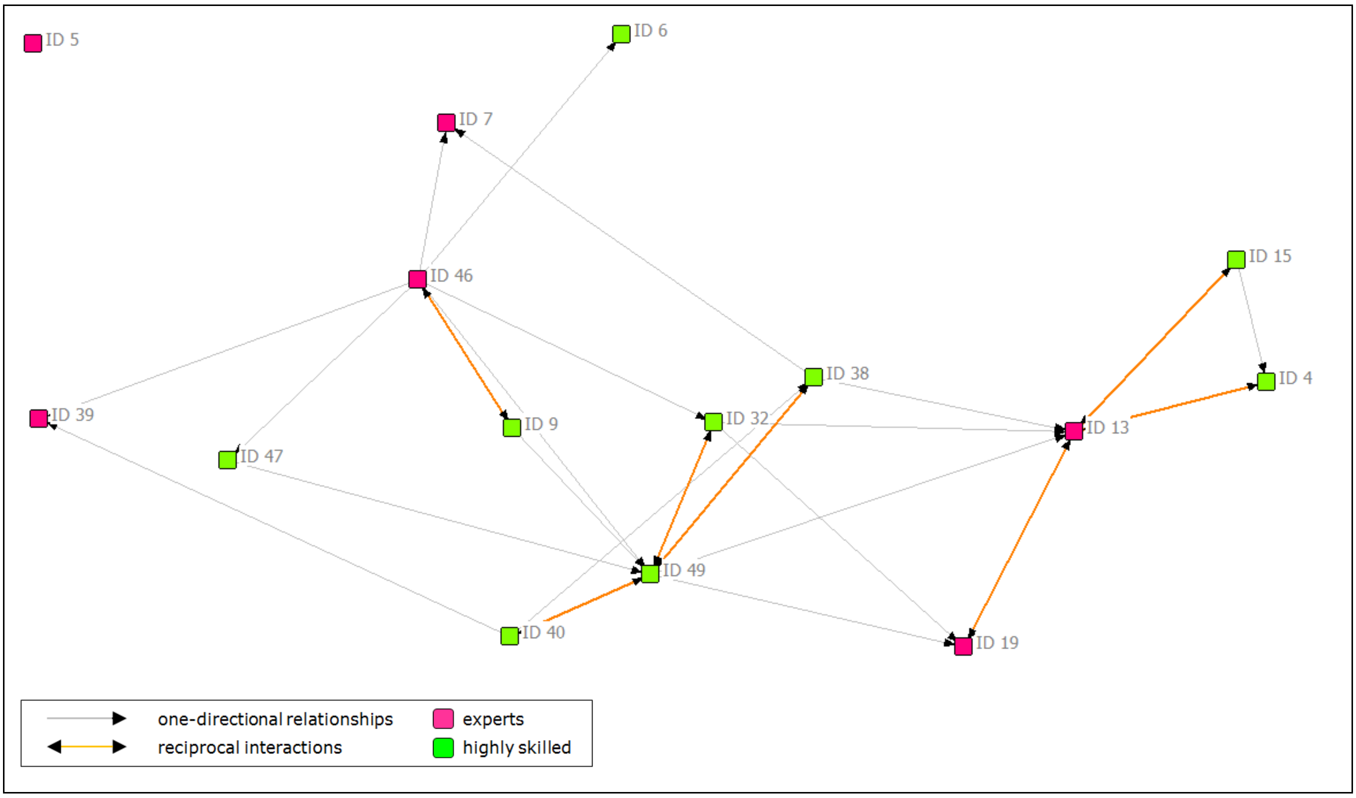


**Figure 5.7: DAM network concerning experts and highly skilled members only**

In view of the relations between DAM experts and highly skilled members (***Figure 5.7***), it became evident that:

- Apart from isolate ID5, all highly skilled and expert DAM members were directly linked to at least one peer.
- As for collaboration between highly skilled members and experts in the DAM network, there was no direct interaction between experts ID19 and ID13 and experts ID7, ID46 and ID39.
- The experts and highly skilled members with the highest in-degree centrality overall (ID13, ID49 and ID19) were also the members who were mostly approached for information by their peers.
- ID13 and ID46 played important brokerage roles among the highly skilled and expert members, since without them ID15 and ID4 as well as ID7 would become separated from their peers and would need to reconnect via non-experts.

#### *5.2.1.3 Single Registration network*

With 46 members, the SR network contained four experts and 14 highly skilled members.

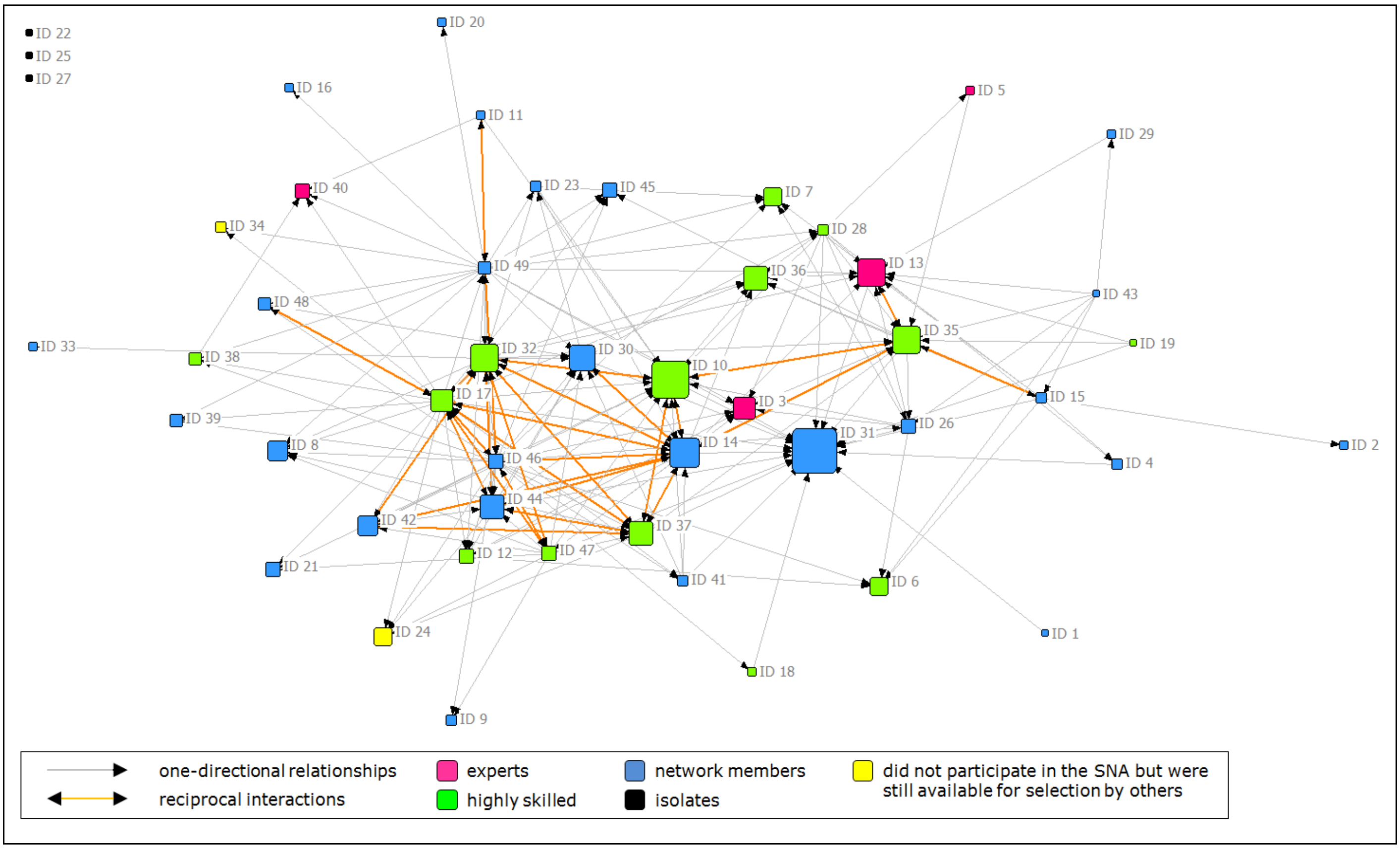


**Figure 5.8: SR network regarding in-degree centrality**

When considering the in-degree centrality in the SR network as depicted in ***Figure 5.8*** above, it became apparent that:

- Two experts (ID13 and ID3) and six highly skilled members (ID10, ID32, ID35, ID36, ID37 and ID17) were also treated as knowledge authorities.
- Surprisingly, the network members who were approached by most (39%) regarding SR information were neither considered to be experts nor highly skilled members in that domain[31]. This could also explain ID31's low rate of reciprocity. According to management, ID31 was very knowledgeable regarding many tax related subjects. As a consequence this member was contacted for any tax related issue, even if she was not the expert in that particular field. In addition, when

[31] As per the skills audit.

asked about any tax related matter, this individual would make it her task to find the correct answer if she did not know it herself.

- ID14, also not a recognised expert or highly skilled member of the SR network, ranked third as far as in-degree centrality was concerned. In this case there was a very high rate of reciprocity between ID14 and the other network members indicating that information was exchanged between ID14 and his direct contacts.
- Some experts (ID40 and ID5) and highly-skilled members (ID12, ID38, ID18 and ID19) turned out to be mere peripheral members.

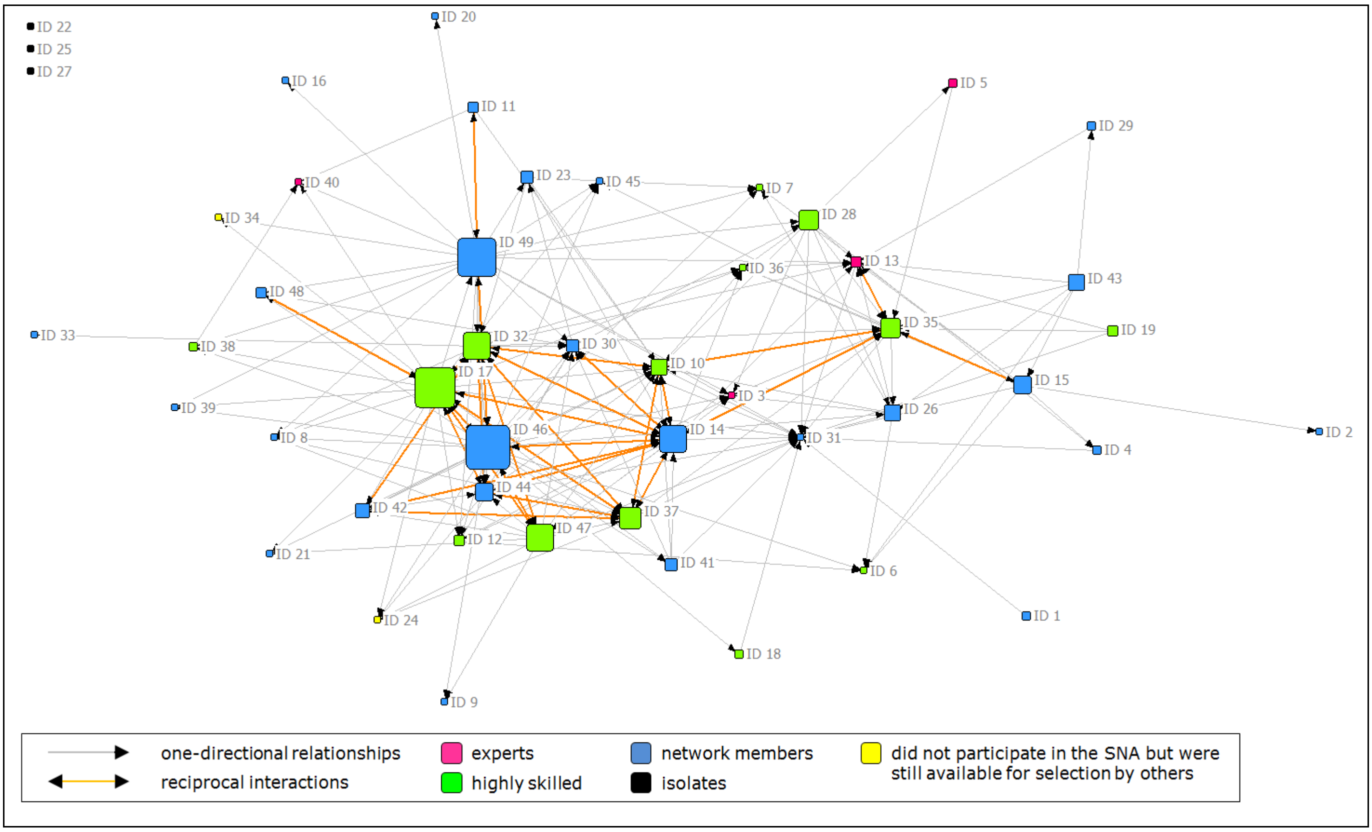


**Figure 5.9: SR network regarding out-degree centrality**

By examining the out-degree centrality in the SR network (***Figure 5.9***), the following could be discerned:

- Non-expert ID46 approached most network members regarding SR information. Although ID46 did not contact any of the four SR experts directly for information, there were many direct ties between ID46 and highly skilled SR members.
- The many reciprocal ties between the network members with the highest out-degree centrality scores (ID46, ID17, ID49, ID14, ID32 and ID47) suggest that some form of information exchange was taking place.

- The top six positions regarding network members looking for SR information constituted three non-experts (ID46, ID49 and ID14) and six highly skilled members (ID17, ID32, ID47, ID37, ID28 and ID35).
- Three of the four SR experts (ID5, ID3 and ID40) and five of the 14 highly skilled members (ID18, ID38, ID6, ID7 and ID36) approached two or less contacts for information pertaining to SR.

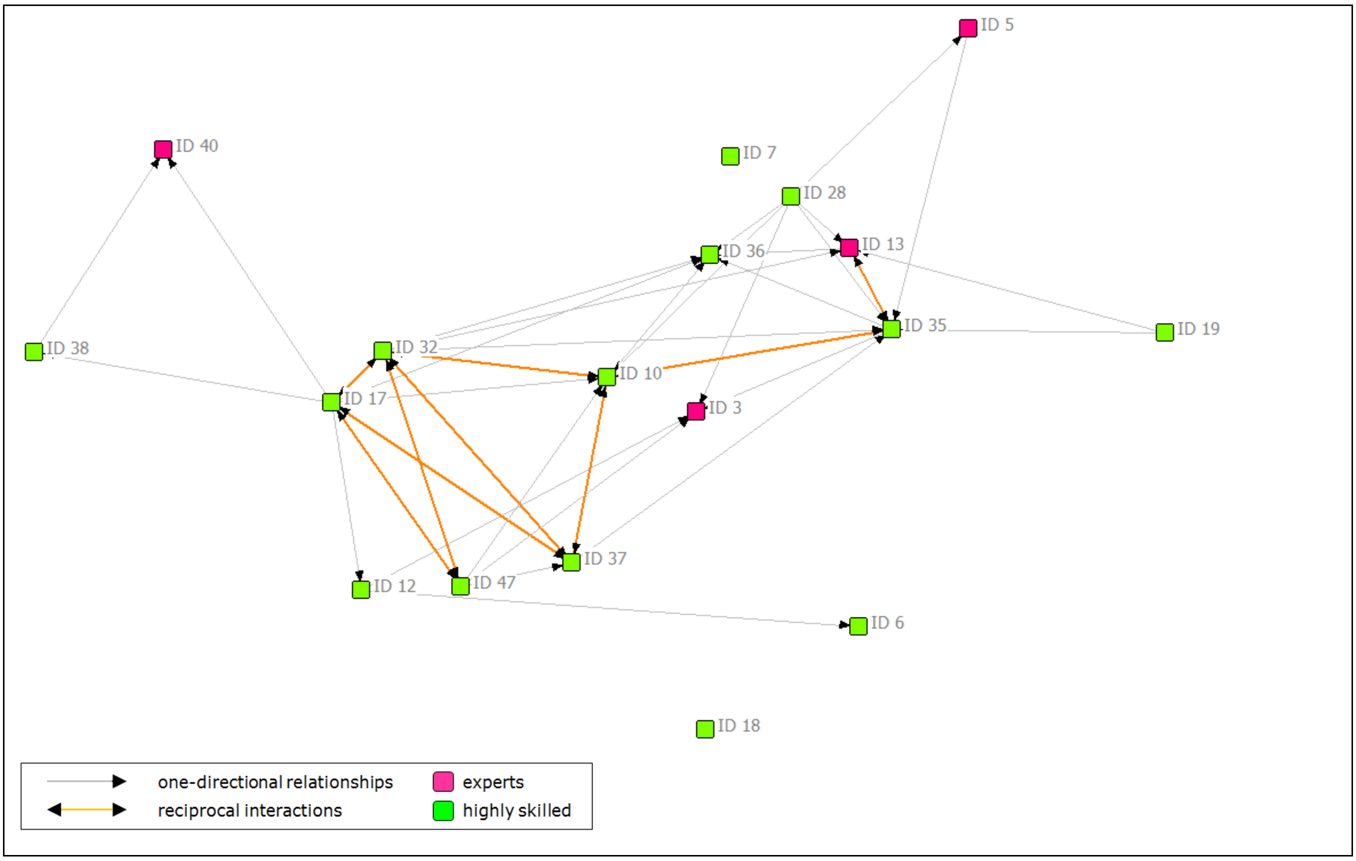


**Figure 5.10: SR network concerning experts and highly skilled members only**

Studying the knowledge exchange between SR experts and highly skilled members (***Figure 5.10***), it became apparent that:

- Highly skilled members ID7 and ID18 had no direct relationship with the other highly skilled members or experts.
- None of the experts (ID13, ID3, ID40 and ID5) had any direct contact with each other regarding SR.
- ID17 and ID12 acted as brokers since without them, ID38, ID40 and ID6 would become disconnected from the other experts and highly skilled network members, forcing them to work through non-experts in order to reach experts or highly skilled peers.

#### *5.2.1.4 Service Manager Cases network*

Similar to CC, the SMC network comprised 47 of the 49 members in the division. This network boasted two experts and 20 highly skilled network members.

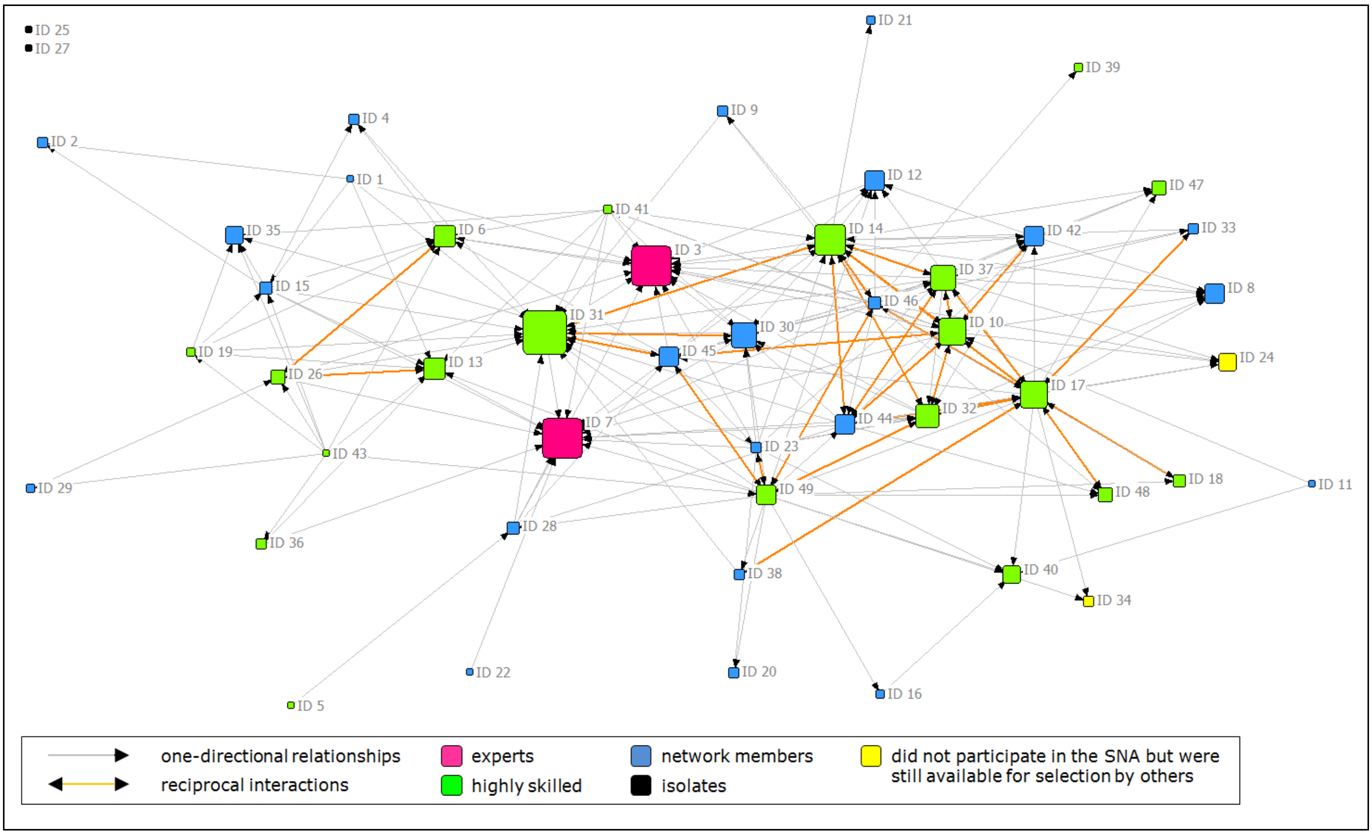


**Figure 5.11: SMC network regarding in-degree centrality**

By studying in-degree centrality in the SMC network as depicted in ***Figure 5.11*** above, one could appreciate that:

- Of the members who were considered to be knowledge authorities, only one (ID30, a line manager) was not a recognised expert or highly skilled member.
- Highly skilled member ID31 was contacted by 38% of the network followed by experts ID3 and ID7 who were contacted by 34%.
- Four highly skilled members (ID19, ID39, ID41 and ID5) had only one or less SMC network member contacting them for information.

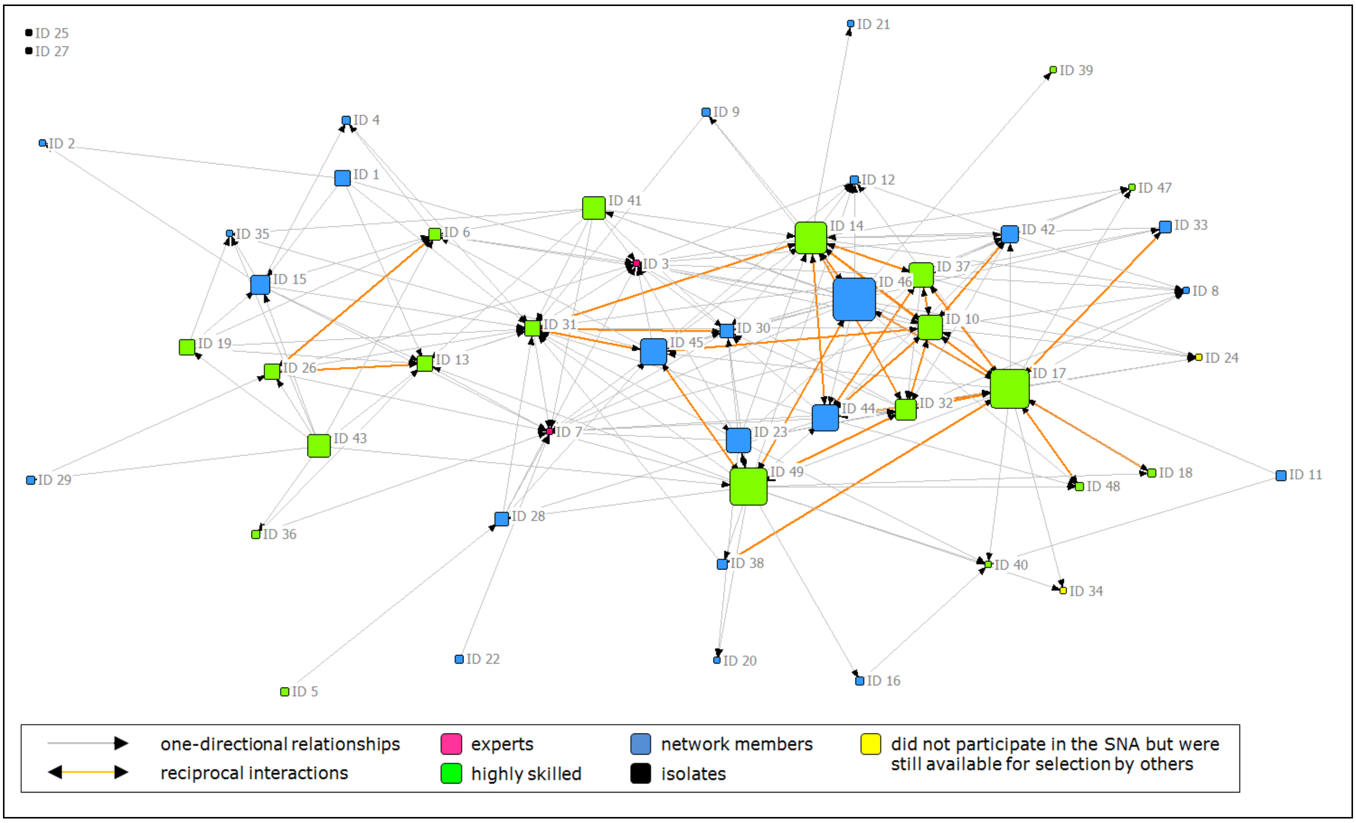


**Figure 5.12: SMC network regarding out-degree centrality**

As far as the out-degree centrality in the SMC network was concerned, the following was observed in ***Figure 5.12*** above:

- The nine highest scores pertaining to out-degree centrality were held by four ordinary network members (ID46, ID44, ID45 and ID45) and eight highly skilled members (ID17, ID49, ID14, ID10, ID37, ID41, ID43 and ID32).
- Members with the highest out-degree rankings also enjoyed a relatively high level of reciprocity within this network.

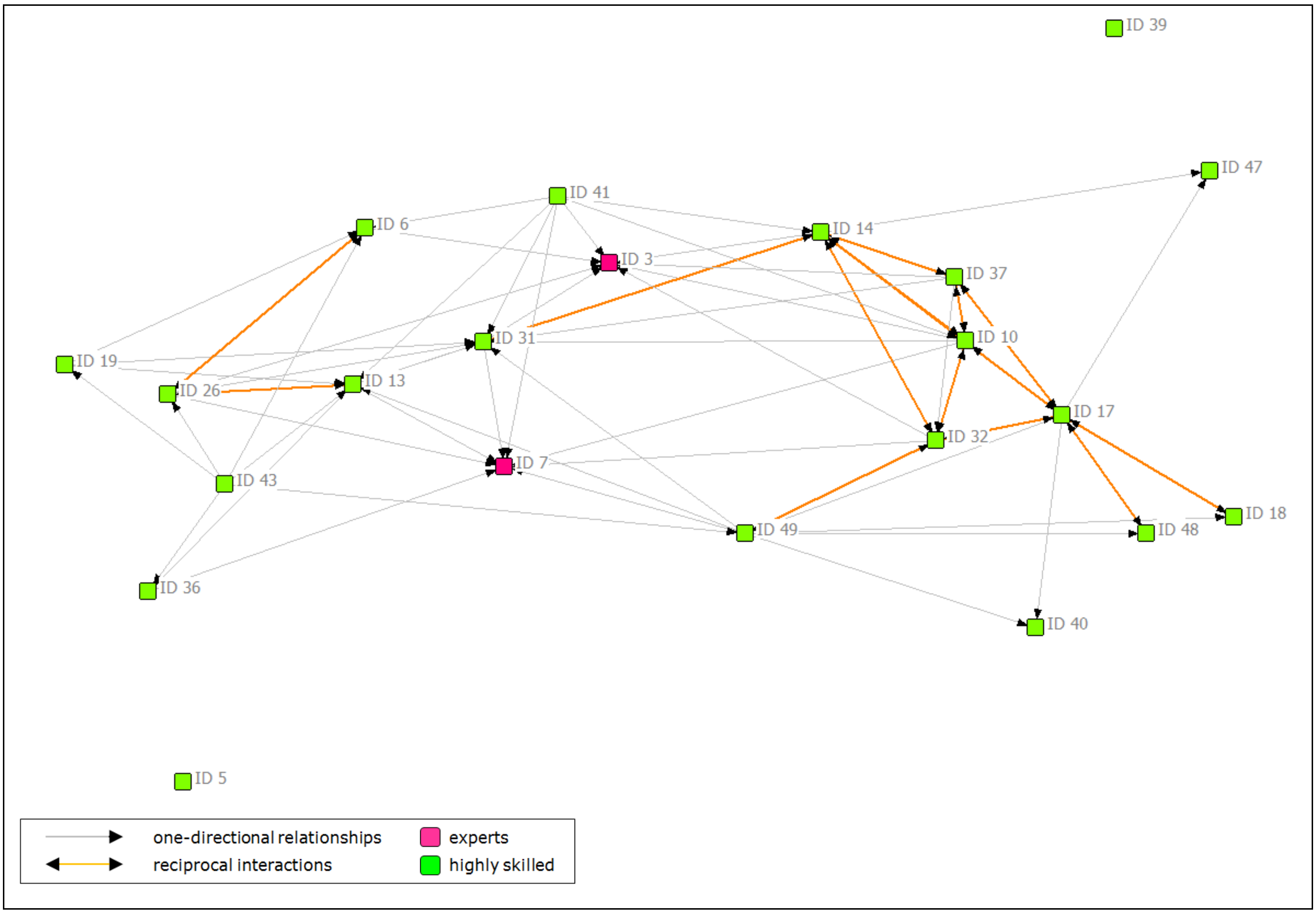


**Figure 5.13: SMC network concerning experts and highly skilled members only**

By studying the relations between the SMC experts and highly skilled members (***Figure 5.13*** above), it became noticeable that:

- Apart from ID5 and ID39 who did not have any direct ties with their SMC peers, all highly skilled network members were well connected. However, there existed no direct ties between the network's experts (ID3 and ID7).
- The SMC experts (ID3 and ID7) had no outgoing ties, meaning that they did not approach others for information.
- Highly skilled member ID17 held the most reciprocal ties among the skilled members and experts in the SMC network.

***Figure 5.2*** to ***5.13*** above offered a comparison between domain experts (pink) and highly skilled (green) network members, as identified during the skills audit, as well as members who were either predominantly contacted for information (high in-degree centrality) or members who approached various others for information (high out-degree centrality) in the respective networks. The affiliation between experts and highly skilled members within the particular networks were also presented.

### 5.2.2 Linking CoP participation with key network positions

Four online CoPs were designed and divisional members were invited to join one or more of these communities. Nonetheless not all network members were interested in becoming members of the corresponding CoPs.

In order to understand why some members opted to join the CoPs while others were not interested, the location of the respective actors in the network were evaluated. SNA applies centrality measures to identify network members whose connectivity promotes them to specific influential positions (Baum & Vlok 2013:53). Subsequently, network centrality measures[32] were once again employed to gain insight into the various roles and groupings in each network.

The respective knowledge networks are illustrated below (***Figures 5.13*** to ***5.24***) in terms of:

- network centrality roles;
- network members who opted to join CoPs; and
- levels of participation within the CoPs.

[32] Members with a high in-degree centrality were regarded as authorities/knowledge experts, i.e. people who were approached based on their knowledge. These people were classified as experts based on the number of network members that approached them for information, and were not necessarily the same individuals that were identified as experts during the skills audit. Network members with a high out-degree centrality were seen as knowledge consumers. Agents scored high on betweenness centrality and knowledge brokers achieved a high overall degree centrality rating. Network members with a high closeness centrality were regarded as 'independent' as they had the best visibility of what was happening in the network and could thus monitor the information flow of the network. Noteworthy nodes were defined as nodes with centrality measures greater than two standard deviations above the mean.

To make sense of the different roles network members played considering centrality (***Figures 5.14***, ***5.17***, ***5.20*** and ***5.23***), it is important to explain some structural features:

- *Arrows* indicate the direction of interaction.
- *Grey lines indicate* one-directional relationships, while *orange lines* indicate reciprocal interactions.
- Different *node colours* and *shapes* have been used to differentiate between the various roles allocated to network members:
  - Degree centrality:
    - red squares = *authorities/knowledge experts* – high in-degree centrality, low out-degree centrality. These individuals were not necessarily the same as the experts identified during the skills audit, but were rather regarded as experts based on their high in-degree score.
    - blue squares = *knowledge consumers* – high out-degree centrality, low in-degree centrality
  - green squares = *knowledge brokers* – high in-degree centrality, high out-degree centrality
  - grey squares = *peripheral players* – low in-degree centrality, low out-degree centrality
  - Betweenness centrality:
    - yellow circles = *agents* (boundary spanners/gatekeepers) – high betweenness centrality
  - Out $\kappa$-reach centrality:
    - turquoise triangles = *independent nodes* – high closeness centrality
- *Black squares* represented members who did not form part of the knowledge network (isolates)
- In order to provide a better analysis of the different roles all nodes except the isolates and peripheral players have been manually increased.

***Figures 5.15***, ***5.18***, ***5.21*** and ***5.24*** present an overview of network members who opted to join particular CoPs. Here it is essential to consider the following:

- *Arrows* indicate the direction of interaction.
- *Grey lines indicate* one-directional relationships, while *orange lines* indicate reciprocal interactions.
- Different *node colours* have been used to distinguish between the respective network members:
  - *yellow squares* = members who were not invited to participate in CoPs either due to secondment or maternity leave
  - *grey squares* = network members who opted *not to join* the particular CoP
  - *green squares* = network members who joined the CoP
  - *red ID labels* = members who were regarded as experts (as per the skills audit) within the network
  - *green ID labels* = members who were regarded as highly skilled (as per the skills audit) network members

***Figures* 5.16**, ***5.19***, ***5.22*** and ***5.25*** aimed to offer an indication of the level of participation within the CoPs. It is imperative to <u>note that the layout of these figures does not represent the CoP network itself, but simply compares the individual's position within the knowledge network</u>, with their participation in the corresponding CoP. It is important to take note of the following:

- Only *members who joined* the respective CoPs are displayed.
- *Grey lines indicate* one-directional relationships, while *orange lines* indicate reciprocal interactions among these members <u>in their knowledge networks.</u>
- Different *node colours* have been used to distinguish between the community members:
  - *red ID labels* = members who were regarded as either *highly skilled* members or *experts* (as per the skills audit), or members who were identified as *knowledge authorities* (experts based upon their high in-degree centrality) within the respective knowledge networks
  - *sky blue squares* = *lurkers* – member participation was limited to viewing the contributions
  - *yellow diamonds* = *sparkers* – members who asked questions and who sparked debates
  - *green squares* = *sole contributors* – members who stated a case/who provided interesting pieces of information
  - *red triangles* = *advisors* – members who aimed to answer questions published in the CoPs or who commented on questions or answers given

### *5.2.2.1 Commodity Control*

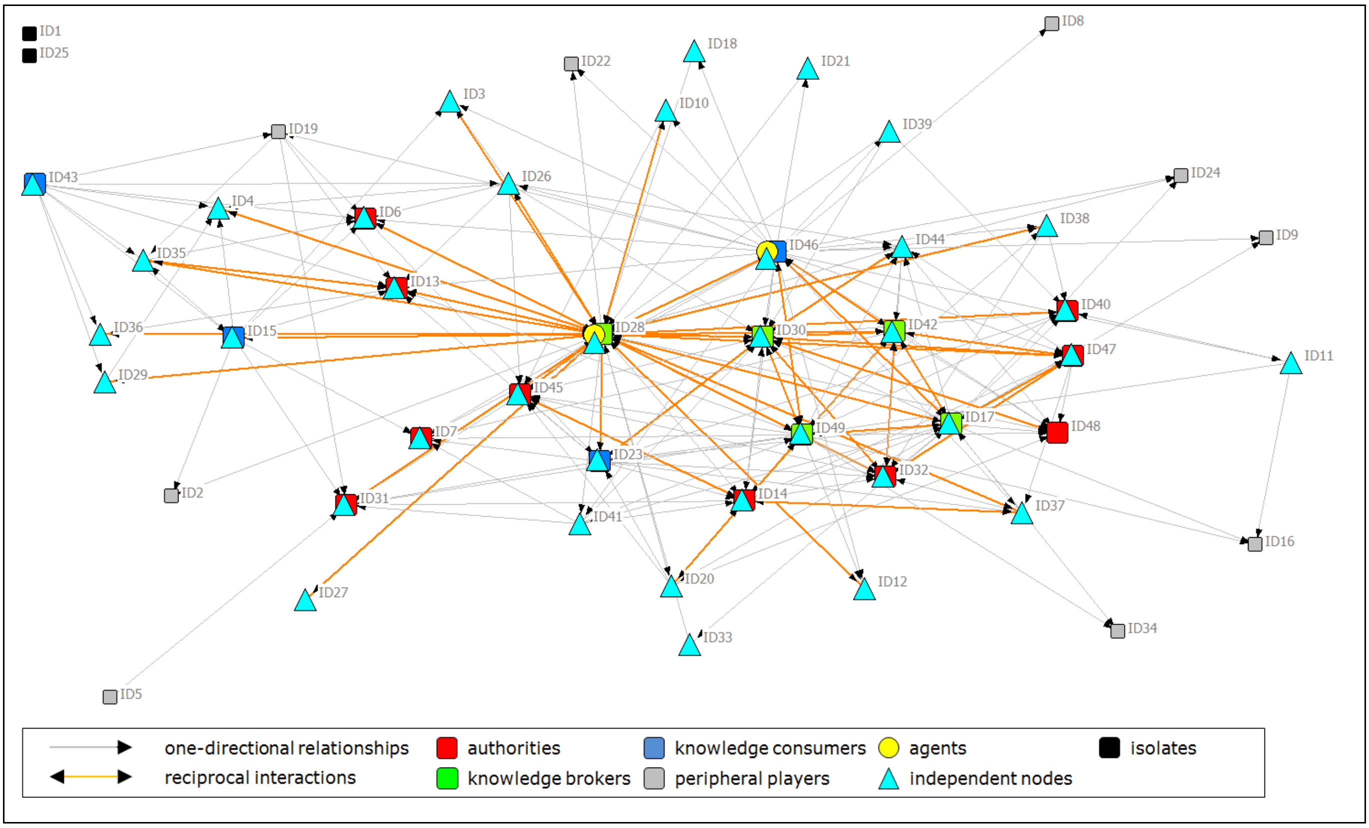


**Figure 5.14: CC network considering network centrality roles**

By studying the CC knowledge network illustrated in ***Figure 5.14*** above, the following network centrality roles have been detected:

- There were 10 knowledge authorities (ID32, ID13, ID31, ID45, ID48, ID14, ID40, ID6, ID7 and ID47), four knowledge consumers (ID46, ID23, ID15 and ID43) and five knowledge brokers (high in- and out-degree centrality) (ID28, ID30, ID49, ID17 and ID42) present.
- ID28 and ID46 scored high on betweenness centrality and were thus considered agents or gatekeepers, serving as intermediaries between central and peripheral network members.

- Thirty-six of the 47 network members scored rather high concerning *out κ*-reach[33] and were therefore regarded as independent[34] as they could reach other CC network members promptly.

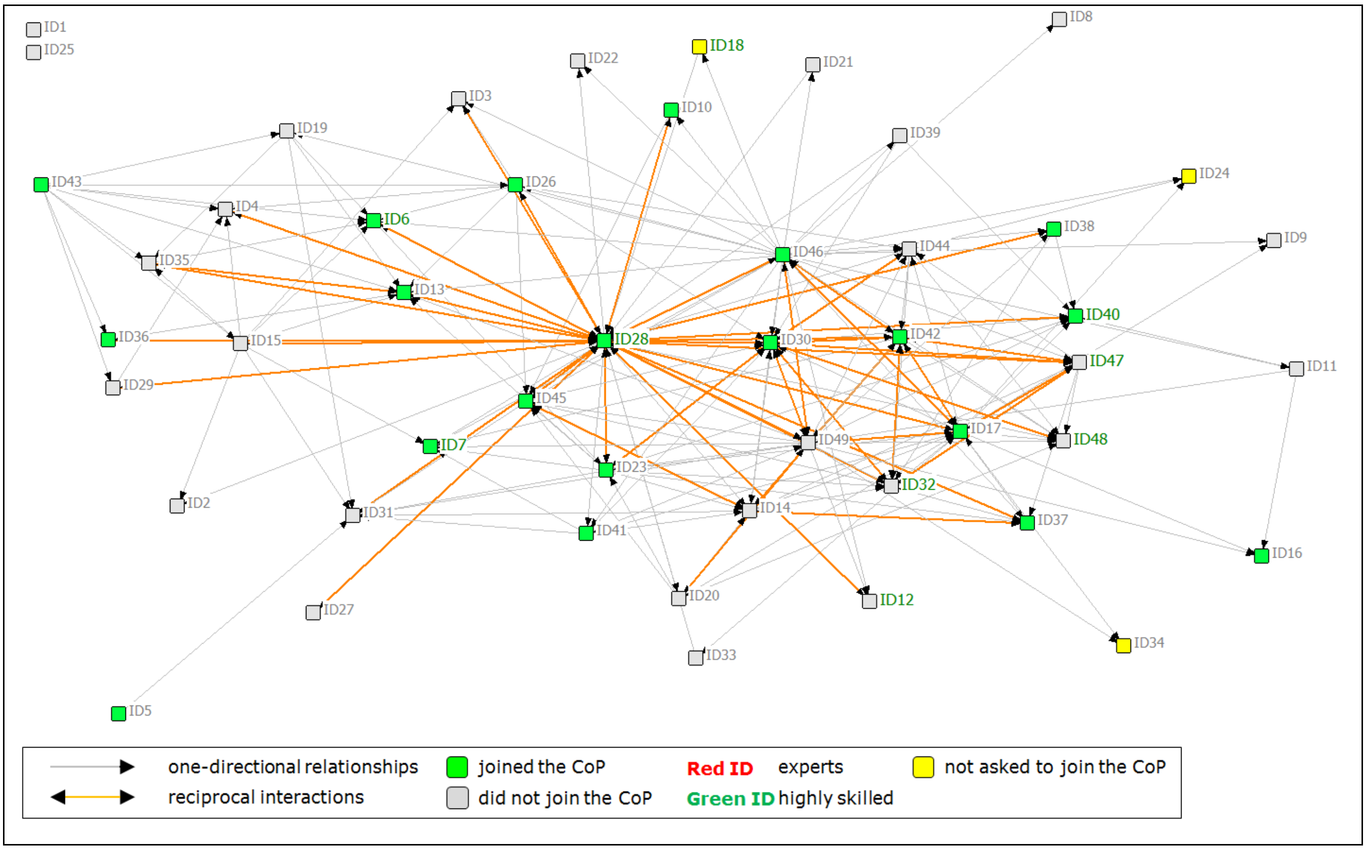


**Figure 5.15: Network members who joined the CC CoP**

Twenty of a possible 46[35] network members were interested in joining the CC CoP (***Figure 5.14***). From the above figure the following is evident:

- Of the members who were not interested in participating in this CoP, two (ID1 and ID25) were isolates in the original knowledge network and 6 (ID19, ID2, ID22, ID33, ID8 and ID9) were peripheral network players (scoring low on in- and out-degree centrality).

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[33] For the purpose of this study out κ-step reach (with κ=2) was considered.
[34] Reach underscores an actor's autonomy. Considering out κ-reach, actors who are able to reach other actors by shorter path lengths have advanced positions. Actors with more ties have better opportunities since they have choices as to whom they prefer to contact. This independence makes them less dependent on any specific other actor and thus more powerful (Hanneman & Riddle 2005).
[35] The three network members who were either on maternity leave or assigned to another division were not available to join any of the online CoPs created.

- Seventeen members who did not join the CC CoP scored relatively high regarding out $\kappa$-reach centrality.
- Five of the eight[36] highly skilled network members identified were not interested in joining the CC CoP, with two of them (ID32 and ID48) operating as knowledge authorities within the CC network. Of the seven knowledge authorities, only three (ID13, ID45 and ID40) opted to join the CC CoP.
- Only one knowledge consumer, ID15 (who also had a high out $\kappa$-reach centrality), did not join the CC CoP.
- Network members who did not join the CC CoP thus comprised original isolates, peripheral players, independent members (based on out $\kappa$-reach centrality) and knowledge authorities.

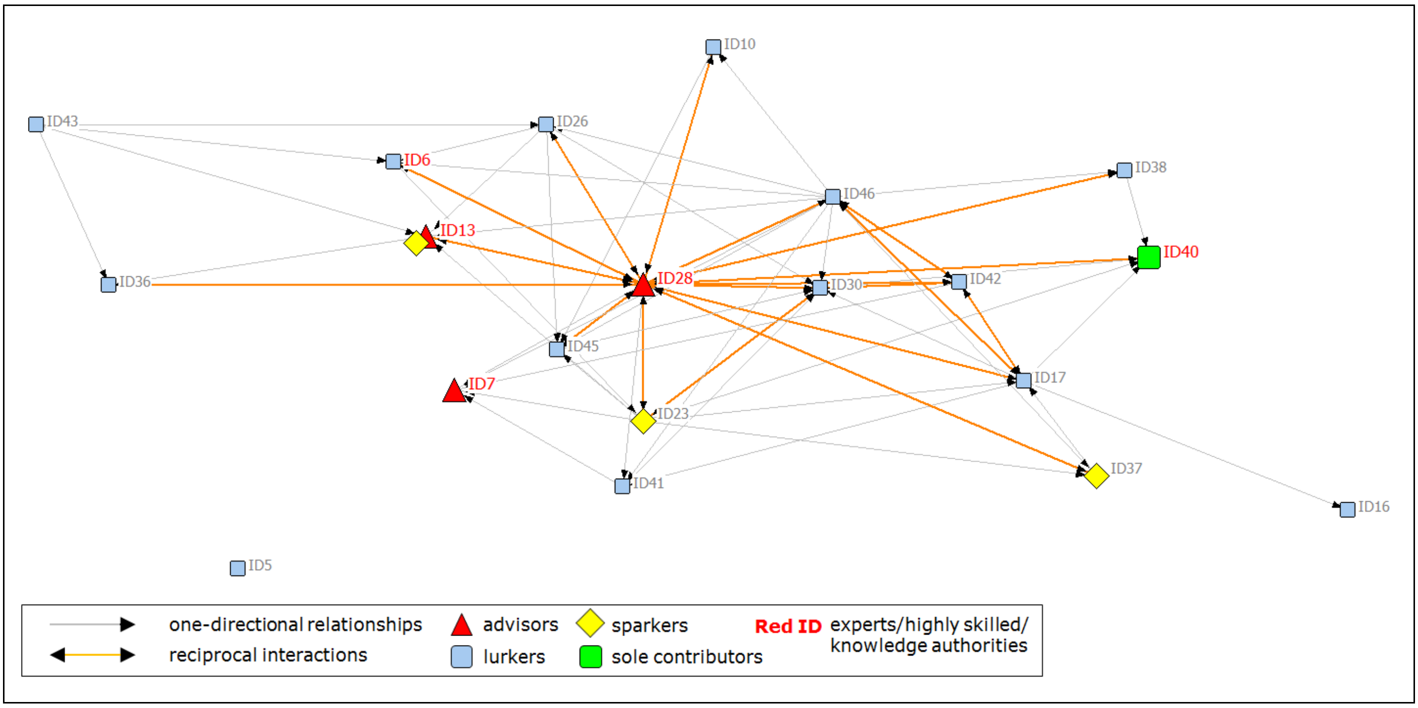



**Figure 5.16: Member roles within the CC CoP**

***Figure 5.16*** provides an overview of the level of participation that existed within the CC CoP:

- Of the 20 people who joined the CC CoP, there were 14 *lurkers*, one *sole contributor*, three *sparkers* and four *advisors*.

[36] Originally there were nine skilled CC members in the division, but one went on maternity leave before the CoPs were established.

- Most of the actions in the CC CoP could be attributed to highly skilled network members.[37]
- Four (ID7, ID13, ID28 and ID40) of the six community members who were either regarded as highly skilled or who operated as knowledge authorities in the network participated actively.
- All questions posted on this CoP were answered by members who were considered highly skilled in terms of CC.

***Figures 5.14*** to ***5.16*** provided an overview of the various roles that existed within the CC knowledge network, outlined which members were motivated to join a CoP pertaining to CC and revealed what their respective levels of participation within the CoPs were.

[37] According to the skills audit, there were only highly skilled CC members and no experts present in the division.

### *5.2.2.2 Data Analytics and Mining*

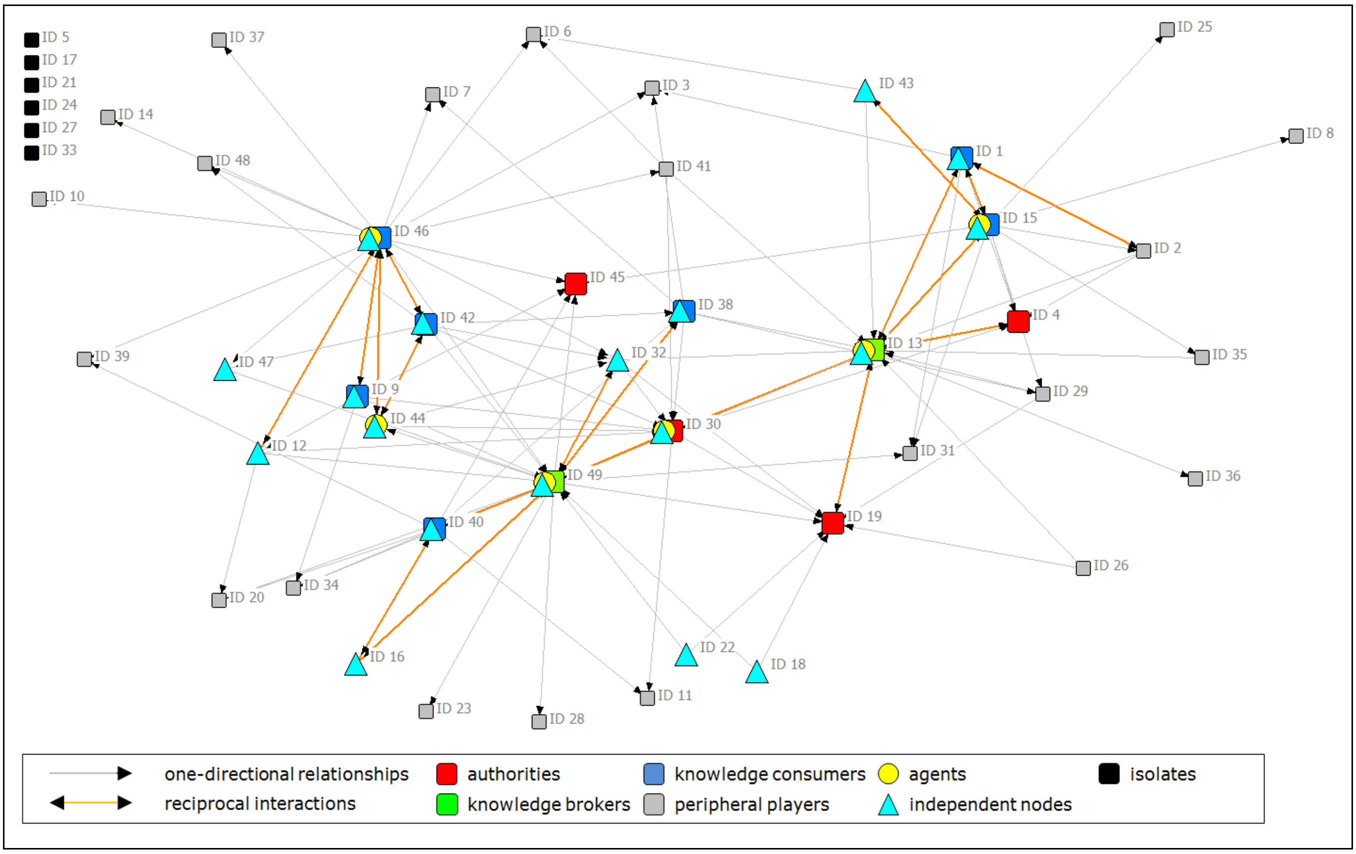



**Figure 5.17: DAM network considering network centrality roles**

Network centrality roles within the DAM network are depicted in ***Figure 5.17*** above. The following is evident from the figure:

- The DAM network contained four knowledge authorities (ID30, ID19, ID4 and ID45), seven knowledge consumers (ID46, ID15, ID40, ID42, ID1, ID9 and ID38) and two knowledge brokers (ID13 and ID49).
- Gatekeeper roles were performed by ID49, ID13, ID30, ID44, ID46 and ID15 who (due to their high betweenness centrality) acted as agents between central and peripheral network members.
- Eighteen of the network members rated high in terms of *out* κ-reach and could thus access information within the DAM network without being dependent on a specific member.

Of the 46 members in the division, only 22 opted to participate in the DAM CoP as depicted in ***Figure 5.18*** below.

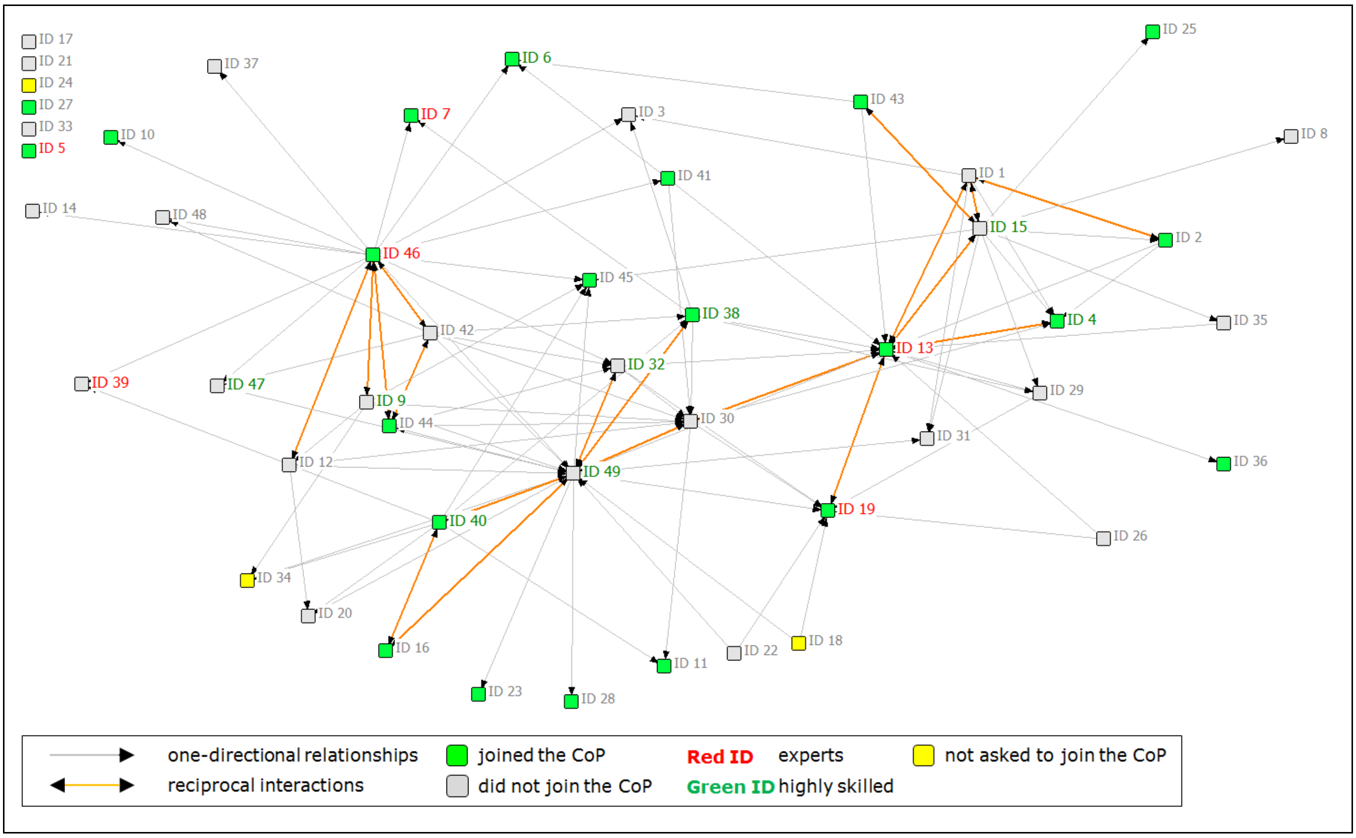



**Figure 5.18: Network members who joined the DAM CoP**

The following was evident from the figure:

- Members who did not want to join included three isolates (ID17, ID21 and ID33) from the original knowledge network[38], 10 peripheral network players (scoring low on in- and out-degree centrality) and 10 members who ranked high in terms of autonomy with a high out $\kappa$-reach centrality score and one member (ID39) who was considered a DAM expert.
- Of the 6 experts identified during the skills audit only one (ID39) was not interested in joining the DAM CoP. Incidentally this was also the expert with the lowest in-degree centrality in this network.
- Nonetheless only four (ID4, ID6, ID38 and ID40) of the nine members who were regarded as highly skilled in terms of DAM joined the DAM CoP.

[38] ID24 was not considered an isolate who did not want to join the DAM CoP as she was with maternity leave at the time of this study.

- One knowledge authority (ID30) and one knowledge broker (ID49) were not interested in joining this CoP. In both instances they also scored high regarding out $\kappa$-reach centrality.
- Two members who were originally isolated from this knowledge network (ID5, a confirmed DAM expert and ID27) chose to join the DAM CoP.
- Four of the knowledge consumers (ID15, ID42, ID1 and ID9) chose not to join the DAM CoP. All these members could be regarded as independent due to their out $\kappa$-reach centrality score. ID15 and ID9 were also regarded as highly skilled regarding DAM.

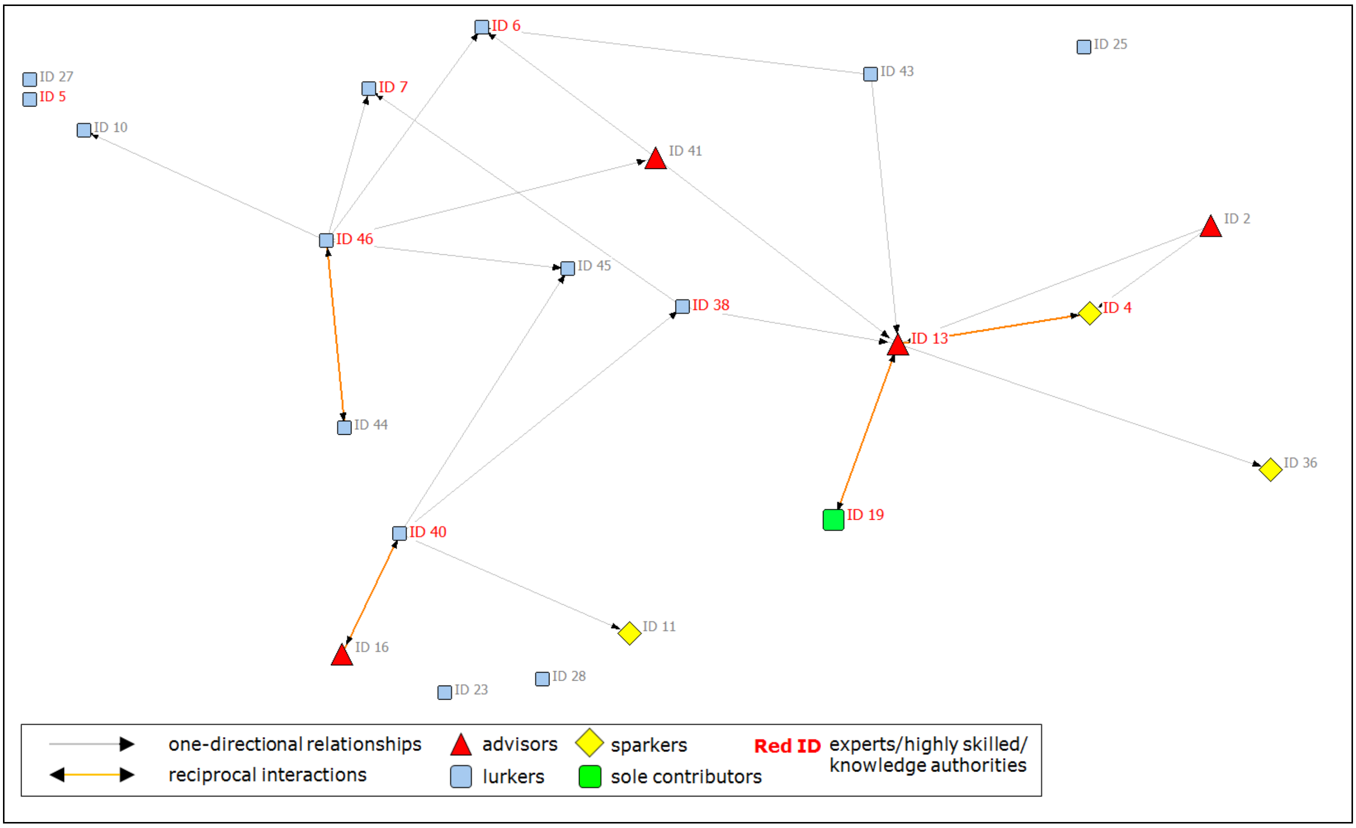



**Figure 5.19: Member roles within the DAM CoP**

An outline of the level of participation that existed within the DAM CoP is illustrated in ***Figure 5.19*** above:

- The DAM CoP had 22 members of which 14 were *lurkers*, one *sole contributor*, three *sparkers* and four *advisors*.
- Of the nine experts/highly skilled members who joined the DAM CoP, only three actively participated - ID19 made a DAM contribution, ID13 responded to an information request and ID4 posted a question.
- Non-experts, ID2 and ID41, made an effort to answer DAM related questions.

- Peripheral player ID16 attempted to participate in the CoP by commenting on an answer.
- For the duration of the DAM CoP, the two original isolates who joined this CoP (ID5 and ID27) acted as lurkers and did not actively participate.

In ***Figures 5.17*** to ***5.19*** the different roles from a centrality perspective within the DAM network have been delineated followed by an indication of which members wanted to join the DAM CoP. An outline of the extent to which all participated in this CoP was also provided.

### 5.2.2.3 Single Registration

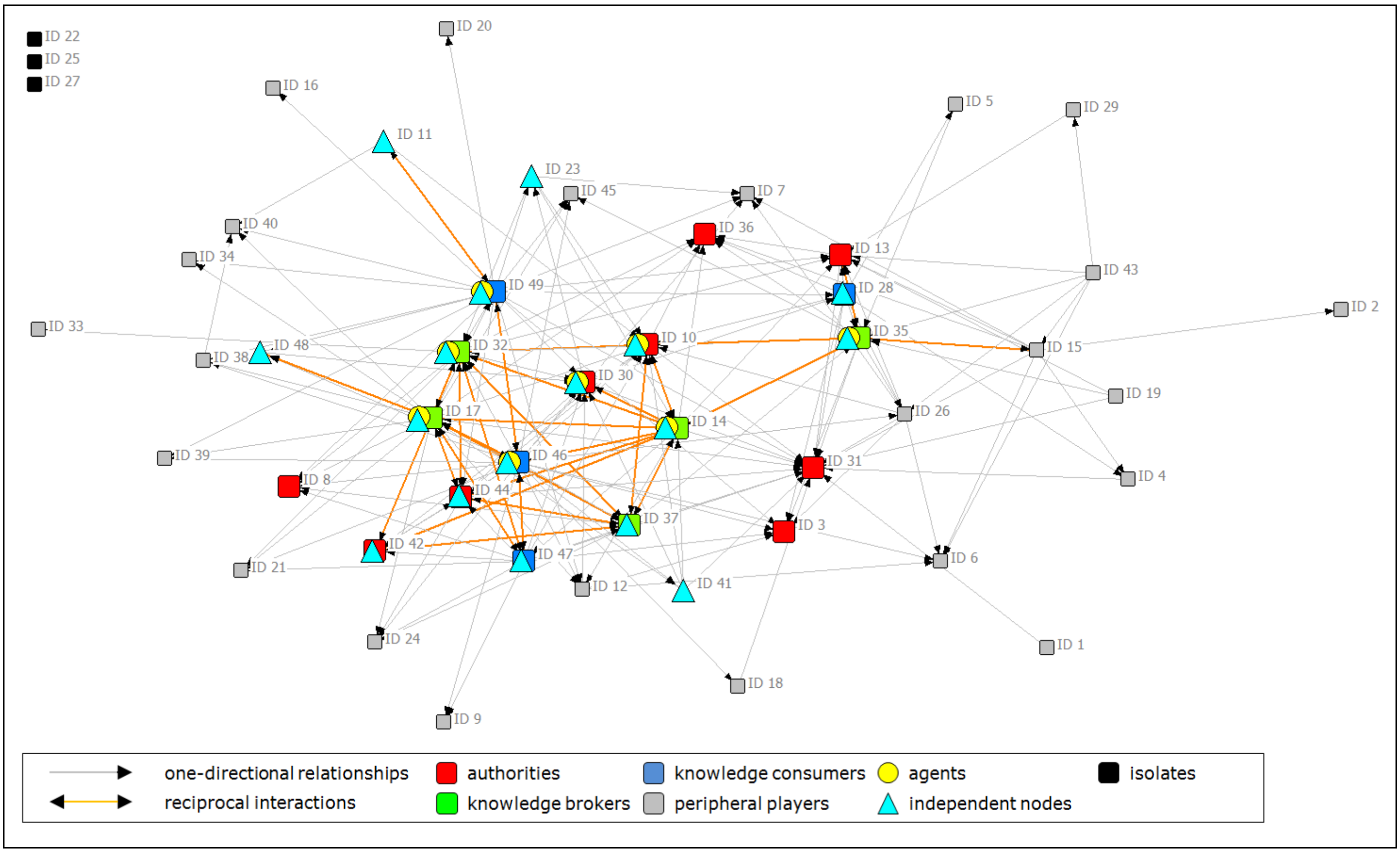



**Figure 5.20: SR network considering network centrality roles**

***Figure 5.20*** above portrays the network centrality roles that existed within the SR network:

- Nine network members scoring high on in-degree centrality (ID31, ID10, ID13, ID30, ID36, ID44, ID3, ID8 and ID42) acted as knowledge authorities in the SR network. This network also featured four knowledge consumers (ID46, ID49, ID47, and ID28) and five knowledge brokers (ID17, ID14, ID32, ID37 and ID35).
- With their high betweenness centrality rankings, ID14, ID35, ID17, ID46, ID49, ID30, ID10 and ID32 operated as gatekeepers mediating between central and peripheral SR network members.

The SR network comprised 17 independent actors with prominent out $\kappa$-reach centrality levels.

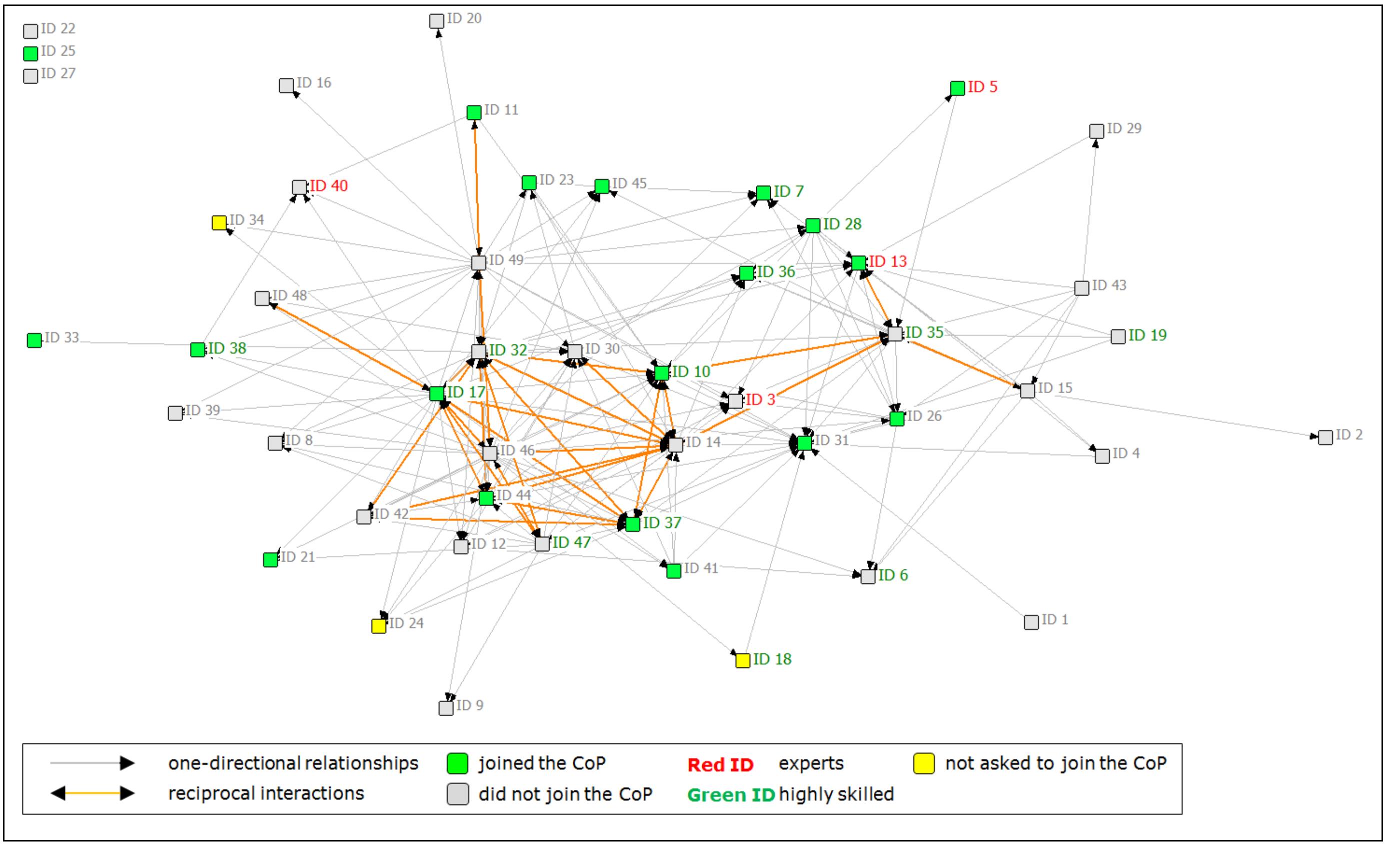



**Figure 5.21: Network members who joined the SR CoP**

Nineteen of the 46 divisional members were interested in joining the SR CoP. This is evident from ***Figure 5.21*** above.

- Isolate ID25 opted to join the SR CoP.
- Members who refrained from joining included two isolates (ID22 and ID27), six members who were considered independent based on their out $\kappa$-reach centrality ranking (ID49, ID46, ID14, ID48, ID30 and ID42), eight members who were either considered as experts/highly skilled or who functioned as knowledge authorities within the SR network and 11 peripheral members.
- Two of the four experts (ID3 and ID40) and six (including one on maternity leave) of the 13 identified highly skilled SR members (ID6, ID18, ID19, ID32, ID35 and ID47) did not join the SR CoP, while an additional three knowledge authorities (ID30, ID8 and ID42) did not join the SR CoP. Nonetheless 10 of the 19 SR CoP members were either experts, highly skilled or recognised as knowledge authorities by their colleagues.
- Three (ID46, ID49 and ID47) of the four identified knowledge consumers did not join the SR CoP. All three were regarded as independent due to their out $\kappa$-reach

centrality rankings with one (ID47) being recognised as highly skilled regarding SR.

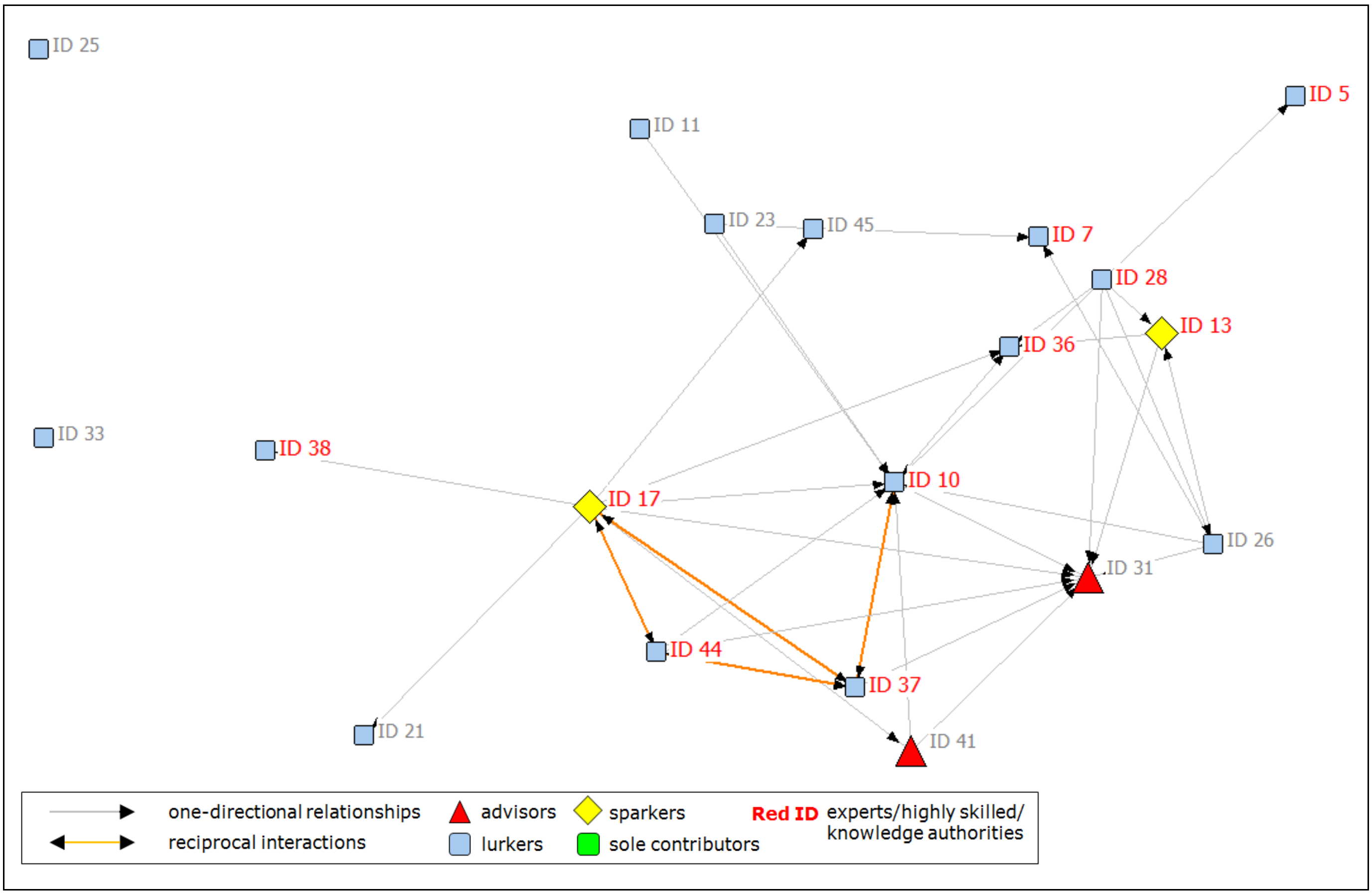



**Figure 5.22: Member roles within the SR CoP**

***Figure 5.22*** above illustrates the level of participation that took place in the SR network.

- Of the 19 SR CoP members 15 were *lurkers*, two were *sparkers* and two acted as *advisors*.
- None of the answers to SR questions were provided by recognised experts, highly skilled members or knowledge authorities, who accounted for more than 50% of the SR CoP population.
- Only two of the nine experts/highly skilled members who joined this CoP, actively participated.

***Figures 5.20*** to ***5.22*** above portrayed the diverse roles that existed within the SR knowledge network concerning centrality rankings along with an outline of which members chose to join the SR CoP and what their involvement in the CoP entailed.

#### *5.2.2.4 Service Manager Cases*

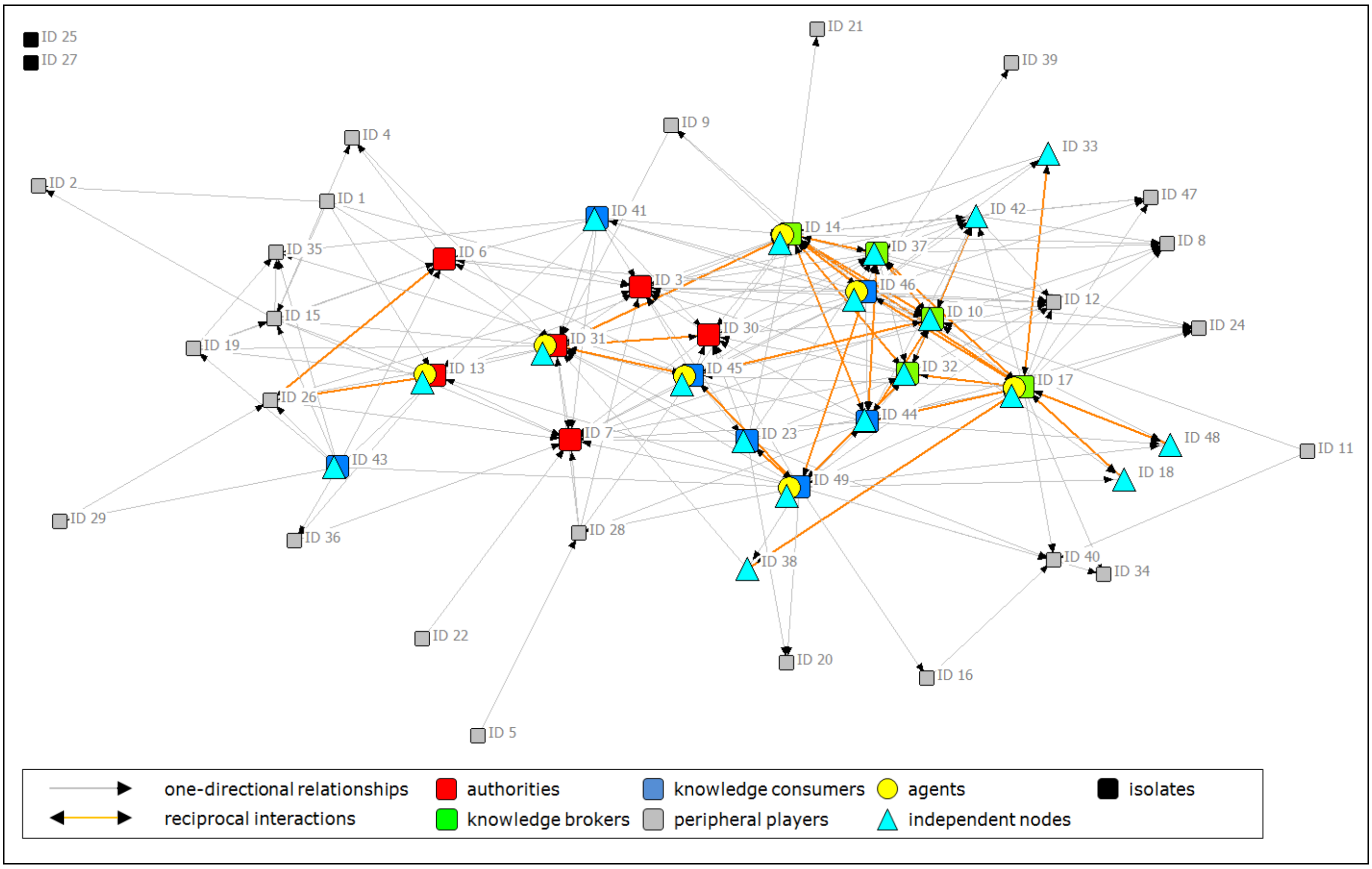



**Figure 5.23: SMC network considering network centrality roles**

The different network centrality roles within the SMC network are illustrated in ***Figure 5.23*** above.

- The SMC knowledge network comprised six knowledge authorities (ID31, ID3, ID7, ID30, ID6 and ID13), seven knowledge consumers (ID46, ID49, ID44, ID45, ID23, ID41 and ID43) and five knowledge brokers (ID17, ID14, ID10, ID37 and ID32).
- The SMC network boasted with seven network members (ID14, ID31, ID17, ID45, ID49, ID46 and ID13) scoring high pertaining to betweenness centrality, and who operated as agents/gatekeepers between central and peripheral network members.
- With a high out $\kappa$-reach centrality score, 19 of the network's members were able to function independently.

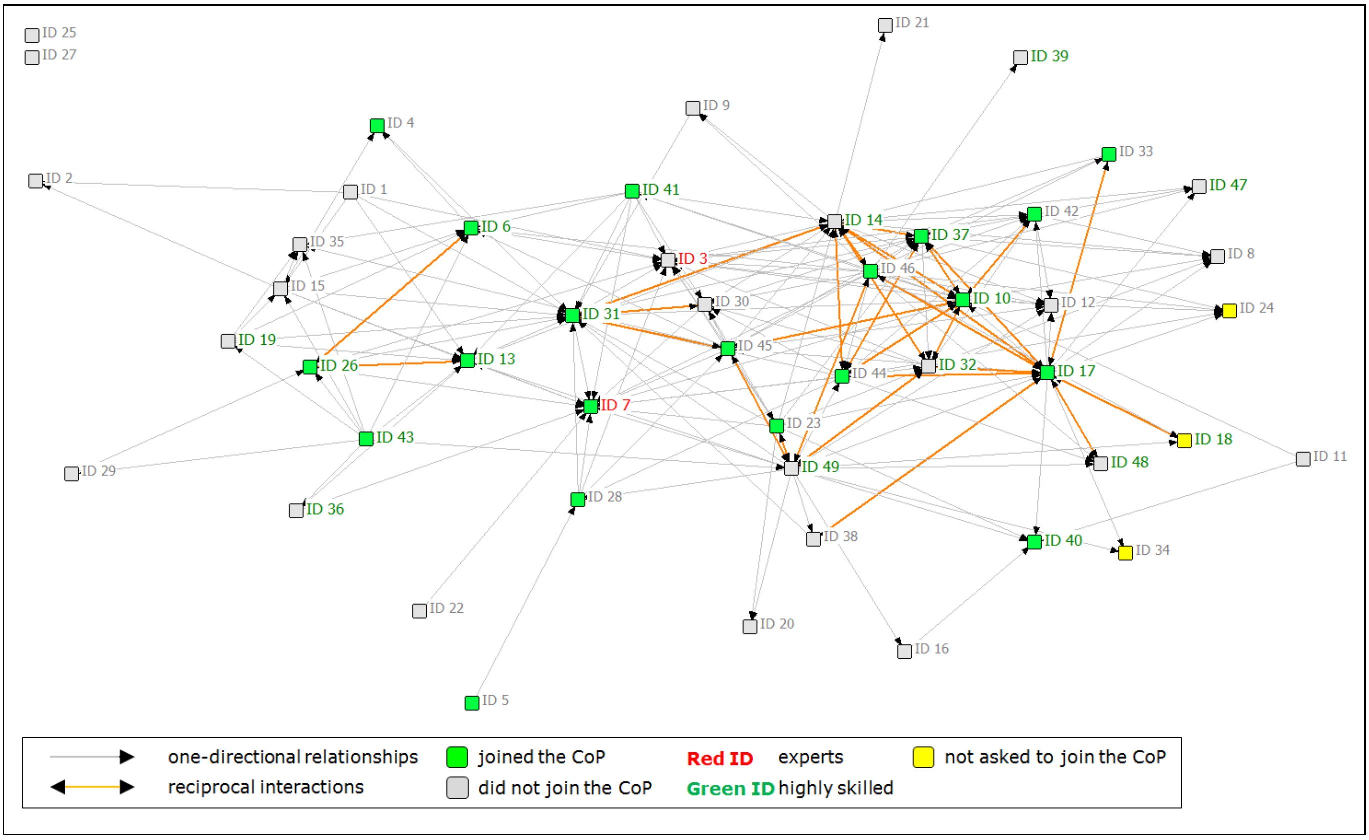



**Figure 5.24: Network members who joined the SMC CoP**

***Figure 5.24*** above portrays the 19 SMC network members who elected to join the SMC CoP and illustrates the following:

- Members who did not want to connect to this CoP included two members who were originally isolated from the SMC network (ID25 and ID27), 13 periphery network members and five members (ID49, ID32, ID14, ID38 and ID48) who ranked high in terms of out $\kappa$-reach centrality.
- One of the two network experts (ID3) and nine (ID19, ID14, ID32, ID36, ID39, ID47, ID48, ID49 and ID18 who was on maternity leave) of the 20 highly skilled network members did not join this CoP. SMC knowledge authority ID30 also refrained from joining this CoP.
- Of the seven knowledge consumers in the SMC network, only ID49 (who scored high regarding out $\kappa$-reach centrality and who was also considered to be highly skilled in the subject) chose not to join the SMC CoP.

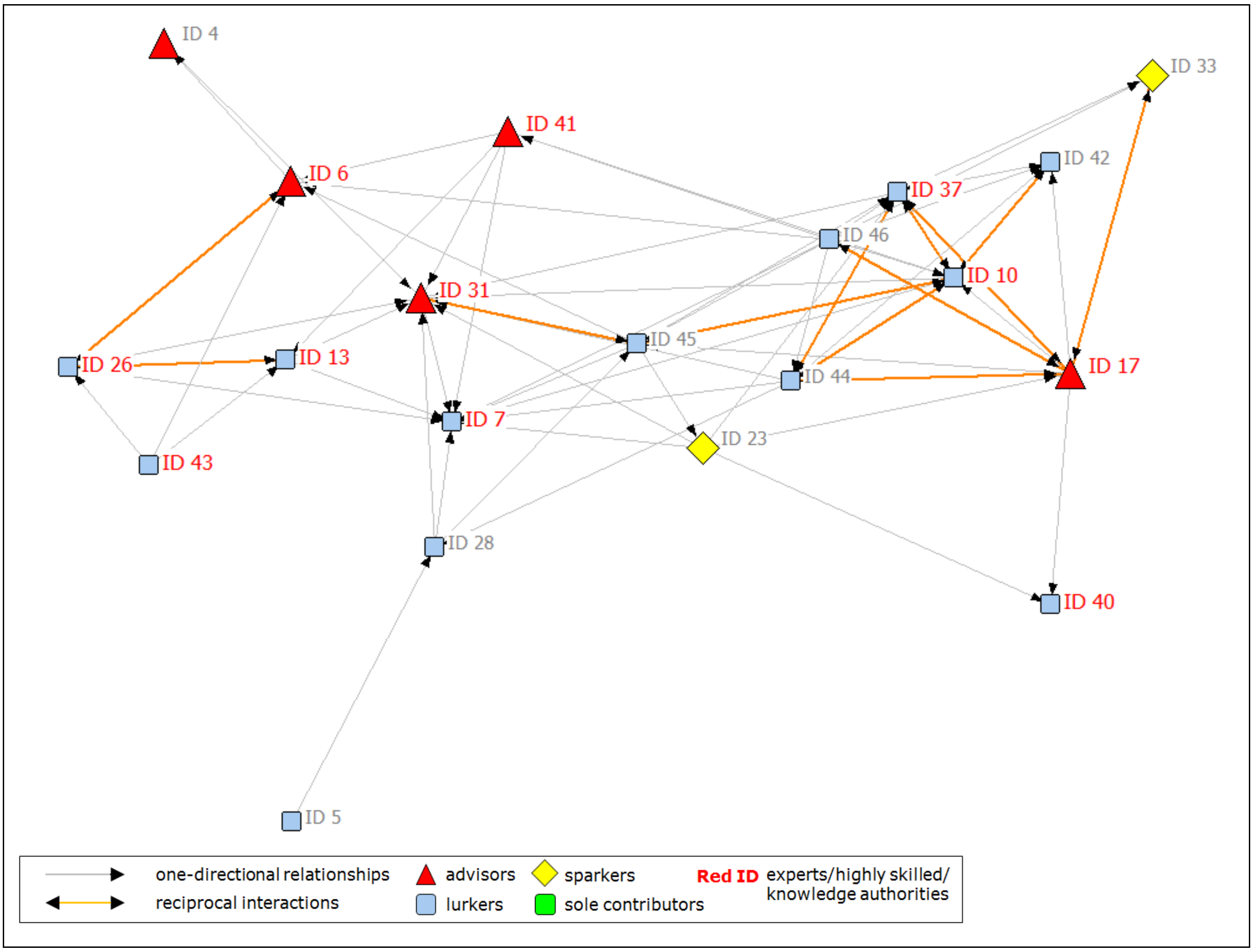



**Figure 5.25: Member roles within the SMC CoP**

The level of participation of the 20 members who joined the SMC CoP is illustrated in ***Figure 5.25*** below:

- The SMC CoP represented 13 *lurkers*, two *sparkers* and five *advisors*.
- Four of the five advisors were regarded as network experts, highly skilled members or knowledge authorities.
- Of the 11 experts/highly skilled members who joined this CoP, only four actively participated.

***Figures 5.23*** to ***5.25*** depicted the SMC network roles from a centrality perspective followed by an overview of which members eventually joined the SMC CoP and what their levels of participation were.

Based on three network centrality dimensions (degree, betweenness and out $\kappa$-reach) different roles were assigned (Müller-Prothmann, 2007:228) to members of the respective networks. ***Figures 5.14*** to ***5.25*** mapped the respective network centrality roles of each knowledge network (CC, DAM, SR and SMC) in order to illustrate any connection between centrality roles and members who opted to join a particular CoP or not. The level of member participation within each CoP was presented, yet again to illustrate any correlation between centrality roles and CoP involvement.

### 5.2.3 Comparing knowledge network structures

In this study knowledge networks were constructed at two different points in time – before and after *the introduction of corresponding CoPs* and before and after *the distribution of the knowledge maps constructed from the skills audit*. Not all divisional members who participated in the first KNA cared to join the respective CoPs. Thirty of a possible 46 divisional members opted to join at least one of the four CoPs. Consequently, to compare the same data sample, the data collected from the first and second KNAs were limited to members who joined the respective CoPs.[39].

***Figures 5.26*** to ***5.49*** below present a comparison between the structures of the corresponding knowledge networks in terms of cohesion, cut-points and hubs, before and after the implementation of KM interventions[40].

#### *5.2.3.1 Cohesion (cliques)*

Cohesion furthers knowledge creation and is revealed by the existence of cliques or clusters of expertise (Müller-Prothmann, 2007:225). Cliques indicate which sub-sets of actors are more intensely linked within a network. Hanneman and Riddle (2005) contend that the transfer of knowledge and information within networks increases where cliques overlap. Moreover, network members who form part of more than one clique turn out to be better connected.

To make sense of the diverse cliques as presented in ***Figures 5.26*** to ***5.33***, it is necessary to explain some underlying elements.

[39] When comparing knowledge network structures pre- and post-CoP implementation, the sample population was altered to only include network members who participated in at least one CoP.
[40] In this document 'KM Interventions' imply the establishment of the corresponding CoPs as well as the distribution of knowledge maps constructed from the skills audit.

- Different *node colours* and *shapes* have been used to differentiate between cliques and network members:
  - *blue triangles* = cliques with three members
  - *green triangles* = cliques with four members
  - *red triangles* = cliques with five members
  - *yellow triangles* = cliques with six members
  - *pink triangles* = cliques with seven members
  - *turquoise squares* = members who belonged to at least one clique in the network
  - *black squares* = members who did not belong to any clique within the network
- *Black lines with arrows* point to clique(s) that a node belonged to.

### *5.2.3.1.1 Cliques in the CC networks*

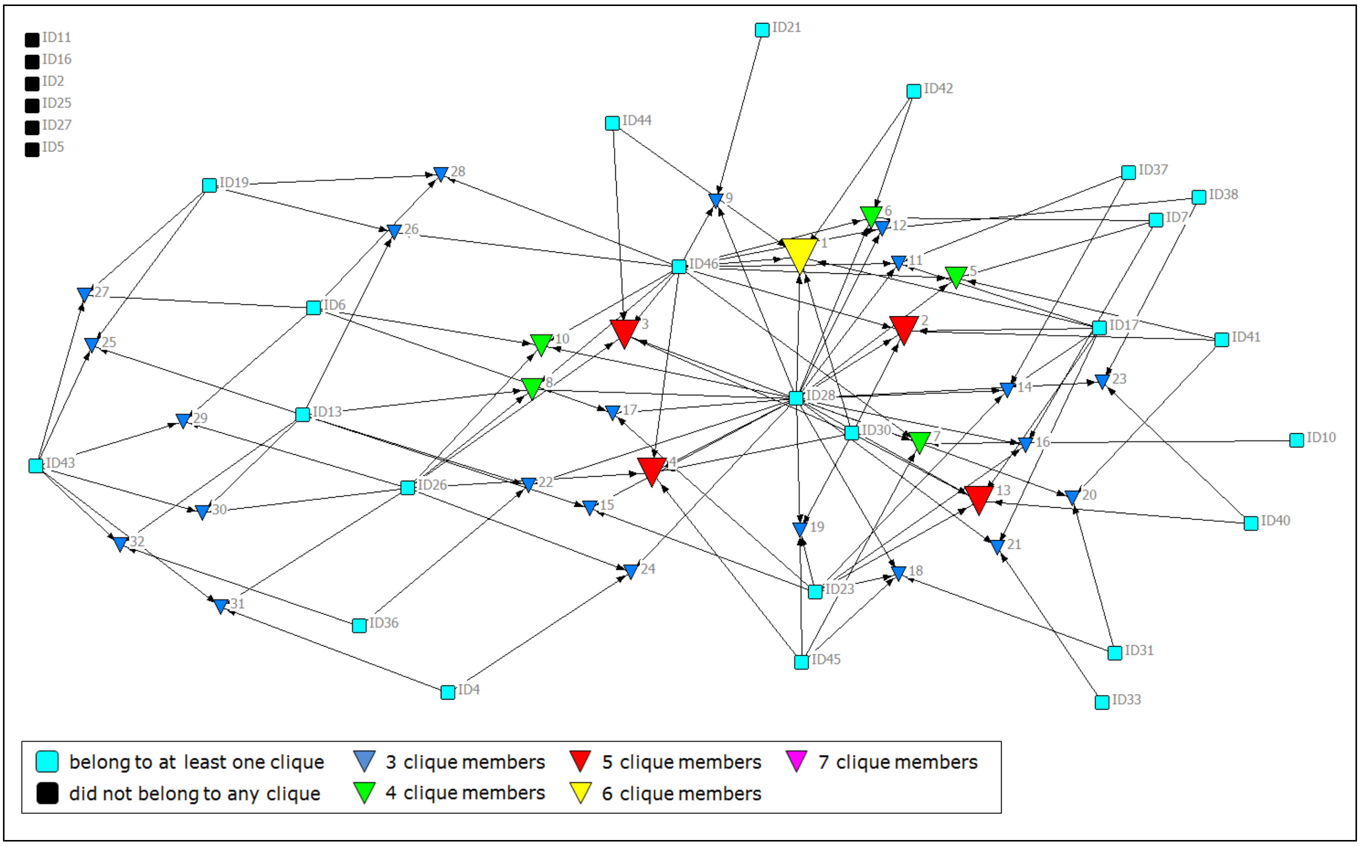



**Figure 5.26: CC cliques before implementing KM initiatives**

***Figure 5.26*** above depicts the cliques that existed in the original CC network and illustrates the following:

- Initially the CC network consisted of 32 cliques, with ID28 belonging to 24 of them.
- Six members (ID2, ID5, ID11, ID16, ID25 and ID27) - with one (ID25) being originally isolated from this network - did not belong to any of these cliques.

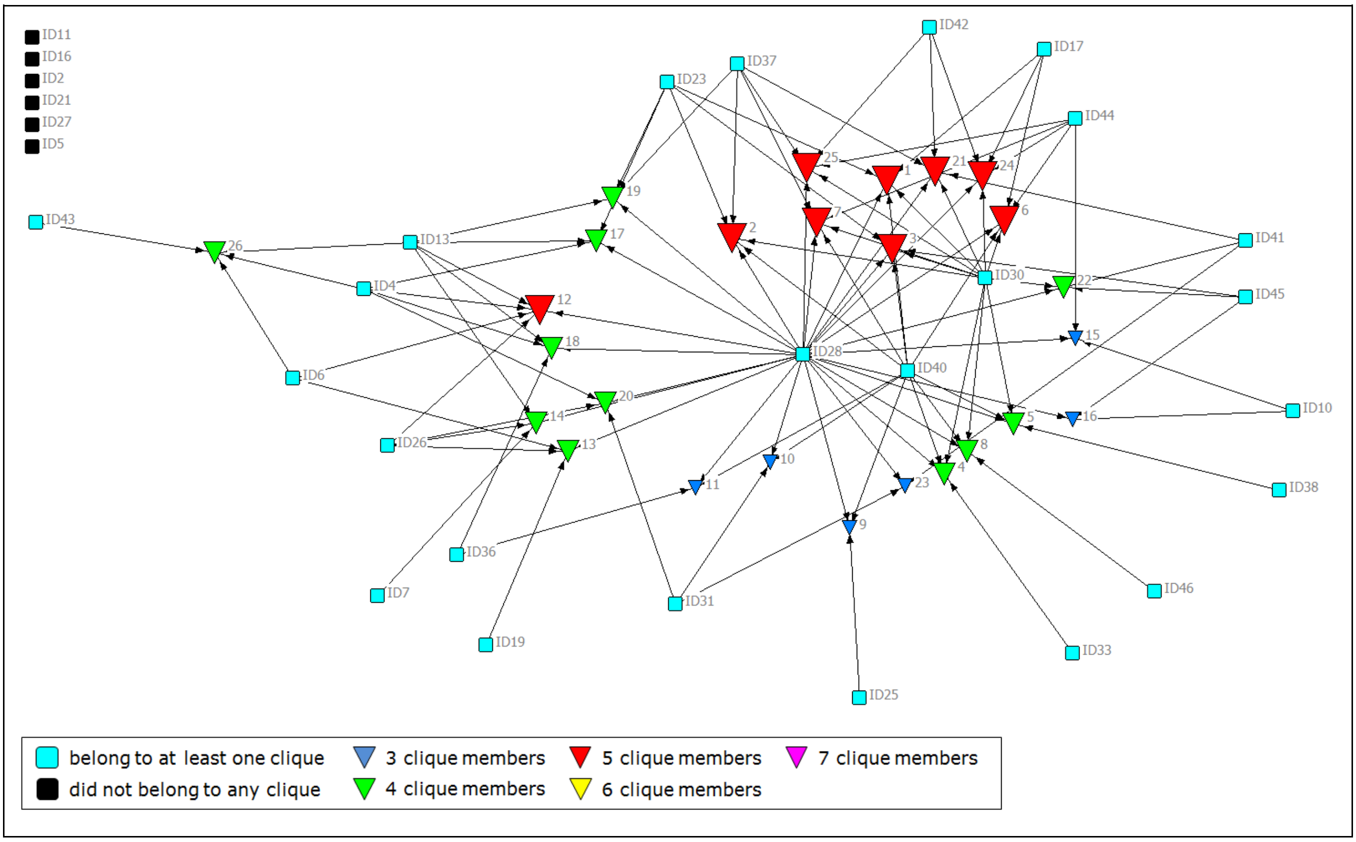



**Figure 5.27: CC cliques after implementing KM initiatives**

After introducing the CC CoP and communicating skills maps, the network structure changed in terms of cohesion resulting in the following as is evident from ***Figure 5.27*** above:

- Cliques became fewer (decreased from 32 to 26), yet more engaged (***Table 5.2***).
- This network had six members who were excluded from the existing cliques. Five of these 'isolates' were the same network members who were detached from cliques before implementing CoPs. After the implementation of the CoPs, ID21, who opted not to join the CC CoP, did not form part of any clique in the CC network, whereas the original isolate, ID25, who connected to the CC CoP became part of CC's clique nine.
- The overlap in clique membership increased after the implementation of the KM initiatives and highly skilled ID28 remained central to 25 of the 26 cliques.

***Table 5.2*** offers an overview of the number of members that constituted each clique before and after implementing KM initiatives.

**Table 5.2: Number of members per CC clique before and after implementing KM initiatives**

| Members | Number of CC Cliques | |
|---|---|---|
| | Before KM initiatives | After KM initiatives |
| 6 members | 1 clique | n/a |
| 5 members | 4 cliques | 9 cliques |
| 4 members | 9 cliques | 11 cliques |
| 3 members | 18 cliques | 6 cliques |
| TOTAL | 32 | 26 |

### *5.2.3.1.2 Cliques in the DAM networks*

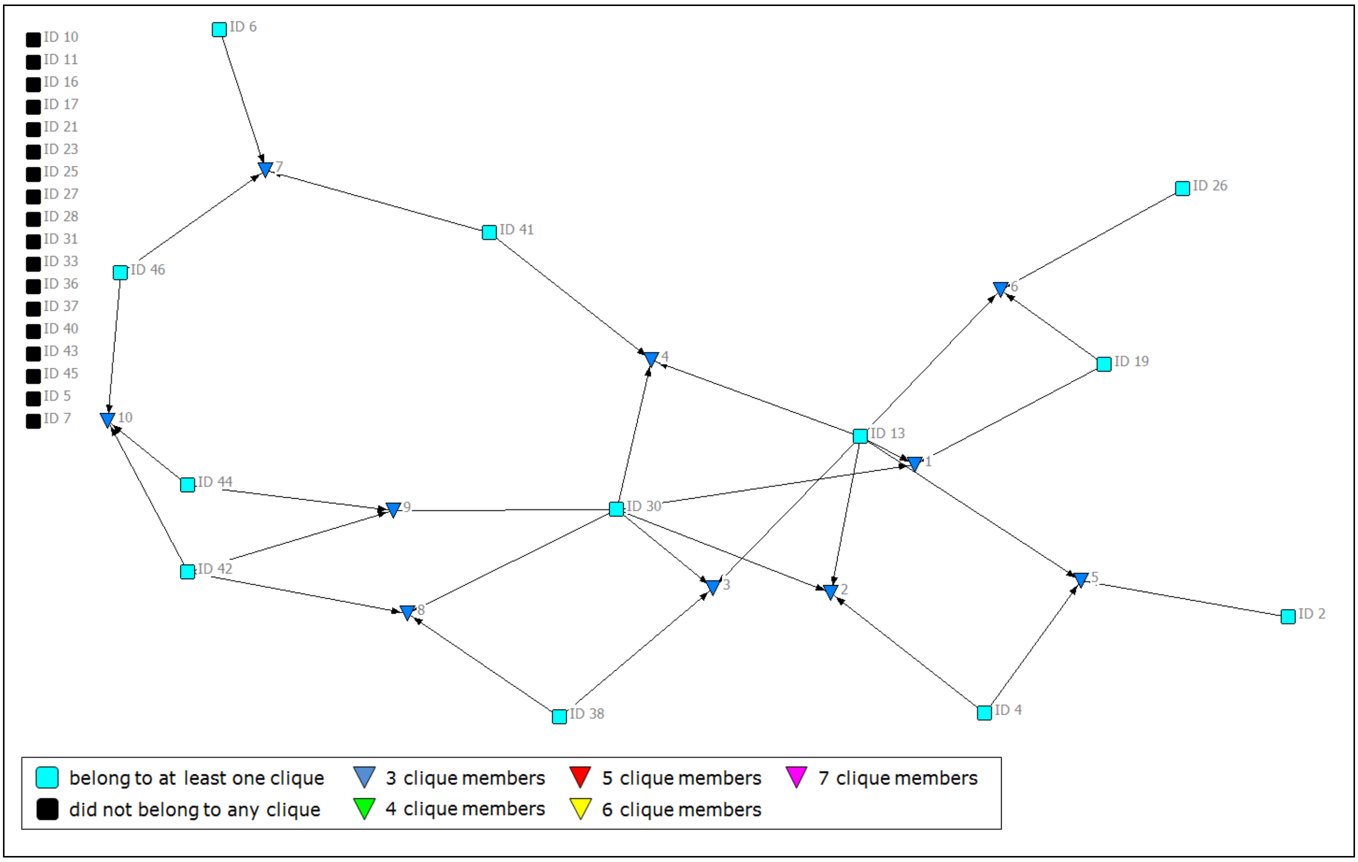



**Figure 5.28: DAM cliques before implementing KM initiatives**

Cliques that existed in the original DAM network are illustrated in ***Figure 5.28*** above which indicates the following:

- Initially the DAM network comprised ten cliques of simply three members each. Both expert and line manager ID13 and line manager ID30 belonged to six of these cliques.

- Nine of the 18 network members who did not belong to any of these cliques had been originally isolated from this network (ID5, ID17, ID21, ID23, ID25, ID27, ID28, ID31 and ID33).

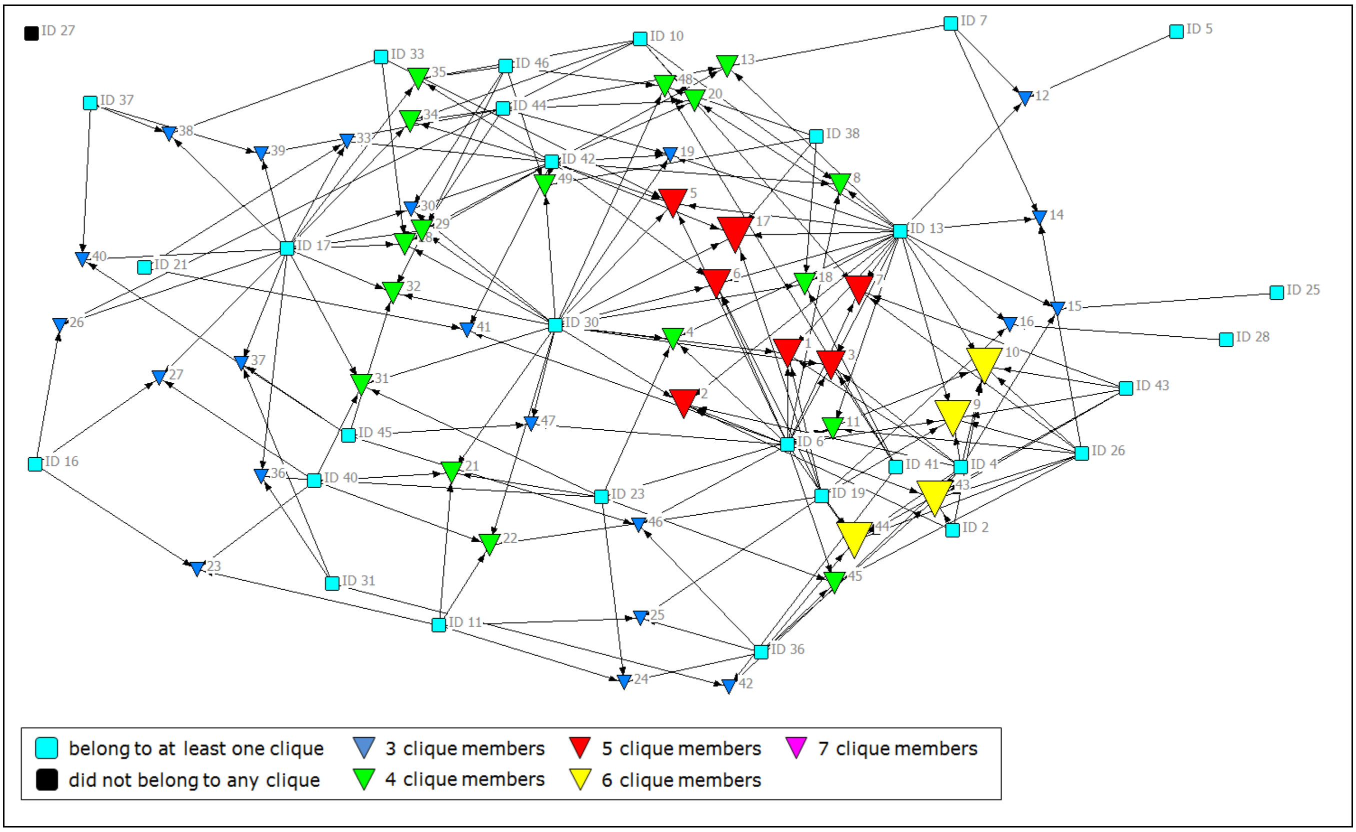



**Figure 5.29: DAM cliques after implementing KM initiatives**

Once the CoPs had been put in place and the skills maps communicated, the state of cliques in the DAM network changed dramatically. The following can be seen in ***Figure 5.29*** above:

- All the isolates, but ID27, became part of at least one clique.
- Moreover the cliques, or clusters of expertise, expanded from ten to 49, containing members ranging from three to six.
- ID13 and ID30 remained central to these cliques belonging to 20 and 19 of the 49 cliques respectively. ID13 had more influence since the size of the cliques he belonged to were overall larger than the cliques ID30 formed part of.

***Table 5.3*** presents an outline of the number of members that constituted each of these cliques before and after implementing KM initiatives.

**Table 5.3: DAM clique representation before and after implementing KM initiatives**

| Members | Number of DAM Cliques | |
|---|---|---|
| | Before KM initiatives | After KM initiatives |
| 6 members | n/a | 4 cliques |
| 5 members | n/a | 7 cliques |
| 4 members | n/a | 19 cliques |
| 3 members | 10 cliques | 19 cliques |
| TOTAL | 10 | 49 |

### *5.2.3.1.3 Cliques in the SR networks*

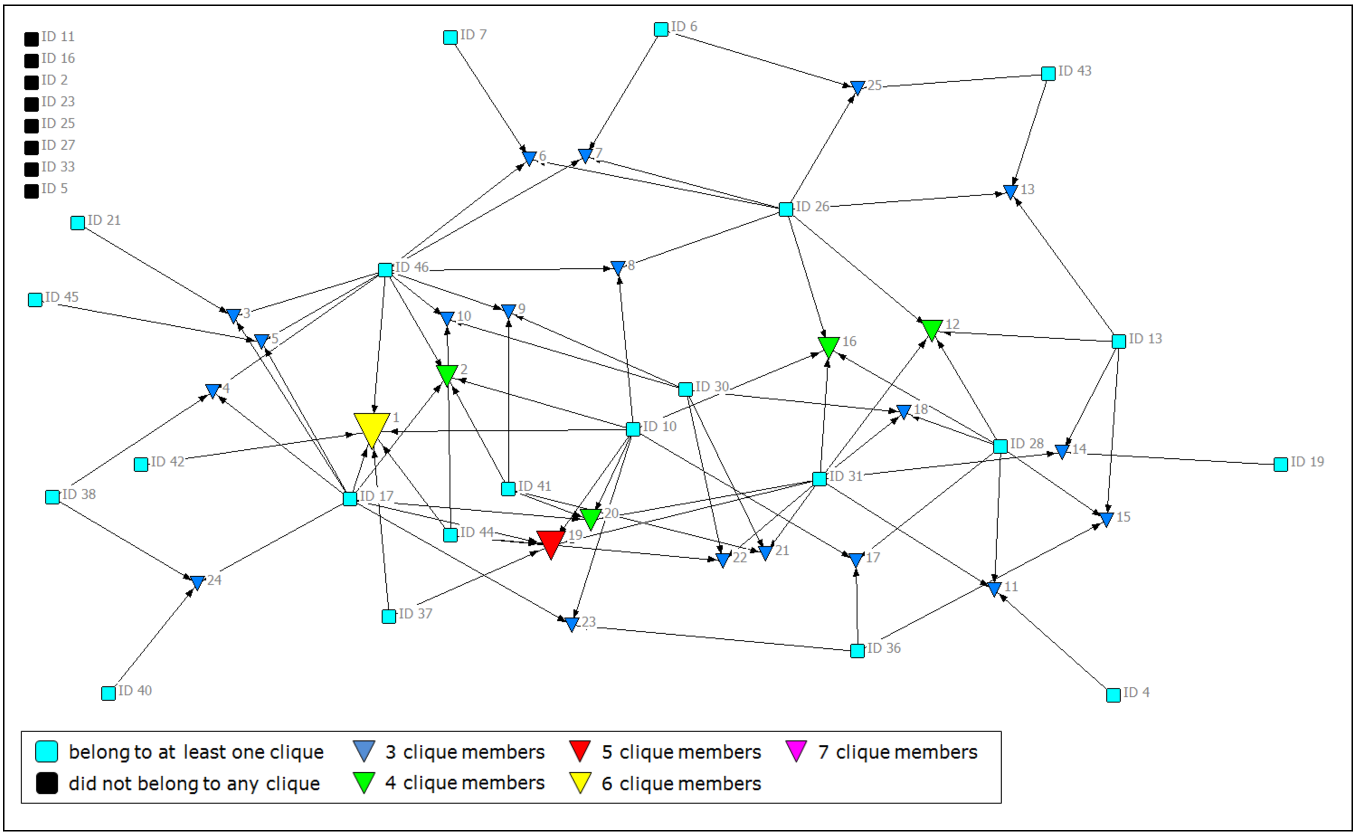



**Figure 5.30: SR cliques before implementing KM initiatives**

***Figure 5.30*** above offers an overview of the cliques that existed within the SR network before implementing KM initiatives:

- At the outset of this research, the SR network consisted of 25 cliques. ID46 belonged to ten of them followed by ID17 and ID31 who formed part of nine of these cliques.
- Eight members in the division did not form part of these cliques, with five (ID2, ID16, ID25, ID27 and ID33) being originally isolated from this network.

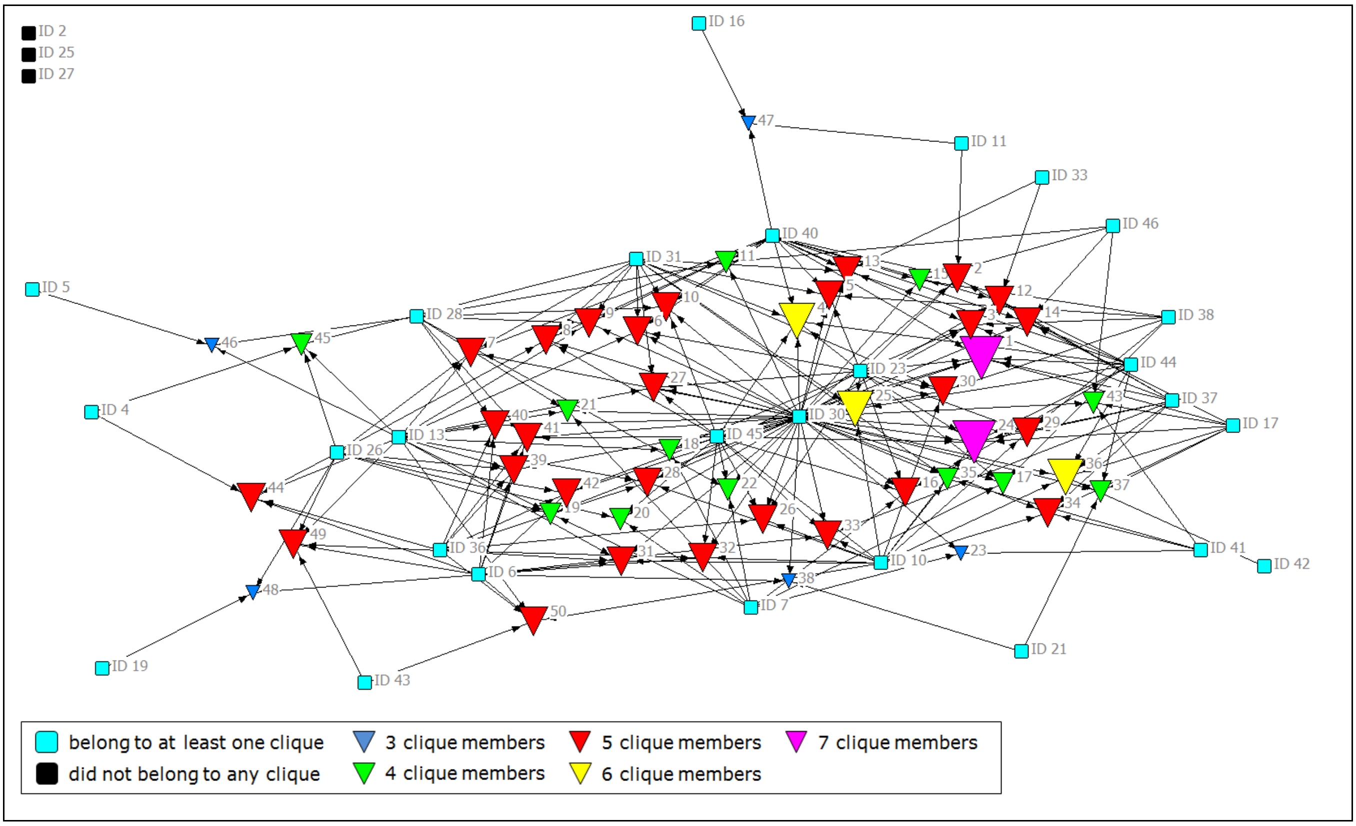



**Figure 5.31: SR cliques after implementing KM initiatives**

As depicted in ***Figure 5.31*** above, after introducing CoPs and communicating knowledge maps, the following cliques in the SR network structure emerged:

- Members who did not form part of any SR clique shrunk from eight to three (ID2, ID25 and ID27). All three counted among the isolates in the original SR network, and of the three only ID25 joined the SR CoP (although only as a lurker).
- Clique numbers doubled from 25 to 50 and became much more engaged, encompassing cliques consisting of up to seven members.
- ID30's involvement in the SR cliques increased from belonging to five cliques originally to participating in 43 cliques. This widespread clique membership is an indication of the level of informal networking assumed by this line manager.

The number of members appearing in the SR cliques before and after implementing the respective KM initiatives is illustrated in ***Table 5.4***.

**Table 5.4: Number of members per SR clique before and after implementing KM initiatives**

| Members | Number of SR Cliques | |
|---|---|---|
| | Before KM initiatives | After KM initiatives |
| 7 members | n/a | 2 cliques |
| 6 members | 1 clique | 3 cliques |
| 5 members | 1 clique | 28 cliques |
| 4 members | 4 cliques | 12 cliques |
| 3 members | 19 cliques | 5 cliques |
| TOTAL | 25 | 50 |

#### *5.2.3.1.4 Cliques in the SMC networks*

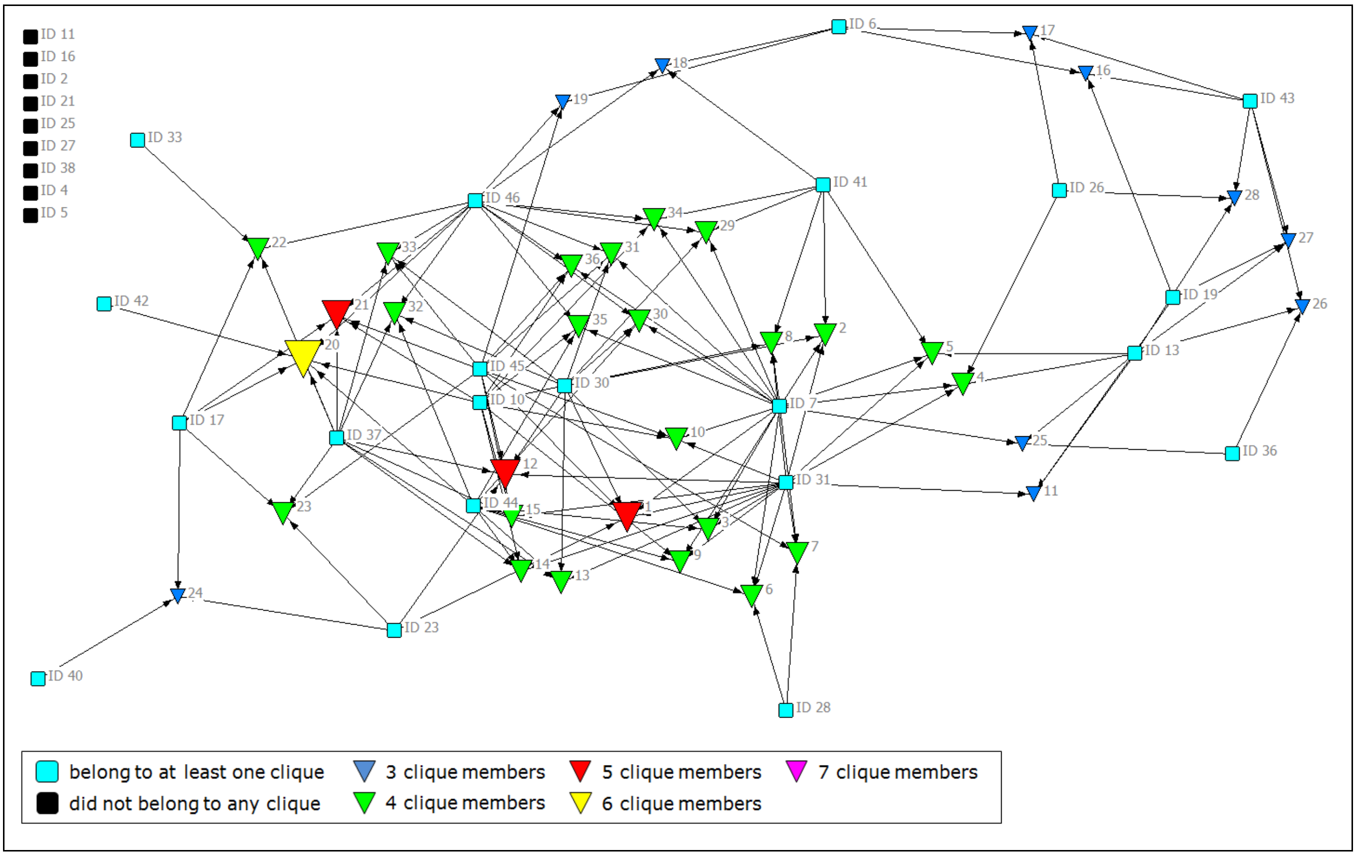



**Figure 5.32: SMC cliques before implementing KM initiatives**

***Figure 5.32*** above provides an overview of the cliques that originally existed within the SMC network and illustrates the following:

- Initially the SMC network contained 36 cliques.
- Even though ID7 had no outgoing SMC links, he belonged to most (17) cliques in this network. Next in line was ID31 who formed part of 15 of the 36 cliques.
- Nine members in the division did not form part of these cliques with four (ID2, ID21, ID25 and ID27) being originally isolated from the SMC network.

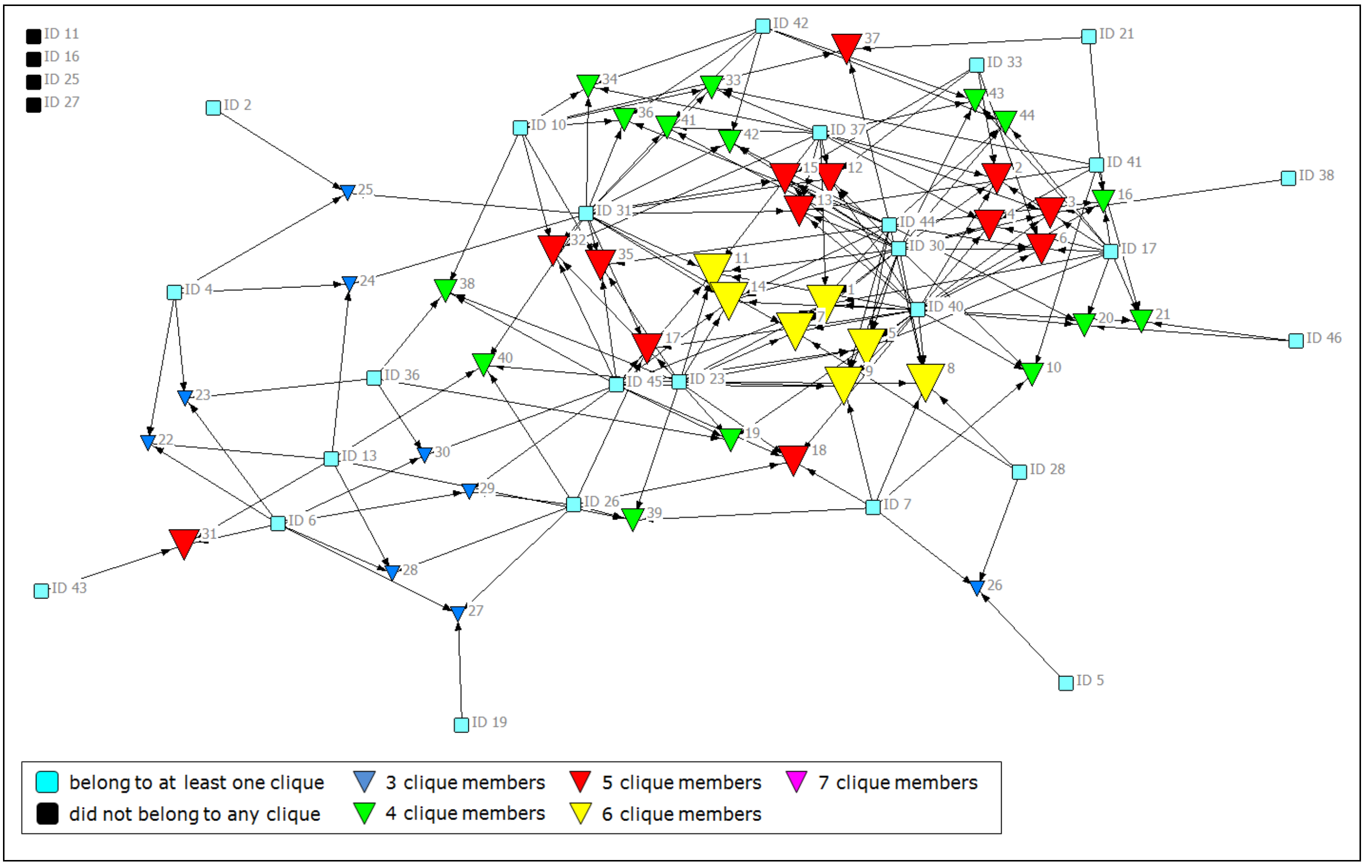



**Figure 5.33: SMC cliques before implementing KM initiatives**

After the implementation of the respective KM initiatives, the SMC network featured the following as is evident from ***Figure 5.33*** above:

- Not only did the number of SMC cliques increase from 36 to 44, but the number of cliques comprising more members also rose.
- Line manager and expert, ID40, became a focal point in this network, belonging to 21 of the 44 cliques.
- Members who did not form part of any clique dropped from nine to four with two of these (ID25 and ID27) being originally isolated from the SMC network and none of them being interested in joining the SMC CoP.

The number of members represented in each of these cliques is depicted in ***Table 5.5*** below.

**Table 5.5: Number of members per SMC clique before and after implementing KM initiatives**

| Members | Number of SMC Cliques | |
|---|---|---|
| | Before KM initiatives | After KM initiatives |
| 6 members | 1 clique | 7 cliques |
| 5 members | 3 cliques | 11 cliques |
| 4 members | 22 cliques | 15 cliques |
| 3 members | 10 cliques | 11 cliques |
| TOTAL | 36 | 44 |

#### *5.2.3.2 Cut-points*

Within networks the presence of *cut-points* implies that a network would become disconnected into isolated blocks should such a node be removed (Liebowitz 2006:83). De Nooy *et al.* (2011:162) maintains that these nodes could also be considered potential bottlenecks as they control the flow of information from one segment to another part of the network. As these nodes are essential in holding elements of the network together, links between them are often referred to as *bridges* (Müller-Prothmann 2007:225). ***Figures 5.34*** to ***5.41*** illustrate the existing cut-points within the respective networks. The following is important to take note of:

- Different *node colours* and *shapes* have been applied to pinpoint cut-points as well as separate blocks existing within the particular networks:
  - *yellow circles* = network members who operated as cut-points
  - *black squares* = members who did not belong to the specific network (isolates)
  - members belonging to a specific block were all coded in the same colour – typically cut-points belonged to more than one block

#### *5.2.3.2.1 Cut-points in the CC networks*

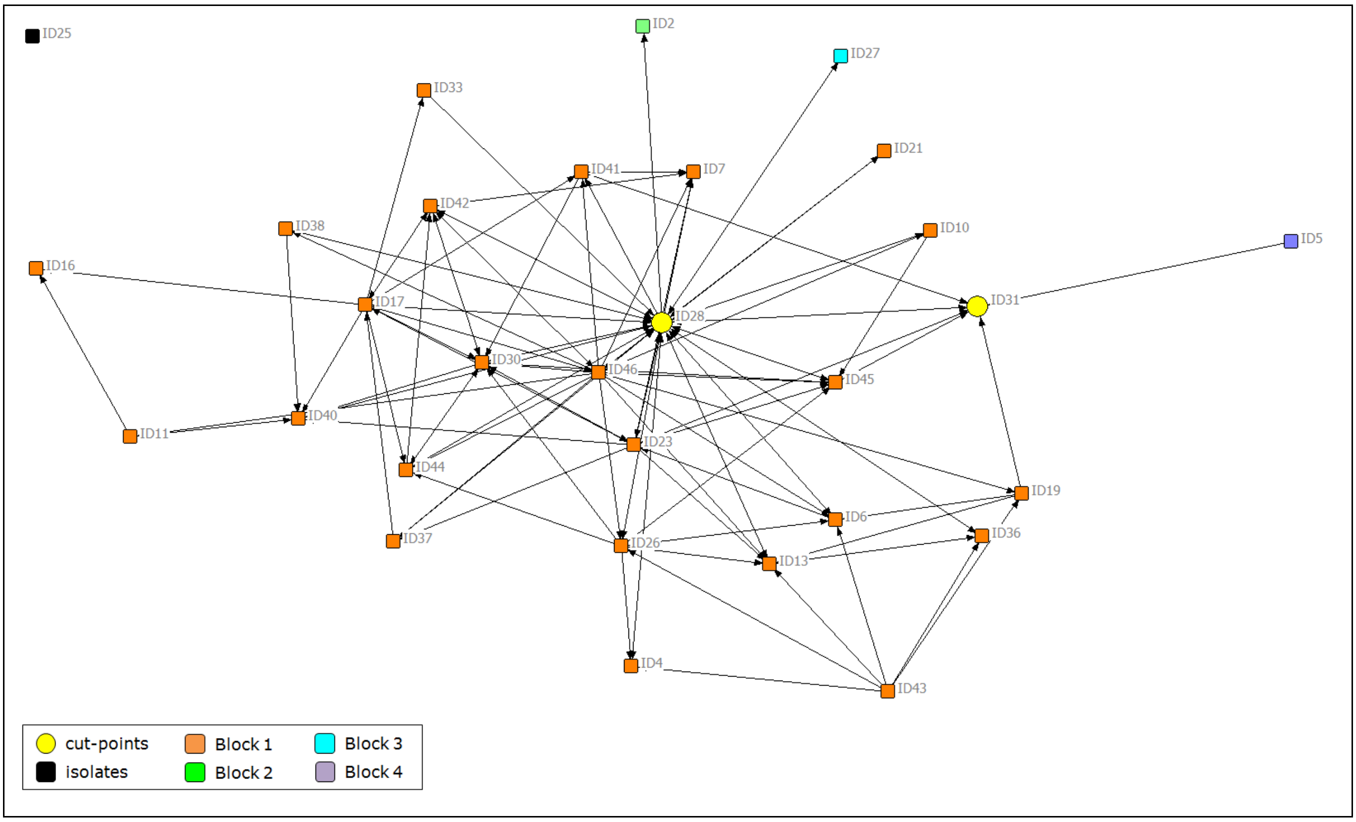



**Figure 5.34: CC cut-points before implementing KM initiatives**

***Figure 5.34*** above depicts the cut-points that existed in the CC network before any KM initiative was implemented and illustrates the following:

- Originally the CC network produced two cut-points (ID28 and ID31) who could theoretically divide the CC network into four distinct blocks. In essence this meant that (apart from isolate ID25), ID2 and ID27 would become disconnected from the network should ID28 be removed. ID5 would also become isolated in the event that ID31 would leave.
- Nonetheless, with their many links ID28 and ID31 were also potential bottlenecks that could hamper the flow of information in the network.

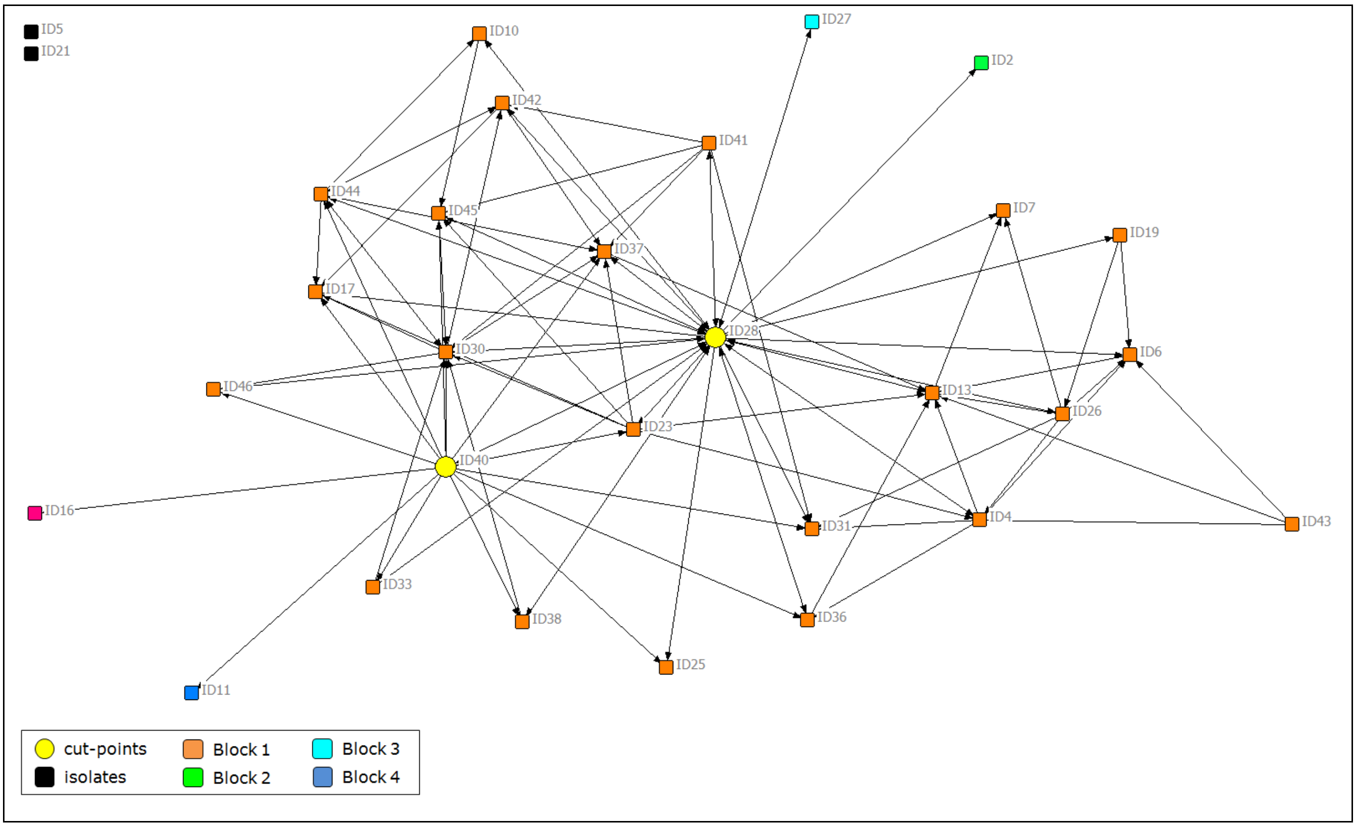



**Figure 5.35: CC cut-points after implementing KM initiatives**

Following the introduction of CoPs and skills maps, the cut-points within the CC network had changed (***Figure 5.35*** above) and the following is evident:

- Highly skilled ID28 remained a cut-point between ID27 and ID2 and the rest of the network.
- ID31 (who was not identified as being an expert or even highly skilled regarding CC and who did not join the CC CoP), lost his cut-point status as ID5 stopped contacting him regarding CC information and he thus became detached from the network.
- Highly skilled ID40 became a cut-point between ID16 and ID11 and the rest of the CC network.
- ID28 and ID40 had the potential of splitting the CC network into five blocks compared to the four underlying blocks that existed before the implementation of CoPs. These 'blocks' that could potentially become detached from the rest of the network, however, remained to comprise just one network member per block.

#### *5.2.3.2.2 Cut-points in the DAM networks*

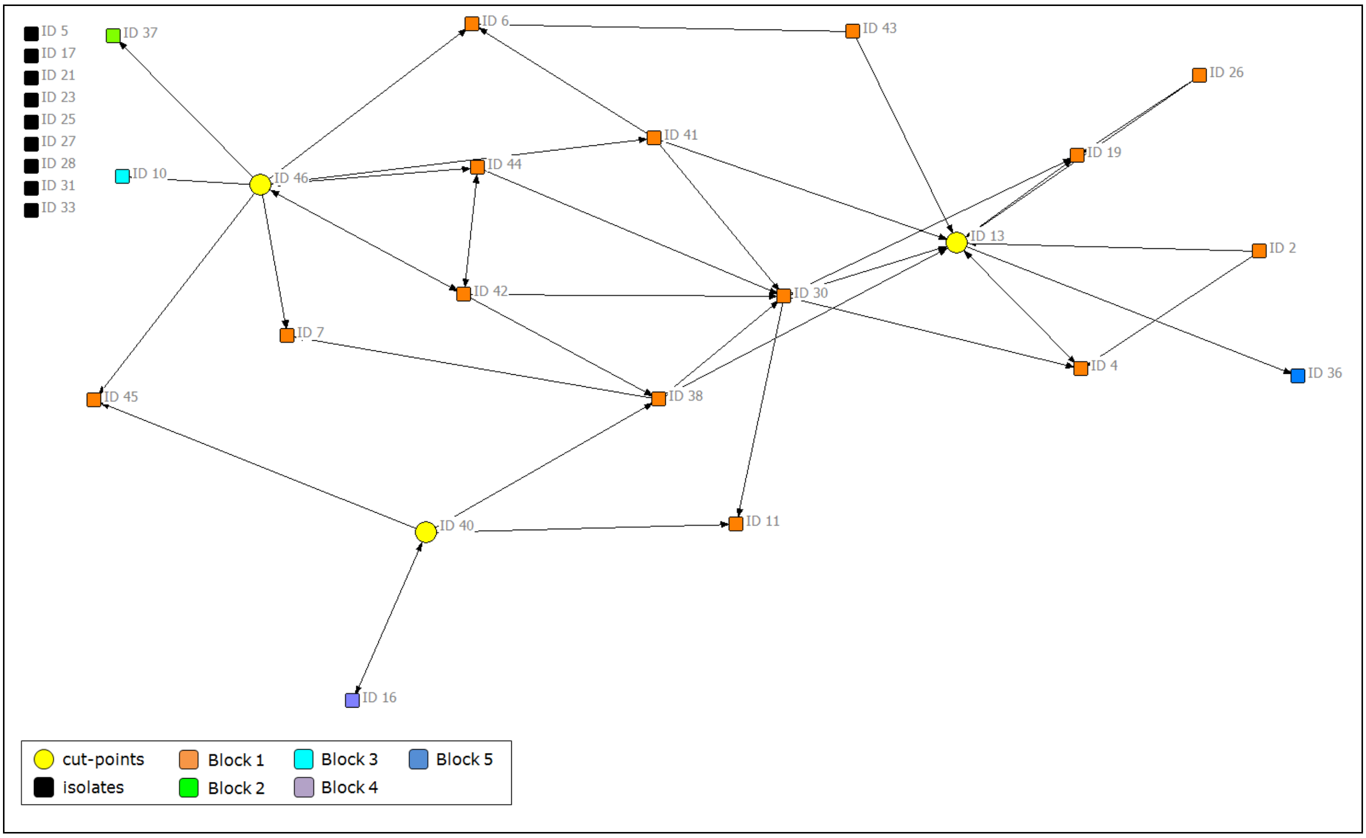



**Figure 5.36: DAM cut-points before implementing KM initiatives**

The cut-points that existed in the DAM network prior to implementing KM initiatives are illustrated in ***Figure 5.36*** above:

- ID46 could potentially isolate ID37 and ID10 from the rest of the DAM network.
- ID13 could likewise detach ID36 whilst ID40 could cut off ID16.
- Both ID46 and ID13 were regarded as experts with ID40 being deemed highly skilled in terms of DAM.

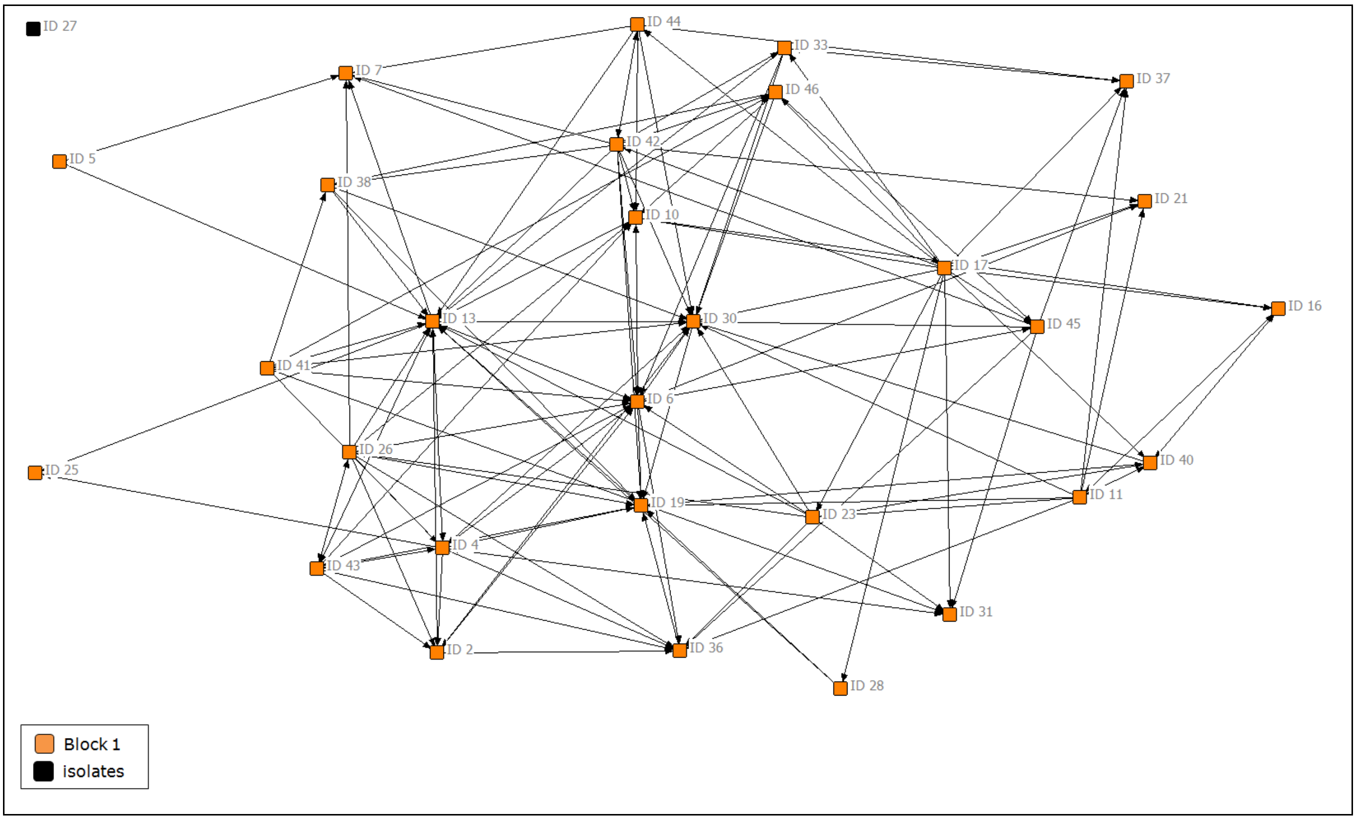



**Figure 5.37: No DAM cut-points after implementing KM initiatives**

Once the CoPs were established and skills maps communicated, the DAM network became much more integrated and consisted of only one block with no potential cut-points as can be seen from ***Figure 5.37*** above.

#### *5.2.3.2.3 Cut-points in the SR networks*

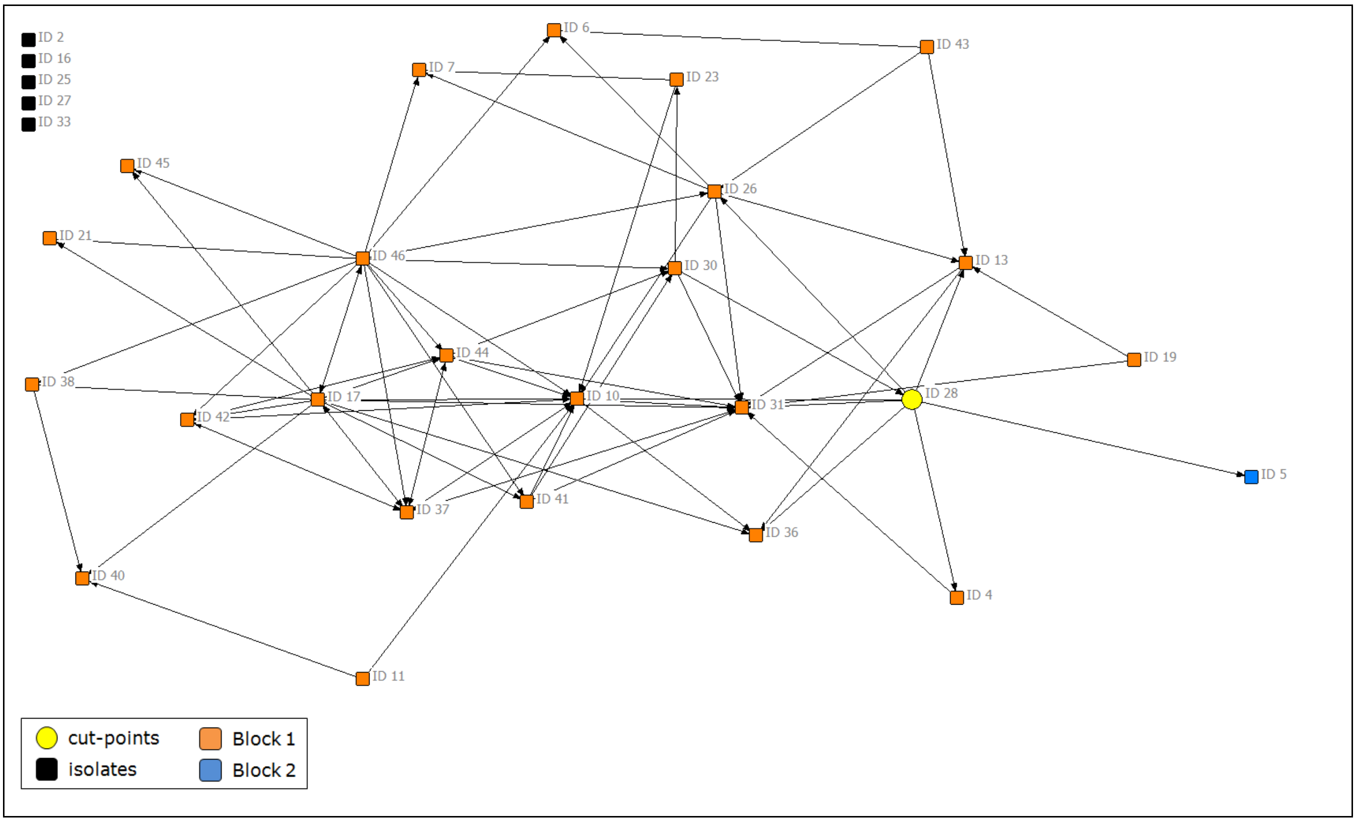



**Figure 5.38: SR cut-points before implementing KM initiatives**

***Figure 5.38*** above depicts the cut-points that existed in the original SR network. The following is evident:

- The SR network initially had only one cut-point in the form of highly skilled ID28, who could hypothetically separate ID5 from the rest of the network.

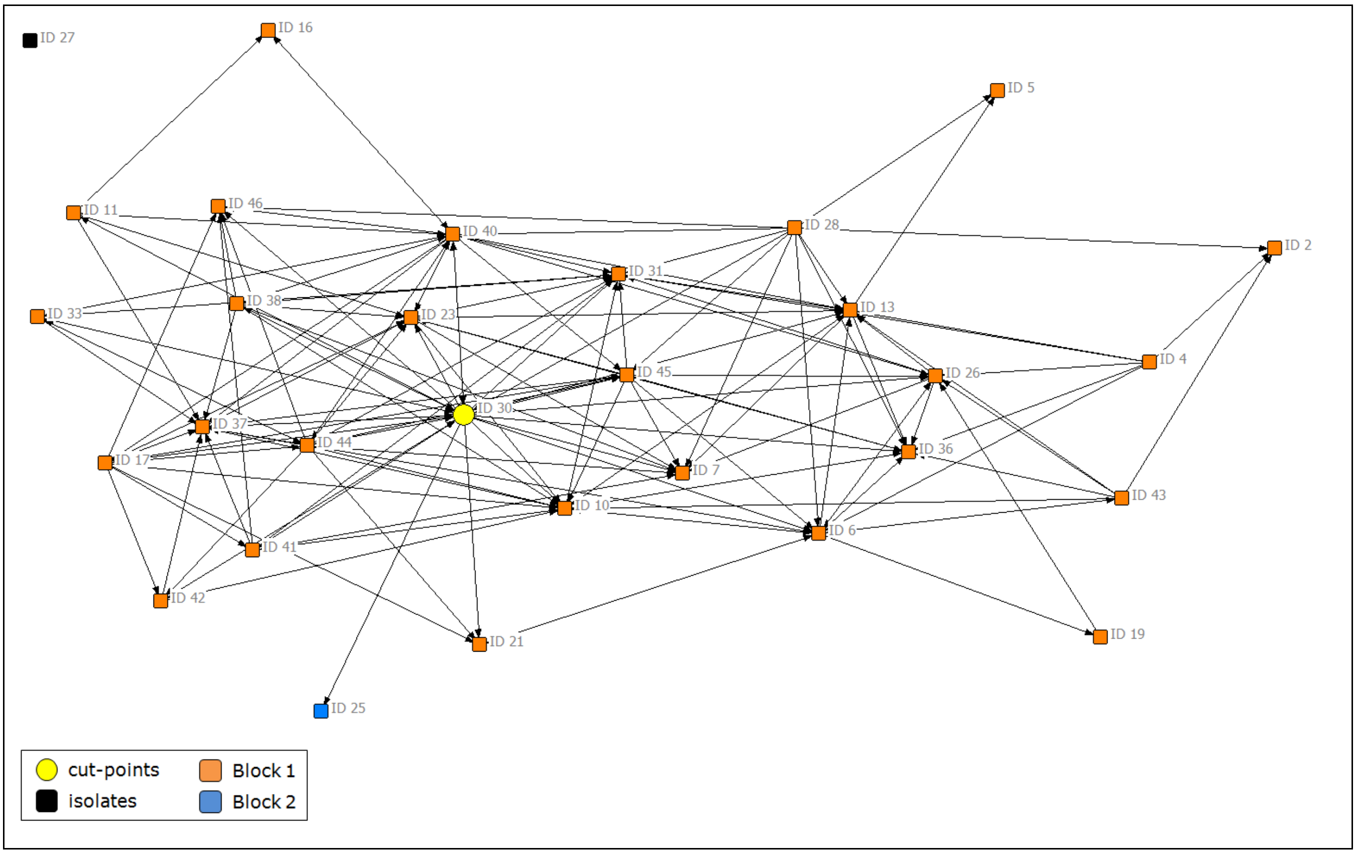



**Figure 5.39: SR cut-points after implementing KM initiatives**

With the establishment of CoPs and the distribution of skills maps, the SR network became more integrated as is seen in ***Figure 5.39*** above.

- ID28 was no longer regarded a cut-point as ID5 (who joined the SR CoP and was identified as highly skilled in terms of SR) became more connected.
- A new cut-point emerged in ID30 (a knowledge authority) who became the only connection between once isolated ID25 and the rest of the SR network.

### 5.2.3.2.4 Cut-points in the SMC networks

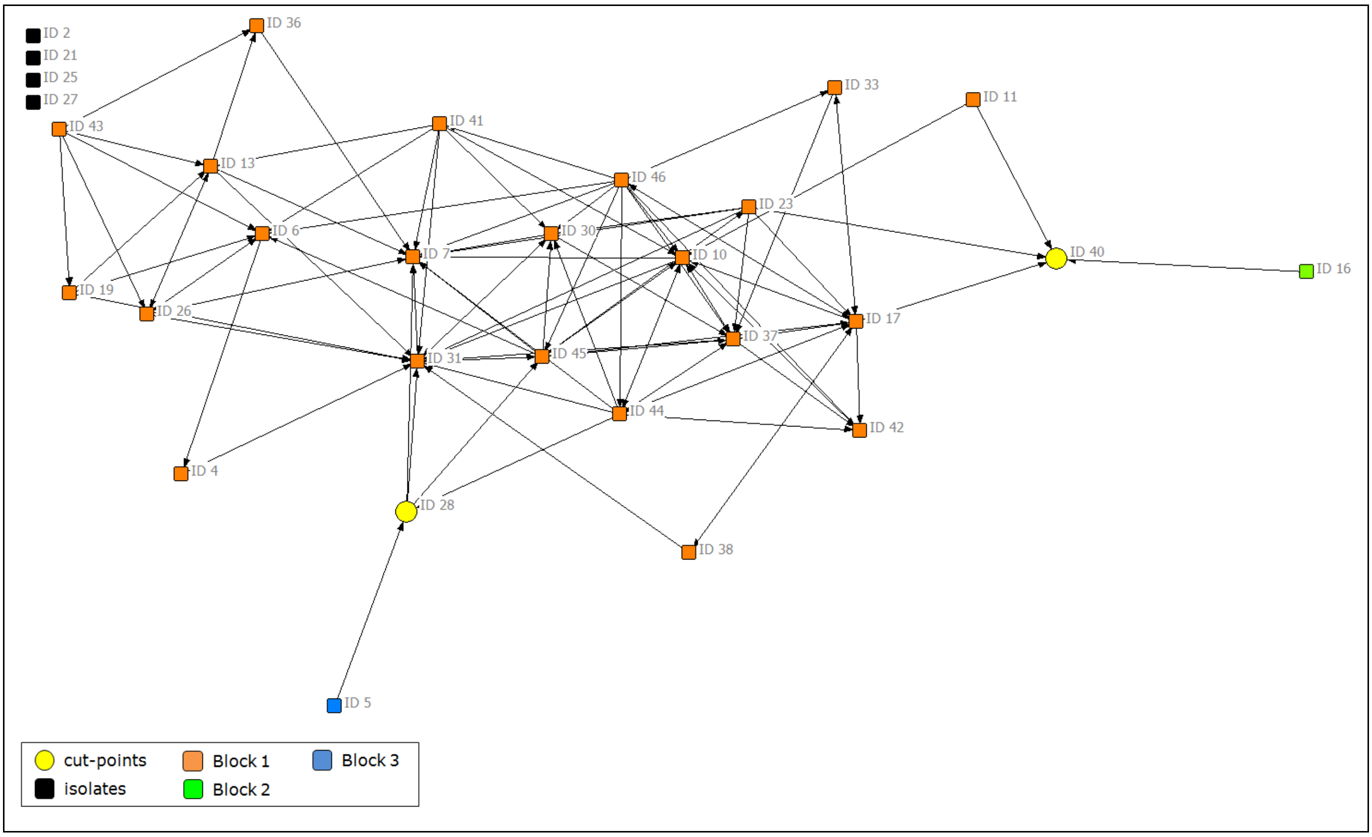



**Figure 5.40: SMC cut-points before implementing KM initiatives**

***Figure 5.40*** above offers an overview of cut-points in the SMC network prior to the implementation of any KM initiatives.

- Initially the SMC network comprised two cut-points with ID40 being the only connection between ID16 and the rest of the network and ID28 who formed the only link between the SMC network and newcomer ID5.

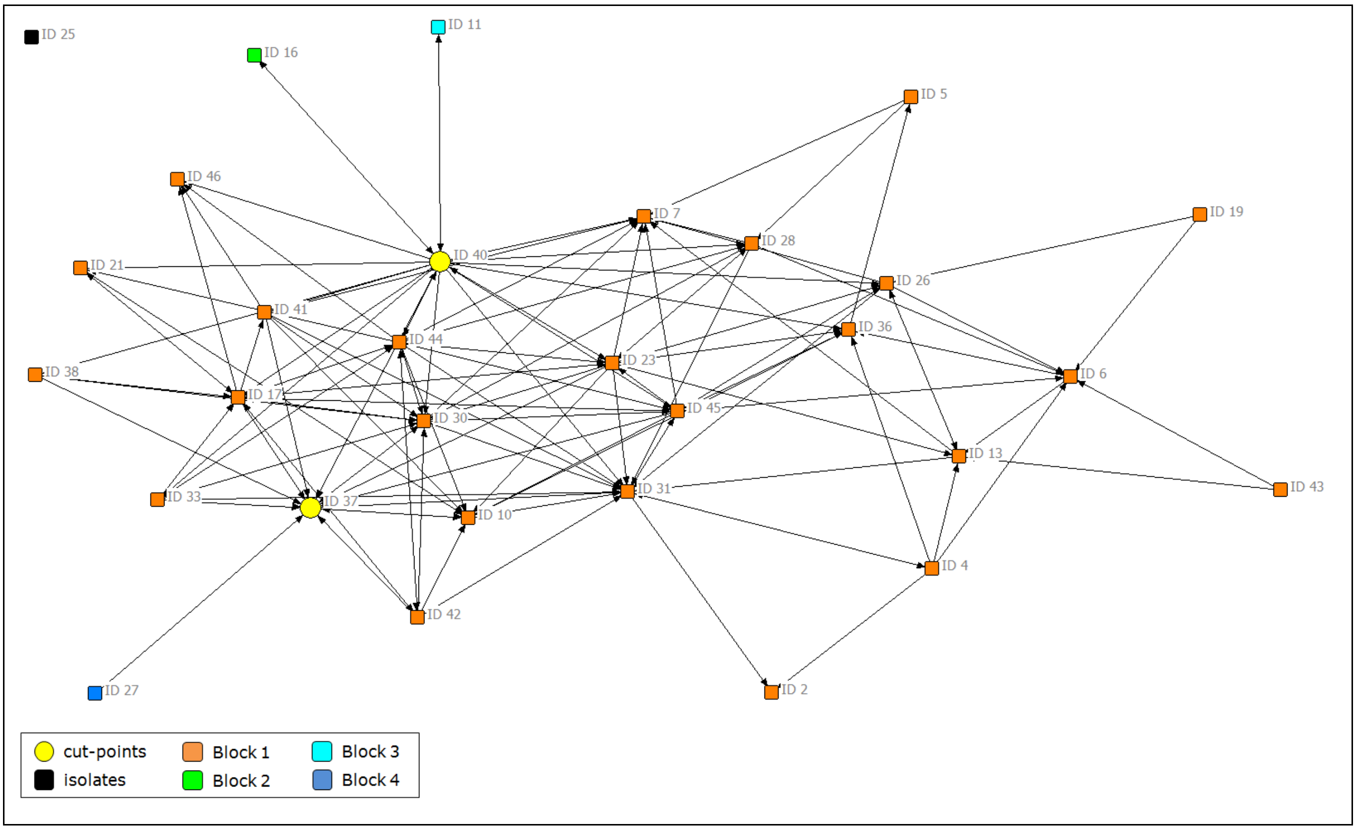



**Figure 5.41: SMC cut-points after deploying KM initiatives**

The SMC network structure changed after the introduction of the particular KM initiatives (***Figure 5.41*** above)**.**

- Similar to what happened in the SR network, ID28 was no longer regarded a cut-point when ID5 (who joined the SMC CoP and was recognised as an SMC expert) became more integrated.
- ID40 who remained a cut-point between ID16 and the rest of the SMC network, also became a link between ID11 and the SMC network.
- Moreover ID37 turned into a cut-point connecting ID27, an original isolate within the SMC network.

In all four networks, the different potential blocks that were formed by the various cut-points all consisted of a core group (the network itself) and individuals. Apart from the core group, there were no blocks that consisted of more than two individuals (the cut-point and the individual it connected).

***Table 5.6*** offers an overview of the various cut-points in the respective networks.

**Table 5.6: Cut-points per network before and after implementing KM initiatives**

| Network | Before KM initiatives | | | After KM initiatives | | |
|---|---|---|---|---|---|---|
| | Block | Cut-point | Connect | Block | Cut-point | Connect |
| CC | 1 | ID28, ID31 | Rest of the network | 1 | ID28, ID40 | Rest of the network |
| | 2 | ID28 | ID2 | 2 | ID28 | ID2 |
| | 3 | ID28 | ID27 | 3 | ID28 | ID27 |
| | 4 | ID31 | ID5 | 4 | ID40 | ID16 |
| | | | | 5 | ID40 | ID11 |
| DAM | 1 | ID13, ID40 & ID46 | Rest of the network | 1 | DAM network | |
| | 2 | ID13 | ID36 | | | |
| | 3 | ID40 | ID16 | | | |
| | 4 | ID46 | ID10 | | | |
| SR | 1 | ID28 | Rest of the network | 1 | ID30 | Rest of the network |
| | 2 | ID28 | ID5 | 2 | ID30 | ID25 |
| SMC | 1 | ID28, ID40 | Rest of the network | 1 | ID37, ID40 | Rest of the network |
| | 2 | ID28 | ID5 | 2 | ID40 | ID11 |
| | 3 | ID40 | ID16 | 3 | ID40 | ID16 |
| | | | | 4 | ID37 | ID27 |

By examining ***Table 5.6*** one can conclude that of all four networks, the DAM network advanced the most after introducing the KM initiatives, in that it became one integrated block with no actor being at risk to be detached from the network. In the SR network, the number of blocks remained the same although the actors that formed the cut-points changed. Both the CC and the SMC networks developed an additional block, with some of the cut-points being replaced by other actors.

#### 5.2.3.3 Hubs

Nodes with a high degree and betweenness centrality, often referred to as hubs, facilitate effective knowledge transfer as they effectively connect different sub-groups in a network (Krebs 2006). Network members were considered important hubs if they measured greater than two standard deviations above the mean. These network members are illustrated in ***Figures 5.42*** to ***5.49***. Here it is important to note the following:

- *Arrows* indicate the direction of interaction.
- *Grey lines indicate* one-directional relationships, while *orange lines* indicate reciprocal interactions.
- Different *node colours* and *shapes* have been used to differentiate between the various roles allocated to network members:
  - *green diamonds* = top six hubs (members with the highest degree- and betweenness centrality)
  - *blue squares* = members who formed part of the network
  - *black squares* = members who did not form part of the knowledge network (isolates)
- To offer a better analysis of the hubs present in the network, all node sizes have been altered to reflect their combined degree- and betweenness centrality ranking.

##### 5.2.3.3.1 Hubs in the CC networks

***Figures 5.42*** and ***5.43*** below offer an overview of the CC hubs before and after the implementation of the KM initiatives.

- Noteworthy hubs in the original CC network were ID28, ID46, ID23, ID26, ID17, ID42 and ID30.
- As the network changed, the number of important hubs increased to nine and top ranks were held by ID28, ID40, ID23, ID41, ID44 and ID30.
- ID46 and ID17 lost their hub positions, whilst ID40, ID41, ID44 and ID4 were considered to be important hubs after establishing CoPs and communicating knowledge maps.

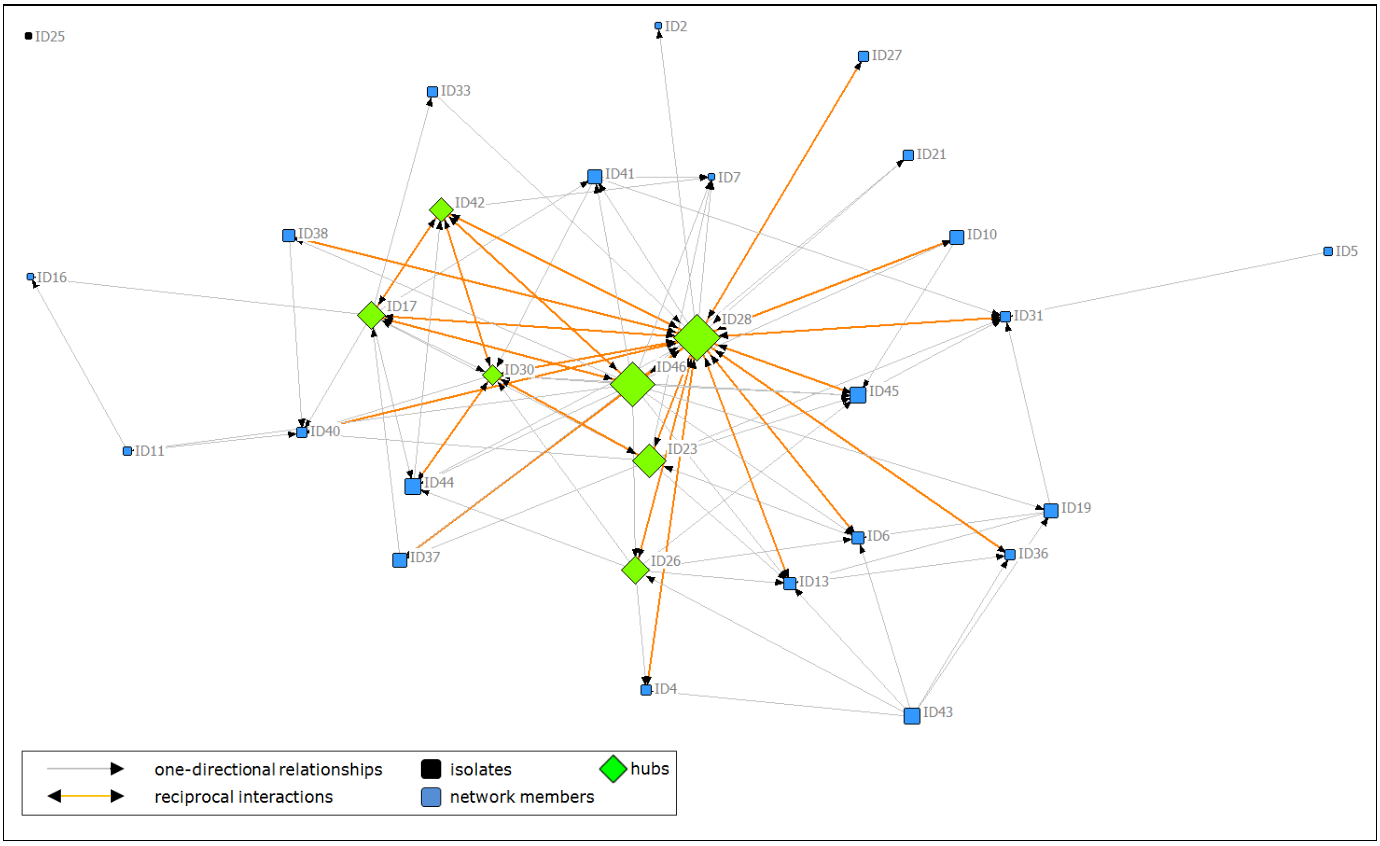



Figure 5.42: Top CC hubs before implementing KM initiatives

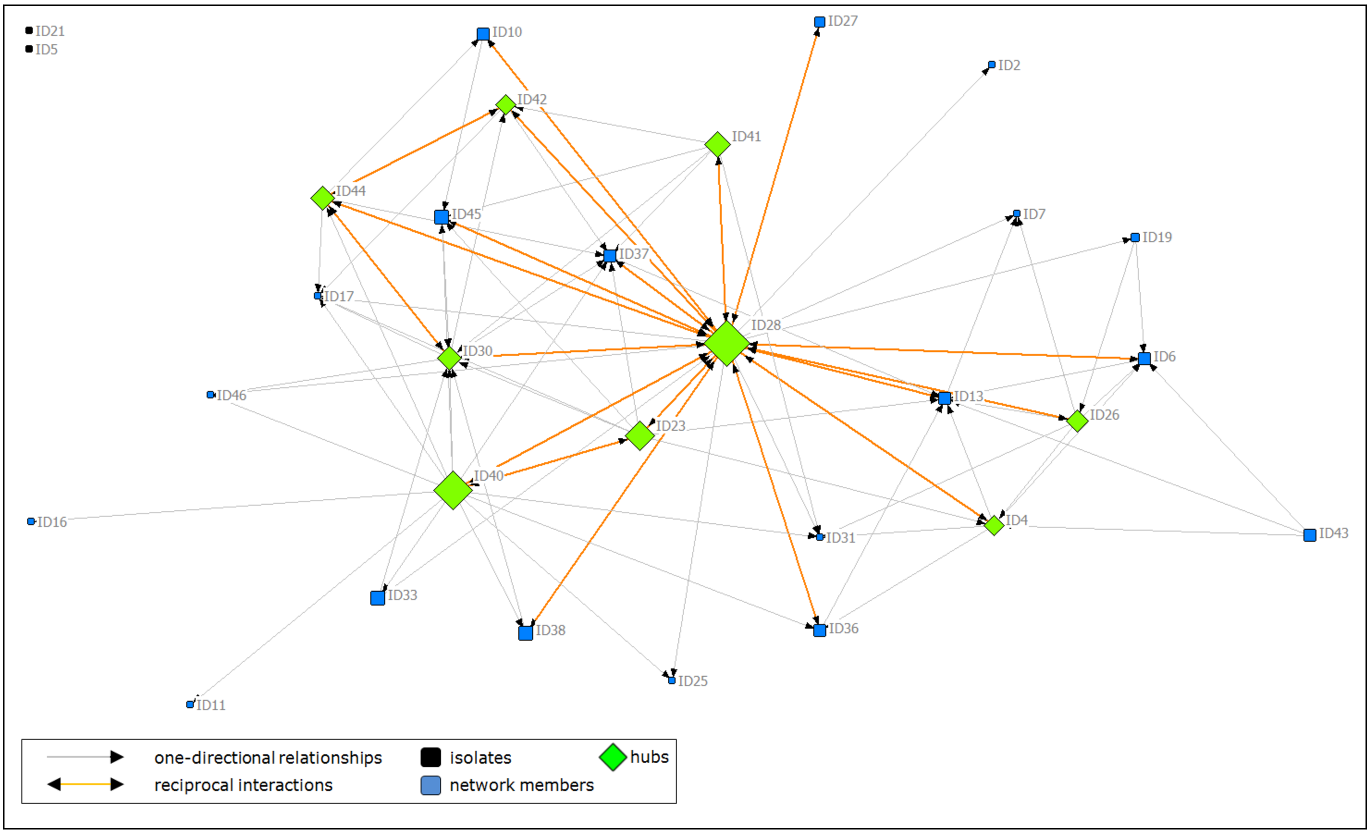



Figure 5.43: Top CC hubs after implementing KM initiatives

### *5.2.3.3.2 Hubs in the DAM networks*

DAM network members with a high degree- and betweenness centrality before and after implementing KM initiatives are depicted in ***Figures 5.44*** and ***5.45***:

- Originally the DAM network consisted of 12 nodes (ID41, ID30, ID38, ID46, ID13, ID43, ID2, ID26, ID42, ID44, ID4 and ID19) that operated as hubs.
- After the implementation of the KM initiatives, the DAM network increased and so did its hubs. The number of hubs grew from 12 to 17.
- Two members (ID46 and ID19) lost their hub positions with ID6, ID23, ID17, ID11, ID45, ID33 and ID40 now positioned as hubs.
- ID17, ID23 and ID33 who used to be isolated from the DAM network emerged as prominent hubs after implementing KM initiatives.

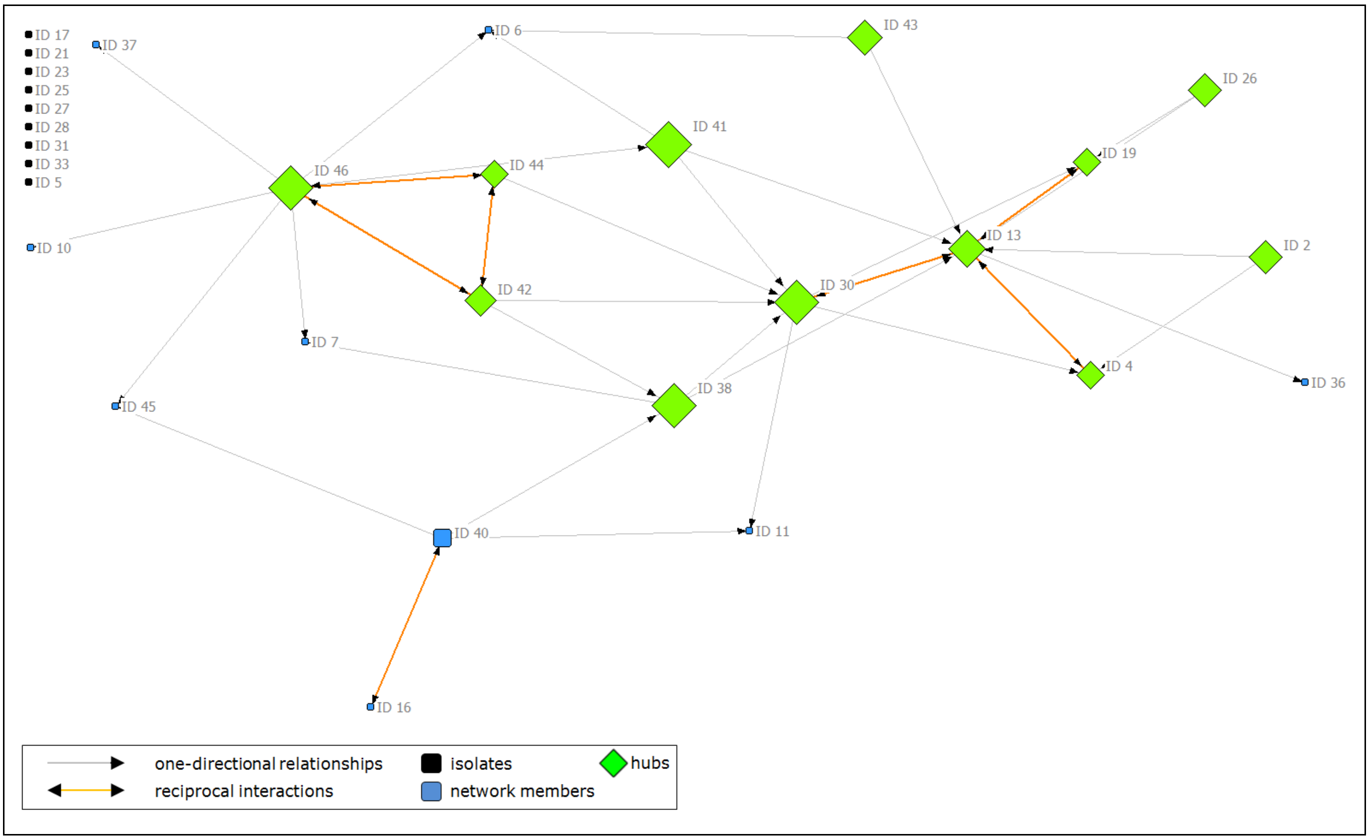



**Figure 5.44: Top DAM hubs before implementing KM initiatives**

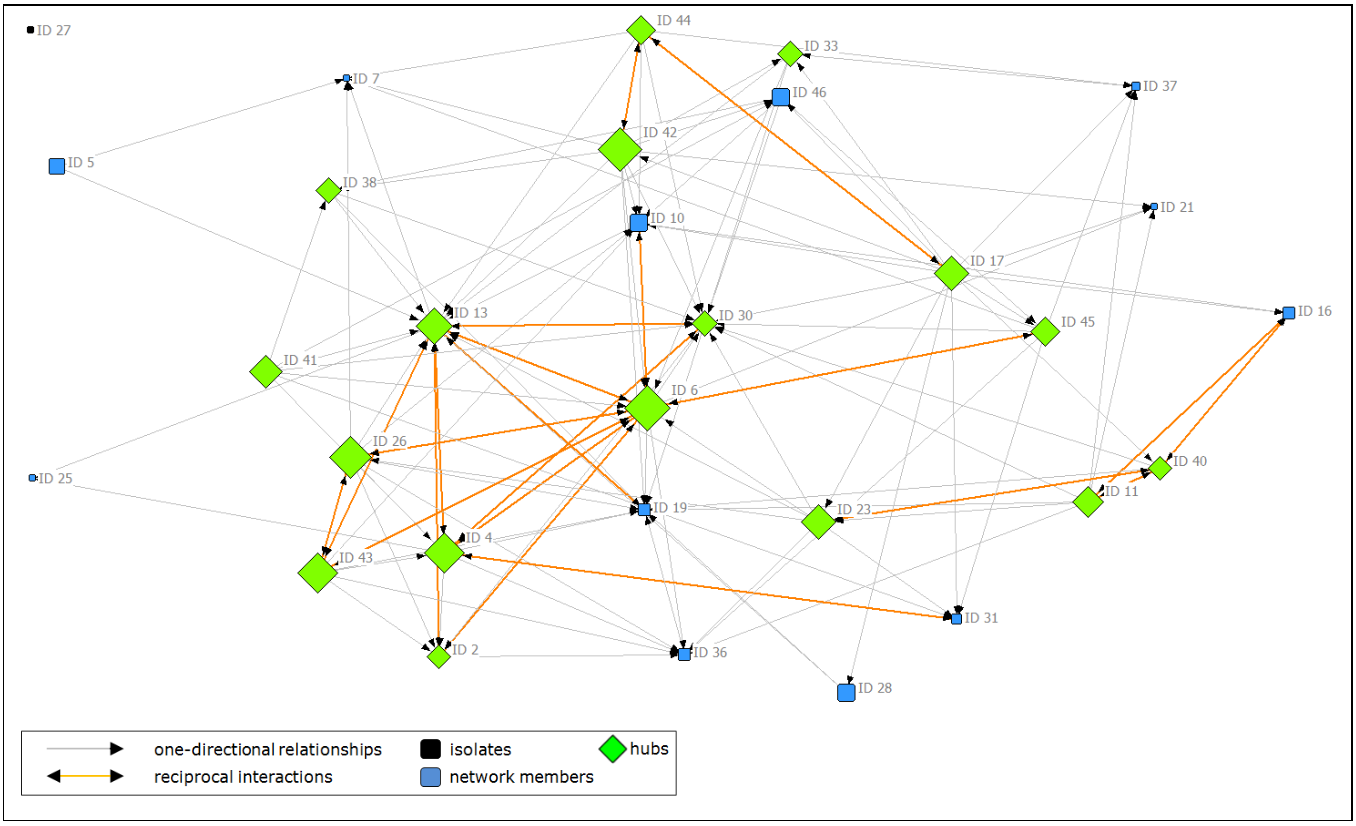



**Figure 5.45: Top DAM hubs after implementing KM initiatives**

### *5.2.3.3.3 Hubs in the SR networks*

***Figures 5.46*** and ***5.47*** depict the hubs that facilitated the effective transfer of knowledge between the different sub-groups of the SR network before and after implementing KM initiatives and illustrate the following:

- Initially ID46, ID17, ID37, ID44, ID28, ID26, ID41 and ID42 operated as the most notable hubs in the SR network.
- After implementing KM initiatives the top hub positions increased from eight to 11 network members.
- Three hubs (ID46, ID37 and ID42) lost their top hub positions after the implementation of the KM initiatives. In addition ID30, ID40, ID45, ID38, ID23 and ID4 became principal network hubs.

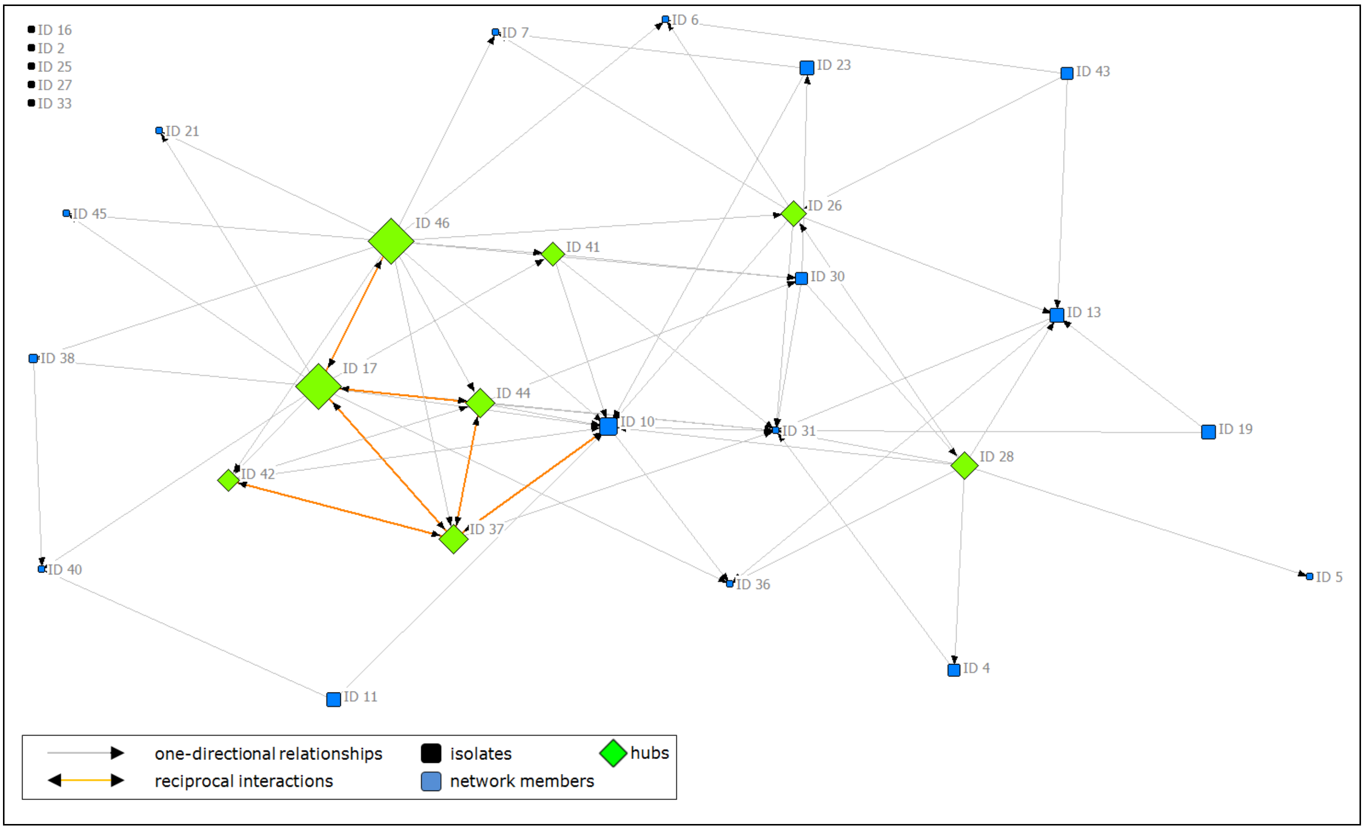



**Figure 5.46: Top SR hubs before implementing KM initiatives**

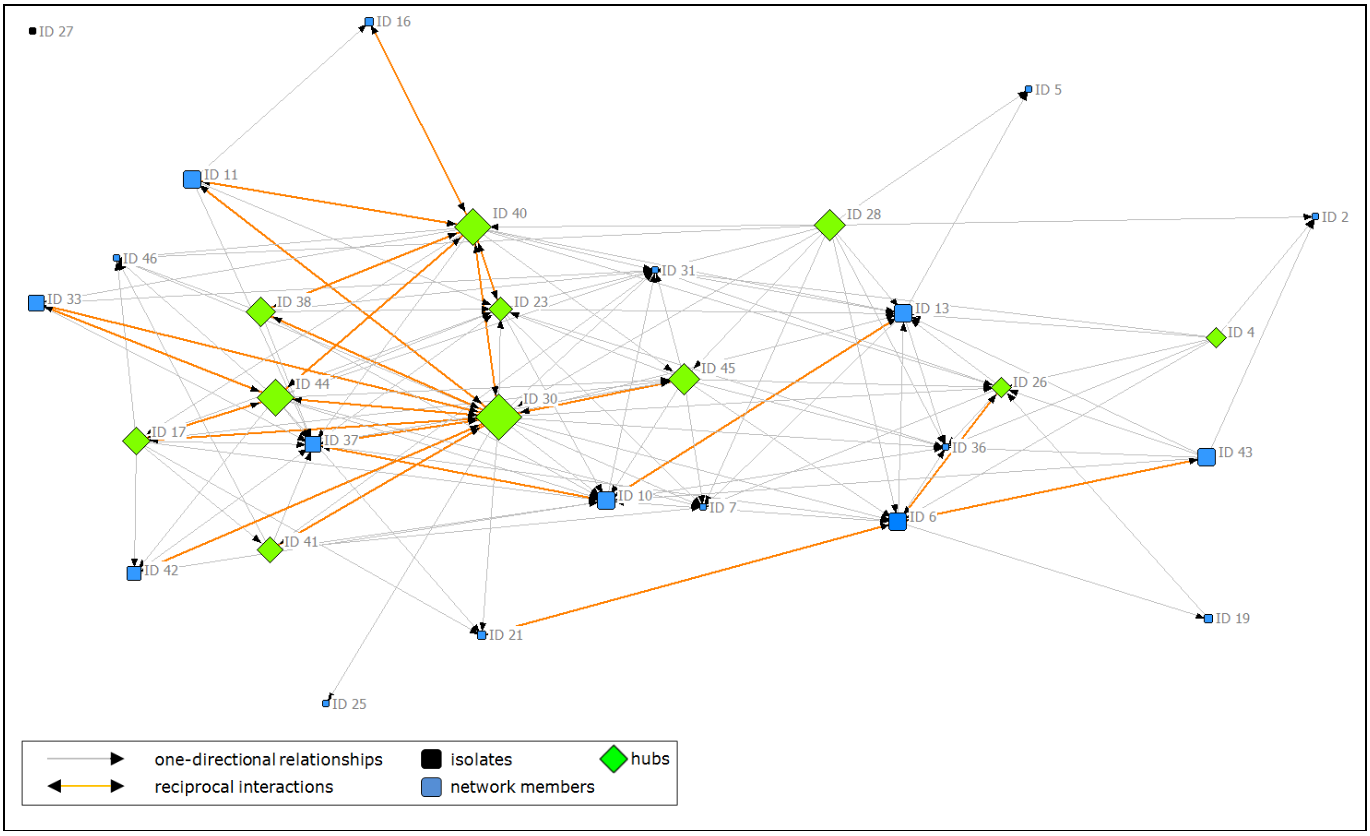



**Figure 5.47: Top SR hubs after deploying KM initiatives**

### *5.2.3.3.4 Hubs in the SMC networks*

Members who were considered top hubs and who were predominantly responsible for the transfer of knowledge and information in the SMC network prior and after the implementing of particular KM initiatives are depicted in ***Figures 5.48*** and ***5.49*** below:

- Within the SMC network, knowledge was initially primarily distributed by ID46, ID44, ID45, ID10, ID23, ID37, ID41, ID17, ID30, ID26, ID28 and ID13.
- Of the aforementioned hubs, ID46, ID10, ID37 and ID26 lost their statuses, with ID40, ID42 and ID33 being added to the top hub positions after establishing CoPs and communicating knowledge maps.

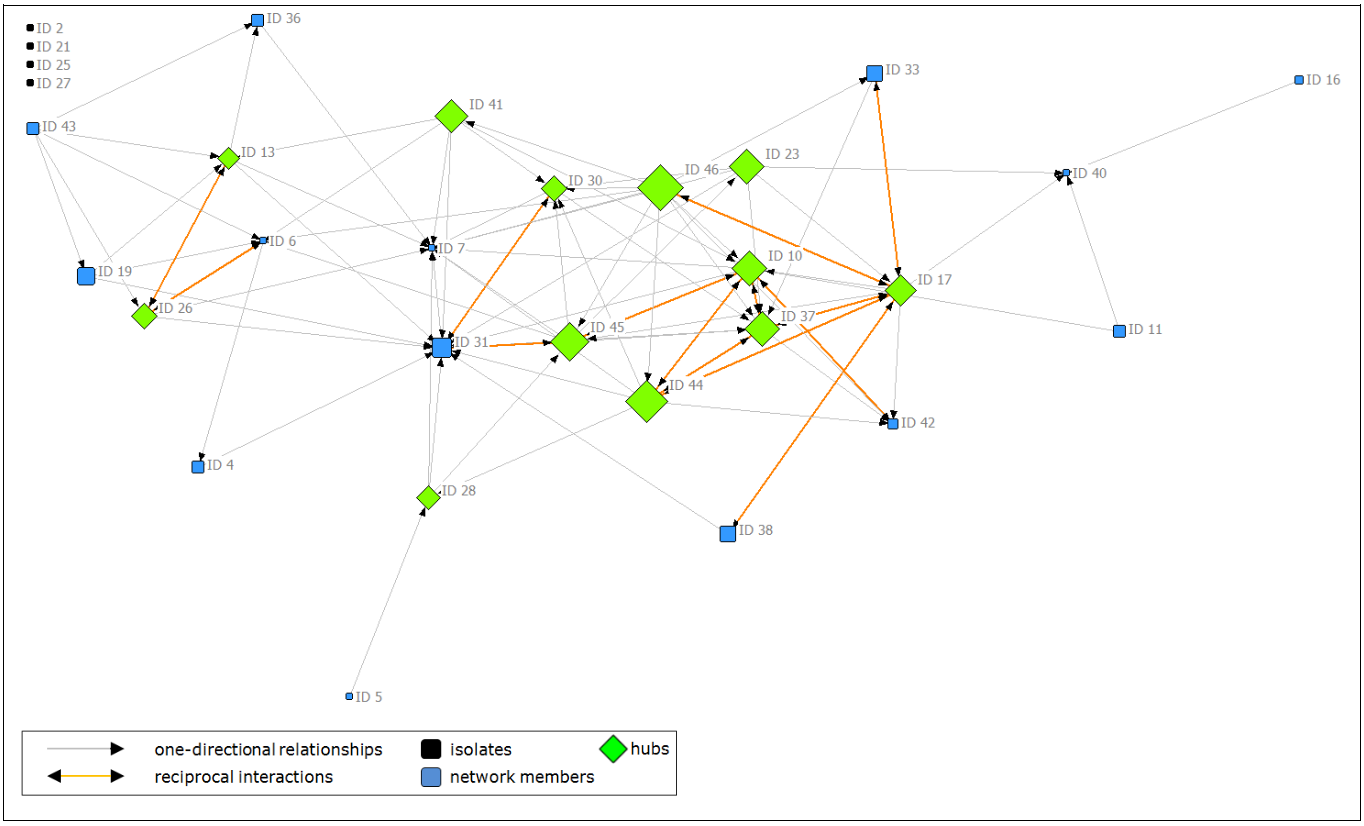



**Figure 5.48: Top SMC hubs before implementing KM initiatives**

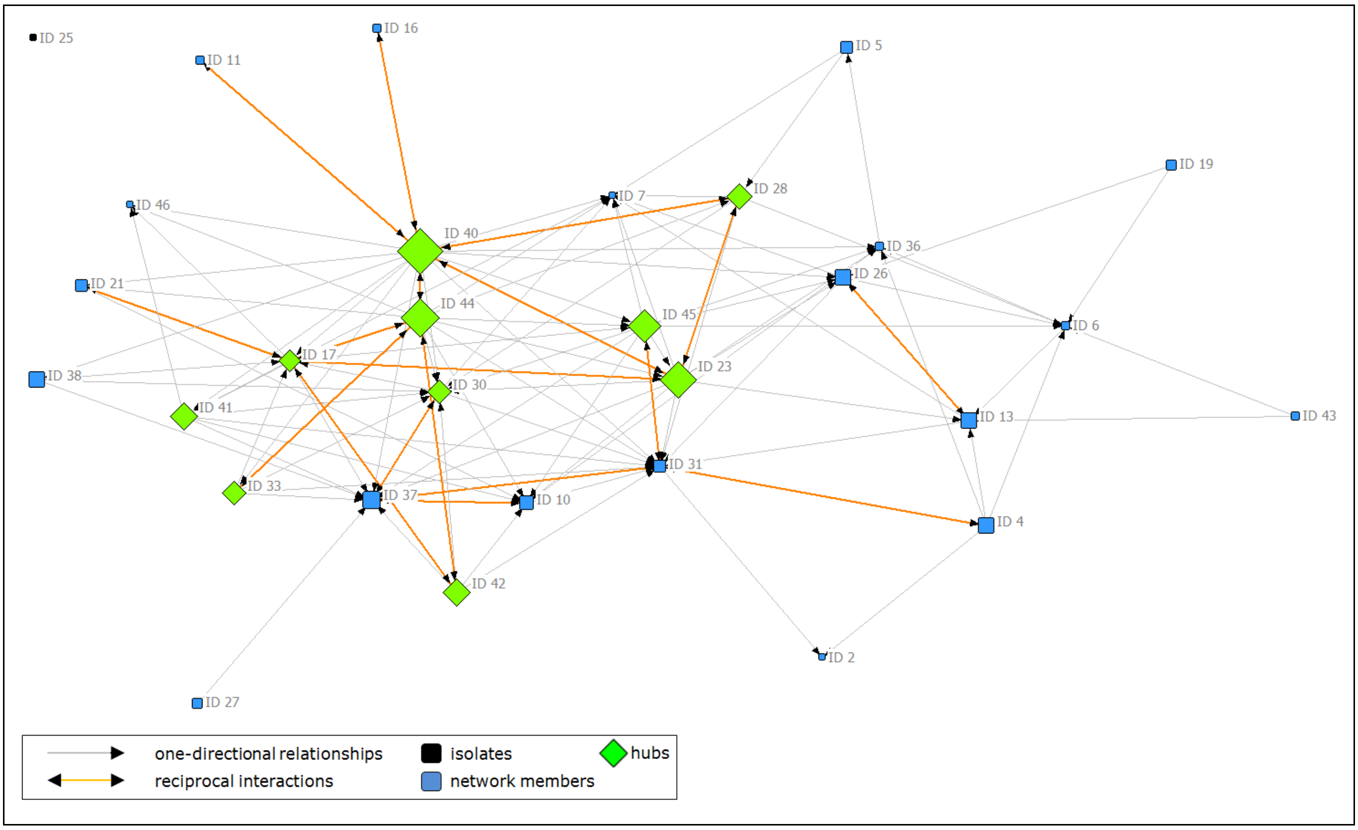



**Figure 5.49: SMC hubs after implementing CoPs**

***Figures 5.26*** to ***5.49*** depicted the transformation that took place regarding knowledge diffusion in terms of cliques, cut-points and hubs in the four knowledge networks that were examined in this study. As a result, a definite change regarding these network structures can be observed regarding their composition before and after the implementation of the KM interventions.

### 5.2.4 The influence of CoPs and knowledge maps on network connectivity

This study also intended to investigate in which way KM interventions could influence network connectivity. As it is rather challenging to compare whole-network metrics of networks that differ in size (Prell 2012:171), apart from constructing *knowledge networks* which focused on relationships regarding specific subject matters, four other interactions have also been plotted, namely *recurrence*, *responsiveness*, *engagement* and *trust*.

In order to construct the latter four networks, the data collected considered both frequency and intensity of relations to allow for greater discrimination. Cutting-points were applied[41] to allow the measuring of the most significant relationships within these networks. (***Table 5.7***).

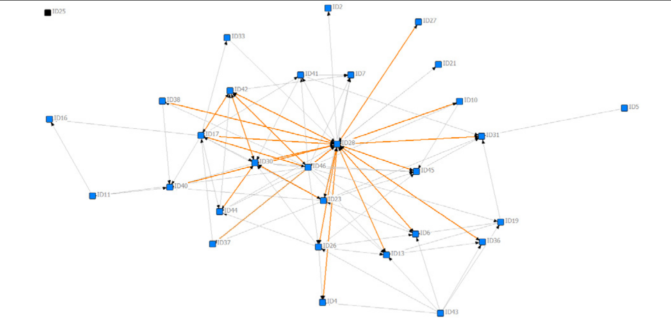
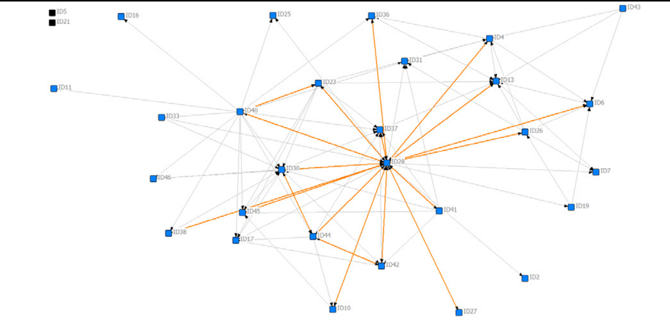
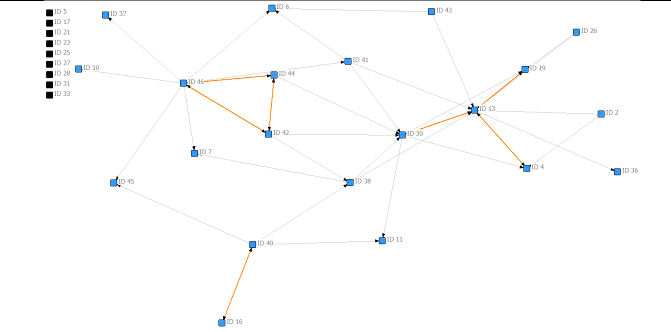
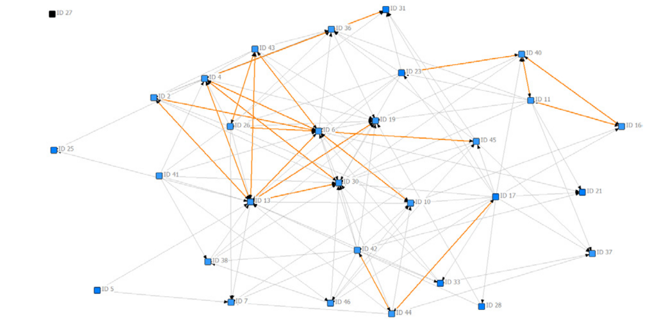
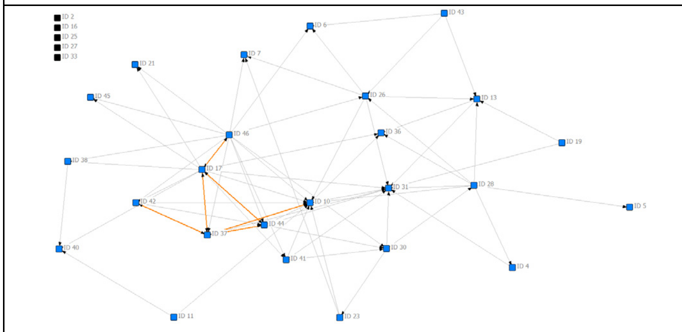
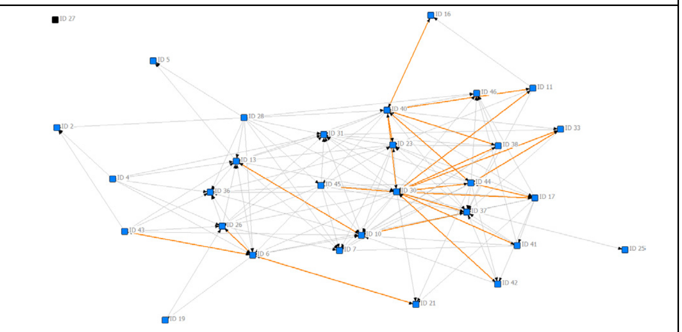
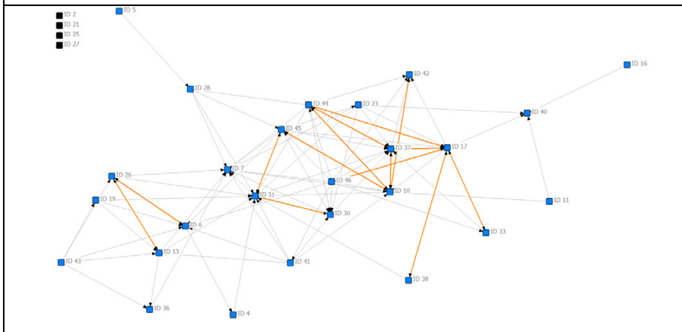
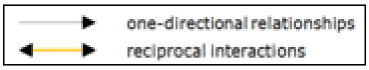
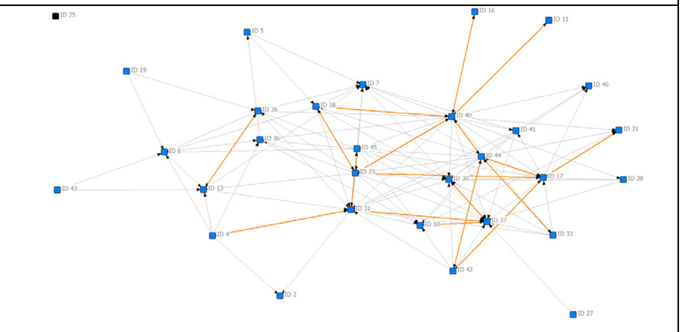
**Table 5.7: Relationships considered when calculating SNA metrics**

| Network Dimension | Binary Code "1" (Relationships contemplated) | Binary Code "0" (Disregarded relationships) |
|---|---|---|
| Recurrence | ▫ At least once a week<br>▫ At least every month | ▫ At least every quarter<br>▫ *Ad hoc* - (less than 4 times per year)<br>▫ No contact |
| Access | ▫ Always responds within time<br>▫ Usually responds within time | ▫ Responds, but usually late<br>▫ Often fails to respond<br>▫ No contact |
| Engagement | ▫ Learns from this person regarding work-related problems<br>▫ Actively assists to reflect on work-related problems and provides guidance to reach effective solutions | ▫ Only points to information<br>▫ Input hardly ever assists to resolve work-related problems<br>▫ No contact |
| Trust | ▫ Comfortable to share ideas<br>▫ Very comfortable to share ideas | ▫ Not so comfortable to share ideas<br>▫ Very uncomfortable to share ideas<br>▫ No contact |

***Tables 5.8*** to ***5.12*** depict the five different relations that were measured in the respective network dimensions before and after the implementation of KM interventions.

[41] In line with conventional analysis, when two individuals reveal a mutual connection, the most popular method is to average these two elements as the strength of the relationship. However, this becomes challenging when one person indicates a weak relationship and the other a strong relationship (Norman & Huerta 2006:5). Given that most of the mathematical and graphical tools used by network analysts were developed for simple graphs, Hanneman and Riddle (2005) recommend that one *"reduce even interval data to the binary level by choosing a cutting-point, and coding tie strength above that point as "1" and below that point as "0"."*

**Table 5.8: Knowledge networks before and after implementing KM interventions**

| Knowledge network before KM interventions | Knowledge network after KM interventions |
|---|---|
|  CC Network |  CC Network |
|  DAM Network |  DAM Network |
|  SR Network |  SR Network |
|  SMC Network   |  SMC Network |

According to Hanneman and Riddle (2011:341), size is essential to networks due to "…the limited resources and capacities each actor has for building and maintaining ties". With the exception of the CC network, that had one network member less, all knowledge networks (DAM, SR and SMC) increased in relation to size, after implementing the respective KM initiatives. The DAM network increased most, boasting eight new network members (***Table 5.13***).

Isolates existed in all knowledge networks, indicating that not all divisional members were reachable. The CC network originally contained only one isolate, who joined the network after the KM interventions. However two original CC network members became isolates instead. In the DAM, SR and SMC networks, original isolates ranged between four and nine and shrunk to only one isolate per knowledge network (***Table 5.13***). This meant that more members could be reached. Besides, the average path length also shrunk in general, implying that the networks were becoming more efficient (Coulon 2005:9).

Considering that reciprocity is often regarded as a depiction of trust, it can be associated with the sharing of information and knowledge within a network (Scarbrough et al. 2014). With incompatible sizes of knowledge networks before and after implementing the KM initiatives, it was difficult to compare reciprocity scores. Nonetheless, from studying ***Table 5.8***, it was possible to attest that overall, reciprocity had increased in all four knowledge networks.

Moreover, from a knowledge network assessment, the out-degree centralisation increased substantially throughout the analysed networks (CC, DAM, SR and SMC) ***(Table 5.13)*** after implementing the KM initiatives. This indicates that the number of network members who contacted others for information within the respective knowledge networks, had increased significantly.

From studying the networks pertaining to *frequency of interaction* before and after the implementation of KM interventions (***Table 5.9***), it appears that although interaction between members who interacted *once a month* and *once a week* remained strong, network density declined slightly from 49% to 44% (***Table 5.14***). All members interacted at least once a week as everyone was reachable in this network as members with no incoming ties were connected to others with outgoing ties and vice versa. While all members were still reachable, the low network density impeded on the tempo at which this interaction took place. Ad hoc contact also declined significantly, implying that overall there were more frequent interaction between network members.

**Table 5.9: Frequency of interaction between network members before and after implementing KM interventions**

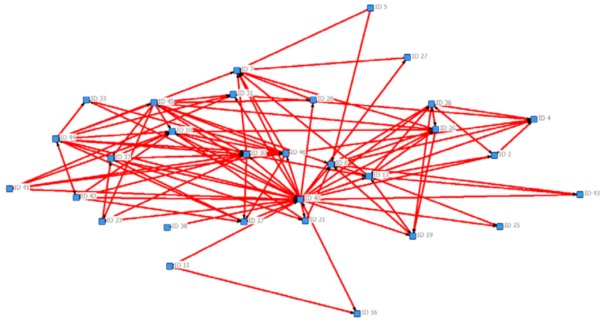
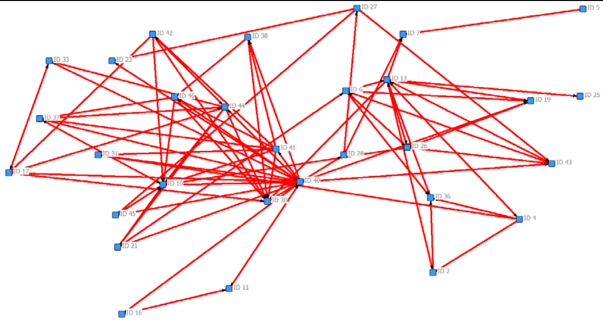
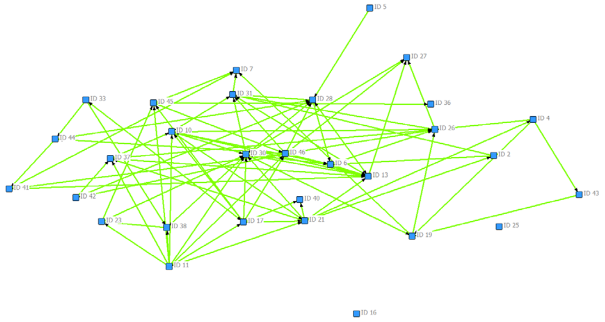
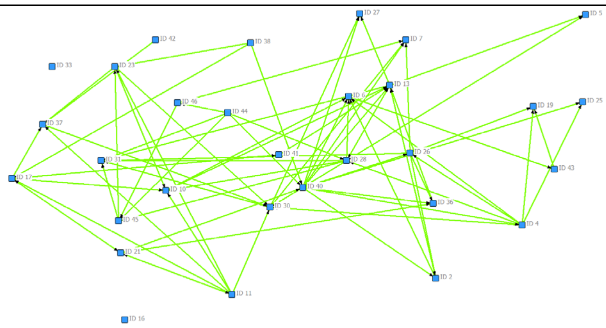
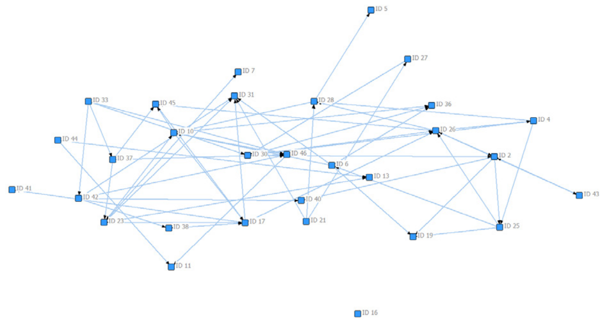
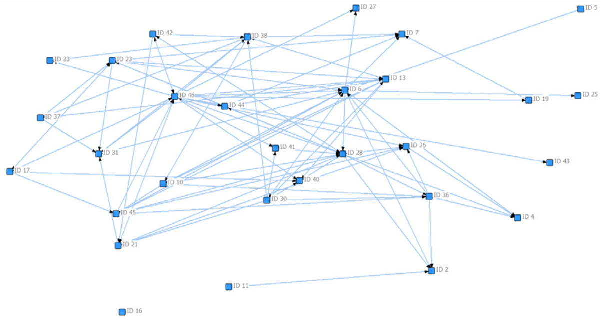
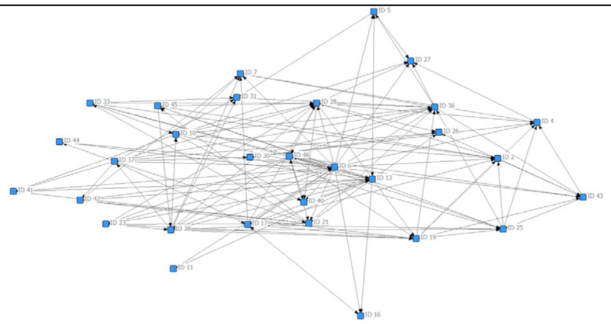
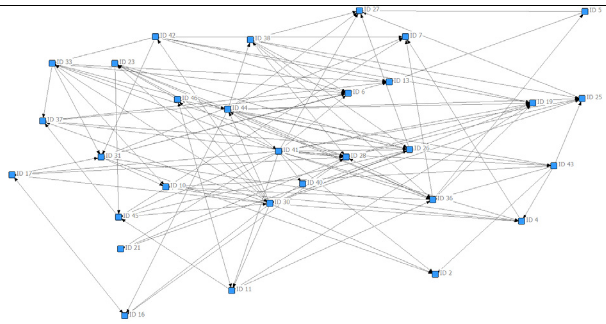
| Recurrence network before KM interventions | Recurrence network after KM interventions |
|---|---|
|  Contact once a week |  Contact once a week |
|  Contact once a month |  Contact once a month |
|  Contact at least quarterly |  Contact at least quarterly |
|  *Ad hoc* contact |  *Ad hoc* contact |

**Table 5.10: Responsiveness between network members before and after implementing KM interventions**

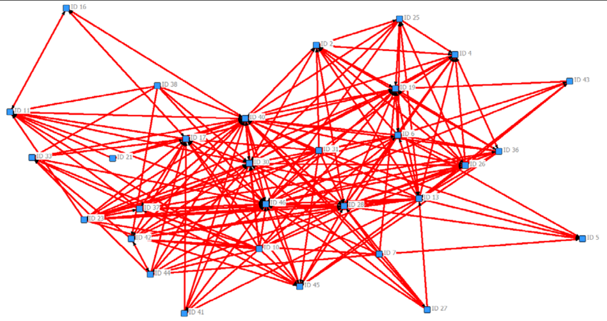
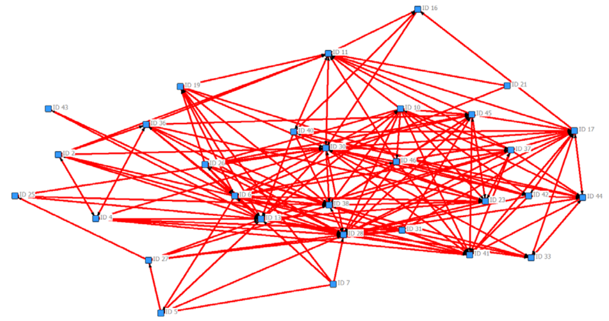
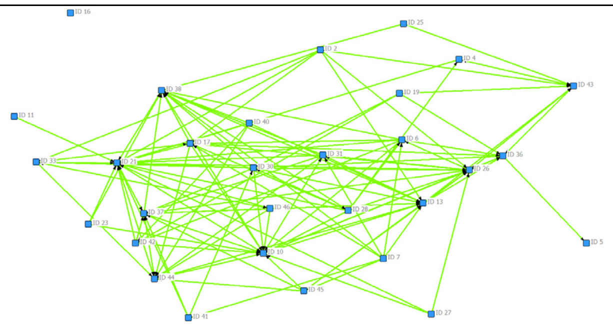
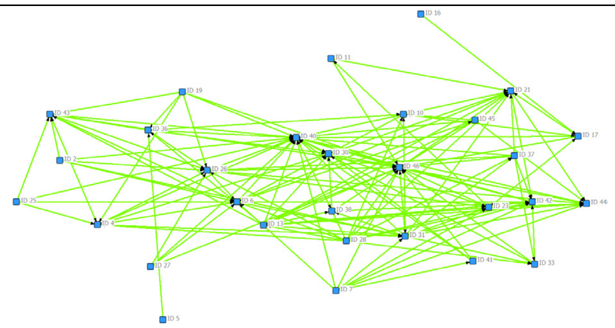
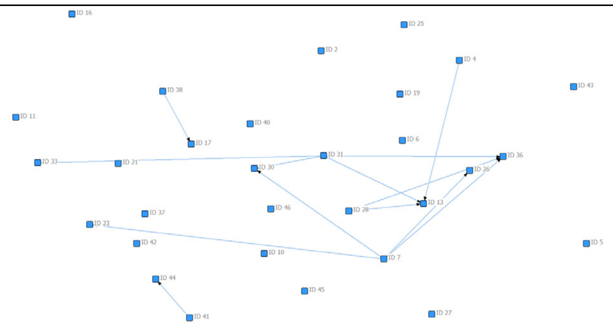
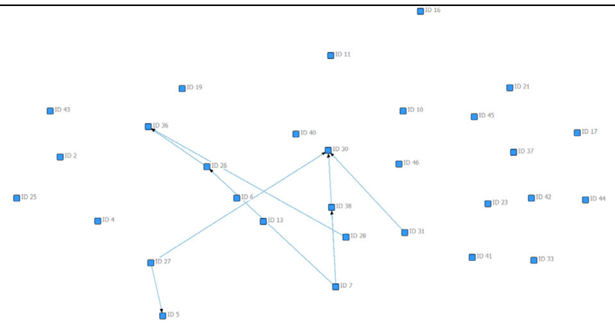
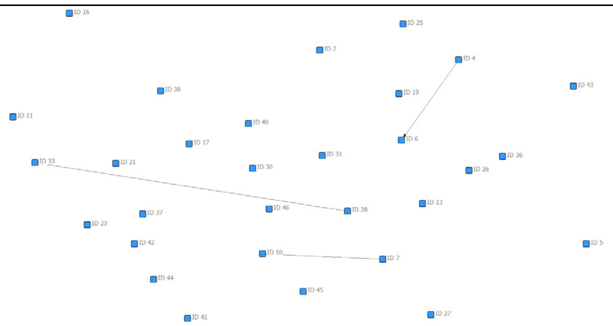
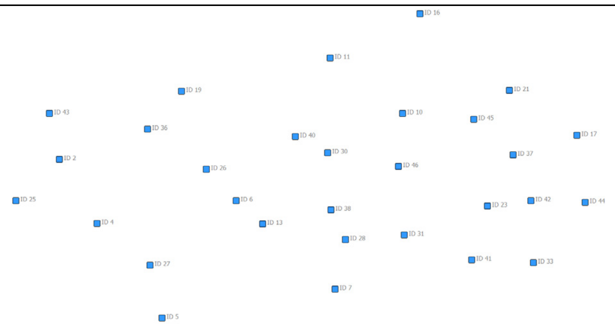
| Responsiveness before KM interventions | Responsiveness after KM interventions |
|---|---|
|  Always responds within time |  Always responds within time |
|  Usually responds within time |  Usually responds within time |
|  Responds, but usually late |  Responds, but usually late |
|  Often fails to respond |  Often fails to respond |

***Table 5.10*** depicts the different outcomes considering the *responsiveness* networks before and after employing KM interventions. Although the density within the networks where members *always or usually responded within time* declined slightly

with 2% after KM initiatives were deployed, the in-degree centralisation increased from 52.6% to 58.7%, implying that network members were more readily providing information or answers to questions within time (***Table 5.14***). This corresponds with a decline in instances where networks members responded late and a total elimination of occurrences where network members failed to respond.

Networks concerning the *level of engagement* before and after KM interventions are illustrated in ***Table 5.11***. The fact that all network members were reachable in networks where *members actively received guidance and assistance* or *learned from* their colleagues, indicated that all network members either learned from someone in their network, or was able to actively assist a colleague regarding a work-related problem. The slight decline regarding out-degree centralisation together with the minor increase pertaining to in-degree centralisation (***Table 5.14***) indicated that although less network members were actively teaching their colleagues, more network members were learning from other network members. Group interviews (***Appendix 3***) concurred that the increase in the number of network members that only pointed to information could be attributed to three reasons. Either the wrong people were contacted (despite the distribution of the skills map) or the experts who were contacted were very busy and consequently only pointed to information. It could also have been that the information requested was contained within a database, hence the mere 'pointing' to information. According to group interviews (***Appendix 3***) the increase in the number of network members whose input hardly ever assisted, could be attributed to the fact that since many non-experts joined the CoPs, it could be that their input did not add much value. This should not necessarily be regarded as undesirable, considering that it indicates that less experienced members within the social networks gained confidence to actively participate within these networks. Similarly due to political and cultural reasons network members could still be contacting the wrong people, i.e. inexperienced or non-skilled members, who could not contribute much.

**Table 5.11: Engagement between network members before and after implementing KM interventions**

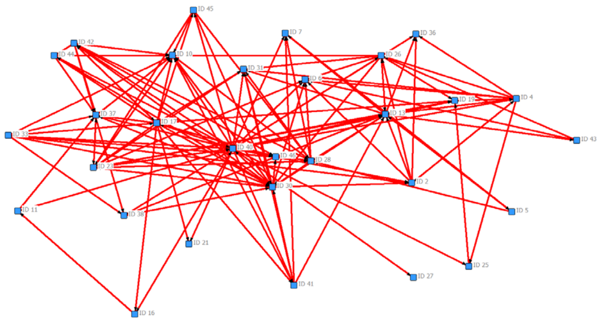
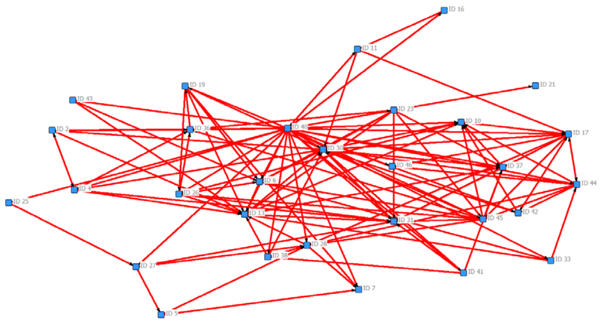
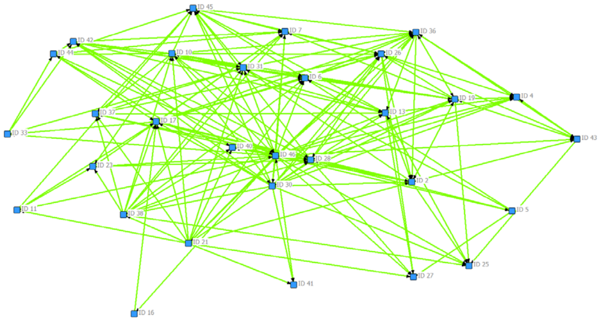
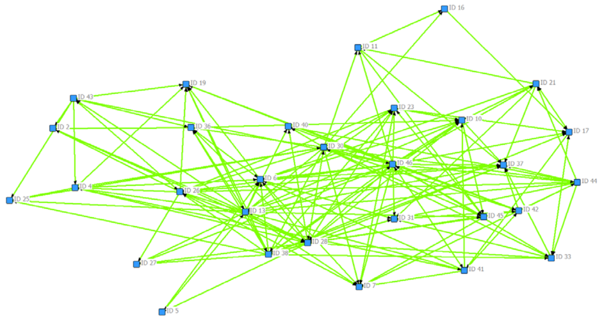
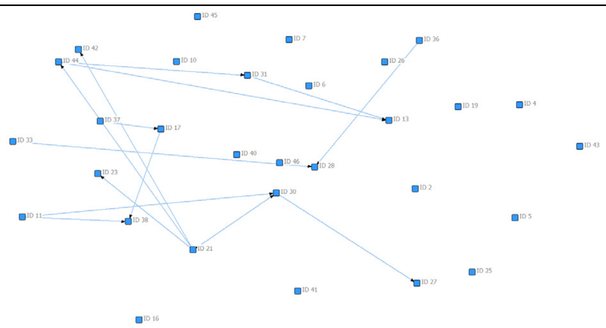
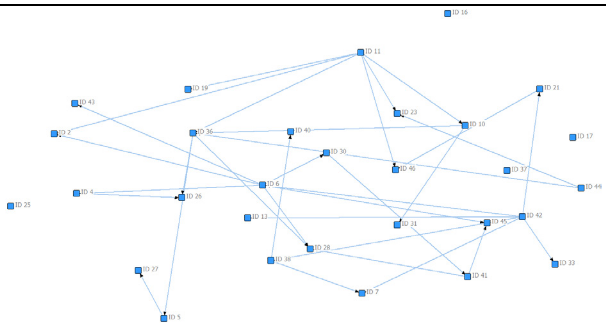
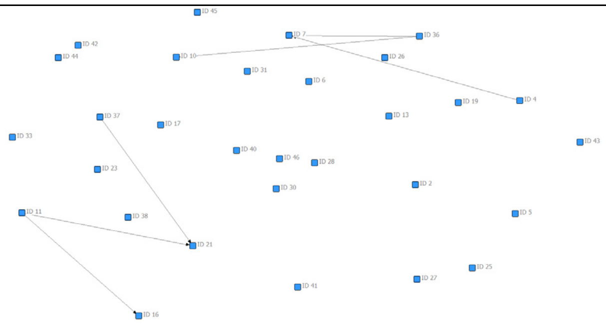
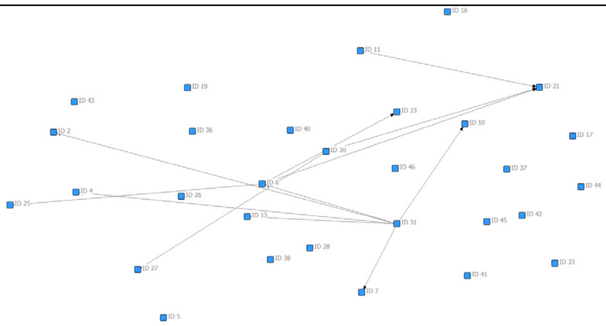
| Engagement before KM interventions | Engagement after KM interventions |
|---|---|
| <br>Provides guidance and actively assists to reflect on work-related problems | <br>Provides guidance and actively assists to reflect on work-related problems |
| <br>Learns from | <br>Learns from |
| <br>Only points to information | <br>Only points to information |
| <br>Input hardly ever assists | <br>Input hardly ever assists |

**Table 5.12: Levels of trust between network members before and after implementing KM interventions**

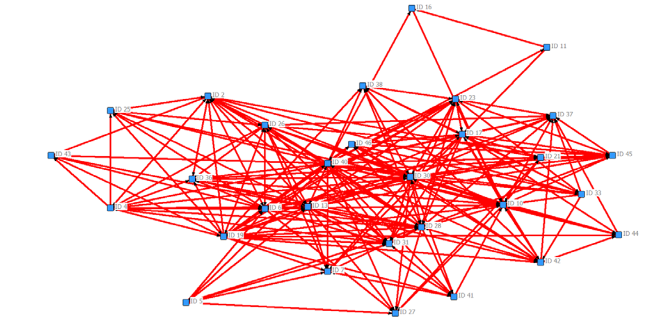
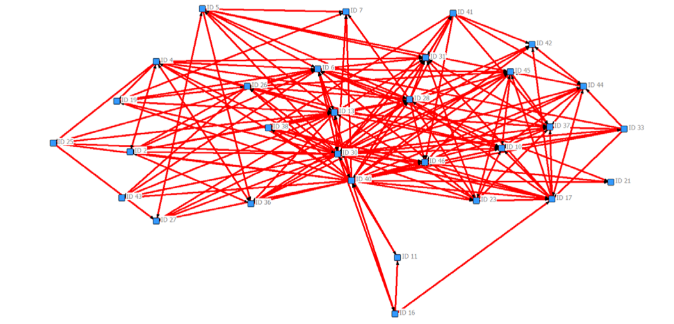
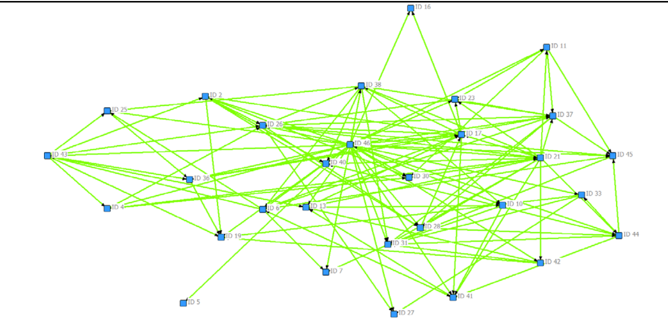
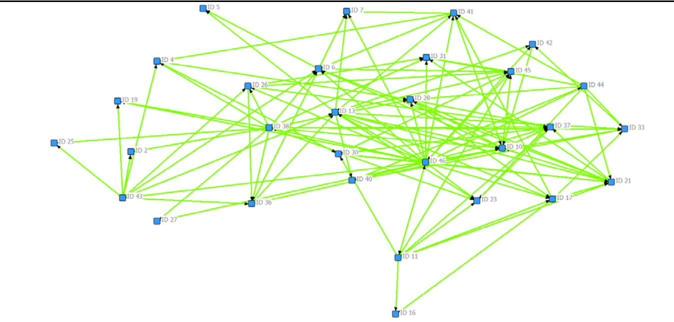
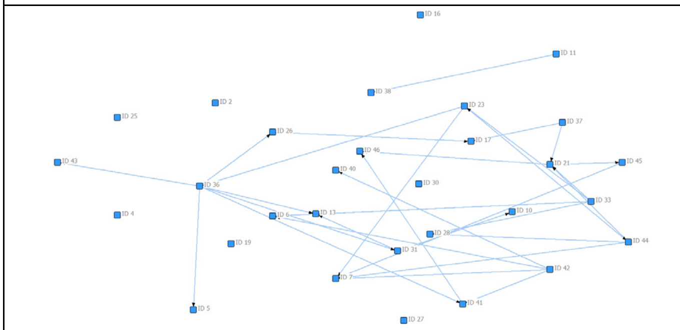
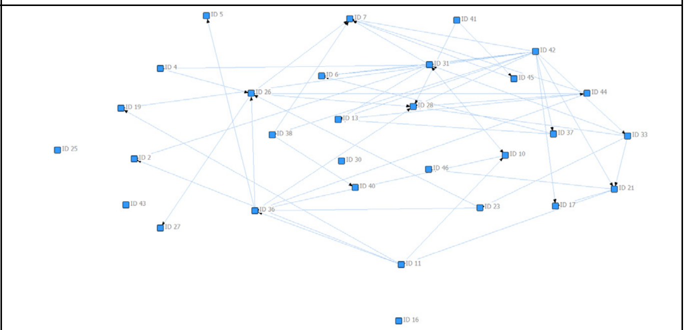
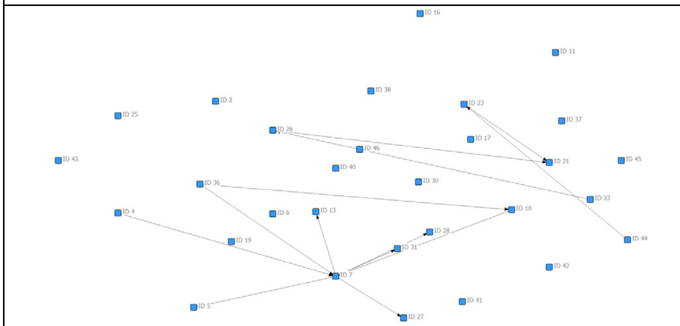
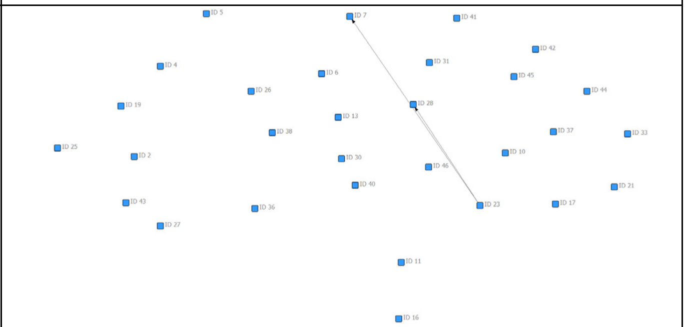
| Levels of trust before KM interventions | Levels of trust after KM interventions |
|---|---|
| <br>Very comfortable to share ideas | <br>Very comfortable to share ideas |
| <br>Comfortable to share ideas | <br>Comfortable to share ideas |
| <br>Not so comfortable to share ideas | <br>Not so comfortable to share ideas |
| <br>Very uncomfortable to share ideas | <br>Very uncomfortable to share ideas |

***Table 5.12*** portrays the *trust networks* before and after implementing KM initiatives. Networks where members felt *very comfortable* and *comfortable* to share ideas with their colleagues declined with 7% in terms of density. Even so, both the out-degree centrality and the in-degree centrality increased, from 35.4% to 42.1% in both

instances (***Table 5.14***), which meant that more network members trusted and were trusted by their colleagues. This trend was confirmed by the fact that the number of members who were very uncomfortable to share ideas with some of their colleagues, dropped from nine individuals to one.

The above outcomes are considered in more detail in ***Section 5.2.4*** addressing network density (***Section 5.2.4.2***), reachability (***Section 5.2.4.3***) and centrality (***Section 5.2.4.4***).

***Table 5.13*** and ***5.14*** offer comparisons between these respective networks before and after establishing CoPs and communicating who the experts in the division were as per the knowledge maps, in terms of:

- size;
- density;
- reachability; and
- centralisation.[42]

#### 5.2.4.1 Size

All 30 network members who participated in both SNAs were considered when evaluating the size of the knowledge networks. Apart from the CC network, that had one network member less,[43] the knowledge networks (DAM, SR and SMC) all increased in terms of size after implementing the particular KM initiatives. With eight new members, the DAM network increased most (***Table 5.13***).

Considering the *recurrence*, *responsiveness*, *engagement* and *trust* networks, all 30 network members were involved both before and after executing the KM initiatives. Consequently these network sizes remained the same (***Table 5.14***).

#### 5.2.4.2 Density

Prell (2012:171) maintains that when comparing density between networks in order to calculate which network is more cohesive, one needs to ensure that the networks measured are the same size. As a result the *average degree* of all nodes was

[42] Closeness centrality is not well suited to directed data (Borgatti *et al.* 2013:177). Consequently only degree- and betweenness network centralisation were calculated in this study.
[43] Isolate ID25 became part of the CC network, while ID5 and ID21 became isolated.

implemented to calculate structural cohesion within the knowledge networks, as it is not influenced by network size (de Nooy *et al*. 2011:74).

When examining the respective knowledge networks before and after the implementation of KM interventions it became evident that, apart from the CC network where the average degree dropped slightly, it increased significantly in two and slightly in one of the remaining knowledge networks (***Table 5.13***).

In terms of the *recurrence, responsiveness*, *engagement* and *trust* networks, density decreased somewhat after implementing the KM initiatives (***Table 5.14***).

Although relationships of members who either failed to respond or responded late, were not measured as part of the density score, it is worthwhile to point out that after implementing KM initiatives, the number of relationships where members failed to respond had dropped from three to zero, and the number of instances where members usually responded late had decreased from seven to five. Similarly, instances where members did not trust one another and where they were very uncomfortable with sharing ideas, declined from nine individuals to one.

#### *5.2.4.3 Reachability*

With isolates[44] present in all the knowledge networks, not all divisional members were reachable. The CC network originally comprised one isolate and although this isolate became part of the CC network after implementing KM interventions, two original CC network members became isolates instead. In the case of the DAM, SR and SMC networks, isolates ranged between four and nine originally and decreased to only one isolate per knowledge network. In each of these cases the remaining isolates (ID27 and ID25 respectively) formed part of the original list of isolates and these members did not opt to join the corresponding CoP (***Table 5.13***).

Apart from isolates, each knowledge network contained members with no outgoing ties, meaning they did not approach anyone for information. However, they were still connected to the network as other members in the corresponding knowledge network approached them. The same could be said for members with no incoming ties, who

[44] Divisional members who did not form part of a specific knowledge network.

remained part of the network due to the fact that they contacted other network members for related information.

All divisional members were reachable pertaining to the *recurrence*, *responsiveness*, *engagement* and *trust* networks both before and after the implementation of KM initiatives. Where members had no incoming ties, they were connected with outgoing ties and vice versa (***Table 5.14***). In terms of average geodesic distance, as discussed in ***Section 5.1.1***, there were marginal changes in all networks before and after implementing KM initiatives, as portrayed in ***Table 5.13***.

Scarbrough *et al*. (2014) maintain that as reciprocity is often used as a proxy for trust, it can be associated with the sharing of knowledge and information within a network. As the sizes of the knowledge networks differed before and after implementing the KM initiatives, it proved challenging to compare reciprocity scores. However, from studying ***Table 5.8***, it was possible to ascertain that in general, reciprocity had increased in all four knowledge networks.

#### *5.2.4.4 Centralisation*

Since the networks studied were directed, degree centralisation was measured in terms of in-degree and out-degree centralisation. From a knowledge network perspective out-degree centralisation increased significantly after the implementation of KM initiatives throughout the analysed networks (CC, DAM, SR and SMC). This means that the number of members contacting other network members for information within the respective knowledge networks had increased. Conversely, the same could not be said for in-degree centralisation where no specific trend could be detected as scores varied from declines (CC and SR), to extensive increases (DAM), to almost no significant changes (SMC) (***Table 5.13***).

Considering the *recurrence*, *responsiveness, engagement* and *trust* networks out-degree centralisation increased regarding *recurrence*, *responsiveness* and *trust*, but decreased slightly in terms of *engagement*. In terms of recurrence, this indicated that after the implementation of KM initiatives more members in the division were looking for information. Additionally they were more inclined to respond to requests for information and tended to trust their co-workers more. In contrast divisional members appeared to be actively coaching fewer of their colleagues. Similarly, there existed an upward trend regarding in-degree centralisation scores in all four networks. This meant that overall network members were approached more frequently for information, network members were more inclined to receive information from their colleagues in time, more members felt that they were learning something from their colleagues and more network members were trusted by their colleagues (***Table 5.14***).

These observations were triangulated by the scores provided in ***Table 5.13*** and ***Table 5.14*** as well as from confirmations obtained during the group interviews (***Appendix 3***).

Apart from the CC network, the betweenness scores of all the networks that were analysed increased after implementing the respective KM initiatives. Despite this escalation the scores remained low to moderate.

**Table 5.13: Network connectivity results before and after implementing KM interventions: knowledge networks**

| Connectivity Metric | | CC | | DAM | | SR | | SMC | |
|---|---|---|---|---|---|---|---|---|---|
| | | Before | After | Before | After | Before | After | Before | After |
| Size | Respondents[45] | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 |
| | Network participants | 29 | 28 | 21 | 29 | 25 | 29 | 26 | 29 |
| Density | Possible connections[46] | 812 | 756 | 420 | 812 | 600 | 812 | 650 | 812 |
| | Actual connections | 110 | 101 | 42 | 139 | 72 | 150 | 96 | 125 |
| | Density | 12,6% | 11,6% | 4,8% | 16% | 8,3% | 17,2% | 11% | 14,4% |
| | Average degree | 3.7 | 3.4 | 1.4 | 4.6 | 2.4 | 5.0 | 3.2 | 4.2 |
| Distance / Reachability | No outgoing ties | 3 (ID2, ID7 & ID16) | 8 (ID2, ID7 ID11, ID16, ID17, ID25, ID31 & ID46) | 7 (ID6, ID7, ID10, ID11, ID36, ID37 & ID45) | 3 (ID7, ID21 & ID25) | 8 (I57, ID6, ID7, ID21, ID31, ID36, ID40 & ID45) | 7 (ID2, ID5, ID7, ID25, ID31, ID36 & ID46) | 2 (ID7 & ID40) | 3 (ID7, ID2 & ID46) |
| | No incoming ties | 2 (ID5 & ID43) | 1 (ID43) | 3 (ID2, ID26 & ID43) | 2 (ID41 & ID45) | 3 (ID11, ID43 & ID19) | 2 (ID4 & ID28) | 4 (ID5, ID11, ID16 & ID43) | 3 (ID19, ID27 & ID43) |
| | Isolates | 1 (ID25) | 2 (ID5 & ID21) | 9 (ID5, ID17 ID21, ID23, ID25, ID27, ID28, ID31 & ID33) | 1 (ID27) | 4 (ID2, ID21, ID25 & ID27) | 1 (ID25) | 5 (ID2, ID16, ID25, ID27 & ID33) | 1 (ID27) |
| | Average geodesic distance | 2.2 | 2.0 | 1.8 | 2.1 | 2.8 | 2.4 | 2.8 | 2.7 |
| Centrali-sation | Out-degree | 58.3% | 70.0% | 23.5% | 33.4% | 37.8% | 57.1% | 27.8% | 49.3% |
| | In-degree | 58.3% | 48.6% | 23.5% | 40.5% | 30.7% | 28.5% | 35.0% | 35.1% |
| | Betweenness | 57,4% | 46,3% | 3,9% | 13,3% | 12,2% | 24,1% | 15,5% | 16,8% |

[45] 47 members participated in the first SNA. Nonetheless in order to make a comparison with the same sample population, only the responses of the 30 members that also participated in the second SNA are considered in the first SNA.
[46] Possible connections are only considered between members who belonged to the network – i.e. isolates were omitted.

**Table 5.14: Network connectivity results before and after implementing KM interventions: recurrence, responsiveness, engagement and trust networks**

| Connectivity Metric | | Recurrence | | Responsiveness | | Engagement | | Trust | |
|---|---|---|---|---|---|---|---|---|---|
| | | Before | After | Before | After | Before | After | Before | After |
| Size | Respondents | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 |
| | Network participants | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 |
| Density | Possible connections | 870 | 870 | 870 | 870 | 870 | 870 | 870 | 870 |
| | Actual connections | 217 | 165 | 365 | 338 | 324 | 296 | 388 | 314 |
| | Density | 49% | 44% | 42% | 40% | 40% | 39% | 66% | 59% |
| Distance / Reachability | No outgoing ties | 1 (ID7) | 2 (ID7 & ID31) | 0 | 0 | 2 (ID7 & ID27) | 2 (ID7 & ID31) | 2 (ID7 & ID27) | 0 |
| | No incoming ties | 1 (ID5) | 0 | 1 (ID7) | 1 (ID7) | 0 | 0 | 0 | 0 |
| | Average geodesic distance | 1.5 | 1.6 | 1.6 | 1.7 | 1.7 | 1.7 | 1.3 | 1.4 |
| Centrali-sation | Out-degree | 53.2% | 54.7% | 31.2% | 37.3% | 62.4% | 59.3% | 35.4% | 42.1% |
| | In-degree | 31.7% | 33.3% | 52.6% | 58.7% | 33.9% | 34.4% | 35.4% | 42.1% |
| | Betweenness | 21,5% | 25,5% | 7% | 15,6% | 9,1% | 16,6% | 6,2% | 15,4% |

## 5.3 CONTEMPLATING THE OUTCOMES

The main aims of the analysis in this report were to:

(a) establish the level of interaction with the actual experts in knowledge networks by linking key network positions with the experts pinpointed in knowledge maps;

(b) determine whether any correlation exists between the levels of CoP participation and network positions held by individuals;

(c) investigate how the establishment of CoPs and the distribution of knowledge maps could influence knowledge network structures, specifically in terms of cohesion, cut-points and hubs; and

(d) examine in what way CoPs can influence network connectivity considering whole-network assessments.

### 5.3.1 Linking key network positions and identified experts as per the skills audit

The first objective of this study aimed to investigate how SNA could disclose to what extent network members collaborate with actual experts (as per the skills audit) for information[47]. This was done by comparing network members with high in-degree centrality rankings with experts/highly skilled members (***Section 5.2.1***). Müller-Prothmann (2007:228) differentiates between *knowledge authorities* (actors with a high in-degree centrality) and *knowledge brokers* (actors with both a high in- and out degree centrality). However, for the purpose of this exercise, all network members who ranked high considering in-degree centrality were deemed *knowledge authorities*, regardless of their out-degree centrality score.

Four knowledge networks (CC, DAM, SR and SMC) were studied when linking accepted domain experts and members with high in-degree centrality rankings.

In all these networks, at least three experts/highly skilled members counted among the top ten percent of members that were approached for information, with the SR network being the only network where a non-acclaimed expert ranked highest regarding in-degree centrality. Save for the DAM network (where expert and

[47] As several experts/highly skilled members refrained from joining the respective CoPs and participating in the second SNA, a reflection on whether experts/highly skilled members were contacted more readily as a result of CoP participation and the distribution of skills maps could thus not be provided.

newcomer ID5 had no incoming ties), no expert counted under the bottom ten percent of members approached for information in the respective networks. This implies that even though not every expert/highly skilled member ranked high regarding in-degree centrality, most network members did turn to recognised experts/highly skilled members for advice. Furthermore, many of the non-recognised experts[48] rated high regarding in- as well as out-degree centrality and could therefore be regarded as *knowledge brokers*. Knowledge brokers either collect knowledge and pass it on, or could be an expert in some areas and a consumer in others (Müller-Prothmann 2007:228).

Apart from the CC network, (where only ID28 counted under the highly skilled members who ranked high regarding out-degree centrality), all other networks had at least two highly skilled members among the top ten percent of members that were looking for information. All four networks also had some experts/highly skilled members that accounted for the bottom ten percent of members looking for information in the respective networks. This indicates that, while some recognised experts/highly skilled members did not experience a need to contact other network members regarding their knowledge domain, others did.

Considering interaction between acknowledged experts/highly skilled members, the respective KNAs also revealed weaknesses regarding direct links, e.g. in the case of the CC network where many highly skilled members will become isolated from the highly skilled network should ID28 be removed for whatever reason. In addition, these KNAs uncovered experts/highly skilled members who did not have any direct links with their peers and exposed instances where any direct links between experts did not exist.

### 5.3.2 Comparing CoP participation with key network positions

This study also aspired to determine whether a correlation existed between individuals who chose to participate in CoPs and their respective knowledge network positions.

[48] Non-recognised experts are members with a high in-degree centrality, who were not identified as experts/highly skilled members as a result of the skills audit.

After plotting the first SNA and the knowledge maps, a quick poll was conducted amongst the participants in order to identify the subject domains that appealed to them most. Based on these outcomes four CoPs were constructed by making use of SharePoint technology. Network members were invited to join the respective CoPs in order to engage in a shared learning agenda. CoP members were then encouraged to submit and respond to questions, to share interesting information and to engage in thought-provoking discussions. It was anticipated that these CoPs would offer members opportunities to connect and to learn from one another.

Certain movements were identified when considering which members did not join the CoPs, which members joined the CoPs and what their respective levels of interaction were.

Overall, most network members who opted not to join the particular CoPs were either peripheral players or deemed independent based on their high out $\kappa$-reach centrality ranking. Yet, in the CC, SR and SMC networks, there were network members who were neither peripheral players, nor highly autonomous, who did not care to join the respective CoPs. With a high in-degree centrality ranking, these network members were all considered to be knowledge authorities and in some instances (ID48 and ID3) they were also regarded as experts/highly skilled within the corresponding domains.

Considering network members who joined the respective CoPs, it was observed that most of the recognised experts/highly skilled members who also scored high regarding in-degree centrality, connected to the corresponding CoPs. Except for ID3 (SR and SMC network) and ID48 (CC network), the few recognised experts/highly skilled members who did not want to join the respective CoPs, scored high regarding out $\kappa$-reach centrality. Correspondingly, in most instances individuals who functioned as knowledge authorities (but who were not considered experts/highly skilled members as per the skills audit), opted to join the respective CoPs.

Each network contained knowledge consumers who wanted to join the corresponding CoPs as well as knowledge consumers who did not care to do so. On the whole, knowledge consumers who did not join the CoPs were regarded as rather independent, with most of them scoring among the top ten percent regarding out $\kappa$-reach centrality. Many of these were also deemed to be highly skilled in their respective domains as per the skills audit.

All knowledge brokers who chose not to join the respective CoPs rated high regarding out $\kappa$-reach centrality in the corresponding knowledge network. Apart from the CC network, all knowledge brokers who opted to join the respective CoPs were considered experts/highly skilled members in the respective knowledge networks.

In effect network members who were rather dependent on others for access to information, as well as members who were often contacted for their know-how, were more inclined to enter CoPs than highly independent members and peripheral players. This contention is in line with the statement of Creech *et al.* (2012:9) that *"… within collaborative approaches, it is not uncommon to find smaller, focused, more purposeful groups embedded in a broader, extensive network."*

Pertaining to CoP participation, four types of members were identified namely lurkers, advisors, sparkers and sole contributors. These members were classified according to their participation in terms of contributions.

Most CoP members, including all network isolates that chose to join a particular CoP, acted as observers (lurkers) only. This meant they only read threads and contributions, but did not actually produce any input themselves. This should not be regarded as an undesirable outcome as the objective of the CoPs was to provide a learning platform and to share knowledge within the communities. It was thus anticipated that some CoP members would not be actively contributing. It is, however, thought-provoking that members who used to be isolated from the network, started to observe what was being discussed in the various communities, but did not yet have the valour to actively participate via questions, answers or general contributions.

All general knowledge contributions posted in the four CoPs came from experts/highly skilled members as per the skills audit. This observation makes sense as more experienced members ought to recognise what information should be shared with their colleagues. It is also interesting to note that knowledge authorities who were not acknowledged as experts/highly skilled members following the skills audit, did not post any general knowledge contributions.

Questions that sparked conversations in the various CoPs were posted by network members who ranked high, as well as members who ranked very low in terms of out-degree centrality. It was thus not only knowledge consumers or knowledge brokers that were looking for information within the CoPs, but also knowledge experts and in some cases peripheral players. This could be interpreted as a positive outcome as it revealed that network members on all levels were ready to learn from one another.

Even though most questions were answered by either experts/highly skilled network members or knowledge authorities, there were instances where non-experts aimed to act as advisors. In contributing to the respective questions/discussions these non-experts increased the overall CoP connectivity by means of prompting debate and encouraging communication between members.

### 5.3.3 The influence of CoPs and knowledge maps on knowledge network structures

Three essential outlines of network structures pertaining to knowledge sharing processes were compared within four knowledge networks before and after the establishment of CoPs and the distribution of knowledge maps. This was done to ascertain the potential influence of the implemented KM initiatives on these knowledge network structures.

As far as cohesion was concerned, it was perceived that network members had become much more involved. Overall there were network members who initially did not belong to any clique and after implementing the KM initiatives, became associated with one or more cliques. In addition, in all four networks the cliques became much more occupied. Save for the CC network, the number of cliques also increased significantly. This could be an indication of more underlying collaboration within the networks, or just a sign that members started to interact more directly.

The overall high level of cliques implies a degree of detachment across all four knowledge networks. This is consistent with the low network density levels that existed in these networks. Nonetheless, there existed an extensive degree of overlap between several of the cliques within the respective knowledge networks. This overlap assisted not only in distributing knowledge and information across these networks, but also pushed the process of knowledge creation as a result of their strong relations (Aviv *et al.* 2003:5).

It is also of interest to underline the role of line manager, ID30. After implementing the KM initiatives, ID30 formed part of the second highest number of cliques in the SMC, DAM and CC networks and the highest number of cliques in the SR network. Although he was not recognised as an expert/highly skilled member in any of these networks, his extensive clique membership correlated with the level of his informal networking across the knowledge networks.

While considering the effect that the KM initiatives had on cut-points, it was noted that originally all four knowledge networks consisted of one dominant block and between one and four smaller blocks. Each of these smaller blocks comprised individual nodes.

Following the implementation of the KM initiatives, ID5, a newcomer who was initially depending on cut-points (ID28 and ID31) to form part of the CC, SR and SMC networks, became much more integrated into each of these networks. Furthermore, the DAM network, which originally comprised three cut-points, became one unified block with no potential cut-points. This suggests that no individual in the DAM network was entirely dependent on another member for connecting to the rest of the network. The aforementioned could be explained by the fact that everyone within the respective sub-divisions possessed at least some knowledge pertaining to DAM and managers were of the opinion (***Appendix 3***) that technically, employees should be conversing much more considering this subject matter.

Cut-points in both the SR and SMC networks included relations between nodes that provided the only link between the respective networks and individuals that used to be isolated from the original networks. In the SR network, knowledge authority ID30 started to connect with previously isolated ID25 and in the SMC network once isolated ID27 made contact with highly skilled ID37.

Moreover, in both the CC and the SMC networks, ID40 became the only connection between ID16 and ID11 and the rest of the network. Both ID16 and ID11 were rather new to the division and reported to ID40.

Nonetheless, in the CC network, highly skilled ID28 remained the only connection between ID2 and ID27.

ID28 and ID40 thus remained fundamental in holding components of the various knowledge networks together, while ID37 and ID30 became just as important by connecting to members who used to be isolated from the respective knowledge networks.

Hubs are nodes with high degree- and betweenness centrality (Rupnik 2006) and perform a very important function in distributing knowledge and information within networks. Although hubs can link different sub-groups of a network and accelerate knowledge flows, network efficiency can also be deeply dependent on hubs. Klepac *et al*. (2014:116) point out that as highly centralised networks are dominated by one or a few hubs, they risk being divided into unconnected sub-networks should these hubs be removed or disabled. None of the four knowledge networks that were studied were extremely centralised. In fact, with their many noteworthy hubs, there existed no single points of failure in any of them. This means that should various nodes within these networks disintegrate, the remaining nodes would still be able to contact each other across different network paths.

Save for the SMC network, the number of significant hubs within the respective knowledge networks increased after the implementation of the KM initiatives. Although most of these hubs involved the same members before and after constructing CoPs and communicating knowledge maps, there were instances in all four networks where between two and five of the original noteworthy hubs were replaced by other network members. In the case of the DAM network, three previously isolated members, ID17, ID23 and ID33, became hubs.

Apart from the CC network, where the number of actual links decreased marginally, the increased number of links in the remaining knowledge networks after the completion of the KM initiatives could be regarded as a reflection of better collaboration between the respective network members. This occurrence was triangulated by group interviews (***Appendix 3***) during which managers contemplated that everyone within the sub-divisions had at least some knowledge regarding DAM and SMC. Moreover SR was only recently introduced and many people experienced some difficulties with the concept. Accordingly managers expected network members to be conversing a lot more regarding these subject matters.

### 5.3.4 The influence of CoPs and knowledge maps on whole-network metrics

Ultimately this study was also aimed at investigating the potential effect of the formation of CoPs and the dissemination of knowledge maps on network connectivity, taking whole-network assessments into account. It was expected that the analysis of the two sets of data (i.e. SNA 1 and SNA 2) would reveal changes within the respective networks as a whole.

Apart from the four *knowledge* networks, whole-network measurements, before and after implementing the KM initiatives, were also performed on four additional types of connections, namely *recurrence*, *responsiveness*, *engagement* and *trust*. This was primarily done in order to be able to compare metrics between networks of the same size.

Size plays a vital role in the structure of social relations due to the limited resources and capacities actors have considering the development and upholding of relationships (Hanneman & Riddle 2005). The knowledge networks considered in this study varied between 21 and 29 members.

Scarbrough *et al*. (2014) emphasise the value of network size considering the exchange of knowledge and information by revealing that *"… the more knowledge contacts a person has relationships with, the greater the chance that one of them has the resource he or she needs.*"

All knowledge networks, apart from the CC network, became more populated and in the case of the DAM network, an isolated expert joined the network as a result of the implemented KM initiatives. One can therefore postulate that as a result, these greater knowledge networks could potentially better attend to the knowledge and information needs of its members.

As stated by Wasserman and Faust (1994), network density is the most commonly used SNA dimension. It determines the interconnectedness of network members and is often regarded as *"… an overall measure of interaction"* (Patterson *et al*. 2013).

Considering structural cohesion within the four knowledge networks (where network sizes differed before and after implementing KM initiatives), average degree rather than density was calculated as it is not affected by network size (de Nooy *et al*. 2011:74).

While average degree declined slightly in the case of the CC network, it increased in all other knowledge networks, indicating that after implementing the KM initiatives, a greater degree of interaction existed within three of the four knowledge networks.

When deliberating density in the *recurrence*, *responsiveness, engagement* and *trust* networks, an overall decline came about after implementing the KM initiatives. Despite these low scores, with average geodesic distances ranging between 1.3 and 1.7 within the respective networks, these networks did not become fragmented (***Table 5.14***). Relationships were still maintained via frequency of interaction, responsiveness, instruction and reliance, but the low network density impacted on the speed at which this interaction took place among network members. As Patterson *et al.* (2013) point out, networks with low density levels imply that members may lack understanding or awareness of one another, dexterity between peers may be limited and time to accomplish tasks may be prolonged, compared to high-density settings.

In view of the contention of Ghali *et al.* (2012:10) that the shorter the average path length is in relation to the network size, the more efficient the network will be, it can be reasoned that the efficiency of knowledge networks increased after the implementation of the knowledge initiatives.

Network reachability relates to the degree to which any network member can connect with others either directly or via intermediaries. It thus depends on the distance of paths in a network. Conversely Mitchell (1989:325) points out that a change in distance does not necessarily reflect a change in reachability. This study aimed to determine whether the implemented KM initiatives could have any effect on the reachability of the four knowledge networks. Even though two original network members became isolates in the CC network, the remaining knowledge networks all increased remarkably in terms of reach, resulting in only one remaining isolate per network.

Considering reachability in the *recurrence*, *responsiveness*, *engagement* and *trust* networks before and after the implementation of KM initiatives, all members remained accessible, either via incoming or outgoing ties or both.

Contemplating in-degree centralisation within the knowledge networks before and after implementing the KM initiatives, rankings fluctuated between decreases, increases and virtually no change. Scores in general remained low to moderate. This means that only a few members were approached for information by the rest of the networks.

In the *recurrence*, *responsiveness*, *engagement* and *trust* networks in-degree centralisation increased slightly but remained rather low overall.

The out-degree centralisation scores in all knowledge networks increased significantly overall. This means that on the whole more network members began to interact with their co-workers for information.

The out-degree centralisation scores increased within the *recurrence*, *responsiveness* and *trust* networks, while it decreased to some extent in the *engagement* network.

Betweenness network centralisation declined somewhat in the CC network, but increased in the remaining three knowledge networks. Yet the overall score remained rather low. This implied that although group cohesiveness in the DAM, SR and SMC networks was not dependent on a few individuals, some individuals began to play a more fundamental role within these networks after the implementation of the KM initiatives. In the case of the CC network it means that although the betweenness centralisation score remained moderate, the importance of a small number of individuals regarding connectedness started to weaken. This low betweenness centralisation confirmed that limited structural constraints existed regarding the flow of information in the networks.

The same trend continued in the *recurrence*, *responsiveness*, *engagement* and *trust* networks where betweenness centralisation increased remarkably, yet the overall score remained moderate to low.

## 5.4 CONCLUDING INTERPRETATIONS

Research focussing on one particular organisation as a case has been made susceptible to criticism based on arguments relating to non-representativeness and a lack of statistical generalisability (Conford & Smithson 1996). According to Pettigrew (1985:66-67) case studies can be suitable in developing and cultivating generalizable concepts and that multiple case studies can lead to generalisations in terms of propositions. Moreover Yin (2014) maintains that case studies can be intended for rational generalisations, where the researcher aspires to generalise a specific outcomes to some broader theoretical propositions. Adding to these arguments Denzin and Lincoln (1998:193) assert that case studies can be generalised seeing that *"… looking at multiple actors in multiple settings enhances generalisability"*. Notwithstanding this critique, Flyvbjerg (2006:227) argues that formal generalisation is just one of many means whereby people obtain and accumulate knowledge and that when knowledge cannot be formally generalised, it does not imply that it cannot penetrate the collective process of knowledge accumulation in a particular discipline or in a society. The researcher aimed to describe this research in sufficient detail so that readers will be able to consider the substance of the meanings attributed to this study in order to make their own assessment about the generalisation and the transferability of the research outcomes to the body of knowledge associated with KM, SNA and CoPs. Moreover, the actual value of this study lies within the development of a methodological process map that was developed using this single organisation as a case in point but can be transferred and tested in any other organisation where it is applied.

### 5.4.1 Knowledge networks can ascertain if actual experts are approached for information

One of the fundamental benefits of knowledge networks is that it depicts who is actually being approached for knowledge and information within a network, thereby facilitating the process of locating relevant expertise in an organisation (Eppler 2001). Experts can be located and knowledge uncovered by continuously constructing and enhancing knowledge networks. Moreover by analysing the interaction of people and organisational units, as depicted in detailed graphs of knowledge networks, communication gaps can be identified (Jahn & Nielsen 2013:219).

In this study KNA was implemented in order to determine whether the actual experts/highly skilled members (as identified per skills audit) were contacted for knowledge and information as well as to discover any overlooked informal expertise. It was interesting to note that apart from the SR network, in all other knowledge networks, the individual contacted by most network members was either an expert or a highly skilled member as per the skills audit. Overall, only a small percentage of the recognised experts/highly skilled members were either not approached or contacted by only a few network members.

### 5.4.2 By combining knowledge networks and skills maps one can pinpoint non-expert authorities

Network analysis exposes the strengths and weaknesses of a network. It reveals for instance who are the key information brokers (and bottlenecks) as well as who are the boundary spanners. Key information brokers are regarded as the most *central* members in a network, linking colleagues and improving knowledge diffusion. Alas, sometimes these knowledge brokers can become bottlenecks obstructing the knowledge flow within networks (Denner 2012:28). Although these role players could obstruct the flow of information and knowledge purposefully (e.g. for financial or political gain), it could also be attributed to the fact that they are just trying to keep up with their own work while also fulfilling their roles in the network (Cross *et al.* 2003:252).

During this study, it was established that there were knowledge authorities who did not count among the recognised experts/highly skilled members identified during the skills audit. These authorities were either in management positions or possessed at least some proficiency and experience regarding the specific topic. Although no new experts were located per se, the discovery of *non-expert* knowledge authorities provided the organisation with an indication of which *non-expert* network members individuals turn to for information. Knowing who the non-expert authorities are, afford organisations opportunities to invest in these individuals to ensure that they transmit the correct knowledge and information to their peers.

### 5.4.3 Fusing knowledge networks and skills maps expose the nature of specialist relationships

The KNA revealed the characteristics of the relationships that existed between the experts and the highly skilled members within the respective knowledge networks. Overall there occurred very little direct rapport in the networks between experts themselves. However, apart from the CC network (where there were only highly-skilled members and no experts) there was considerable interaction between highly skilled members, indicating that some form of knowledge exchange or learning was taking place. A combination of SNA and skills maps can thus assist in identifying relationship traits between experts and highly skilled members within knowledge networks. This observation is in line with Müller-Prothmann's (2007:222) opinion that SNA enables organisations to measure and increase knowledge sharing occurrences by advancing personal competencies and expertise and by way of assimilating concealed expertise.

### 5.4.4 Knowledge network positions influenced members' disposition to join CoPs

It was observed that on the whole, network members who did not join the respective CoPs comprised mainly of *peripheral players* who did not have much interest in the specific domain and *independent members* who were less reliant on specific network members based on their $\kappa$-reach centrality ranking. In only a few instances *knowledge authorities* and recognised experts/highly skilled members, who were deemed to be well skilled in the respective subjects, opted not to join the CoPs. Even though other experts/highly skilled members did join the respective CoPs, it is possible that some knowledge could be lost to the CoP as a result.

In most cases recognised experts/highly skilled members who also scored high regarding in-degree centrality connected to the corresponding CoPs. As this was also the case with non-expert knowledge authorities one can infer that proficient members who were often approached for information were motivated to join the respective CoPs.

In short, network members who were not very independent as well as network members who were regarded as experts/highly skilled and were often approached because of their knowledge were more inclined to join CoPs than peripheral network members who were not especially interested in a specific subject matter as well as members who could operate independently within knowledge networks. Since peripheral players can bring new ideas and resources into the core of the network and independent players can monitor the flow of information within knowledge networks, it could benefit organisations to encourage these members to join CoPs.

### 5.4.5 CoP participation levels can be linked to knowledge network positions

By studying CoP activities it was observed that although network isolates that joined the CoPs began to perceive what was being discussed in the various communities, they remained unobtrusive and operated as bystanders only. Only experts/highly skilled members offered general knowledge contributions, while members throughout the knowledge networks submitted questions, general discussions and answers to the respective CoPs.

### 5.4.6 Knowledge and information is transferred more effectively within knowledge networks as a result of CoPs

In agreement with Wenger and Snyder's (2000) contention that CoPs are ideal to distribute knowledge within organisations, this study also established that CoPs facilitated the effective transfer of knowledge and information within knowledge networks. Cliques signify sub-sets in a network where actors are more intensely linked (Hanneman & Riddle 2005). After implementing the respective CoPs the number of cliques increased in three of the four networks and the number of network members who became part of these cliques increased significantly overall. Most of these cliques overlapped, indicating that the transfer of knowledge and information through these networks expanded. Most network members, who initially did not belong to any clique in the respective networks, became part of at least one clique.

While most of the original cut-points in the respective knowledge networks disappeared, a few new cut-points emerged as a result of CoP interaction. New cut-points developed as a result of previously isolated network members becoming connected to the respective knowledge networks.

In most cases the number of significant hubs in the knowledge networks studied increased after the implementation of CoPs, suggesting even better collaboration between the respective network members.

One can thus contend that due to the formation of CoPs, the number of isolates decreased and network members turned out to be better connected. Consequently knowledge and information were circulated more effectively throughout the respective networks.

### 5.4.7 CoP activity can impact on the size of knowledge networks

Hanneman and Riddle (2011:341) maintain that *"… size is critical to networks because of the limited resources and capacities each actor has for building and maintaining ties"*. Network size is generally considered to be a constructive element concerning the exchange of knowledge and information within networks (Scarbrough *et al*. 2014). The more skilled people someone has connections with, the higher the likelihood that one of them will have the knowledge that person needs. After executing the respective CoPs, network sizes in all four knowledge networks had changed. Apart from the CC network, the general trend was a significant increase in network size after the implementation of the CoPs. One can thus assume that overall CoP activity led to more members in the division contacting one another thus resulting in larger knowledge networks.

### 5.4.8 Network density can indicate if CoPs produced more trusted relationships and faster knowledge transfer

Pouliot (2015:87) points out that size often correlates with network density – as the size of a network increases, the number of possible ties also increases.[49] In addition, networks with a high density are more likely to be regarded as cohesive communities (Kadushin 2012:29). Although the density in all four knowledge networks remained rather low, there was a general increase after implementing the CoPs. This notion of more dense connections within the respective networks suggests that relationships

[49] To accommodate this occurrence, average degree was implemented to compare density in networks before and after implementing KM initiatives.

have advanced and that trusted communities have been established. This assumption is supported by the observation that the number of relationships where network members were very uncomfortable to share ideas with one another had diminished significantly (***Table 5.12***). The increase in the number of cliques, clique membership and the overlapping of clique memberships can also be regarded as confirmation of an increase in trust among network members as cliques represent a sub-group 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 (Hanneman & Riddle 2005).

Moreover, the implementation of the respective CoPs enabled network members to gain faster access to knowledge and information as the number of members who failed to respond vanished, while the members who responded late diminished to a great extent (***Table 5.10***).

### 5.4.9 The formation of CoPs can result in improved connectivity within knowledge networks

An increase in density also implies higher levels of reachability and connectivity across nodes (Pouliot 2015:87). It was thus not surprising to note that after implementing the KM initiatives, the knowledge networks had fewer isolates and more members could be reached. Moreover, the average path length shrunk in general indicating that the networks were becoming more efficient (Coulon 2005:9). This research revealed that all four, knowledge networks were better connected and included fewer isolates after the implementation of CoPs.

### 5.4.10 CoPs can influence the level of interaction within knowledge networks

Changes in degree centrality measures were used to determine what effect CoPs had on knowledge networks. In the case of this study for example it became clear that regarding the knowledge element, the formation of CoPs had a considerable effect on out-degree centrality. The out-degree centrality increase indicated that the overall activity in the networks had increased too.

### 5.4.11 The implementation of CoPs can lead to improved dissemination of knowledge

After implementing CoPs, the highest betweenness centralisation figure dropped to some extent. Nonetheless, betweenness centralisation remained rather low, indicating that the networks were not dependent on one or a few central members to diffuse knowledge. This trend was confirmed by the number of hubs identified during the second SNA. One can thus contend that although some actors became more popular after the CoPs were implemented, networks were not dependent on only a few individuals to maintain group cohesiveness.

## 5.5 SUMMARY

In order to illustrate the synergies between CoPs, knowledge maps and SNA, this chapter presented and analysed the key findings obtained from conducting two SNAs, before and after implementing particular CoPs and distributing knowledge maps.

As a result, comparisons were made between skills maps and knowledge networks in terms of four different subject matters; levels of CoP participation were linked to positions individuals occupied within knowledge networks; the perceived influence CoPs had on knowledge network structures was illustrated in terms of cliques, cut-points and hubs and the effect CoPs could have on network connectivity relating to knowledge, frequency of interaction, responsiveness, engagement and trust.

The final chapter reiterates findings from the conducted research and compares it to the original problem statement as presented in ***Chapter 1***.

# CHAPTER 6

***"Every new beginning comes from some other beginning's end."***

**- Seneca**

# 6 SYNTHESIS, RECOMMENDATIONS AND CONCLUSION

## 6.1 INTRODUCTION

The capacity of organisations to manage their knowledge has become fundamental to their competitiveness (Dalkir 2011:2). Given that it is often not possible to capture or document tacit knowledge, knowledge is frequently created and shared via social interaction (Nonaka & Takeuchi 1995). Relationships are thus critical to knowledge creation and the dissemination thereof (Levin & Cross 2004:1477). Similarly innovation and knowledge creation depend largely on organisational knowledge networks and how these networks encourage or prevent various knowledge domains to connect in new and meaningful ways (Amidon 2002).

This study aimed to investigate how the interrelationships that exist between SNA, CoPs and knowledge maps could enhance knowledge networks within organisations. Accordingly this research aimed to link up with the socialisation stance of KM, as presented in the works of Hansen *et al.* (1999) and Nonaka and Takeuchi (1995), where knowledge creation and knowledge sharing happens predominantly as a result of social interaction between individuals.

## 6.2 SYNTHESIS

In this study, the researcher endeavoured to demonstrate how synergies between SNA, CoPs and knowledge maps can enable organisations to produce stronger knowledge networks. In an attempt to resolve this undertaking, the following objectives were identified:

- *Objective 1* - Establish the level of interaction with the actual experts in knowledge networks by linking key network positions with the experts pinpointed in knowledge maps.
- *Objective 2* - Determine whether any correlation exists between the levels of CoP participation and network positions held by individuals.
- *Objective 3* - Investigate how the establishment of CoPs and the distribution of knowledge maps could influence knowledge network structures, specifically in terms of cohesion, cut-points and hubs.
- *Objective 4* - Examine in what way CoPs can influence network connectivity considering whole-network assessments.

Subsequently a process map was developed with the aim of answering the research question together with its objectives. ***Figure 6.1*** below offers a simplified illustration of this process map.

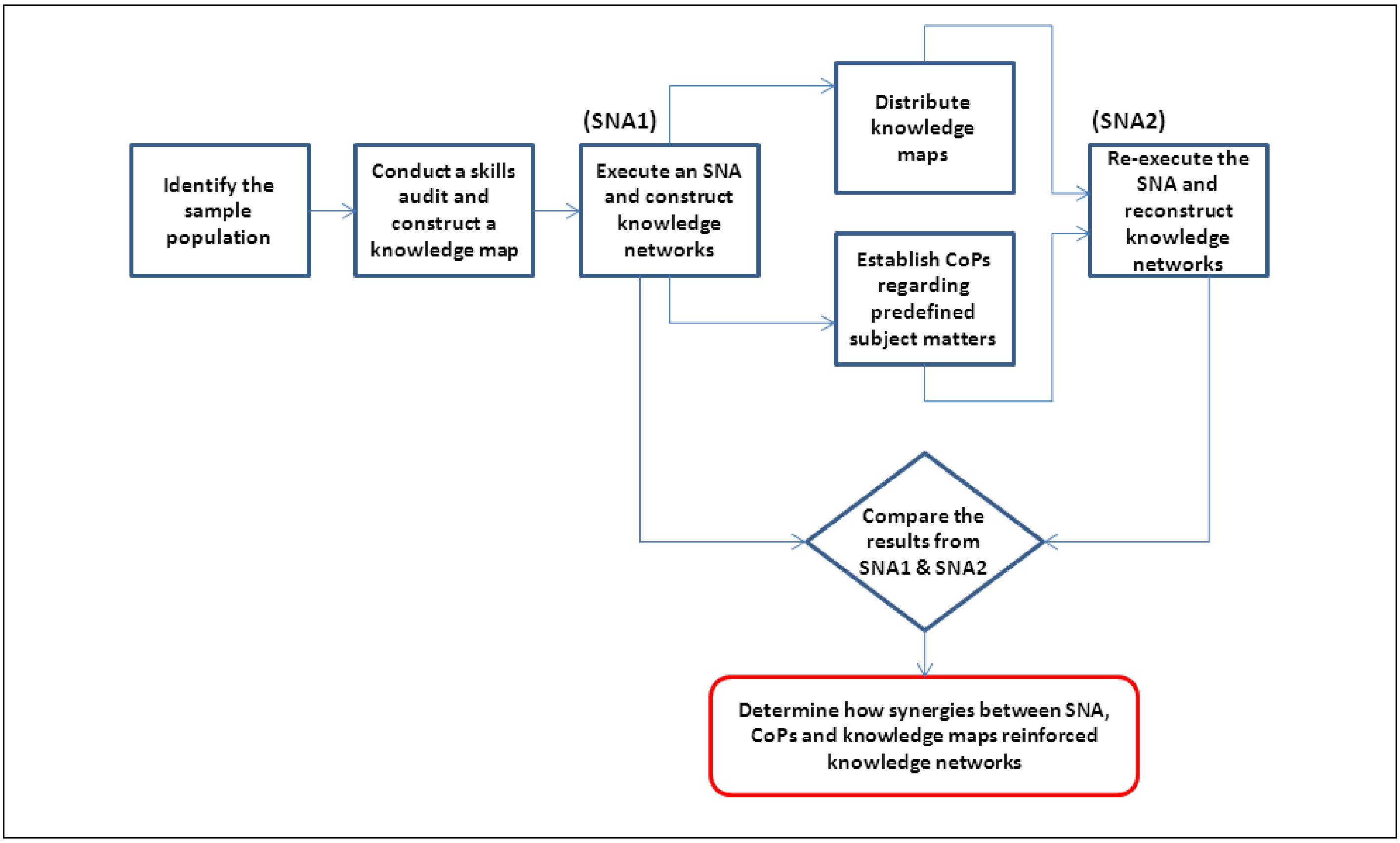



**Figure 6.1: Process map established to address the research question**

A skills audit (***Appendix 2***) - based on knowledge of 18 subject matters required to operate in the particular work environment - was conducted in an effort to resolve *Objective 1*. Next, with experience and proficiency as key qualifiers, experts and highly skilled members were identified, and a knowledge map was constructed for each subject matter (***Appendix 6***). Thereafter an SNA was performed on the exact same subject matters that were evaluated in the skills audit. SNA tools turned out to be very effective in plotting relations between the skills maps and knowledge networks as one could immediately determine whether actual experts or highly skilled members were being approached for information or not, as well as which experts and highly skilled members were collaborating with one another. Once all the data was collected and interpreted, network members with high in-degree centrality rankings were compared with experts/highly skilled members (***Section 5.2.1***). Although this was done for all 18 subject matters, the results of only four of these subject matters (CC, DAM, SR and SMC) were presented, as only these four subject matters were considered when constructing CoPs and performing the second SNA. ***Section 5.3.1*** deliberated the outcomes of these comparisons in more detail. Key results involved the following:

- Although not every expert/highly skilled member were contacted by many other network members, overall most network members consulted recognised experts/highly skilled members for advice.
- Some experts/highly skilled did not experience a need to contact other network members on the subject of their knowledge domain.
- A thought-provoking observation revealed occasions where no direct links existed between experts/highly skilled members and their peers.

*Objective 2* was addressed by distributing the constructed knowledge maps before launching four corresponding CoPs (based on a quick poll whereby network members indicated which of the 18 predefined subject matters appealed to them most). Network members were invited to join these respective CoPs aiming to offer members opportunities where they could connect with and learn from one another. Subsequently two sets of comparisons were made so as to:

- verify if there existed any connection between individuals who opted to join the CoPs or not; and their respective knowledge network positions (***Figures 5.15, 5.18, 5.21 and 5.24***); and
- establish if there was a correlation between a member's network position and their level of participation within the corresponding CoP (***Figures 5.16***, ***5.19***, ***5.22*** and ***5.25***).

The researcher demonstrated that by constructing knowledge maps, associations could be drawn between network members' dispositions to join CoPs and the intensity of their participation with the positions they occupied within the respective knowledge networks. While ***Section 5.3.2*** presented a comprehensive discussion of the results, significant outcomes included the following:

- Network members who opted not to join particular CoPs were either peripheral members with not much fascination for the subject matter or, members who were regarded as very independent (based on their high out $\kappa$-reach centrality ranking) and in some instances also knowledge authorities.
- Parallels between CoP members and their level of participation in the corresponding CoPs revealed that for the most part, members acted as mere

observers whereas all general knowledge contributions made to the four CoPs were made by experts/highly skilled members.

- Peripheral members as well as experts/ highly skilled members posted questions suggesting that network members on all levels were ready to learn from one another.
- Whereas most questions were answered by either experts/highly skilled network members or knowledge authorities, there were occurrences where non-experts attempted to answer questions suggesting that they gained confidence in actively voicing their thoughts.

Both *Objective 3* and *Objective 4* could only be dealt with once the second SNA was completed. With some network members declining to take part in the CoPs and in several instances also to participate in the second SNA, the second SNA was confined to members who opted to join the respective CoPs. In order to enable the researcher to assess comparable data, the networks constructed (CC, DAM, SR and SMC) after the first SNA, had to be recomposed featuring only network members who participated in both the CoPs and the second SNA.

SNA is a very effective method to construct knowledge networks which can be used to investigate the flow of knowledge within organisations as it is important to understand who controls the distribution of information and who performs the essential brokerage roles across structural holes (i.e. linking otherwise disconnected subgroups (Hansen *et al.* 2005). Three types of network structures namely cliques, cut-points and hubs were compared within four knowledge networks in order to attend to *Objective 3*. These network structures were selected based on Müller-Prothmann's (2007:225) contention that cliques, cut-points and hubs are fundamental to knowledge sharing processes. Comparing these network structures - before and after implementing CoPs and distributing knowledge maps - enabled the researcher to determine the potential influence the implemented KM initiatives had on the composition of knowledge networks. ***Section 5.3.3*** considered these comparisons in more detail. Key findings are listed below:

- With regard to cohesion (cliques), it was discovered that network members became much more engaged and that the number of cliques increased significantly in three of the four networks. Moreover an extensive degree of overlap between several of the cliques within the respective knowledge networks was observed (***Figures 5.26*** to ***5.33***).

- When considering cut-points, it was observed that originally all four knowledge networks consisted of one dominant block and some smaller blocks ranging between one and four. After implementing the respective KM initiatives, these blocks increased marginally in two of the networks, remained the same in one network and decreased to one block with no cut-points in another (***Table 5.6***).
- The number of significant hubs increased within three of the four knowledge networks after the implementation of the KM initiatives. In all four networks between two and five of the original noteworthy hubs were replaced by other network members (***Figures 5.42*** to ***5.49***). Nonetheless, these hubs comprised predominantly the same network members before and after constructing CoPs and communicating knowledge maps.

*Objective 4* was met by comparing whole-network measurements between the four knowledge networks (CC, DAM, SMC and SR) (***Table 5.13***) as well networks depicting elements of *recurrence*, *responsiveness*, *engagement* and *trust* (***Table 5.14***). Overall eight networks were thus compared before and after implementing the respective KM initiatives. SNA metrics applied to conduct the whole network assessment included network size, density, reachability and centralisation. However, the network size metric was not applied to the networks pertaining to *recurrence*, *responsiveness*, *engagement* and *trust* considering that these networks were all the same size, both before and after implementing the KM initiatives. Although the outcomes of these comparisons are discussed in ***Section 5.3.4***, important results included the following:

- In terms of size, three of the four knowledge networks became more populated. Correspondingly the average degree increased in these three networks, signifying more interaction between network members after implementing the KM initiatives. Considering density in the *recurrence*, *responsiveness, engagement* and *trust* networks, an overall decline came about after implementing the KM initiatives, impacting on the speed at which this interaction took place among network members.
- Yet again the same three knowledge networks increased significantly regarding reachability, resulting in only one remaining isolate per network, while the remaining knowledge network (CC) had one more isolate after implementing the KM initiatives. In general members of the knowledge networks became thus more accessible. Considering the *recurrence*, *responsiveness*, *engagement* and *trust*

networks, all members remained accessible, either via incoming or outgoing ties or both.

- Despite some fluctuations, in-degree centrality scores remained low to moderate in all eight networks, implying that that only a few members were approached by the rest of the network members.
- Apart from the *engagement* network, out-degree centralisation scores increased in all networks. This signifies that on the whole more network members began to interact with their co-workers.
- Betweenness network centralisation scores remained moderate to low in all eight networks notwithstanding specific fluxes. This low betweenness centralisation verified the existence of limited structural constraints concerning the flow of information in the networks.

By following the process map (***Figure 6.1***) the researcher was thus able to attend to the four research objectives and in so doing, to answer the research question.

## 6.3 RECOMMENDATIONS AND SIGNIFICANCES

This study aimed to illustrate the interrelationships that existed between SNA, CoPs and knowledge maps whilst focusing on a knowledge domain perspective. What the research did not investigate was to reveal how relationships between recognised experts and highly-skilled members within knowledge networks could be affected by CoPs and knowledge maps. The first SNA disclosed that there was not much direct interaction between domain experts themselves and that they almost seemed to operate in autonomous spaces within the networks. It is recommended that this study be repeated with the purpose of determining how these relationships could potentially be affected by CoPs.

Moreover this study only touched on the influence CoPs and knowledge maps had in terms of whole-network analysis regarding the *frequency*, *recurrence*, *engagement* and *trust* elements of knowledge networks. It would be insightful to conduct a similar study on the knowledge component by comparing cliques, cut-points and hubs in terms of the aforementioned elements.

The practice of SNA can be applied to a wide variety of applications ranging from the mapping of knowledge flows to the establishment of collaborative networks. Recently SNA has been gaining momentum across an assortment of disciplines as it is ideal to identify important knowledge as well as prevailing relationships within organisations (Borgatti & Halgin 2011).

The value of knowledge networks in organisations should not be underestimated. With knowledge being considered the new competitive advantage in business, KM is increasingly regarded as a vital instrument for organisational existence, competitiveness and profitability (Omotayo 2015:9). However, a considerable amount of knowledge, especially tacit knowledge, can only be created and shared through processes of social interaction (Nonaka & Takeuchi 1995:8, 57, 60, 72, 85). This study assents with the belief that direct relationships are essential to the creation and transfer of knowledge (Nahapiet & Ghoshal 1998; Levin & Cross 2004:1477) and adds to the contention that social networks contribute fundamentally to these processes. It is thus important that organisations encourage the formation of social networks and communities in order to promote knowledge sharing and learning.

SNA permits scientists to take a relational based perception of incidents that are challenging to comprehend from more traditional individual-attribute approaches (Hollenbeck & Jamieson 2015:382). In an effort to contribute to SNA from a KM perspective, this research aimed to investigate how the interrelationships that exist between SNA, CoPs and knowledge maps could enhance knowledge networks. In consequence the researcher made use of a mixed-methods approach to identify experts and to understand collaboration within CoPs. SNA was implemented to quantitatively examine individual network positions, network structures and to conduct a whole network analysis of the respective knowledge networks.

In order to execute this study, the researcher developed a process map (***Figure 6.1***) with the aim of demonstrating exactly how knowledge networks could be advanced as a result of synergies between SNA, CoPs and knowledge maps. This process map needs to be tested in different contexts. It is suggested that instead of conducting research on a particular business area within a specific organisation, future research should be conducted across various business areas and diverse organisations to expose a more comprehensive representation of the research objectives.

## 6.4 CONCLUSION

This study aimed to reveal how synergies between SNA, CoPs and knowledge maps could enhance knowledge networks within organisations. The researcher attempted to illustrate via this question that cultivating synergies between SNA, CoPs and knowledge maps will enable organisations to produce stronger knowledge networks and ultimately increase their social capital.

When assessing CoPs and knowledge networks, various similarities emerge: both stem from social learning principles; both deal with the significance of boundaries, peripheries, linkages and interfaces; and both focus on an element of participation and the leveraging of knowledge sharing (Cummings & van Zee 2005:18). Associating knowledge maps (in terms of expertise) with CoP participation and knowledge network positions will enable organisations to integrate underlying expertise as well as to confirm that the correct sources are being approached for information. Besides, relating knowledge maps to CoPs and knowledge networks will facilitate effective knowledge transfer within organisations – more trust will develop between members and organisations will be able to ensure that the correct people form part of specific CoPs (McInerney & Koenig 2011:60). Moreover, KNA can assist organisations to uncover and develop existing CoPs and to establish new ones (Cross *et al.* 2006: 37-38). Conversely, organisations can deploy CoPs in an effort to improve the transfer and sharing of knowledge within knowledge networks.

An attempt to demonstrate how synergies between SNA, CoPs and knowledge maps can enable organisations to produce stronger knowledge networks and ultimately increase their social capital, resulted in the creation of a process map. It is anticipated that this research will enable organisations to enrich their knowledge networks and expand their social capital by building on the process map that was developed and implemented in this study.

Considering that this topic is very applicable to organisational practice, the researcher trusts that this study has contributed to the academic body of knowledge relating to KM, SNA and CoPs.

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***"Knowledge is in the end based on acknowledgement."***

**- Ludwig Wittgenstein**

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# APPENDICES

*"We feel in one world, we think and name in another. Between the two we can set up a system of references, but we cannot fill in the gap."*

**- Marcel Proust**

## Appendix 1: Divisional Social Network Analysis

Divisional Social Network Analysis

This survey attempts to conduct a SNA to assess the health/dynamics of this divisional network regarding collaboration and knowledge sharing. Please note that your input is vital as a 100% response rate is essential to ensure the validity of the results. Please take 30 minutes of your time and complete this questionnaire as honestly as possible.

| NAME | | SURNAME | | DIVISION | |
|---|---|---|---|---|---|

WORKSHEET 1

Please indicate on WHICH SUBJECT MATTERS you interact with the selected person by making an 'x' in the appropriate column (KNOWLEDGE DIMENSION)

| Colleague | Subject A | Subject B | Subject C | Subject D... | Subject R |
|---|---|---|---|---|---|
| ID 1 | | | | | |
| ID 2... | | | | | |
| ID 49 | | | | | |

WORKSHEET 2 (drop down values)

Please indicate your level of interaction with the corresponding person by selecting the appropriate choice from the drop-down list

| Colleague | 1. FREQUENCY<br>How often do you contact this person about work? | 2. ACCESS<br>Regarding work-related matters, how well does this person respond to your requests? | 3. ENGAGEMENT<br>How helpful is this person in assisting you in solving work-related problems? | 4. TRUST<br>How comfortable are you to share ideas with this person and potentially create new knowledge? |
|---|---|---|---|---|
| ID 1 | | | | |
| ID 2... | | | | |
| ID 49 | | | | |

| RELATION | DROP DOWN VALUES[50] |
|---|---|
| 1. FREQUENCY<br>How often do you contact this person about work? | 0. - Never / I do not know this person<br>1. - At least once a week<br>2. - At least every month<br>3. - At least every quarter<br>4. - *Ad hoc* (less than 4 times per year) |
| 2. ACCESS<br>Regarding work-related matters, how well does this person respond to your requests? | 0. - I never contact this person regarding work-related matters<br>1. - Often fails to respond<br>2. - Responds, but usually late<br>3. - Usually responds within time<br>4. - Always responds within time |
| 3. ENGAGEMENT<br>How helpful is this person in assisting you in resolving work-related problems? | 0. - I never contact this person regarding work-related matters<br>1. - This person's input hardly ever assists me to resolve work-related problems<br>2. - Only points me to information and does not attempt to understand the problems I experience<br>3. - I do learn from this person regarding work-related problems<br>4. - Actively assists me to reflect on work-related problems & guide me to reach effective solutions |
| 4. SAFETY<br>How comfortable are you to share your ideas with this person and potentially create new knowledge? | 0. - I never interact with this person regarding work-related matters<br>1. - Very uncomfortable<br>2. – Not so comfortable<br>3. - Comfortable<br>4. - Very comfortable |

[50] Adapted from Cross *et al.* (2004:28).

## Appendix 2: Skills Audit Questionnaire

Divisional Skills Audit

*"If only we knew what we know."*

Please take 10 minutes and complete this questionnaire as honestly as possible in order to assist us in plotting skills and expertise in some areas within this division. All results will be made available to you once it has been reviewed and analysed.

Name: Surname:

| 1. Please indicate your PROFICIENCY per subject matter | | | | | |
|---|---|---|---|---|---|
| SUBJECT MATTER | I am **not skilled** in this subject. | I am **slightly skilled** in this subject. | I have **some experience** in this subject but need to improve. | I have **a good level of skill** in this subject but there is room to improve. | I am an **expert** in this subject and could train others on it. |
| Subject A | 0 | 1 | 2 | 3 | 4 |
| Subject B | 0 | 1 | 2 | 3 | 4 |
| Subject C | 0 | 1 | 2 | 3 | 4 |
| Subject D | 0 | 1 | 2 | 3 | 4 |
| Subject E | 0 | 1 | 2 | 3 | 4 |
| Subject F | 0 | 1 | 2 | 3 | 4 |
| Subject G… | 0 | 1 | 2 | 3 | 4 |
| Subject R | 0 | 1 | 2 | 3 | 4 |

| 2. Please indicate your LEVEL OF EXPERIENCE per subject matter | | | | | |
|---|---|---|---|---|---|
| SUBJECT MATTER | I have **no experience** in this topic. | 1 - 2 Years | 2 – 6 Years | 6 – 10 Years | 10 Years + |
| Subject A | 0 | 1 | 2 | 3 | 4 |
| Subject B | 0 | 1 | 2 | 3 | 4 |
| Subject C | 0 | 1 | 2 | 3 | 4 |
| Subject D | 0 | 1 | 2 | 3 | 4 |
| Subject E | 0 | 1 | 2 | 3 | 4 |
| Subject F | 0 | 1 | 2 | 3 | 4 |
| Subject G… | 0 | 1 | 2 | 3 | 4 |
| Subject R | 0 | 1 | 2 | 3 | 4 |

## Appendix 3: Summary of the conducted group interviews

### Determining the subject matters and the sample population

| Group Interview 1 | |
|---|---|
| Purpose: | ▫ to identify the most important subject matters (domains), members of this division were occupied with.<br>▫ to establish if there existed any key individuals outside the specific business area that members were supposed to engage with in order to better their knowledge in the identified knowledge domains. |
| When conducted: | This interview was organised right at the beginning of the research; soon after the researcher was granted permission to conduct her research within this business unit. |
| Duration: | One hour. |
| Questions asked: | 1. *In your opinion, what are the main subject matters that the people within your respective sub-divisions are occupied with?*<br>a. *Think about their day to day activities and what they are predominantly busy with.*<br>b. *Also consider on which of these identified subject matters most employees within this division should be engaging with one another.*<br>2. *Considering these identified subject matters (question 1), are there any individuals within other business areas that your employees should be engaging with in order to learn more about these subject matters?* |
| Outcomes: | ▫ Overall the four managers presented 18 subject matters they considered to embrace the main endeavours their employees were occupied with on a daily basis.<br>▫ The identified subject matters included: *CC, SR, Queue Management (QM), Debt and Credit Book, SMC, Data Warehousing, Business Intelligence (BI) Reports, Extract, Transform, Load (ETL), DAM, Geographical Information Systems (GIS), Programming* and *Tool Administration* as well as seven other undisclosed areas[51].<br>▫ All four managers were of the opinion that there were no key individuals in other business areas that their employees needed to engage with regarding the identified subject matters. |
| Implementation of answers: | The identified subject matters were applied to:<br>▫ the Skills Audit (where employees had to rate themselves in terms of proficiency and experience with regards to the identified subject matters); and<br>▫ the first SNA (where employees had to indicate their level of interaction with their peers regarding these subject matters) |

### Confirming the accuracy of the outcomes of the skills audit

| Group Interview 2 | |
|---|---|
| Purpose: | ▫ to confirm the correctness of the results obtained from the Skills Audit questionnaire. |

[51] In order to protect the confidentiality of the organisation, the identities of these subject matters remain confidential.

| | |
|---|---|
| When conducted: | This interview was organised just after the results of the Skills Audit were combined into a PowerPoint document. |
| Duration | Three hours. Due to the lengthy discussions in reviewing the correctness of these results, this interview had to be conducted over two sessions. |
| Questions asked: | The researcher presented a PowerPoint document to the participants. Each slide represented one of the 18 subject matters (that were identified during the first group interview) and by means of a bubble chart (very similar to the charts presented in ***Appendix 6***) indicated the participants' skills level as well as their years of experience.<br>1. *Have a look at this slide indicating the proficiency of the members within your division in terms of the subject matter indicated on top. The bubble chart represents their skills level in terms of experience as well as proficiency. The more experienced they are (in terms of years), the bigger the bubble. To make it easier to differentiate between the numbers of years' experience, the bubbles have also been colour coded. The level of proficiency is indicated by the legend on the left where '4' means someone is an expert; '3' signifies a good level of skill but the person can still improve; '2' implies someone has some experience but still need to develop and '1' indicates that someone has had very little experience regarding this subject matter.*<br>a. *Do you agree with where each individual is plotted?*<br>b. *Why? / Why not?* (depending on the answer to the above question)<br>The above questions were repeated for each participant within each of the 18 subject matters. |
| Outcomes: | ▫ While the managers agreed with many of the original ratings of participants, the following amendments were noted:<br>o Regarding *registration*, *revenue*, *debit and credit book*, *cash collection* and *data warehousing*, ID18 had to be moved down from and expert to a highly skilled level and ID13 had to be moved upwards from a highly skilled to an expert level.<br>o In terms of *undisclosed subject matter A and undisclosed subject matter B ,* ID2, ID10, ID15, ID21, ID23 and ID31 had to be moved upwards from a highly skilled to an expert level, while ID18 had to be moved down from and expert to a highly skilled level.<br>o On the topic of *income tax*, ID18 had yet again to be moved down from and expert to a highly skilled level while ID31 and ID35 had to be moved upwards from a highly skilled to an expert level.<br>o Considering *CC*, ID40 had to be moved down from and expert to a highly skilled level.<br>o Once again ID40 had to be moved down from and expert to a highly skilled level on the subject of *undisclosed area C* while ID10, ID31 and ID35 had to be moved upwards from a highly skilled to an expert level.<br>o With regards to *QM*, ID7 and ID22 had to be moved upwards from a highly skilled to an expert level, while ID40 had to be moved down from a highly skilled to a somewhat experienced level.<br>o Concerning *returns*, ID10, ID31 and ID35 had to be moved upwards from a highly skilled to an expert level, while ID43 had to be moved down from a highly skilled to a somewhat experienced level.<br>o In terms of *BI reports*, ID7, ID13, ID26, ID29 and ID30 all had to be moved upwards from a highly skilled to an expert level, while ID8, ID19, ID38 and ID43 had to be moved down from and expert to a highly skilled level and ID17 and ID47 had to be moved down from a highly skilled to a somewhat experienced level. |

| | |
|---|---|
| | o Reflecting on the results of *ETL*, ID6, ID13, ID19 and ID35 had to be moved upwards from a highly skilled to an expert level, while ID40 had to be moved down from and expert to a highly skilled level and ID18, ID17, ID42, ID44 and ID47 all had to be moved down from a highly skilled to a somewhat experienced level.<br>o As for *DAM*, ID7 and ID13 ID35 had to be moved upwards from a highly skilled to an expert level, ID4 had to be moved upwards from a somewhat experienced to a highly skilled level. Similarly ID40 had to be moved down from and expert to a highly skilled level and ID18 and ID48 had to be moved down from a highly skilled to a somewhat experienced level.<br>o Considering *GIS*, ID2 and ID15 ID35 had to be moved upwards from a highly skilled to an expert level, while once again ID40 had to be moved down from and expert to a highly skilled level and ID17 and ID18 had to be moved down from a highly skilled to a somewhat experienced level.<br>o Finally, with regards to *programming*, ID13, ID25 and ID29 all had to be moved upwards from a highly skilled to an expert level, while ID40 had to be moved down from and expert to a highly skilled level. |
| Implementation of answers: | A list of confirmed experts and highly skilled members were needed in order to:<br>▫ compile the skills map that were distributed amongst participants; and<br>▫ to identify who the experts and highly skilled members were when conducting both SNA's. |

## Assessing the findings of the first SNA

| Group Interview 3 | |
|---|---|
| Purpose: | ▫ to communicate the results of the first SNA to the respective managers in order to see if they could affirm or explain what was mapped. |
| When conducted: | This interview was prearranged once the results of the first SNA have been plotted and analysed. |
| Duration | One hour and 30 minutes. |
| Questions asked: | The researcher presented a PowerPoint document to the participants. Each of the 18 subject matters that were originally investigated was presented in terms of two slides regarding responsiveness indicating: *in-degree centrality* as well as *out-degree centrality*. Four additional slides representing *responsiveness, engagement and trust* were also presented. In addition members of each sub-division were assigned a different colour.<br>*1. Do you think that this network depicts a real reflection of how people interact within and between your respective sub-divisions?*<br>*a. Is there anything that stands out from this network that you find surprising?*<br>*b. Are the correct people being approached for information?*<br>c. *If not, why do you think they are not being approached?*<br>The above questions were repeated for each of the 18 subject matters.<br>*2. In terms of responsiveness, how would you explain the following observations*<br>*a. Although not one person stood out as not responding to many others, ID8 identified various members who often failed to respond to her requests.*<br>*b. ID13, ID26 and ID36 identified some network members who usually responded late to them.*<br>*3. Regarding the level of engagement, do you agree that:*<br>*a. ID8 and ID21 were identified by quite a few members as colleagues* |

| | |
|---|---|
| | *whose 'input hardly ever assists'.*<br>*b. Various network members regarded ID19 and ID28 as members 'who only point to information'.*<br>*c. ID1, ID3, ID6, ID7, ID10, ID13, ID14, ID17, ID31, ID32, ID35, ID36, ID39, ID40, ID47, D48 and ID49 have been identified by many as network members who 'actively assists regarding work related problems whom they learn from'.*<br>*4. Concerning trust within the network, do you think the network is correct when it depicts that:*<br>*a. Most network members felt very comfortable in sharing their ideas and opinions with ID1, ID3, ID4, ID6, ID8, ID12, ID13, ID14, ID17,ID19, ID28, ID29, ID30, ID31, ID37, ID38, ID39, ID40, ID43, ID44, ID45, ID46, ID47, ID48 and ID49*<br>*b. A few network members were very uncomfortable with sharing ideas with ID7 and ID9.* |
| Outcomes: | 1. Interaction in terms of the knowledge dimension (in- and out-degree centrality)<br>a. In general managers believed that overall the correct people were approached for knowledge and information.<br>b. They attributed incidents where experts or highly-skilled members were not approached by others for information to the fact that they were not currently working in that specific domain.<br>c. Managers also acknowledged the fact that the sub-divisions were working in silos, hence someone in one sub-division would rather approach a peer in the same sub-division than an expert in another sub-division.<br>d. Experts not contacting one another directly could be attributed to underlying competition that existed between experts.<br>e. It was also noted that ID31 was often contact in areas where she was not regarded as an expert or even highly skilled. Managers attributed this phenomenon to the fact that since ID31 was very knowledgeable regarding many tax related subjects she was often contacted for any tax related issue. Moreover, this individual would make it her task to find the correct answer if she did not know it herself.<br>2. Responsiveness<br>a. Managers were of the opinion that ID8 was notorious for approaching others to do her work. As a consequence it could be that some people grew tired of this, hence the non-responsiveness.<br>b. It was also noted that ID13, ID26 and ID36 had very high standards and that they expected the same from their colleagues. The reason for a 'late' response could thus potentially be that the response was in time but not necessarily days before the set deadline.<br>3. Engagement<br>a. Managers were of the opinion that ID8 and ID21 were not very skilled employees in general. Their lacking ability could thus be a reason for their peers indicating that as a rule their input is not of much help.<br>b. ID28 and ID19 were identified as very competent employees with very high workloads. Managers concurred that these employees could be pointing to information but underlined that the information they could be pointing to was very comprehensive.<br>c. Managers agreed with the employees who were indicated as people whom their peers actively learned from, yet is was pointed out that ID7 and ID35 only did so when they had time available, if not, they would only |

| | |
|---|---|
| | point to information.<br>4. Trust<br>a. Managers agreed that the correct individuals were identified as people whom others felt very comfortable with in sharing their ideas and opinions with. They were of the opinion that their level of expertise as well as personality played an important part in this regard.<br>b. It was concurred that ID9 and ID21 did not possess much in depth knowledge regarding the work the others performed and as a result could be the reason why some of their peers seemed very uncomfortable in sharing work-related ideas with them. |
| Implementation of answers: | ▫ These answers were used to put some of the SNA results into perspective i.e. why experts in general did not contact one another directly; and to confirm if the overall results were a true reflection of the relationships between and within the respective sub-divisions. |

## Confirming the CoP subject matters

| Group Interview 4 | |
|---|---|
| Purpose: | ▫ to convey the CoP subject matters that participants showed most interested in based on a quick poll.<br>▫ to decide on the subject matters of the CoPs. |
| When conducted: | This interview was organised once the results of the first SNA have been plotted and analysed; and after a quick poll was conducted amongst participants in order to determine on which subject matters they would most like to establish a CoP. |
| Duration | Ten minutes |
| Questions asked: | The researcher presented a PowerPoint document to the participants. Each of the 18 subject matter networks that were originally investigated was presented. Each slide also indicated the number of participants (including the number of experts and the number of highly skilled members) who showed interest in joining a CoP on that particular subject.<br>*1. Based on this presentation, which four subject matters do you think CoPs should be created on?* |
| Outcomes: | ▫ The managers all agreed that in order for the CoPs to succeed, it was important for user buy-in and therefore believed that it would be best to create CoPs that most people were interested in joining. |
| Implementation of answers: | ▫ As a consequence CoPs were created for the following domains:<br>o CC;<br>o DAM;<br>o SMC; and<br>o SR. |

## Considering the results of the second SNA and CoP participation

| Group Interview 5 | |
|---|---|
| Purpose: | ▫ to convey the level of CoP participation as well as the results of the second SNA to the respective managers in order to see if they would agree with the results. |
| When conducted: | This interview was arranged after the online CoPs came to an end and the results of the second SNA have been plotted and analysed. |
| Duration | One hour. |
| Questions asked: | The researcher presented a PowerPoint document to the participants. This time two slides (depicting the status before and after KM interventions) were presented for |

| | |
|---|---|
| | each of the following dimensions: *knowledge dimension*, *frequency of interaction*, *responsiveness*, *engagement* and *trust*. The researcher also indicated which network members opted not to participate in the respective CoPs and who were as a result not part of the second SNA.<br>*1. In terms of the knowledge element it became clear that in the CC network ID25 became part of the network while ID5 and ID21 became isolates.*<br>*a. How would you explain this?*<br>*b. How would you explain the increased 'in-degree' rating of ID37?*<br>*2. Studying the DAM, SR and SMC networks, after implementing CoPs, isolates dropped to only one per network (remaining isolates were ID27 in the DAM and SR networks and ID25 in the SMC network).*<br>*a. How would you explain this?*<br>*b. How would you explain the overall increase regarding reciprocity in these networks?*<br>*3. As far as frequency of interaction is concerned, there was a decline in the network density indicating that people were contacting one another less frequently on a monthly and weekly basis. The number of ad hoc instances where people contacted one another for information also declined.*<br>*a. How would you explain this decline in contact?*<br>*4. In terms of responsiveness, how would you explain the following observations?*<br>*a. No one failed to respond. The number of actual participants who responded late, diminished significantly. (Instances where two or more network members identified colleagues that responded late went down from three to only one. Only ID30 was still identified as responding usually late to both ID7 and ID31.*<br>*5. After deploying the KM interventions, the levels of engagement changed especially in terms of the number of participants whose input hardly ever assist and network members who only pointed to information. In both instances these numbers increased.*<br>*a. Do you think this observation is accurate?*<br>*b. Why?*<br>*6. In terms of network members' level of comfort in sharing ideas and ultimately creating new knowledge, only ID23 indicated that she was still very much uncomfortable in sharing ideas with both ID7 and ID28. Conversely, the number of network members who indicated that they felt 'not so comfortable' in sharing ideas with their colleagues increased somewhat.*<br>*a. Do you agree with this observation?*<br>*b. Why do you think it happened?* |
| Outcomes: | 1. Knowledge element: CC network<br>a. Managers reasoned that ID25 became part of the CC network as she did have some knowledge and experience regarding CC (she was contacted by both ID40 and ID28 for information) but was not actively working on that subject matter. ID5, a new person, could have lost his connection with this network since ID31 (his only connection to this network) was seconded to another division and he did not build any new relations since. ID21 lost his connection to the network due to the fact that highly skilled member ID28 stopped contacting him regarding CC.<br>b. The occurrence where ID37 was now contacted by so many regarding CC could be attributed to the fact that she has been with the organisation for many years and although she was not recognised as a CC expert or highly skilled member, she did now quite a lot about CC.<br>2. Knowledge element: DAM, SR and SMC networks |

<table>
<tr><td></td><td>
a. ID27 was functioning more in an administrative role, although she expressed an eagerness to expand her skills. As mentioned before, ID25 does not really work with SMC data. This could also explain why ID25 was not interested in joining the SMC CoP.<br>
b. Everyone in the sub-divisions has some knowledge regarding DAM, SR and SMC so technically they should be conversing a lot more. In general managers believed that overall the correct people were approached for knowledge and information. SR was rather newly introduced to the division and everyone seemed to be experiencing some difficulties in understanding it. This could also explain the increased participation and the increase in reciprocity.<br>
3. Frequency of interaction<br>
a. Managers pointed out that the second SNA was conducted during a very busy period of the organisation, especially within their division, where tight deadlines had to be met. This could impede on the frequency of interaction within the division.<br>
4. Responsiveness<br>
a. According to the managers, there could be some elements of ego attributed to the one person who was identified as usually responding late. Then again, it could also be that he was just very busy and therefore could not respond in time.<br>
5. Engagement<br>
a. Managers concurred that as many non-experts joined the CoPs and became part of these networks, it could be that their input did not add much value. In addition - despite the distribution of the list indicating who the experts were - individuals could still be contacting the wrong people for information due to cultural and political reasons, hence they could not actively assist and therefore only pointed to information.<br>
6. Trust<br>
a. In general managers attributed the reason for ID23 to feel very uncomfortable, despite the KM interventions, to share ideas with ID7 and D28, to a personality issue. Both ID7 and ID28 were very busy and not always immediately available to ID23 and as a result she could have decided that she does not feel comfortable to share her ideas with them.
</td></tr>
<tr><td>Implementation of answers:</td><td>▫ This interview served to confirm if the overall results were a true reflection of the relationships between and within the respective sub-divisions. It also assisted to put some of the specific SNA outcomes (e.g. why people only pointed to information) into context.</td></tr>
</table>

**Appendix 4: Letter of Informed Consent**

## Participant Informed Consent

1. **Research Project:** Enriching knowledge networks – considering synergies between Social Network Analysis, Communities of Practice and Knowledge Maps.

2. I, _______________, hereby voluntarily grant my permission for participation in the project as explained to me by Ronèl Davel.

3. The nature, objective, possible safety and health implications have been explained to me and I understand them.

4. I understand my right to choose whether to participate in the project and that the information furnished – including my name and surname as well as the division I work for - will be handled confidentially. I am aware that the results of the investigation may be used for the purposes of publication.

5. Upon signature of this form, you will be provided with a copy.

Signed: _______________________ Date: _______________

Witness: _______________________ Date: _______________

Researcher: _______________________ Date: _______________

## Appendix 5: CoP Membership and Level of Participation

### Summary of CoP activity

| | | CC | DAM | SR | SMC |
|---|---|---|---|---|---|
| Participation | Number of members who joined the CoP | 20 | 22 | 19 | 20 |
| | Experts/highly skilled members/knowledge authorities who joined | 5 | 8 | 10 | 12 |
| | Number of questions posed | 4 | 6 | 2 | 2 |
| | Number of general contributions posted | 1 | 1 | 0 | 0 |
| | Average number of replies posted per question | 1.75 | 1.3 | 2 | 2 |
| | Average number of likes per answer/contribution | 1.3 | 0.75 | 0.5 | 1 |
| | Number of discussions that were not responded to[52] | 0 | 1 | 0 | 0 |

### CC CoP participation

| Participant | General Contributions | Questions | Comments | Answers | Likes Received |
|---|---|---|---|---|---|
| ID5 | 0 | 0 | | 0 | 0 |
| ID6 | 0 | 0 | | 0 | 0 |
| ID7 | 0 | 0 | 1 | 2 | 2 |
| ID10 | 0 | 0 | | 0 | 0 |
| ID13 | 0 | 2 | 1 | 2 | 2 |
| ID16 | 0 | 0 | 0 | 0 | 0 |
| ID17 | 0 | 0 | | 0 | 0 |
| ID23 | 0 | 1 | | 0 | 0 |
| ID26 | 0 | 0 | | 0 | 0 |
| ID28 | 0 | 0 | | 1 | 2 |
| ID30 | 0 | 0 | | 0 | 0 |
| ID36 | 0 | 0 | | 0 | 0 |
| ID37 | 0 | 1 | | 0 | 0 |
| ID38 | 0 | 0 | | 0 | 0 |
| ID40 | 1 | 0 | | 0 | 2 |
| ID41 | 0 | 0 | | 0 | 0 |
| ID42 | 0 | 0 | | 0 | 0 |
| ID43 | 0 | 0 | | 0 | 0 |
| ID45 | 0 | 0 | | 0 | 0 |
| ID46 | 0 | 0 | | 0 | 0 |

52 An important measure of community responsiveness, which in turn affects key factors such as trust (Connected Educators, 2011:15).

## DAM CoP participation

| Participant | General Contributions | Questions | Comments | Answers | Likes Received |
|---|---|---|---|---|---|
| ID2 | 0 | 0 | | 1 | 2 |
| ID4 | 0 | 1 | | 0 | 0 |
| ID5 | 0 | 0 | | 0 | 0 |
| ID6 | 0 | 0 | | 0 | 0 |
| ID7 | 0 | 0 | | 0 | 0 |
| ID10 | 0 | 0 | | 0 | 0 |
| ID11 | 0 | 3 | 2 | 0 | 0 |
| ID13 | 0 | 1 | | 1 | 2 |
| ID16 | 0 | 0 | 1 | 0 | 0 |
| ID19 | 1 | 0 | | 0 | 0 |
| ID23 | 0 | 0 | | 0 | 0 |
| ID25 | 0 | 0 | | 0 | 0 |
| ID27 | 0 | 0 | | 0 | 0 |
| ID28 | 0 | 0 | | 0 | 0 |
| ID36 | 0 | 1 | | 0 | 0 |
| ID38 | 0 | 0 | | 0 | 0 |
| ID40 | 0 | 0 | | 0 | 0 |
| ID41 | 0 | 0 | 1 | 4 | 2 |
| ID43 | 0 | 0 | | 0 | 0 |
| ID44 | 0 | 0 | | 0 | 0 |
| ID45 | 0 | 0 | | 0 | 0 |
| ID46 | 0 | 0 | | 0 | 0 |

## SR CoP participation

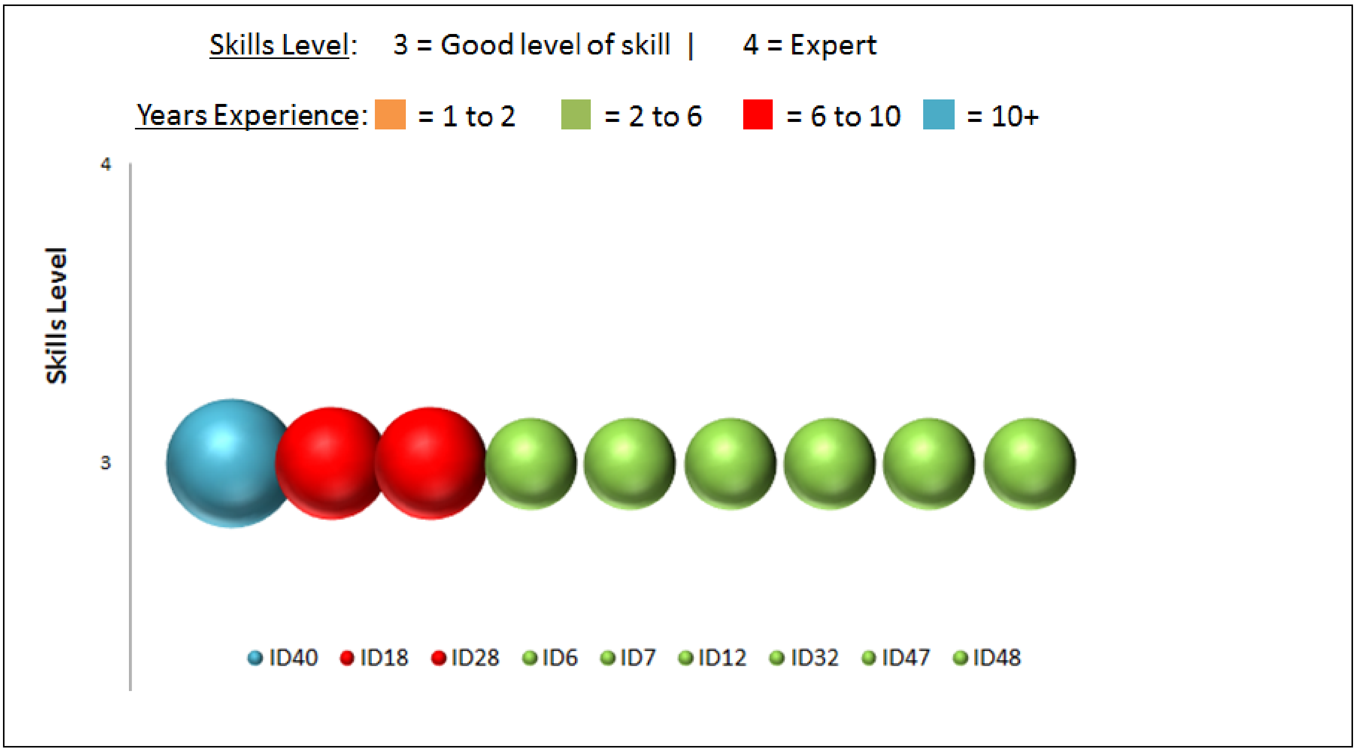
| Participant | General Contributions | Questions | Comments | Answers | Likes Received |
|---|---|---|---|---|---|
| ID5 | 0 | 0 | 0 | 0 | 0 |
| ID7 | 0 | 0 | 0 | 0 | 0 |
| ID10 | 0 | 0 | 0 | 0 | 0 |
| ID11 | 0 | 0 | 0 | 0 | 0 |
| ID13 | 0 | 1 | 0 | 0 | 0 |
| ID17 | 0 | 1 | 1 | 0 | 1 |
| ID21 | 0 | 0 | 0 | 0 | 0 |
| ID23 | 0 | 0 | 0 | 0 | 0 |
| ID26 | 0 | 0 | 0 | 0 | 0 |
| ID28 | 0 | 0 | 0 | 0 | 0 |
| ID31 | 0 | 0 | 0 | 2 | 0 |
| ID33 | 0 | 0 | 0 | 0 | 0 |
| ID36 | 0 | 0 | 0 | 0 | 0 |
| ID37 | 0 | 0 | 0 | 0 | 0 |
| ID38 | 0 | 0 | 0 | 0 | 0 |
| ID41 | 0 | 0 | 0 | 2 | 1 |
| ID44 | 0 | 0 | 0 | 0 | 0 |
| ID45 | 0 | 0 | 0 | 0 | 0 |
| ID46 | 0 | 0 | 0 | 0 | 0 |

### SMC CoP participation

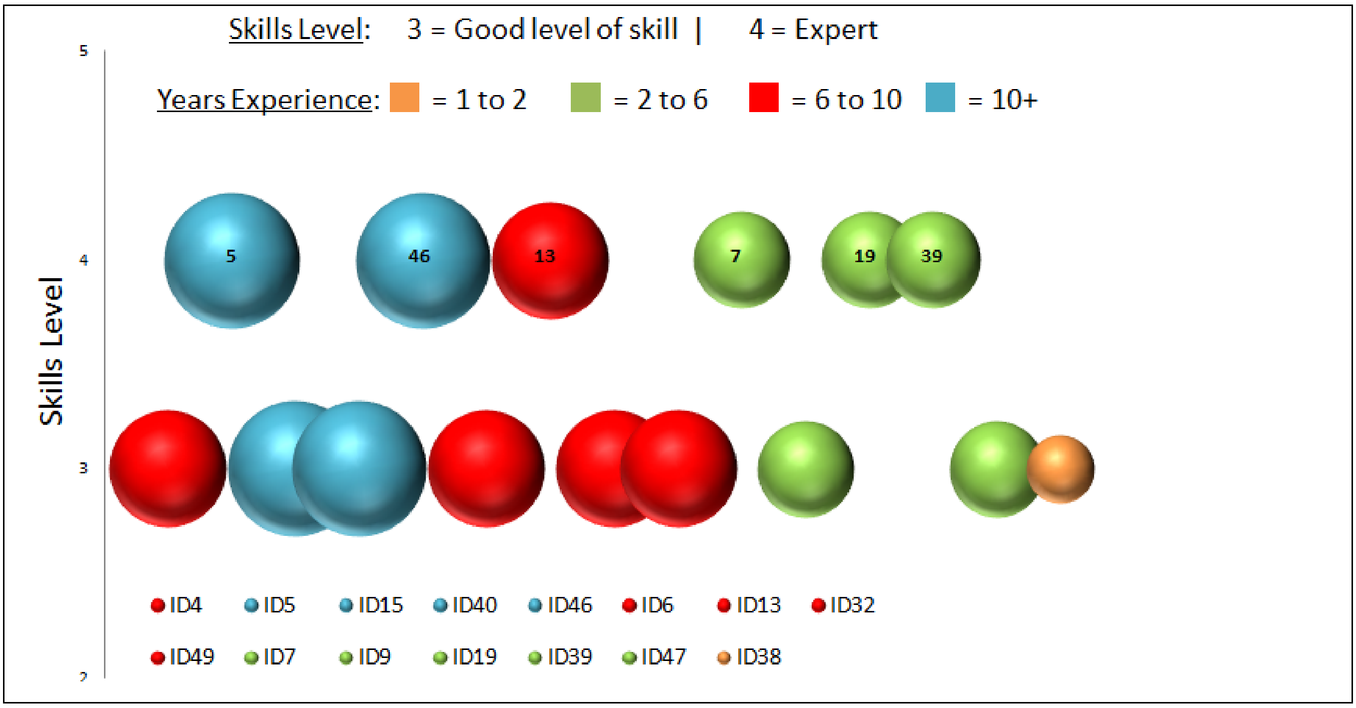
| Participant | General Contributions | Questions | Comments | Answers | Likes Received |
|---|---|---|---|---|---|
| ID4 | 0 | 0 | 0 | 1 | 0 |
| ID5 | 0 | 0 | 0 | 0 | 0 |
| ID6 | 0 | 0 | 0 | 1 | 1 |
| ID7 | 0 | 0 | 0 | 0 | 0 |
| ID10 | 0 | 0 | 0 | 0 | 0 |
| ID13 | 0 | 0 | 0 | 0 | 0 |
| ID17 | 0 | 0 | 0 | 1 | 0 |
| ID23 | 0 | 1 | 0 | 0 | 0 |
| ID26 | 0 | 0 | 0 | 0 | 0 |
| ID28 | 0 | 0 | 0 | 0 | 0 |
| ID31 | 0 | 0 | 1 | 0 | 0 |
| ID33 | 0 | 1 | 1 | 0 | 0 |
| ID37 | 0 | 0 | 0 | 0 | 0 |
| ID40 | 0 | 0 | 0 | 0 | 0 |
| ID41 | 0 | 0 | 0 | 1 | 1 |
| ID42 | 0 | 0 | 0 | 0 | 0 |
| ID43 | 0 | 0 | 0 | 0 | 0 |
| ID44 | 0 | 0 | 0 | 0 | 0 |
| ID45 | 0 | 0 | 0 | 0 | 0 |
| ID46 | 0 | 0 | 0 | 0 | 0 |

### Appendix 6: Results of the Skills Audit

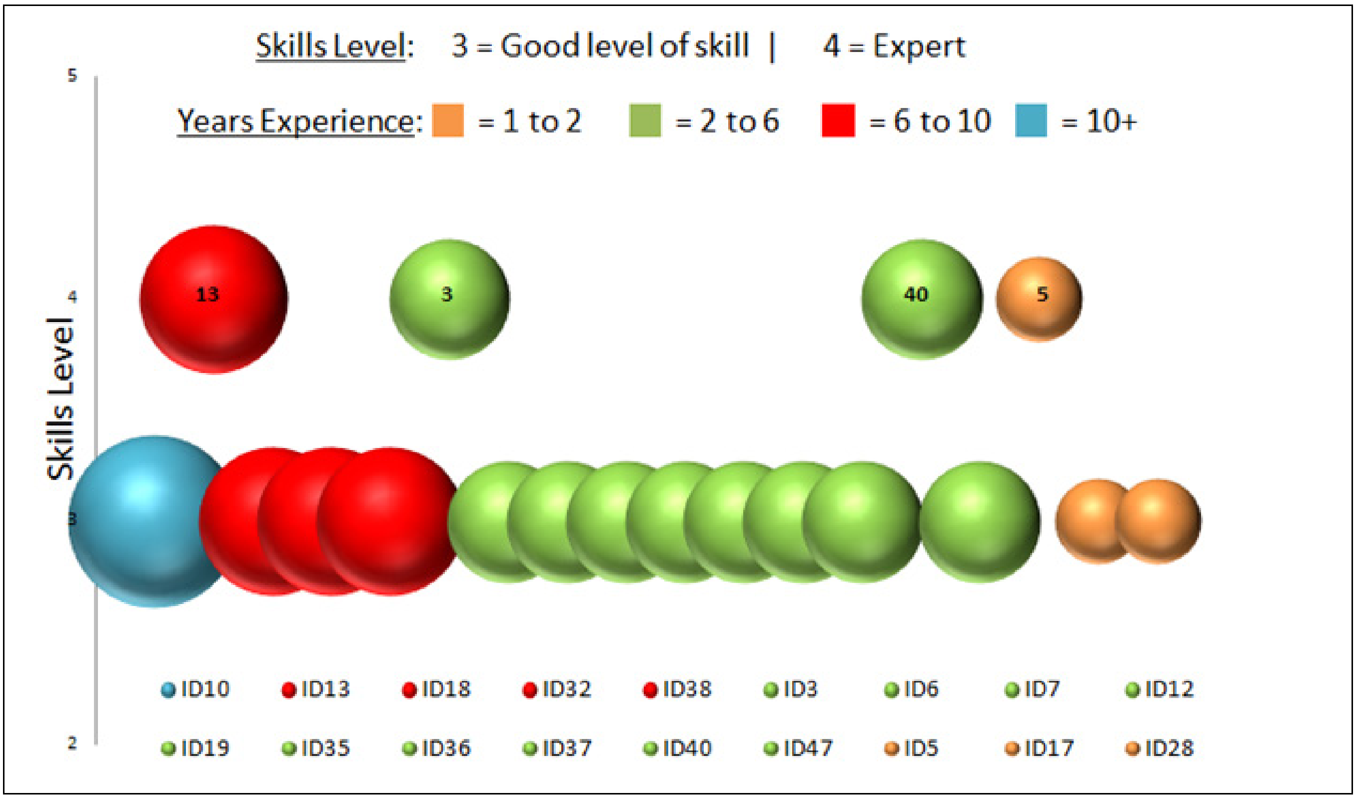
Of the 18 subject matters investigated, only four online CoPs were constructed. As a result only the skills audits of the corresponding subject matters are specified.



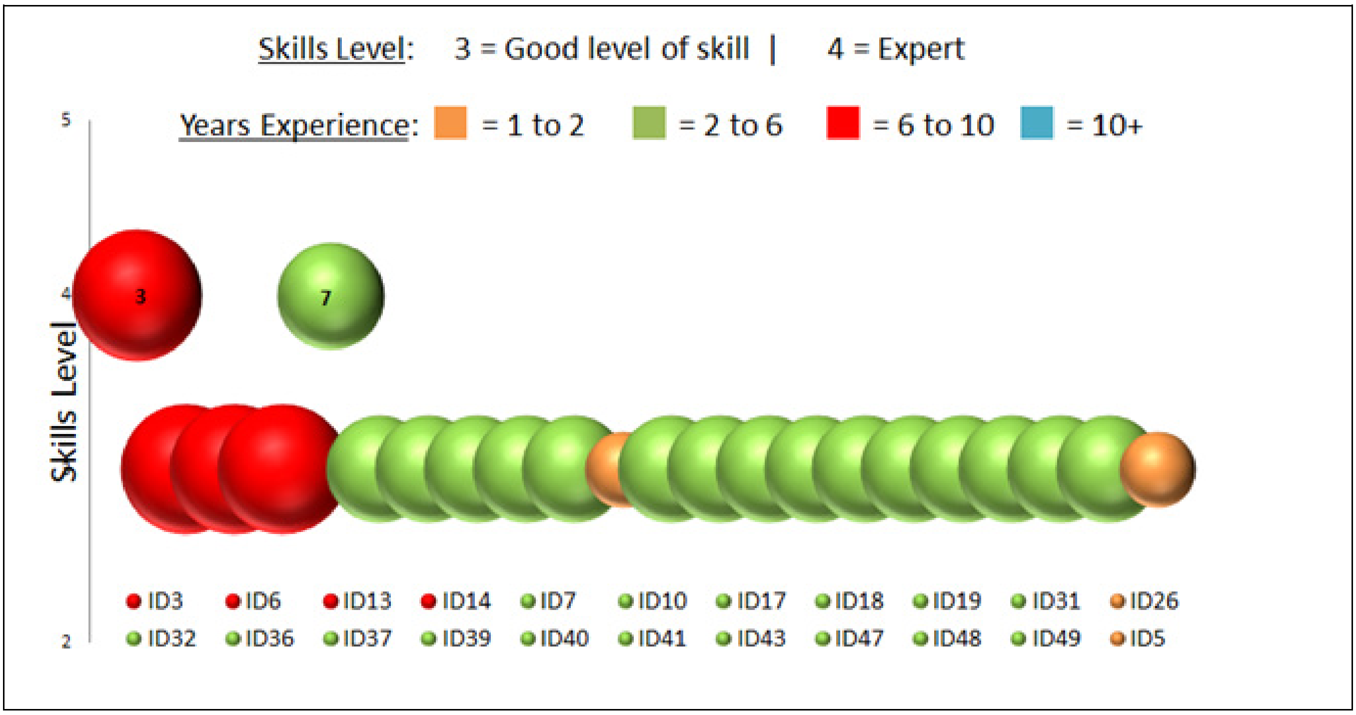

**Recognised experts in terms of Commodity Control**




**Recognised experts in terms of Data Analysis and Mining**




**Recognised experts in terms of Single Registration**




**Recognised experts in terms of Service Manager Cases**