

## **APPLICATION OF KNOWLEDGE NETWORK ANALYSIS TO IDENTIFY KNOWLEDGE SHARING BOTTLENECKS AT AN ENGINEERING FIRM**

Helms, Remko, Institute of Information and Computing Science, Utrecht University,  
Padualaan 14, Utrecht, The Netherlands, r.w.helms@cs.uu.nl

Buijsrogge, Kees, Department of Innovation Studies, Utrecht University, Heidelberglaan 2,  
Utrecht, The Netherlands, c.m.buijsrogge@geog.uu.nl

### **Abstract**

*The knowledge of an organization's employees is a valuable asset. Therefore organizations should ensure that their employees share their knowledge among each other. Knowledge exchanges between employees can be modelled as a network of relationships. To study these networks we have developed the Knowledge Network Analysis technique, which is based on Social Network Analysis and supports visual as well as quantitative analysis of knowledge networks. The goal of this technique is to identify bottlenecks in knowledge sharing in a particular knowledge area. In this paper we present the results of the application of Knowledge Network Analysis in an explorative case study. The goal of the case study is to explore the usefulness of Knowledge Network Analysis in identifying knowledge sharing bottlenecks. The case study results in a deeper understanding of how to translate the characteristics of the knowledge network and the employees in this network to the context of the case study organization. Moreover, the case study results have also been used to formulate recommendations to improve knowledge sharing at the case study organization.*

*Keywords: Knowledge Networks, Knowledge Network Analysis, Social Network Analysis, Knowledge Viscosity, Knowledge Velocity.*

## 1 INTRODUCTION

Informal networks are important for organizations because they promote the lateral sharing of knowledge within the organization (Wenger, 1998; Davenport & Prusak, 1998). These so-called knowledge networks make employees more effective in dealing with knowledge (Kanter, 2001), which contributes to the performance of the organization (Cross & Parker, 2004; Epple, Argote & Murphy, 1996). For example, Hansen (2002) studied 120 new product development projects in 41 business units of a large multiunit electronics organization and found that project teams completed their projects faster when they had short inter unit network paths to units that possessed related knowledge.

For companies it is important to know whether the knowledge networks in their organization function properly. A useful technique to study these knowledge networks has been developed in the field of social sciences: Social Network Analysis (Faust & Wasserman, 1994; Cross et al., 2004). This technique is used to study the social interaction between members of a particular group of people. It models the people in the group as nodes and the interaction between these people as arcs between the nodes, hence resulting in a social network. Besides visual analysis of social networks, the technique also provides algorithms to study the network quantitatively. Social network analysis has already been used to study knowledge networks by authors such as Anklam (2004), Cross et al. (2004), Meuller-Protmann & Finke (2004), and Liebowitz (2005). Their results show that these applications were useful in identifying knowledge management problems. However, these authors have typically applied social network analysis as it is and did not customize it for knowledge management. Therefore, we developed an extension to social network analysis that we refer to as: Knowledge Network Analysis (Helms & Buijsrogge, 2005). Instead of studying social networks we study knowledge networks, these networks focus on the lateral sharing of knowledge between the members of the network. Therefore, we added typical knowledge management aspects to social network analysis, such as knowledge management roles, expertise levels, knowledge flow viscosity and knowledge flow viscosity. These additions are used to identify knowledge management bottlenecks in these knowledge networks. In this paper we present the results of applying Knowledge Network Analysis at an engineering firm. It concerns an explorative case study to gain a deeper understanding of how particular characteristics of knowledge network can be translated to bottlenecks in knowledge sharing.

The remainder of this paper is organized as follows: In the following section we present two different types of knowledge networks that we identified. In section 3 we present our Knowledge Network Analysis technique. The application of our technique at an engineering firm is presented in section 4. The results of the case study are presented in section 5 and finally the discussion and conclusion are presented in section 6.

## 2 TYPES OF KNOWLEDGE NETWORKS

In knowledge networks the members of the network exchange knowledge with each other. Based on literature research we identified two types of knowledge networks that we refer to as: *knowledge pull networks* and *knowledge push networks*. Both types of knowledge networks are discussed in more detail in the following two sections.

### 2.1 Knowledge push network

Our knowledge push network (further referred to as push network) is inspired by the idea of “deep smarts” (Leonard & Swap, 2005). Deep smarts enable an employee to quickly analyze a situation and come up with a smart solution. An example is a computer engineer that is able to quickly identify a hardware problem without having to go through all the possible failure options systematically. When

the job performance of an employee with deep smarts is compared to an employee without deep smarts, the first will come up with a better solution and within a shorter time (Leonard et al., 2005). Therefore, it is important that employees with these deep smarts share their knowledge with their colleagues that have not developed that same level of deep smarts yet. An organization cannot leave it to chance that employees share their deep smarts. They should stimulate sharing of knowledge from experts to their less knowledgeable colleagues (Leonard et al., 2005). We refer to this sharing as the *pushing* of knowledge from the experts to their colleagues.

Knowledge that is referred to as deep smarts is typically stored in the employees' heads and hands. This makes this knowledge difficult to share and therefore not every type of knowledge exchange is as effective as another. For example, the exchange of knowledge by means of a presentation is very superficial while the exchange by means of a master – apprentice relationship is very rich (Leonard et al., 2005). The richness of the transfer is referred to as *viscosity* of the knowledge exchange, a term which was introduced by Davenport et al. (1998). In case of a rich knowledge exchange, we assume that the knowledge of the employee increases more than in the case of a superficial exchange. Consequently, only a rich exchange of knowledge will contribute to a substantial increase of the knowledge level of the receiver.

## 2.2 Knowledge pull network

Our knowledge pull network (further referred to as pull network) is based on the idea that employees are dependent on the knowledge of others to execute their job (Cross et al., 2004; Dixon, 2000). An example is a computer engineer who works on a project to develop a new computer system and consults a colleague to solve a particular design problem. The receiver of the knowledge expects a brief answer, which is based on the deep smarts of his colleague. But the actual deep smarts are not exchanged here.

In the pull network, the person who needs the knowledge *pulls* the knowledge from the person who has it. This requires that an employee has access to the knowledge of his colleagues. There are two possibilities for having access to the knowledge of others: directly and indirectly (Cross et al., 2004). In the case of direct access there is a one on one relation between the owner and the receiver of the knowledge. However, it is not always possible to have direct relationships with everybody, for example in large organizations. In the case of indirect access there is a relation between two employees through one or more other colleagues in the network. Indirect relationships substantially increase the reach of employees in the network (Hanneman, 2005).

An important aspect of having access to knowledge of others is that you can tap into this knowledge quickly, i.e. the speed of the knowledge exchange is important (Cross et al., 2004). For example, if you are working on a project with a deadline for next week, it is not desirable that it takes a month before you receive the knowledge that is required to meet the deadline. The speed of knowledge exchange is referred to as *velocity*, a term which was introduced by Davenport et al. (1998). The velocity of knowledge exchange is the time between contacting a colleague and finally receiving the requested knowledge from this colleague, either directly from him or via him from another colleague. The higher the velocity of the knowledge exchanges in the network the better it is for the job performance (Hansen, 2002).

## 3 KNOWLEDGE NETWORK ANALYSIS TECHNIQUE

This section provides a brief description of the Knowledge Network Analysis technique (Helms et al., 2005). First the basic concepts of constructing knowledge networks are presented. After that, we will present the network graphs and the indicators that are used for analyzing the knowledge networks.

### 3.1 Basic concepts

Social networks consist of peoples (nodes) and the interaction between these people (arcs) (Wasserman & et al., 1994). Translating nodes and arcs to the domain of Knowledge Network Analysis results in two basic concepts: knowledge actors (nodes) and knowledge flows (arcs). For the scope of a knowledge network we introduce a third concept: knowledge areas. This is motivated by the fact that each knowledge area requires its own knowledge management approach (Spek, Hofer-Alfeis & Kingma, 2002). The three basic concepts: knowledge area, knowledge actor and knowledge flow, are briefly described in the remainder of this section.

#### 3.1.1 Knowledge area

A knowledge area is defined as “a coherent cluster of insights, experiences, theories, and heuristics” (Schreiber, Akkermans et al., 2002). It represents a cluster of knowledge within an organization. An example of a knowledge area in an engineering firm is knowledge concerning the design of railroads or the design of jetties. Knowledge areas are a good measure for limiting the scope of the analysis because.

#### 3.1.2 Knowledge Actor

A knowledge actor is a person that exchanges knowledge with other persons, also knowledge actors, in a specific knowledge area. Each knowledge actor has a number of properties, which are used for analysis purposes. We defined the following properties that are of interest from a knowledge management point of view: **knowledge role**, **expertise level**, **function** and **location**.

**Knowledge roles** identify the role of an actor in a knowledge area and are derived from the knowledge management processes as described by Becerra-Fernandez (2004). The first role is the *knowledge creator* and indicates that the actor contributes to the creation of new knowledge in the knowledge area. The second role is the *knowledge sharer* and indicates that the actor acts as a knowledge steward or knowledge broker (Davenport et al., 1998; Dixon, 2000). The last role is the *knowledge user*, which indicates that the actor is a consumer of knowledge.

**Expertise level** is a measure for the degree or quality of the knowledge of an actor (Becerra-Fernandez, 2004). Actors with a high level of expertise are considered to perform their job better than others with a lower level of expertise (Leonard et al., 2005). We identified three levels of expertise. The first level is *trainee*, which indicates that an actor mainly possesses theoretical knowledge and heavily depends on others for the execution of his job. The second level is *specialist*, which indicates that an actor has mastered one aspect of the knowledge area in depth. The third and highest level is *expert*, which indicates that an actor has a broad experience in the knowledge area and contributes to the further development of it.

The **function** specifies the role or responsibility of an actor in the organization. In the research presented in this paper we use the project roles that are distinguished by the case study organization: engineer, project manager, and consultant. An *engineer* is executing the project tasks. A *project leader* is responsible for the project, i.e. meets the time, budget and quality constraints. Finally, a *consultant* is responsible for acquiring new projects.

Allen (1977), Allen & Lientz (1979) Cross et al. (2004) have shown that the geographical location of employees has a negative impact on the likelihood that they will communicate with each other. Therefore, the last property is the **location** of an actor.

### 3.1.3 Knowledge flow

Exchanges of knowledge between two actors are referred to as knowledge flows (Hansen & Kautz, 2005). Two properties of these directed knowledge flows are of interest in the context of knowledge management: viscosity and velocity (Davenport et al., 1998). As mentioned in section 2, these properties provide information on the richness and the speed of the knowledge that is transferred respectively.

## 3.2 Analysis of knowledge networks

Knowledge networks can be analysed visually and quantitatively, just like social networks (Hanneman, 2005). The analysis of knowledge network is used for the identification of knowledge sharing bottlenecks in knowledge networks. For the visual analysis of a knowledge network a knowledge network graph is created, in which nodes represent knowledge actors, arrows represent knowledge flows between individual actors and arrowheads indicate the direction of knowledge flows. Visual cues are used to model the properties of actors and knowledge flows. Knowledge roles are modelled using different shapes for the nodes, knowledge creators are represented by a square (■), knowledge sharers are represented by a dot (●), and knowledge users are represented by a triangle (▲). Furthermore, the level of expertise is indicated by the size of the node, the smallest size representing trainees, medium size representing specialists, and the biggest size representing experts. Finally, the colour of the node indicates the geographical location of an actor. Properties of knowledge flows are indicated as a number besides the arrow. In a push network it represents the viscosity of the knowledge flow and in the pull network it represents the velocity of the knowledge flow. An example of a knowledge network is shown in figure 1.

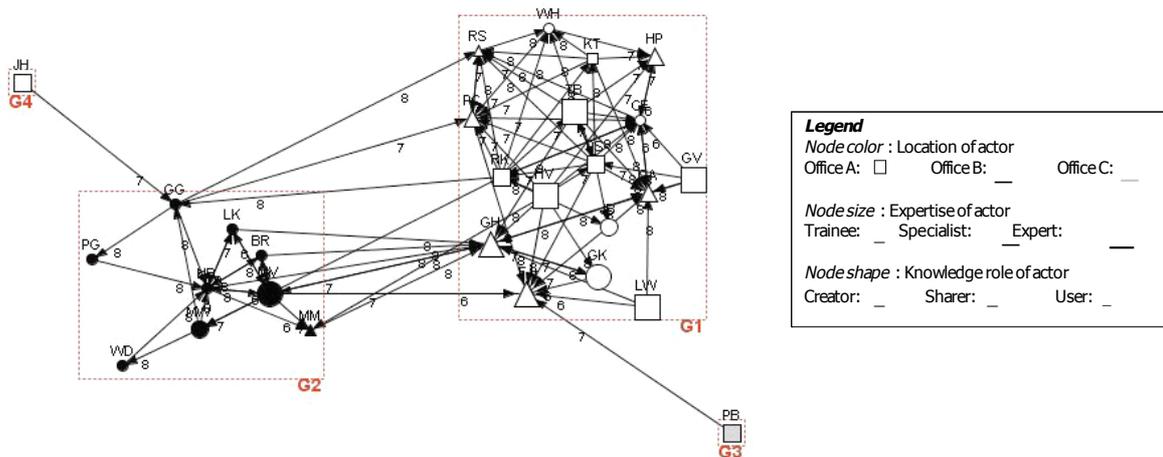


Figure 1. Push network<sup>1</sup>

For quantitative analysis a number of functions and indicators are used, which have been developed for social network analysis and are based on graph theory (Faust et al., 1994). Some of the indicators address analysis on network or group level while other indicators address analysis on the level of individual actors (node level). On network/group level we use the following indicators:

<sup>1</sup> The placement of nodes in the visualization is determined by the SpringEd algorithm, which is a fairly straightforward implementation of Eades' Spring Embedder (Eades, 1984). Fundamentally, repelling forces are given to every pair of non-adjacent nodes, and attractive forces are given to every pair of adjacent nodes. Following this spring model, non-adjacent nodes are spread well one the plane and adjacent nodes are placed near each other.

**(1) Mean shortest path:** An indicator for the distance between actors in the network. As such it is also a measure for the indirect adjacency (i.e. connections) of actors in the network. A low value ( $<2$ ) of this indicator for pull networks indicates that actors have good access to knowledge of other actors; it is just 1 or 2 steps away from them.

**(2) E/I index:** An indicator for the internal or external orientation of a group of actors. Its value can vary from -1 (only internal connections) to 1 (only external connections). The E/I index can be used for both push and the pull networks. This index reveals deficiencies, i.e. too much internal or external orientation, in the orientation of a pre-defined group of actors.

**(3) Community:** An algorithm that determines which actors belong to a specific community, i.e. strong connections within a group of actors and looser connections between the groups. The algorithm is based on the Community algorithm from Girvan and Newman (2002) and provides the community structure of the network. Communities are represented in knowledge network graphs by a box around actors that belong to that community.

On node level we use the following indicators:

**(4) In/out-degree:** The in-degree is an indicator for the number of incoming knowledge flows and the out-degree is an indicator for the number of outgoing knowledge flows of an actor. The in/out degree is used to determine the knowledge role of each actor in (push or pull) a network. An actor is a knowledge creator if the in-degree divided by the out-degree is smaller than 0,5, an actor is a knowledge user if the in-degree divided by the out-degree is bigger than 2,5, and a knowledge sharer if the in-degree divided by the out-degree is between 0,5 and 2,5. In practice knowledge actors do not have just one role but can take different knowledge roles. What is identified here is therefore the dominant role of the knowledge actor. In other words, a knowledge sharer can sometimes also fulfil the knowledge creator role but for most colleagues in the network he is a knowledge sharer.

**(5) Out-degree centrality:** An indicator for the central position of actors in a network. A high value of this indicator shows that the actor provides many people in a (push or pull) network with knowledge. By providing many actors with knowledge the actor is said to be influential (Hanneman, 2005), because he reaches many actors in the (pull or push) network with his knowledge.

**(6) Power:** An indicator for the control that an actor has over other actors. An actor is said to have high power if he has a high out-degree (provides many people with knowledge) and the actors that he is connected to have a low in-degree (have no alternative sources of knowledge). If an actor with high power leaves the organization, the actors that depend on this actor become disconnected what will negatively influence the growth of their expertise level (push network) and their job performance (pull network).

For the visual and quantitative analysis of the knowledge networks we have used the NetMiner tool. A study by Huisman and Van Duijn (2004) showed that this tool offers good support for data manipulation, has a very user-friendly user interface and supports visual, statistical and non-statistical analysis.

## **4 DATA COLLECTION**

The explorative case study was conducted at a knowledge-driven consulting and engineering firm that is active in the following fields: Infrastructure, Facilities and Environment. Worldwide they employ approximately 10,000 people. The department that participated in the case study is located in the Netherlands and employs 65 people. Together with the manager of the department we identified one knowledge area for conducting our knowledge network analysis: Civil Engineering. This knowledge area was selected using the Knowledge Strategy Process, which selects the knowledge area that has the highest contribution to the business goals (Spek et al., 2002). The number of people working in this knowledge area is 31 and 28 of them were able to participate in this research. These 28 people are

spread over 3 offices in different cities, respectively 18, 9 and 1 people. The group of 28 people consists of 14 engineers, 11 project leaders, and 3 consultants.

We have collected the data for our knowledge network analysis by means of a survey. The function, location and expertise level of each actor have been determined with the help of the HRM department. Every respondent in the civil engineering knowledge area was asked (1) from whom they receive knowledge in the push network and (2) who they turn to for knowledge in the pull network. In practice, they could pick the names from a list that contained all their 27 colleagues in the knowledge area. Moreover, we also measured the viscosity and the velocity of knowledge flow using a scale that has been developed by Leonard et al. (2005) and is shown in figure 2. They defined eight different types of knowledge transfer that go from a low viscosity (shown left in figure 2) to a high viscosity (right in figure 2). To give an example, in the case study we encountered knowledge exchange by means of Guided Problem Solving. In that situation a senior engineer is solving a design problem with a novice engineer. Although the senior engineer already knows the answer he helps the novice engineer in solving the problem himself. The end result is that the novice engineer can convert his book knowledge in experience based knowledge.

For the velocity of the knowledge flow we developed our own scale. We defined eight categories for velocity: within an hour (1), within half a day (2), within one day (3), within three days (4), within one week (5), within two weeks (6), within one month (7) and longer than one month (8).

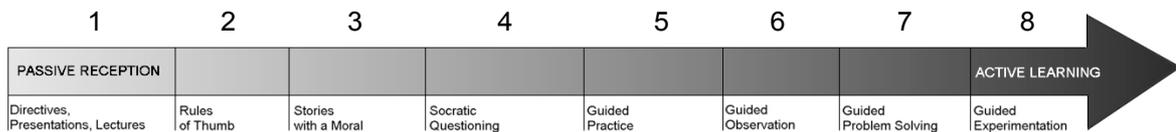


Figure 2. Scale for measuring the viscosity of the knowledge flow

The results of the survey are entered in two adjacency matrices, one for the push network and one for the pull network. The rows and columns of both matrices contain the names of the 28 people in the civil engineering knowledge area. Each cell contained a value between 1 and 8 that represents the knowledge viscosity or the knowledge velocity, depending on the type of network. These matrices were created in Microsoft Excel and then imported into NetMiner for further analysis. Additionally, we defined 4 attributes for an actor in Netminer in order to be able to store information about their knowledge role, expertise level, function, and location. The findings of analyzing these adjacency matrices using NetMiner are presented in the next section.

## 5 FINDINGS

In this section the results of the analysis of the push and pull network of the case study organization are presented. The push and pull network show two types of knowledge sharing between the same group of 28 people in the civil engineering knowledge area. After the analysis, the identification of bottlenecks and recommendations to improve knowledge sharing in the civil engineering knowledge area of the engineering firm are discussed.

### 5.1 Analysis of push network

In figure 1 the visual representation for the push network is shown. It only shows the knowledge exchanges with a viscosity greater than five (>5) because knowledge exchanges with a viscosity of 5 or lower are considered to be too superficial for exchanging deep smarts. The graph contains two major communities, G1 and G2, which have been determined using the community function. These communities coincide with two of the office locations of the organization. The third office consists of just one person, PB, which is not part of one of the two communities. In community G1 there is a nice

mix of employees with different knowledge roles and experience levels. However, in community G2 there are mostly knowledge sharers and the majority of the employees are at the trainee level. Therefore, they are dependent on the employees in community G1, i.e. the other office, for receiving new knowledge to improve their expertise level. Finally, there are two employees, JH and PB, which are disconnected from their colleagues and only provide knowledge and do not receive knowledge.

Besides these general observations, it is also of interest to know from whom employees receive their knowledge and with what viscosity. Using the E&I index it is possible to determine whether different groups of employees receive their knowledge from within or outside the group. Figure 3 shows that employees with different expertise levels have an external orientation (i.e. >0). This could be expected because trainees and specialists can only learn from experts if they have relations outside their own group. The orientation of employees at a particular office location shows a totally different picture. Here the orientation is mainly internal (i.e. <0), with the exception of office location C because it consists of just one person. Finally, the orientation of employees in different functions is also external. Especially project leaders and consultants have a strong external orientation. A possible explanation might be the multidisciplinary nature of their function.

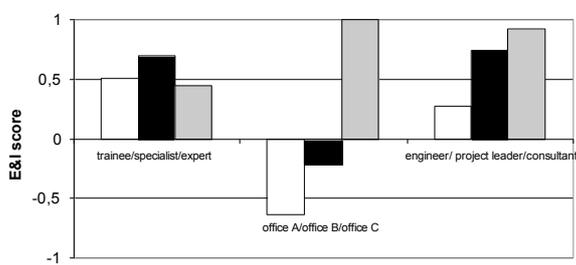


Figure 3. E&I index for different groups of the push network

The knowledge viscosity is an indicator of the quality of knowledge exchange. In the push network the average viscosity is 5,5, i.e. between guided practice and guided observation. It is an indicator that they have adapted active learning approaches for their knowledge exchange. We also studied whether there are differences in the type of knowledge exchange within different groups (see table 1). Only trainees and project leaders use knowledge exchanges that are a little less rich. This might be explained by the inexperience of the trainees and the busy schedules of project leaders.

Actors grouped by function	Avg. viscosity	Actors grouped by expertise	Avg. viscosity
Engineers	5,9	Trainees	4,5
Project leaders	4,4	Specialists	5,0
Consultants	6,0	Experts	5,6

Table 1. Average viscosity of knowledge flows in the push network

In case knowledge is created, it is important that this knowledge is diffused among all actors in a network. The shortest path indicator provides a measure for of how well people are connected with each other (directly and indirectly). In the case study the mean shortest path is 3,3. The ideal mean shortest path is 1, but in that case all actors in the network have direct relations with each other. But this is not preferable in a situation of rich knowledge transfer, because an actor cannot have rich knowledge exchange with all actors in a network. What is more important is that as many as possible actors are reached, either directly or indirectly. In the case study the mean number of reachable nodes is almost 20,6, which equals 74% of all actors.

So far the analysis focused on all actors in the network or on certain groups of actors. On the individual level several actors are notable because they have an out-degree centrality and power score that is higher than the upper limit, which is based on the inter quartile range of the power scores of all 29 actors (Wonnacot & Wonnacot, 1990). The actors with high scores on both indicators are: RK,

MV, HV en PS. Only one of the actors is from office location B, i.e. MV, while the others are from office location A. All actors are considered to be important for effective knowledge sharing in the network, if these actors leave the organization it will damage the effectiveness of the network.

## 5.2 Analysis of pull network

In figure 4 the visual presentation of the pull network is shown. Once again, the graph contains a number of communities that have been determined by the community function. There is only one community that consists of more than one person, i.e. G8 in the middle of the network. All actors in G8 are located in Office A and it involves a mix of mainly knowledge creators and sharers at the expertise level.

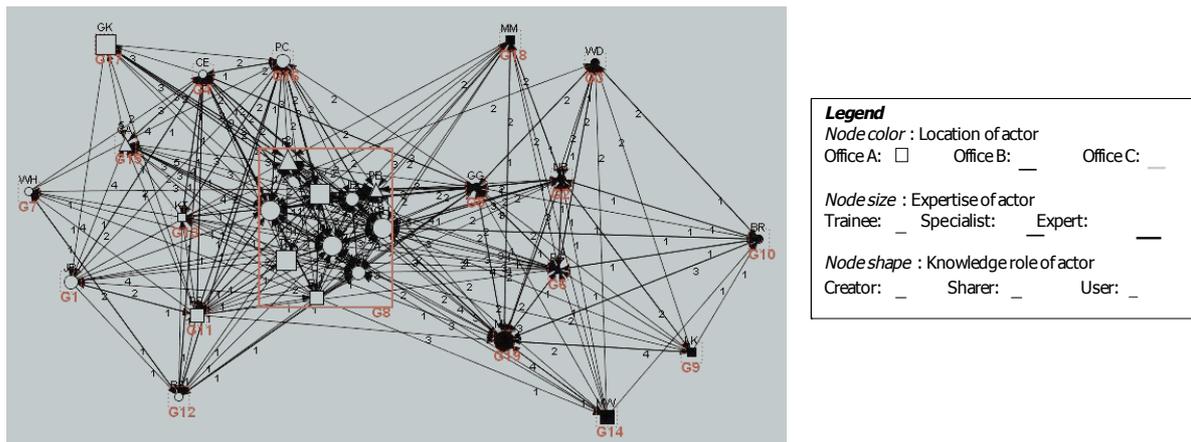


Figure 4. Pull network

The other actors in the network, at mainly the trainee or specialist level, do not belong to a community. However, they are not really disconnected because they have an average of ten connections with other actors in the network. In other words, the experts in the middle are valuable source of knowledge for the specialists and trainees in the periphery. Finally, it should be noticed that there are not so many strong ties at Office B, and that they depend on the knowledge from office A.

The E&I index for the pull network shows a similar pattern as for the orientation of knowledge exchange in the push network. An employee’s function or expertise level is not a barrier for asking knowledge; knowledge is exchanged across all levels. The office location, on the other hand, does seem to function as a virtual barrier. Employees in office A are more oriented internally and employees in Office B more externally, which is in line with what we found in the visual analysis of the pull network.

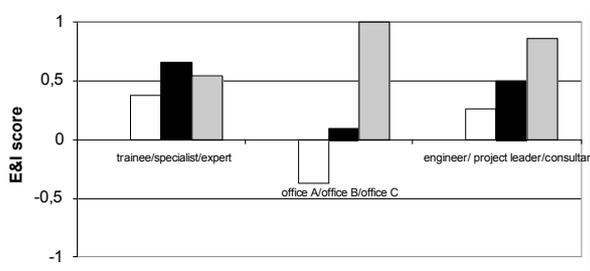


Figure 5. E&I index for different groups of the pull network

In the pull network, quick access to knowledge of colleagues is important. This is guaranteed when the velocity of the knowledge exchange is as fast as possible and the path to the knowledge is as short as possible. Table 2 shows the average velocity for different groups of actors in the pull network. On

average the velocity of the knowledge flows is 2,1, which means that actors get a response within approximately half a day. There are some minor differences if different groups of actors are taken into account. Trainees respond on average almost within an hour to each others questions while experts respond on average between half a day and a day. Moreover, trainees also respond quicker to questions of colleagues with other expertise levels than experts do. These changes might be explained to the workload which is typically higher for experts than for trainees and because experts typically receive more questions than others. Fast responses to knowledge questions are only beneficial if the response is useful for the receiver, i.e. the quality of the response should be high. Therefore, we also asked respondents to indicate if they considered the responses to be useful. The majority (24 of 28) indicated that they considered the responses useful for their work (score  $\geq 3$ ; with a scale from 1 = not very useful to 5 = very useful).

Actors grouped by expertise	Avg. velocity	Actors grouped by expertise	Avg. velocity
Amongst trainees	1,2	From trainees to others	1,8
Amongst specialists	2,2	From specialists to others	2,0
Amongst experts	2,4	From experts to others	2,4

*Table 2. Average velocity of knowledge flows in different groups of the pull network*

The average shortest path length in the pull network is 1,80 and the average number of actors that can be reached is 27 out of 28. Therefore, on average each actor can reach almost every actor within two steps, i.e. directly or indirectly via one other actor. Combining this data with the high velocity of the knowledge flows; it is concluded that employees have quick access to the knowledge of their colleagues.

In the pull network there are also some actors that are more central and have more power than others. There are four actors that have an out degree centrality that is higher than the upper limit (based on the inter quartile range): RK, TB, PS en HV. There are only two actors that have a power score that is higher than the upper limit: HV and MV. Based on these two indicators, HV is the most powerful and influential person in the pull network.

### **5.3 Recommendations to the engineering firm**

Based on the case study results that were presented in the previous two sections we formulated a number of recommendations for the case study organization. On a high level one can conclude that they have adopted active learning approaches for their knowledge exchange (average viscosity between four and five), which results in enduring knowledge for the receiver. But there is still room for improvement to more viscous knowledge exchange, especially for project leaders. There is also a good exchange of knowledge between different functions and expertise levels. However, the different locations of the organization seem to be a barrier for knowledge exchange, because the exchange between the offices is limited. This is not necessarily a problem and therefore we looked more closely to both office locations (we ignore the location with only one person, because he can only exchange knowledge with others). In office A there is a nice mix of knowledge roles, functions, and expertise levels. However, in office B there is only one expert and no knowledge creators. The low level of expertise might be an explanation why employees at office A do not have a need to contact their colleagues in office B. Vice versa, office B is very dependent on office A for acquiring new knowledge. However, the number of ties with office A is limited and almost half of the ties go through one person. If that person leaves the organization it severely damages the flow of knowledge from office A to office B. It is therefore recommended that the organization increases the variety and expertise level in office B and at the same time increases the number of links between the two offices. Both can be realized at the same time by switching employees from one office to another.

There are also some recommendations on the level of individual actors. The out-degree centrality and power scores showed that there is a group of four employees that has substantial higher scores on both

indicators. If these employees leave the organization it will severely influence the connectivity in the network. Moreover, it results in a 'brain drain', because their expertise is at the specialist or expert level. To prevent this from happening, the organization can do two things. First, they can create good career tracks and a challenging work environment so that employees do not want to leave. Secondly, the organization can make sure that these employees have viscous knowledge exchanges with potential successors.

Further detailed analysis of the in- and out-degree of individual employees revealed some more interesting findings on the level of individual actors. For example, it was found that there are two specialist project leaders that do not receive knowledge and provide only one person with their knowledge. Furthermore, it was found that two trainee engineers receive knowledge from just one person and also give their knowledge to just one person. Receiving no knowledge or receiving knowledge from one colleague while you are still at the trainee level is not desirable because the increase of personal knowledge is then limited. It is therefore recommended that these employees start to exchange knowledge with a larger number of colleagues.

Based on the network graph and the indicators, the situation for the pull network looks better. Either directly or indirectly employees have access to the knowledge of all members of the organization. Moreover, on average the knowledge is no further away than one or two colleagues and they receive a response within approximately half a day or a day. Once again the different locations of the organization seem to be a barrier for knowledge exchange. Because it does not necessary involve rich knowledge exchanges here, as is the case for the push network, it could be expected that information and communication technology could overcome these problems (Becerra-Fernandez et al., 2004). Therefore, it might be worthwhile for the organization to study the possible application of such technology in their processes. Finally, the same employees as in the push network have high scores for out-degree centrality and power in the pull network. To prevent that these employees leave the organization, the same measures as for the push network can be applied here.

## **6 DISCUSSION AND CONCLUSION**

Knowledge Network Analysis is a technique to analyze the push and pull networks in a particular knowledge area. The technique is based on Social Network Analysis, which is an accepted research technique in the social sciences (Wasserman et al., 1994). To make Social Network Analysis more suitable for analyzing knowledge networks we added the following concepts to the technique: knowledge management roles, expertise levels, knowledge velocity, and knowledge viscosity. This paper describes the first application of Knowledge Network Analysis in a case study. The goal of the case study was to explore to what extent the technique is capable of identifying knowledge sharing bottlenecks. Therefore, we collected data using a survey and analyzed the data using a tool that is called NetMiner. The resulting knowledge networks have been analyzed using visual as well as quantitative analysis techniques. Especially the combination of both analysis techniques and the comparison of different sub-groups in the network resulted in the identification of bottlenecks and have been translated into concrete recommendations. The recommendations have been presented to the manager who is responsible for the knowledge area. He was surprised by the insight that was provided by our analysis and the concrete recommendations that follow from the results. Moreover, he also demonstrated that the results are rather easy to interpret, because he used the findings to formulate additional recommendations. For example, employees with high expertise and high out degree centrality and power should not be assigned to projects at another location for longer periods of time.

Although the case study provided valuable information about the application of Knowledge Network Analysis it also revealed some shortcomings that we will briefly discuss. First of all, the technique is very labor intensive because all employees have to participate in the research. Therefore, we decided to focus on the knowledge areas that have the highest contribution to the business goals. Secondly, an actor is said to be a knowledge creator if the number of outgoing flows is at least twice as high as the number of incoming flows. Although this indicates that this person possesses knowledge that is of

interest for many others, some additional interviews indicated that these people are not necessarily creating new knowledge. Knowledge providers or knowledge sellers would be a more appropriate name in this context. Finally, respondents were allowed to indicate more than one type of knowledge transfer in the survey. We decided to use the most viscous knowledge transfer for our analysis, which results in the most optimistic observations about the performance of the knowledge network.

Further research is required to further improve the validity of the Knowledge Network Analysis. This could be achieved by further embedding the findings of our case study in literature and by conducting additional case studies. Finally, further research is required to assess the potential value of other functions and indicators in social network analysis for incorporation in our Knowledge Network Analysis technique.

## References

- Allen, T. (1977). *Managing the Flow of Technology*, MIT Press, Cambridge, Massachusetts.
- Allen, J. and B.P. Lientz (1979). *Effective Business Communication*. Prentice-Hall, Englewood Cliff.
- Anklam, P. (2004). KM and the Social Network. *Knowledge Management Magazine*, May issue, p.24-28.
- Becerra-Fernandez, I., A. Gonzalez, and R. Sabherwal (2004). *Knowledge Management: Challenges, Solutions and Technologies*. Prentice Hall.
- Cross, R., and A. Parker (2004). *The Hidden Power of Social Networks: Understanding How Work Really Gets Done in Organizations*. Harvard Business School Press, Boston.
- Davenport, T.H. and L. Prusak (1998). *Working Knowledge: How Organizations Manage What They Know*. Harvard Business School Press, Boston.
- Dixon, N.M. (2000). *Common Knowledge: How companies thrive by sharing what they know*. Harvard Business School Press, Boston.
- Eades, P. (1984), A Heuristic for Graph Drawing, *Cong. Numer.*, 42, p. 149-160
- Epple, D., L. Argote and K. Murphy (1996). An empirical investigation of the micro structure of knowledge acquisition and transfer through learning by doing, *Operations Research*, 44, p. 77-86.
- Girvan, M. and M. E. J. Newman (2002). Community structure in social and biological networks, *Proceedings of the National Academy of Sciences*, 99, p. 8271-8276.
- Hanneman, R.A and M. Riddle (2005). Introduction to social network analysis. Retrieved July 12, 2005 from the University of California website: <http://faculty.ucr.edu/~hanneman/nettext/>.
- Hansen, B. and K. Kautz (2004). Analyzing knowledge flows as a prerequisite to improve systems development practice. In *Proceedings of 13<sup>th</sup> European Conference on Information Systems (ECIS)*, Regensburg, Germany.
- Hansen, M.T. (2002). Knowledge Networks: Explaining Effective Knowledge Sharing in Multiunit Companies. *Organization science*, 13(3), p. 232-248.
- Helms, R.W. and B.M. Buijsrogge (2005). Knowledge Network Analysis: a technique to analyze knowledge management bottlenecks in organizations. In D.C. Martin (Ed.): *Proceedings 6th International Workshop on Theory and Applications of Knowledge Management*, p. 410-414, Los Alamitos, IEEE Computer Society.
- Huisman, M. and M.A.J. van Duijn (2004). Software for social network analysis. In: P.J. Carrington, J. Scott and S. Wasserman (eds.), *Models and methods in social network analysis*, Cambridge: Cambridge University Press.
- Kanter, R. M. (2001). *Evolve! Succeeding in the digital culture of tomorrow*, Harvard Business School Press, Boston.
- Leonard, D. and W. Swap (2005). *Deep Smarts – How to cultivate and transfer enduring business wisdom*. Harvard Business School Press, Boston.
- Liebowitz, J. (2005). Linking social network analysis with the analytical hierarchy process for knowledge mapping in organizations. *Journal of Knowledge Management*, 9(1), p. 76-86.

- Meuller-Protmann, T. and I. Finke (2004). SELaKt – Social Network Analysis as a Method for Expert Localisation and Sustainable Knowledge Transfer. *Journal of Universal Computer Science*, 10(6), p. 691–701.
- Schreiber, A.T., J.M. Akkermans, A.A. Anjewierden, R. de Hoog, N.R. Shadbolt, W. van de Velde and B.J. Wielinga (2002). *Knowledge engineering and management – The CommonKADS methodology*. The MIT press, London.
- Spek, van der, R., J. Hofer-Alfeis and J. Kingma (2002). *The Knowledge Strategy Process*. Springer-Verlag, Heidelberg.
- Wasserman, S. and K. Faust. (1994). *Social Network Analysis: methods and applications*. Cambridge University Press.
- Wenger, E. (1998). *Communities of Practice*. Cambridge University Press, New York.
- Wonnacott, T.H. and R.J. Wonnacott (1990). *Introductory Statistics*. 5th edition, Wiley, New York.