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Exponential Random Graph Models of Social Networks for Engineering Design Firms

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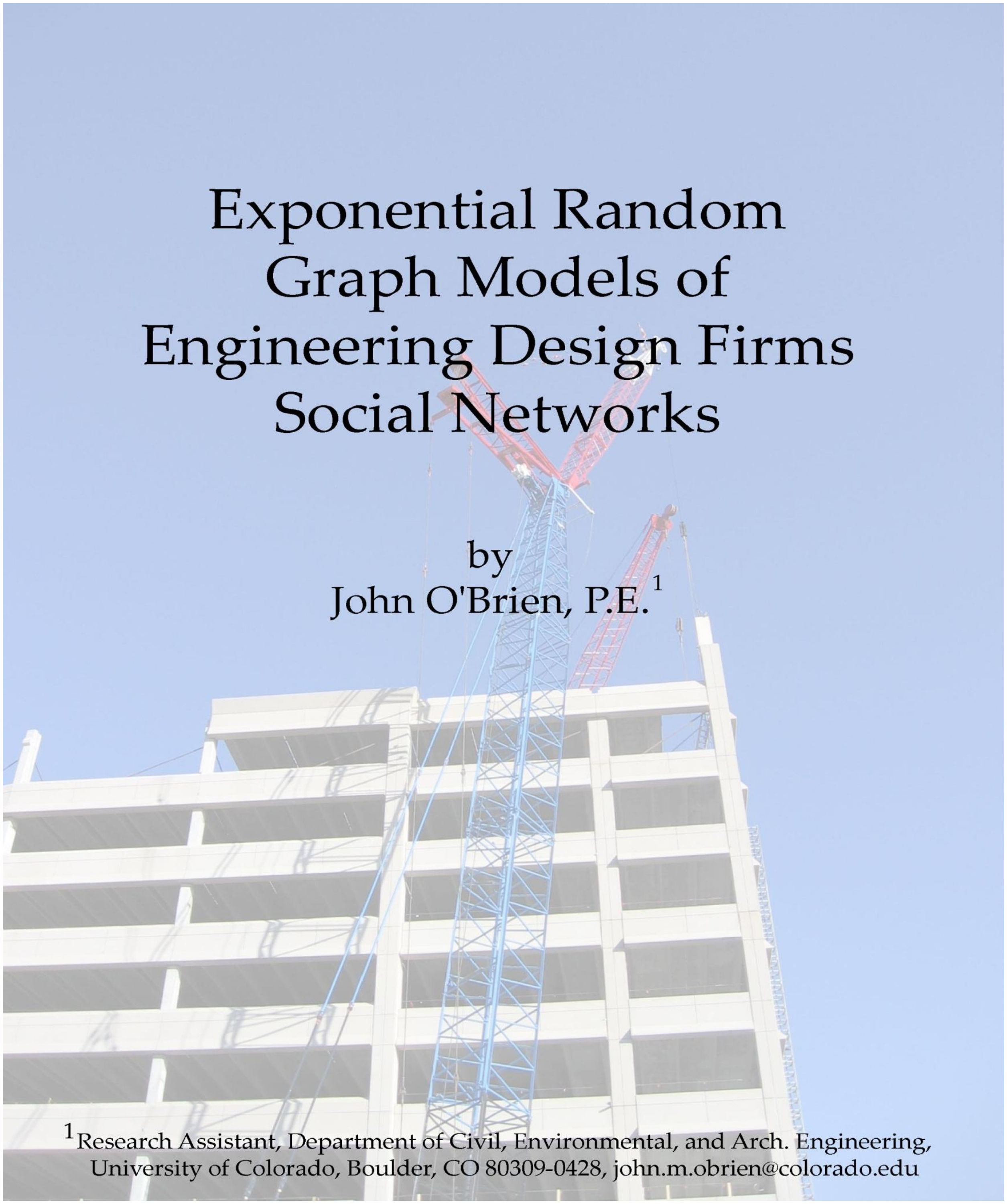

Exponential Random Graph Models of Engineering Design Firms Social Networks

by

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EXPONENTIAL RANDOM GRAPH MODELS OF SOCIAL NETWORKS FOR ENGINEERING DESIGN FIRMS

by

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A thesis submitted to Graduate School Faculty at
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Exponential Random Graph Models of Social Networks for Engineering Design Firms
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The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.

ABSTRACT

O'Brien, John Michael (Ph.D., Civil Engineering [Department of Civil and Environmental Engineering])

Exponential Random Graph Models of Social Networks for Engineering Design Firms

Thesis directed by Professor Paul S. Chinowsky.

Effective teams are created with a mission in mind of members collaborating with each other through trust and communication. The Social Network Model of engineering and construction was developed using a dual-focused approach to enhancing professional trust and communications in creating highly effective organizations. This research investigated applications of social network analysis to engineering and design firms using graphics and statistical methods to analyze the organization and team effectiveness. After I conducted an on-line survey for firms that met certain criteria, I analyzed their networks and made recommendations on how to improve their communications with each other to help them improve on their effectiveness. I analyzed their data using statistical methods such as basic statistics and exponential random graph models that can explain formation of the observed networks. Social network analysis can be used to measure their effectiveness and is intended to visualize communication, reliance and trust in each other and assess knowledge exchange, with the assumption that improvements in these variables will help to achieve high performance.

DEDICATION

To my father Joseph J. O'Brien who inspired me to continue my education.

ACKNOWLEDGEMENTS

My wife Michalene O'Brien for whose patience and understanding I am truly grateful and my mother Delia O'Brien who never quit believing in me.

Professor Paul Chinowsky whose guidance made this research possible.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 – INTRODUCTION

1.1 Overview

A winning strategy for any organization is creating a unique set of activities that set themselves apart from the competition. A key part of that strategy in engineering and construction is the creation of effective project teams. Engineering and construction organizations are geared towards effective project teams. Effective project teams are created with a mission in mind of members collaborating with each other through trust and communication. Using literature on project management, I identified the need to measure and study the collaboration among groups in a network to evaluate the effectiveness of an organization with measures other than schedule and cost. I became interested in not only the relationship of the individuals in the organization chart, but how the individuals collaborate with each other independent of the organizational vertical relationships. Collaboration in design engineering firms can be studied using social network analysis. There are key variables that can be identified and modeled in a social network. Previous research on team building identifies three key variables trust, communication and knowledge exchange. This thesis is a study of engineering organizations using social network analysis.

The motivation for this research centers on the limitations of the traditional construction perspective on project management. In the traditional perspective, project management is increasingly focused on the use of tools to preplan tasks and develops schedules that are as detailed as possible. The concept behind this perspective is that a majority of issues can be identified and engineered prior to the start of the project. Additionally, this emphasis is intended to enhance efficiency of the process by identifying information that is required to be exchanged between participants during project execution. Research in critical success factors has identified the efficiency of information exchange as a key element in producing projects that achieve benchmarks in time, cost and quality.

The first objective was to develop a social network model for engineering and construction that identifies significant variables in an organization's performance other than profit, schedule or rate of returns. The Social Network Model of engineering and construction was developed using a dual-focused approach to enhancing professional trust and communications in creating highly effective teams.

Three design engineering firms with similar characteristics were selected to perform an on-line survey using software specifically designed for social network analysis. Write a report using network statistics such as density, centrality and betweeness as measures of trust, communication and knowledge exchange according to the social network model for engineering and construction. The model was used to study three engineering design and construction firms both analytically and graphically using an on-line survey program.

A main focus of the research is to expand on the network statistics using exponential random graph models to measure an organization's effectiveness by analyzing the configurations within the network to assess collaboration through connectivity. Due to the heterogeneity of organizations, we cannot compare the organizations with each other, rather we can look at the distribution of the configurations to assess the effectiveness of groups in the organization as well as individuals.

This thesis analyzes the survey results both graphically and statistically to examine the underlying parameters that generate social networks. Exponential Random Graph Models can be used to describe collaboration among groups as well as individuals in the context of social networks based on the model of communication, trust and knowledge exchange. By stochastically fitting our observed networks to a theoretical model, we are able to obtain a set of parameter constants that describes how network configurations contribute to collaboration in the networks through connectivity. Using the parameter constants in conjunction with the social network model for engineering and construction we are able to quantitatively describe an organization.

1.2 Need for Research

I have been involved in many project teams over the years. I have worked with highly effective project teams that achieved high performance with a reputation for quality, meeting schedule and budget. These are traditional measures for a high performance organization. Research suggests we need an alternate way to measure an organization's effectiveness in addition to the traditional measures. Social Network Analysis fills that goal as a strategic activity to measure the effectiveness of an organization.

A significant part of performance is related to the make-up of the organization. For example, at the Advanced Engineering Project, the team was well networked with a high degree of centrality among the players. The network densities were high and a high level of communication and trust existed between management and staff.

1.3 Research Hypothesis and Questions

Based on literature on effective teams and social network analysis, the hypothesis for this study was formed. It was projected that data would show an organization's effectiveness can be measured using social network analysis. In order to support the hypothesis several questions needed to be answered. The first question was "what is an effective team and how is effectiveness currently measured?" A social network model for engineering and construction was developed to address this question. The variables were identified and grouped into dynamic and mechanic sides of the diagram which intuitively leads to effectiveness. The second question was "can we use graphical and statistical tools to measure an organization's effectiveness?" An organization's effectiveness can be measured by using Social Network Analysis; specifically

Exponential Random Graph Models for observed networks can describe an organization's effectiveness. The contribution of the research will enable highly effective organizations to utilize the findings in their strategies for success.

1.4 What questions will be answered

The main questions that will be answered in this thesis are: What is effectiveness versus high performance for an organization? What is Social Network Analysis? What is the research trying to do? How will the study be done? How will the data be analyzed? And what is the contribution of the research?

Chapter 2 Problem Statement

2.1 Introduction

Effective teams achieve outcomes that exceed the expectations of the project objectives and often demonstrate unique or innovative approaches. These teams challenge conventional expectations by using combined knowledge to generate solutions. Project objectives measured by traditional benchmarks are easily met and often exceeded with limited resources. The concept is documented and routinely implemented in diverse industries including automotive, government and healthcare. However, effective teams and solutions receive less attention in the construction domain. Rather, the measurement of success within a construction project is often based on meeting historical benchmarks for the classic factors of time, cost and quality. As with any longstanding benchmark, the question of whether these classic benchmarks can be increased to a new level should be periodically examined together with the question of how to achieve a new level of effectiveness. In the context of construction projects, the research effort discussed in this thesis focuses on the development of a model for improving results from project teams including innovation, learning, knowledge exchange, and a notable increase in the classic project benchmarks.

The limitation to the traditional "efficiency" approach is that it produces a reactive project execution model. In this model, the schedule and its logic emphasize the mechanics of requesting and retrieving information from other participants to achieve individual goals. The information exchange is guided by the necessity generated by the engineered schedule. This reactive approach is in direct contrast to the methods employed by effective teams. In highly effective teams, the focus is on the team members and their ability to continuously exchange knowledge and insights, in addition to project information to enhance the collective group output. The success of these teams is not based on an engineered approach to project execution, but rather a social network approach to project execution that emphasizes the dynamics of interaction and knowledge exchange between project participants. This focus on networks as the basis for effectiveness is extended in this paper to present a Social Network Model for construction (Chinowsky, Diekman, Galotti 2008) that emphasizes team development and knowledge exchange as the foundation for producing highly effective construction projects.

2.2 Organizational Performance versus Organizational Effectiveness

Organizational performance is essential in allowing researchers and managers to evaluate firms over time and compare them to rivals (Richard, Devinney, Yip and Johnson); as well as evaluating organizations, their actions, and environments. This importance is reflected in the use of organizational performance as a dependent variable with limited attention paid by researchers to what performance is and how it is measured.

Few studies use consistent definitions and measures of ‘organizational performance’. Researchers commonly reference performance as a dependent variable without definition and its use is generally assumed. The inability to understand and characterize performance consistently reduces the impact and relevance of management research. With a more coherent understanding of the meaning and measurement of performance steps can be taken towards understanding the dependent variable of interest in the research.

In Richard, Devinney, Yip and Johnson’s paper on Measuring Organizational Performance as a Dependent Variable they defined organizational performance and organizational effectiveness. Organizational performance dominates strategic management literature, although performance is only one type of effectiveness indicator. Therefore, they distinguish between organizational performance and the more general construct of organizational effectiveness. Organizational effectiveness is a broader construct that captures organizational performance.

Organizational performance encompasses three specific areas of firm outcomes: (1) financial performance (profits, return on assets, return on investment, etc.); (2) market performance (sales, market share, etc.); and (3) shareholder return (total shareholder return, economic value added, etc.).

Organizational effectiveness is broader and captures organizational performance plus the plethora of internal performance outcomes normally associated with more efficient or effective operations and other external measures that relate to considerations that are broader than those simply associated with economic valuation (either by shareholders, managers or customers), such as reputation. Although innovation and efficiency measures are generally placed into the wider conceptual domain of organizational effectiveness, other management researchers have taken these same variables as their dependent performance measure. It is in this context we will assess the application of the social network model for engineering and construction and an organization’s social networks.

Effective team members collaborate with each other by trusting each other, communication and knowledge sharing (Chinowsky, Diekman and Galotti, 2008). The scope of work of a team often touches or involves the activities of many people beyond the team itself – this external group can be referred to as the community of interest that must be included in the team's communication loop. A successful project manager must be a good leader, other members of the project team must also learn to work together, whether they are assembled from different divisions of the same organization or even from different organizations. Some problems of interaction may arise initially when the team members are unfamiliar with their own roles in the project team. These problems must be resolved quickly in order to develop an effective, functioning team.

Many of the major issues in engineering and construction projects require effective interventions by individuals, groups and organizations. The fundamental challenge is to enhance communication among individuals, groups and organizations so that obstacles in the way, of improving interpersonal relations, may be removed. Some behavior science concepts are helpful in overcoming communication difficulties that block cooperation and coordination. The major symptoms of interpersonal behavior problems can be detected by experienced observers, and they are often the sources of serious communication difficulties among participants in a project. For example, members of a project may avoid each other and withdraw from active interactions about differences that need to be dealt with. They may attempt to criticize and blame other individuals or groups when things go wrong. They may resent suggestions for improvement, and become defensive to minimize culpability rather than take the initiative to maximize achievements. All these actions are detrimental to the project organization.

Therefore, no one should take it for granted that a project team will work together harmoniously just because its members are placed physically together in one location. It must be assumed that good communication can be achieved only through the deliberate effort of the top management of the organization.

2.3 Social Network Analysis

Social Network Analysis (SNA) has been an instrumental tool for researchers focusing on the interactions of groups since the concept was introduced by Moreno in 1934 (Moreno 1960). In the original concept formulation, sociograms were considered a formal representation of the patterns of interpersonal relationships upon which larger social aggregates are created. Since each node in the graph could represent individuals and the links between these nodes could represent relationships such as information exchange, sociograms were put forward as a fundamental tool for investigating the fabric of interpersonal relationships within groups of individuals.

The extension of this concept into group dynamics occurred in combination with the concept that individuals or organizations exchange information during the performance of any activity (Scott 1991; Haythornthwaite 1996). Given the premise that any activity requires a transfer of information, the extension of this foundation is that these exchanges can be mapped within sociograms where actors and information exchange become nodes and links within the graph (Wasserman and Faust 1994).

The translation of these social interactions to a mathematical basis was the foundation of the strength and validity of the network approach to communication analysis. Specifically, the ability to apply mathematical analysis to network information exchange provides the researcher with established measurements for analyzing the effectiveness and weaknesses of the group being studied (Alba 1982).

In formalizing the connection between graph theory and SNA, several key concepts in graph theory were adopted by SNA researchers to formalize the analysis of graphs and relationships including network density, centrality and geodesic distance. These measurements represent only a few of the graph-based measurements available to SNA researchers. However, they represent the core of the theoretical constructs which directly relate to the field of engineering and construction projects.

In terms of the Social Network Model for engineering and construction, the well-established fields of graph theory and network analysis provide a validated foundation for analyzing quantitative relationships, interactions, and attributes between network constituents. Social network analysis provides an excellent opportunity to visualize the relationships between high performance and underperformance engineering and construction networks.

The field of communication research is critical to the Social Network Model. Understanding what affects the transfer of information between individuals and organizations, and improving this communication, is at the core of the model concept. As stated earlier, the motivation for developing the Social Network Model for engineering and construction was to alter the focus of project management from efficiency of projects to high performance projects.

The requirement for creating this change is a greater focus on the individuals within the team and their ability to collaborate to create a higher standard of success for the entire team. This focus on the project team network rather than the project schedule is a shift away from the classic project management emphasis on engineering the project to an optimal schedule.

In the Social Network Model, the underlying hypothesis is that projects need to be managed as social collaborations to achieve results that exceed traditional expectations. Then an increased emphasis will be placed on developing teams that have shared values and trust among the participants. Teams that have this as a basis will focus on sharing knowledge to produce high performance results.

Additionally, these teams will work in a proactive mode that is motivated to excel and encourage the identification and resolution of project issues prior to the issues being discovered as a reaction to the project schedule.

2.4 What is the research trying to do?

The focus of the research is to measure an organizations effectiveness using social network analysis. Using the Social network model for engineering and construction as a basis, a survey will be conducted and the results will be analyzed analytically and statistically to measure an organization's effectiveness. Existing research attempts to compare organizations with measures of performance. This differs from existing research in that engineering organizations are dynamic and need to have their results monitored on a bi-annual basis to stay on top of the changing environment.

CHAPTER 3 – LITERATURE REVIEW

3.1 Introduction

In their text on construction management, Chris Hendrickson and Tung Au discuss the required knowledge of modern management techniques to achieve a specific set of objectives and meet time constraints as required for successfully completing of a project. They describe in detail the management approach to project organizations, management science, and behavioral science approach for human resource development. These approaches to project management are true for engineering projects, construction projects and for similar types of projects in other specialty or technology domains such as aerospace, pharmaceutical and energy developments. This information formed the motivation for our research on social networks. Social network analysis provides a useful technique for measuring and analyzing these management challenges.

According to the Project Management Institute, the discipline of project management can be defined as follows:

> Project management is the art of directing and coordinating human and material resources throughout the life of a project by using modern management techniques to achieve predetermined objectives of scope, cost, time, quality and participation satisfaction.

By contrast, the general management of business and industrial corporations assumes a broader outlook with greater continuity of operations. Nevertheless, there are sufficient similarities as well as differences between the two so that modern management techniques developed for general management may be adapted for project management. Generally, project management is distinguished from the general management of corporations by the mission-oriented nature of a project. In my research, I analyzed a general management organization. The results can be applied at the project level using the same methodology to provide both project management and general management a better analysis of how their organization is performing other than the traditional measures such as scope, cost and time. The objective of participation satisfaction will directly affect quality on a project. Using social network analysis to measure these variables will improve participation satisfaction on a project. I look at high performing team building literature in the next section for the other variables that affect participation satisfaction.

The basic ingredients for a project management framework may be represented schematically in Figure 3.1 (Hendrickson and Au). "A working knowledge of general management and familiarity with the special knowledge domain related to the project are indispensable. Supporting disciplines such as computer science and decision science may also play an important role. In fact, modern management practices and various special knowledge domains have absorbed various techniques or tools which were once identified only with the supporting disciplines. For example, computer-based information systems and decision support systems are now common-place tools for general management. Similarly, many operations research techniques such as linear programming and network analysis are now widely used in many knowledge or application domains. Hence, the representation in Figure 3.1 reflects only the sources from which the project management framework evolves."

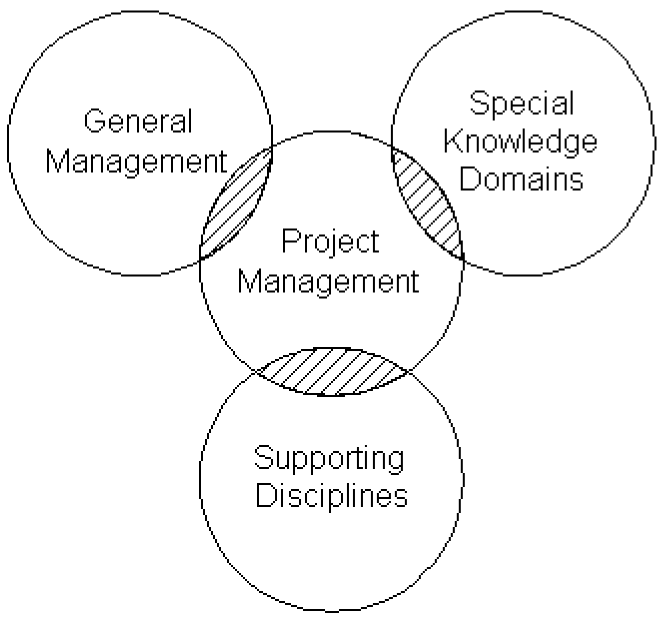

Figure 3.1: Basic Ingredients in Project Management

The social network analysis techniques presented in this thesis can be used to measure the relationships between general management, project management, supporting disciplines and special knowledge domains.

Project management in construction encompasses a set of objectives which may be accomplished by implementing a series of operations subject to resource constraints. There are potential conflicts between the stated objectives with regard to scope, cost, time and quality, and the constraints imposed on human material and financial resources. These conflicts should be resolved at the onset of a project by making the necessary tradeoffs or creating new alternatives. Subsequently, the functions of project management for construction generally include selecting project participants, maximization of efficient resource utilization through procurement of labor, and the development of effective communications and mechanisms for resolving conflicts among the various participants.

The Project Management Institute focuses on nine distinct areas requiring project manager knowledge and attention. Among them is human resource management to develop and effectively employ project personnel and project communications management to ensure effective internal and external communications.

3.2 Project Management Organizations

The management approach to project organizations emphasizes management functions in an organization (Hendrickson and Au, 2003). Management functions can be organized into a hierarchical structure designed to improve operational effectiveness, such as the example of the organization for a construction company shown in Figure 3.2. In Appendix B, I present the organization chart for the organization I studied using social network analysis. Social network analysis allows us to look at the relationship of the whole organization at once, as well as study the relationship of individuals that are connected vertically by the organization chart. The development of a management philosophy results in helping the manager to establish relationships between human resources. The outcome of following an established philosophy of operations helps the manager win support of the subordinates in achieving organizational objectives.

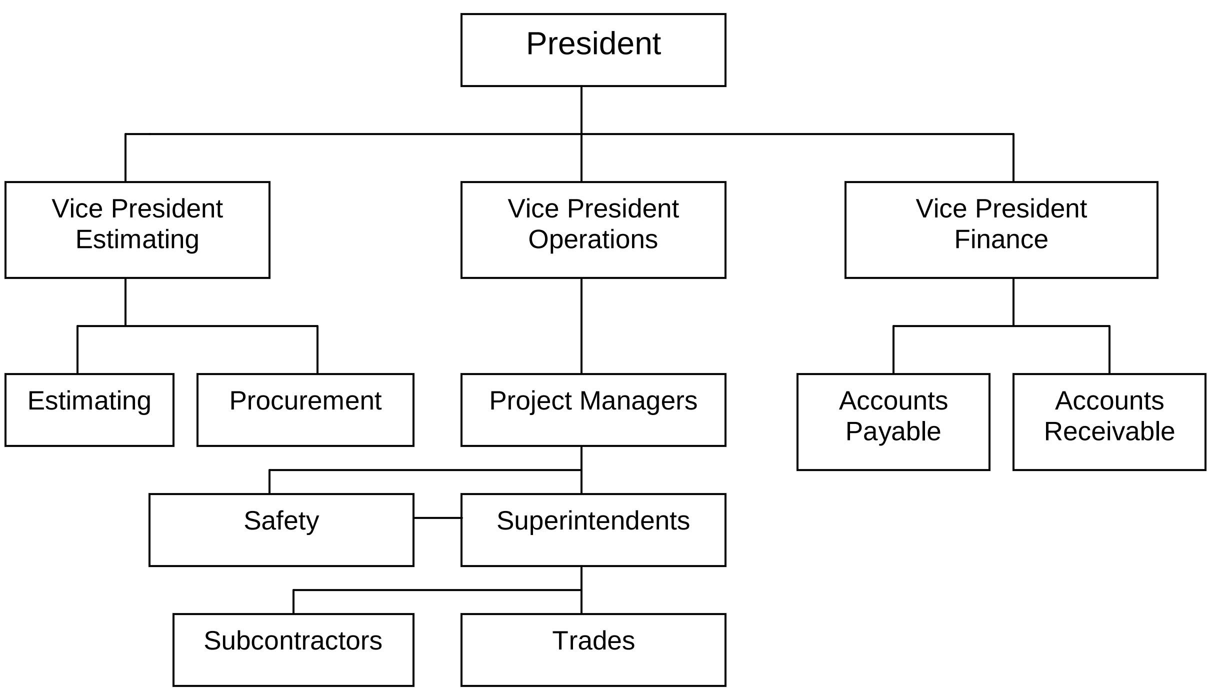

Figure 3.2: Illustrative Hierarchical Structure of Management Functions

The management science and decision support approach contributes to the development of a body of quantitative methods designed to aid managers in making complex decisions related to operations and production (Hendrickson and Au, 2003). In decision support systems, emphasis is placed on providing managers with relevant information such as social network analysis. In management science, a great deal of attention is given to defining objectives and constraints. A topic of major interest in management science is the maximization of profit, or in the absence of a workable model for the operation of the entire system, the sub optimization of the operations of its components. The optimization or sub optimization is often achieved by the use of operations research techniques, such as linear programming, quadratic programming, graph theory, queuing theory and Monte Carlo simulation. In addition to the increasing use of computers accompanied by the development of sophisticated mathematical models and information systems, management science and decision support systems have played an important role by looking more carefully at problem inputs and relationships and by promotional goal formulation and measurement of performance.

The behavioral science approach for human resource development is important because management entails getting things done through the actions of people. An effective manager must understand the importance of human factors such as needs, drives, motivation, leadership, personality, behavior which focuses on the individual and his/her motivations as a socio-psychological being; others emphasize more group behavior in recognition of the organized enterprise as a social organism, subject to all the attitudes, habits, pressures and conflicts of the cultural environment of people. The major contributions made by the behavioral scientists to the field of management includes: (1) the formulation of concepts and explanations about individual and group behavior in the organization, (2) the empirical testing of these concepts methodically in many different experimental and field settings, (3) the establishment of actual managerial policies and decisions for operation based on the conceptual and methodical frameworks. Social network analysis provides the perfect framework for achieving organizational effectiveness.

Sustainable competitive advantage stems from good managerial strategy. As Michael Porter of the Harvard Business School argues:

> Strategy is creating fit among a company's activities. The success of a strategy depends on doing many things well – not just a few – and integrating among them. If there is no fit among activities, there is no distinctive strategy and little sustainability.

In this view, successful firms must improve and align the many processes underway to their strategic vision. Strategic positioning in this fashion requires:

- Creating a unique and valuable position.
- Making trade-offs compared to competitors
- Creating a "fit" among company activities.

Project managers should be aware of the strategic position of their own organization and the other organizations involved in the project. The project manager faces the difficult task of trying to align the goals and strategies of these various organizations to accomplish the project goals.

Project Organizations

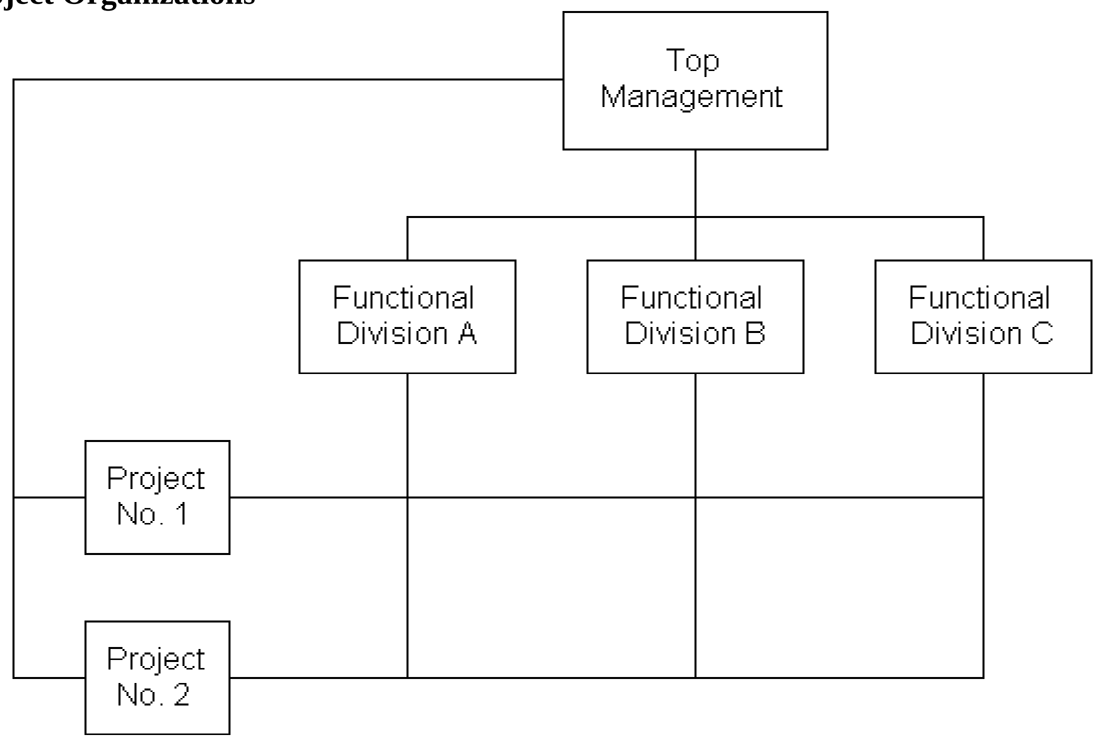

Figure 3.3: A Matrix Organization

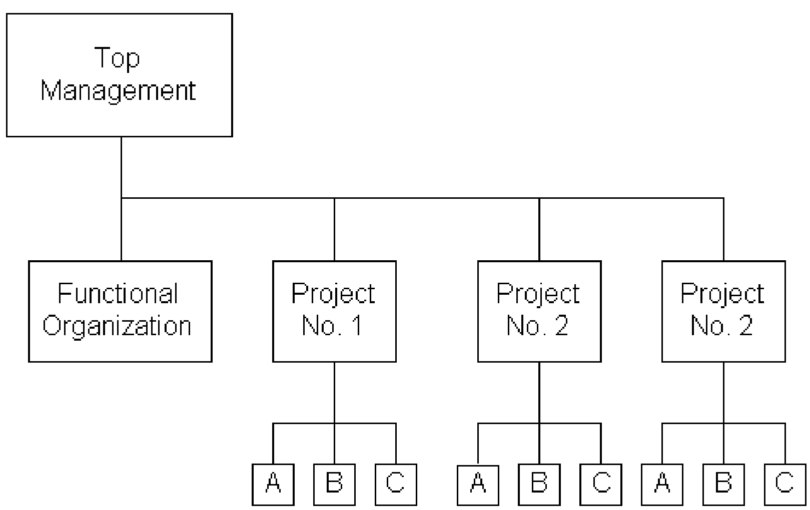

Figure 3.4: A Project-Oriented Organization

Interpersonal Behavior in Project Management (Hendrickson and Au, 1998)

While a successful project manager must be a good leader, other members of the project team must also learn to work together, whether they are assembled from different divisions of the same organization or even form different organizations. Some problems of interaction may arise initially when the team members are unfamiliar with their own roles in the project team, particularly for a large and complex project. These problems must be resolved quickly in order to develop an effective, functioning team.

Many of the major issues in construction projects require effective interventions by individuals, groups and organizations. The fundamental challenge is to enhance communication among individuals, groups and organizations so that obstacles in the way of improving interpersonal relations may be removed. Some behavior science concepts are helpful in overcoming communication difficulties that block cooperation and coordination. In very large projects, professional behavior scientists may be necessary in diagnosing the problems and advising the personnel working on the project. The power of the organization should be used judiciously in resolving conflicts.

The major symptoms of interpersonal behavior problems can be detected by experienced observers, and they are often the sources of serious communication difficulties among participants in a project. For example, members of a project may avoid each other and withdraw from active interactions about differences that need to be dealt with. They may attempt to criticize and blame other individuals or groups when things go wrong. They may resent suggestions for improvement, and become defensive to minimize culpability rather than take the initiative to maximize achievements. All these actions are detrimental to the project organization.

While these symptoms can occur to individuals at any organization, they are compounded if the project team consists of individuals who are put together from different organizations. Invariably, different organizations have different cultures or modes of operation. Individuals from different groups may not have a common loyalty and may prefer to expand their energy in the directions most advantageous to themselves instead of the project team. Therefore, no one should take it for granted that a project team will work together harmoniously just because its members are placed physically together in one location. On the contrary, it must be assumed that good communication can be achieved only through the deliberate effort of the top management of each organization contributing to the joint venture.

3.3 **Highly Effective Teams**[1]

Effective Team Concepts

Effective Teams are created with a mission or purpose in mind. This purpose or mission should be expressed in the form of a written charter. Over time teams develop their own set of norms. Norms are rules or guides for team behavior and decision making. The idea of using teams to solve problems and achieve results is based, in part, on a concept that the collective brain power of a team far exceeds the ability of any manager. Therefore, to a large degree, teams are self-directed. Effective teams are also empowered. Teams are motivated by the challenge of achieving dramatic results within a short time-frame. It is quite normal for teams to thrash and churn during early stages of development. This will usually appear chaotic to outsiders and team members alike. It is also normal for 75 percent of the real work of a team to be accomplished during the last 25 percent of the time allotted. Team members are expected to learn as they work together. Often the scope of work of a team touches or involves the activities of many people beyond the team itself—this external group can be referred to as the community of interest that must be included in the team's communication loop. All teams experience a shortage of resources. This phenomenon must be understood, expected, and available resources defined for the team from the team's inception.

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[1] This section is reprinted from the High Performance Teams website, by Donald J. Bodwell, Dallas, Texas. The Web site is a resource for businesses and organizations interested in harnessing the power of teams to achieve business objectives. Teams and teamwork represent a very powerful mechanism for getting results and achieving significant change in organizations. Over the past several years, much has been learned about the development and implementation of teams-- What works and what doesn't work. Teams are evolving that have the potential of replacing traditional hierarchical organization structures with very flat, self directed, cross functional, process oriented organization. High Performance Teams are a special class of team that has the ability to easily adapt in a rapidly changing world. High Performance Teams may be an essential element of any successful reengineering effort.

The variables outlined in this section were the motivation for the variables in the social network model for engineering and construction.

Team Decision Making

How a team reaches agreement and commits to the agreement is an area of serious struggle for most teams. The common approach for working teams is to elect or appoint a leader who will try to guide their team's discussions to reach team consensus. Most effective teams shun this traditional model as potentially manipulative and detrimental to the building of trust that is so necessary for strengthening an effective team. Since Americans come from democratic roots, it's natural for a team to want to set a standard of unanimous agreement--an ideal state that is difficult and sometimes impossible to achieve. Often the seemingly simple prospect of getting the whole team to agree to the time and place of the next meeting can turn out to be a virtual impossibility.

Effective teams are working under a deadline. The pressure to reach agreement and get started is enormous. As an alternative to unanimous agreement, some teams evolve to the majority rules model: A decision is called for, hands are raised in support and counted, and if more than half the total present agree, the decision is made and everyone is expected to support it. But as human beings we are both intellectual and instinctive. One or more team members may feel that a decision is wrong or will be ineffective but cannot articulate why they have reservations. Others may feel that the decision being agreed to might be right for the group as a whole but not right for them or the area of the organization or process that they represent. Still others may not fully understand what is being agreed to by the team as a whole.

When a team is not in full agreement on a decision or direction, or one or more of the team members disagrees, it is unrealistic to expect that those team members will adequately support the decision. People cannot execute decisions and plans they do not understand, and when they disagree with the majority direction they will be looking for the first opportunity to resurrect the decision for reconsideration. Effective team members understand this phenomenon and work together to test each other's support and understanding. Then there is the issue of absentee team members. Ideally all team members are present when important decisions are being made. Even with careful advance agreement on meeting times and locations, emergencies, both business and personal, do arise. Since the support of all team members is critical to a team's success, effective teams will have to find ways to include absent members in the decision making process and gain their understanding and support.

Self-Directed Teams

Once an effective team understands its charter and has worked through its norms, it is ready to get down to the business of solution building, planning and implementing the plan. Ideally, the team should select its own leader. This person's primary role will be to interface with other teams and coordinate team activities. The team leader should strive to avoid taking over the team, imposing his or her ideas on the team, or becoming the sole conduit of information to management. As the team meets and works together the team leader should assume an equal position with the other team members. Some team's find it helpful to rotate team leadership to give everyone experience. At the pinnacle of high performance team operation anyone on the team should be able to lead the team and everyone would feel comfortable with that possibility.

The sponsoring manager is responsible for defining objectives for the team - the "what" that the team needs to accomplish. To the largest extent possible, "how" the team accomplishes the objectives should be left to the team to decide. The sponsoring manager should be mentally prepared to support the team's chosen approach so long as the approach to achieving the objectives are within moral, ethical, and legal bounds. The sponsoring manager must recognize that the team may choose a path that appears less than optimal to the management team. When this occurs it is critical for management to recognize that achievement of the teams objectives is more dependent on the team's enthusiasm for its own solution than the quality of the solution. Effective teams are asked to accomplish objectives within timeframes that are truly stretch

objectives. Management must give the team the maximum latitude possible for achieving objectives that, at the outset, seem nearly impossible.

The relationship between the team and sponsoring management should be mutually supportive. The team delivers what management needs in the way of results. Management delivers what the team needs in terms of resources, political support, and recognition.

When an effective team meets with top management to report on its activities, the entire team should attend and should, so far as possible, have as many team members as possible involved in the presentation. Team members should be encouraged to speak up during presentations in order to demonstrate co-equality and solidarity with the team. This is very important, as it is quite natural for managers to seek to identify individual team leaders. Once a manager gets the idea that one or two individuals are driving a team, the manager will direct future questions and comments about the team to those individuals. As a result, the other team members will pick up on this phenomenon and may withdraw participation, withdraw support, or defer to the *de facto* team leaders.

Empowered Teams

Much of the modern literature speaks about empowerment. For teams, the idea is that team members have control over the team's performance and behavior. Control is one source of power. Most power derives from the organization's management authority. A team is empowered by virtue of that power that is granted to it by management. A team charter is a very useful tool for helping a team and management understand just exactly what the team has power (or is empowered) to do. This can help avoid the problem that one manager observed about empowered teams, "They are like a tiger cub, at first they are eating all the mice and rats, after a year they are eating you."

Information is another source of power. To be effective, teams need information, and lots of it. Some who are active in building teams believe that the teams should be told everything that could possibly help them in achieving their objectives. They need to know the financial condition of the organization. They need to know about pending organizational changes. They need to know what is going on in the market they are serving. Some top-managers believe that teams don't need this information or that widespread knowledge of this information could be dangerous for the organization. The opposite is more true. Teams that are trusted with sensitive information know that and take care to make certain that non-team members do not pick it up from them. They value that trust and will not betray it. Teams also need to clearly understand the organization's mission, vision for the future, and direction. Armed with this knowledge the team can much more rapidly achieve desired results. Such knowledge gives the team confidence in its decisions and energy to implement those decisions. Little time is wasted debating whether the proposed decision fits with the organization's direction or may be overturned down the road.

Access to resources is another source of power. A team's ability to succeed will depend in part on how free it is to use precious resources. Most people realize that with enough resources,

anything can be accomplished. Yet most organizations are resource constrained. So there is often a very real tension between the team's need for resources to accomplish its objectives and the organization's need to conserve resources. One possible solution is to provide the team with guidance on how quickly any substantial resource investment needs to be paid back in term of savings or new business.

Community of Interest

When a team is commissioned it is often made up of a group of representatives from different parts of the organization. Each person may be a subject matter expert who understands the processes and activities within a department or a different part of a cross-functional process. This is not very unusual. In fact, this is the most frequent form of team composition. This is because it is usually impractical to include every person who will be involved in the operation of process or a significant implementation, in the day to day meeting and work of a high performance team.

Conventional wisdom is that teams over 20 people, some think over 15, become too unwieldy and lose the active participation of all team members. At the same time, a major change management principle embraces the notion that people will more readily accept and support a change in the way they work if they are included in the development of the solution. This presents a major dilemma for teams: How can the team be kept small enough to effectively work together and at the same time involve everyone? This is not a trivial matter in large organizations that may have several hundred people actively supporting a work stream or process. Extend the group to customers of the process and we wind up with a very large group of people whose collective buy-in is needed to assure successful change. This larger, extended team could be thought of as a community of interest.

Special efforts have to be used to involve the community of interest in the understanding of the initial team's charter and the collection of information the team needs to understand the existing operating model. Input and ideas need to be sought from the larger community of interest as the solution set is developed. Then, the community of interest needs to develop a shared understanding of the solution or high level plan and participate actively in the development and implementation of final, detailed plan. Successful teams organize, develop, and implement a communication plan to gain the participation, support, and finally the commitment of the community of interest.

Communication Planning

Communication Planning is extremely important in the building of effective teams. A number of constituent groups need to be informed about the work and progress of the team. An early step in the formation of a team should focus on identifying an individual or sub-team to handle communication both within the team and with the parties that may be interested in the work of the team.

The working, or core team, needs to develop its own conventions and procedures for sharing information between each other. As ideas, research data, political forces, and team operating norms develop, the team needs to define its process for communicating with one another. Given that many teams are made up of members who are scattered around the country or around the world, it may be very impractical for the team to physically meet and work together for the entire duration of charter time-frame. Effective teams learn to take advantage of all the resources available to it. Communication technology is advancing very rapidly: telephone, paging, conference calling, E-mail, Voice-Mail, Lotus Notes, Video-conferencing, the World Wide Web, and emerging personal communication devices expand the team's optional methods of communication.

Beyond the communication needs of the team, are the team's communication needs outside its ranks. Decisions need to be made about the best way and how often to keep the sponsoring management group informed. If the charter is well written, it can serve to break down most barriers and resistance that forms. Occasionally, the sponsoring manager may need to intervene on the team's behalf or rein in its horns when the team exceeds its authority. The team needs to carefully plan its communication with its larger community of interest.

Measurement

Effective teams are established to accomplish something within a timeframe. A clear understanding of the team's objectives is a very important element of creating a successful team. When what needs to be done and how we will know we have done it is known, life is simple. Most organizations do not have effective measures of performance. Indeed, most organizations are unsure about what constitutes organizational performance.

From the sponsoring manager's point of view, the objectives may not be all that clear. The sponsor may "feel" that significant improvement in overall organizational performance (new business or reduced costs, or improve service) is needed. In this more common instance the team has some serious work to do defining and refining performance measures.

A highly effective team can and should be expected to develop and refine its objectives and measures of performance. Even when management provides simple instructions such as a desire to reduce cost, many questions remain: Cost reductions at the expense of sales? Reduce our own costs, but push costs off on some other organization or a supplier? Or the customer? Larger objectives quickly come into play, and the team is going to also have to be given the strategic objectives of the organization so it can figure out whether what is trying to do will contribute to the organizations strategy. Unfortunately, the organization's strategy may be only in one person's head, or it seems to change with the wind, or is not followed at all by anyone in the organization. When a team discovers that it doesn't understand the organization's strategy, it must stop progress and get briefed by someone who does understand it. In the sad event that there is no clear organizational strategy, the team will have to presume a strategy and run it past the sponsoring manager for confirmation.

Once the strategy is set or understood by the team members, work can proceed on refining performance measures. Effective teams are chartered to improve performance in some way. Performance is associated with speed, quality, cost, and effectiveness. Finding good measures on these variables is not always easy. Effectiveness is very elusive and in the service industry. Quality may be difficult to define as well. Cost and speed are less difficult to get a handle on, but they have their pitfalls and problems as well. To top all this off, most of us are blinded by the current set of performance measures we maintain. Most organizations count what can be easily counted, without regard to whether these counts define the organization's performance: Number of telephone calls answered, number of orders processed, number of thing-a-ma-jigs made, or shipped, or serviced, are only the starting point for understanding performance. A fresh start on measurement may be needed. Getting a better handle on performance usually means starting with your customer's point of view about your performance. Finding out what is important to your customers and building a set of measures around these variables is usually much more effective than counting what can be easily counted.

Effective Team Essential Elements

Effective Teams demonstrate the following characteristics and behaviors:

Shared Vision

All team members share and support a common vision that the team is working towards. Team members are highly focused on attaining objectives. Effective teams have developed a vision that brings real meaning to the work that is being performed. The vision describes a future state that team members find personally appealing and exciting. A defensive vision such as "keep our jobs," or "retain market share" are not particularly inspiring. What is needed is a winning vision. One that inspires team members to extraordinary efforts when such efforts are required.

Time Oriented

The team operates under specific deadlines for achieving results. Teams that operate without deadlines will ultimately evolve into rap sessions. Focus shifts from what is to be done to endless discussions about what the real mission of the team is or to finding the best approach to solving the problem. Deadlines can be as much as nine months to a year away. Any longer and the team runs the very real risk of being overrun by larger events that affect the organization: major shifts in organization direction, budget changes, new responsibilities, etc. 90 to 120 day or even shorter timeframes are more desirable and achievable by highly effective teams.

Communication

The team makes extra-ordinary efforts to make certain everyone on the team understands the plan and progress towards its completion. An old military saying is that there are always 10 percent of the people who do not get the word. An effective team recognizes this phenomenon and uses all communication vehicles available to get new information to every team member.

Team members recognize that they have an equally strong obligation to keep themselves informed.

Reviews Quality

The team stops at appropriate times to check the quality of its recent work. This is done to determine where the process could be improved and what learning can be shared with other team members. It is this act of stopping to check quality, even in the anxiety zone, where the team internalizes its learning and improves its collective performance.

Involves Everyone

Team members work to make certain that every member of the team is involved. Watchers and wonderers are mobilized to get behind the team's march toward achieving its vision. It is human to make judgments about the capabilities, intelligence, and motivation of our fellow team members. When we do so, we limit the potential of the team. Every team member has a unique insight or contribution it can make towards team goal achievement. It may very well be true that every team member must contribute for the team to achieve full success. It is the responsibility of each and every team member to search out and discover the capabilities of all the others.

Trust, Respect and Support

Developing trust among team members is at once difficult and essential to becoming an effective team. Team members need to be taught from the start that building trust within the team is critically important to the team's ultimate success.

As the team forms, it is normal that the level of trust is low. Several members, or all team members may have worked together before. Or they may know each other by casual acquaintance or interaction. But trust has something to do with loyalties, and at the outset the

team will not have developed team loyalty. Rather, each team member's loyalties will be to his or her own organization or manager. As the days and weeks of team building proceed, loyalties will naturally build toward fellow team members. This is often a two-step process: one forward, and one step back. During the first few days, it is common for one or more team members to respond negatively about the need for the team, its composition, the coaches, the task before them, or whether this is the most important thing they could be spending their time working on. As a result, several team members are likely to call back to their functional area or manager with negative reports. As these complaints are relayed back to the team coach, and they certainly will be, the coach needs to bring the complaints before the team for consideration as an issue. It is best not to name names. This will send a message to the complainers that they are on the verge of being discovered. Invariably the complainers will change their tune, rather than risk a negative reaction from their fellow team members.

Team members need to be coached to learn that it is important to trust one another. It is not possible, or desirable, for one team member to do all the work for the team. Although, someone

will almost always try. New members need to learn that to get the job done they have to rely on others to do their part. The analog to this principle is that each team member needs to be trustworthy. Team members need to learn that others are counting on them to do what they said they would do. But personal or business problems outside the team come up that affect individual team members' ability to accomplish their agreed tasks. As soon as it becomes clear to a team member that his or her task cannot be completed in time, the team member needs to let the other team members know about the cause of the problem and ask for help. This practice goes a long way to convincing fellow team members that one is trustworthy.

When a call for help comes from a fellow team member, the others should carefully examine their own responsibilities and available skills or time to see if they can help. It's in the best interest of team members to support each other, especially when the team's performance is judged and rewarded as a whole. The time might come when the team member who has been asked for help, needs help himself. If help cannot be offered, the team should pull together and determine how to be revise the plan or bring in additional resources to get the plan back on track.

3.4 Social Network Analysis

Social Network Analysis is used widely in the social and behavioral sciences, as well as in economics, marketing, and industrial engineering (Wasserman and Faust). Although it has not been widely used in the analysis of engineering and construction organizations, this new area of study presents an opportunity to examine relationships between actors in high performance organizations. The Social network perspective focuses on relationships among organizational entities; examples include communications among members of a group, trust among members of an organization, and the exchange of knowledge. The focus on the relationships is an important addition to standard organizational research, which is primarily concerned with attributes of organizational efficiency.

Social network analysis is a distinct research perspective because it is based on an assumption of the importance of relationships among interacting units. The social network perspective encompasses theories, models, and applications that are expressed in terms of relational concepts or processes. That is, relations defined by linkages among units are a fundamental component of network theories. Along with growing interest and increased use of network analysis has come a consensus about the central principles underlying the network perspective. These principles distinguish social network analysis from other research approaches (Wellman 1988). In addition to the use of relational concepts, we note the following as being important:

- Actors and their actions are viewed as interdependent rather than independent, autonomous units.
- Relational ties (linkages) between actors are channels for transfer or “flow” of resources (such as information)
- Network models focusing on individuals view the network structural environment as providing opportunities for or constraints on individual action
- Network models conceptualize structure (organizational, values, communications, knowledge exchange, and so forth) as lasting patterns of relations among actors

Of critical importance for the development of methods for social network analysis is the fact that the unit of analysis in network analysis is not the individual, but an entity consisting of a collection of individuals and the linkages among them. Network methods focus on dyads (two actors and their ties), triads (three actors and their ties), or larger systems (subgroups of individuals, or entire networks). Therefore, special methods are necessary.

Network analysis enters into the process of model development, specification, and testing in a number of ways: to express relationally defined theoretical concepts by providing formal definitions, measures and descriptions, to evaluate models and theories in which key concepts and propositions are expressed as relational processes or structural outcomes, or to provide statistical analysis of multi-relational systems. In the first, descriptive context, network analysis provides a vocabulary and set of formal definitions for expressing theoretical concepts and properties.

Alternatively, network models may be used to test theories about relational processes or structures. Such theories posit specific structural outcomes which may then be evaluated against observed network data. For example, suppose one posits that knowledge exchange is a result of trust and communication. Such a posit can be tested by adopting a statistical model, and studying how trust and communications affect knowledge exchange empirically.

The key feature of social network theories or propositions is that they require concepts, definitions and processes in which social units are linked to one another by various relations.

Both statistical and descriptive uses of network analysis are distinct from more standard organizational analysis and require concepts and analytic procedures that are different from traditional statistics and data analysis.

Given a collection of actors, social network analysis can be used to study the structural variables measured on actors in the set. The relational structure of a group or large social system consists of the pattern of relationships among the collection of actors. The concept of a network emphasizes the fact that each individual has ties to other individuals, each of whom in turn is tied to a few, some, or many others, and so on. The phrase "social network" refers to the set of actors and the ties between them. The network analyst would seek to model these relationships to depict the structure of a group. One could then study the impact of this structure on the functioning of the group and/or the influence of this structure on individuals within the group.

There are several key concepts at the heart of network analysis that are fundamental to the discussion of social networks. These concepts are: actor, relational tie, dyad, triad, subgroup, group, relation, and network.

Actor. As we have stated above, social network analysis is concerned with understanding the linkages among social entities and the implications of these linkages. The social entities are

referred to as *actors*. Actors are discrete individual, corporate, or collective social units. Examples of actors are people in an organization, organizations themselves, or high performance teams.

Relational Arc. Actors are linked to one another by social *arcs*. The range or types of arcs can be quite extensive. The defining feature of an arc is that it establishes a linkage between a pair of actors. Some of the more common examples of arcs employed in network analysis are:

- Evaluation of one person by another (for example shared values)
- Transfer of resources (such as communications, giving information and receiving information)
- Behavioral interaction (such as knowledge exchange)

Dyad. At the most basic level, a linkage or relationship establishes a tie between two actors. The tie is inherently a property of the pair and therefore is not thought of as pertaining simply to an individual actor. Many kinds of network analysis are concerned with understanding ties among pairs. All of these approaches take the *dyad* as the unit of analysis. A dyad consists of a pair of actors and the (possible) tie(s) between them. Dyadic analysis focus on the properties of pair wise relationships, such as whether ties are reciprocated or not, or whether specific types of multiple relationships tend to occur together. The dyad is frequently the basic unit for the statistical analysis of social networks.

Triad. Relationships among larger subsets of actors may also be studied. Many important social network methods and models focus on the *triad*; a subset of three actors and the (possible) tie(s) among them.

Subgroup. Dyads are pairs of actors and associated ties, triads are triples of actors and associated ties. It follows that we can define a subgroup of actors as any subset of actors, and all ties among them. Locating and studying subgroups using specific criteria is an important concern in our use of social network analysis.

Group. Network analysis is not simply concerned with collections of dyads, or triads, or subgroups. To a large extent, the power of network analysis lies in the ability to model relationships among systems of actors. A system consists of ties among members of some (more or less bounded) group. The notion of group has been given a wide range of definitions by social scientists. For our research, a group is the collection of all actors on which arcs are to be measured. One must be able to argue by theoretical, empirical, or conceptual criteria that the actors in the group belong together in a more or less bounded set. Indeed, once one decides to gather data on a group, a more concrete meaning of the term is necessary. A group, then, consists of a finite set of actors who for conceptual, theoretical, or empirical reasons are treated as a finite set of individuals on which network measurements are made.
The restriction to a finite set or sets of actors is an analytical requirement. Though one could conceive of arcs extending among actors in a nearly infinite group, one would have great difficulty analyzing the data on such a network. Modeling finite groups presents some of the more problematic issues in network analysis, including the specification of network boundaries, sampling, and the definition of group. Network sampling and boundary specifications are important issues.

Relation. The collection of arcs of a specific kind among members of a group is called a relation. For example, weekly communication or monthly communication, are arcs that define a relation. For any group of actors, we might measure several different relations (for example, we may measure the number of arcs and the strength of the arcs). It is important to note that a relation refers to the collection of arcs of a given kind measured on pairs of actors from a specific actor set. The arcs themselves only exist between specific pairs of actors.

Social Network. Having defined actor, group, and relation we can now give a more explicit definition of social network. A social network consists of a finite set or sets of actors and the relation or relations defined on them. The presence of relational information is a critical and defining feature of a social network.

Network Data

Network data consists of at least one structural variable measured on a set of actors. There are two types of variables that can be included in a network data set: *structural* and *composition*. Structural variables are measured on pairs of actors and are the cornerstone of social network data sets. Structural variables measure arcs of a specific kind between pairs of actors.

Composition variables are measurements of actor attributes. Composition variables, or actor attribute variables, are of the standard social and behavioral science variety, and are defined at the level of individual actors.

Network data may be collected by observation, interviewing, or questionnaires. Social network data consists of one or more measured relations among the actors. The unit of observation is the entity on which measurements are taken. Thus, the unit of observation is an actor, from whom we elicit information about arcs. In our research, we will mainly deal with survey questionnaires for obtaining our data.

Graphs

Graph theory has been useful in social network analysis for many reasons. Among them are the following: First, graph theory provides a vocabulary which can be used to label and denote many social structural properties. This vocabulary also gives us a set of primitive concepts that allows us to refer quite precisely to these properties. Second, graph theory gives us mathematical operations and ideas with which many of these properties can be quantified and measured (Freeman 1984; Seidman and Foster 1987).
Last, given this vocabulary and these mathematics, graph theory gives us the ability to prove theorems about graphs, and hence, about representations of social structure. Like other branches of mathematics, graph theory allows researchers to prove theorems and deduce testable statements.

In addition to its utility as a mathematical system, graph theory gives us a representation of a social network as a model of a social system consisting of a set of actors and the arcs between them. By *model* we mean a simplified representation of a situation that contains some, but not all, of the elements of the situation it represents (Roberts 1976; Hage and Harary 1983). When a graph is used as a model of a social network, points (called *nodes*) are used to represent actors, and lines connecting the points are used to represent the arcs between actors. In this sense, a graph is a model of a social network. Graphs have been widely used in social network analysis as a means of formally representing social relations and quantifying important social structural properties, beginning with Moreno (1934), and developed further by Harary (Harary 1959a; Harary 1959b; HaraRY 1969; Hage and Harary 1983; Harary, Norman and Cartwright 1965) and others (for example, Frank 1971; Seidman and Foster 1978a, 1987b; Foster and Seidman 1982, 1983, 1984).

The visual representation of data that a graph or sociogram offers often allow researchers to uncover patterns that might otherwise go undetected (Moreno 1934; Hoaglin, Mosteller, and Tukey 1985; Tukey 1977; Vellman and Hoaglin 1981).
Graphs are either nondirectional or directional. Nondirectional graphs are used for nondirectional relations. There is either an arc or there isn't one. Directed graphs have links that are directional, where the arc has an origin and a destination. The arc may either be one way or reciprocated in which case it is a bidirectional arc. Our research will use directed graphs.

Density of Graphs

The *degree* of a node, denoted by $d(n_i)$, is the number of lines that are incident with it. Equivalently, the degree of a node is the number of nodes adjacent to it. The degree of a node is a count that ranges from a minimum of 0, if no nodes are adjacent to a given node, to a maximum of $g – 1$ (where g is the number of nodes) if a given node is adjacent to all the other nodes in a graph. A node with degree equal to 0 is called an *isolate*.

We can also consider the number and proportion of lines in the graph as a whole. A graph can only have so many lines. The maximum possible number is determined by the number of nodes. Since there are g nodes in the graph, and we exclude loops, there are $\frac{g(g-1)}{2}$ possible unordered pairs of nodes, and thus $\frac{g(g-1)}{2}$ possible lines that could be present in the graph. This is the maximum possible number of lines that can be present in a graph.

Centrality

A key measure that reflects the distribution of relationships through the network. In a highly centralized network, a small percentage of the members will have a high percentage of relationships with other members in the network. In contrast, a network with low centrality will have relatively equal distribution of relationships through the network. An example of a highly centralized network is one where an individual such as the project manager serves as a filter for a high percentage of communications rather than communications being distributed throughout the network.

Power

The power variable works in conjunction with centrality. Whereas centrality measures the total number of relationships that an individual may have, power reflects the influence of an individual in the network. Individuals who are giving information to others in the network, who are in turn passing along that information to others, has a high degree of influence or power. Individuals, who are mainly on the receiving end of communications may be central in the network, but have little power as they do not influence the actions taken by others.

Betweeness

This variable measures the amount of information that is routed through an individual to distribute to the team. This rating indicates which individuals are involved in discussions that are occurring within the network.

3.5 Social Network Model for Engineering and Construction

The research foundation for the Social Network Model was developed through a series of incremental steps that researchers at the University of Colorado have undertaken over the past several years (Chinowsky, Diekman, Golatti and O'Brien). In summary, the foundation has been built through the following steps:

1. The researchers initially investigated the hypothesis that project teams experience delays and sub-optimal results due to instability in the project network. Specifically, constant changing of personnel from one situation to the next results in a network that must be continually reformed and refocused.

2. The focus on networks led directly to an investigation of Social Network Analysis (SNA) as a potential methodology and tool for investigating network relationships and modeling. This approach has emerged as a critical aspect of the project and is discussed in more detail below.

3. The selection of SNA methodology as an appropriate modeling tool led to the question of what project variables should be analyzed within the network.

The initial answer to this question emerged from two established bodies of research. The first, critical success factors, provided both a general project approach and a specific construction context to study what variables impact the success of project teams. (Pinto and Slevin 1987; Ashley et al 1987; Ashley and Jaselskis 1991; Chua et al 1999; Cooke-Davis 2002; Chan et al 2004). The second, communication variables, provided a bridge to the social communication research that established a new foundation for developing high performance project teams.

Given the selection of a modeling methodology and an approach to selecting model variables, researchers were able to obtain the initial results necessary to develop the proposed Social Network Model.

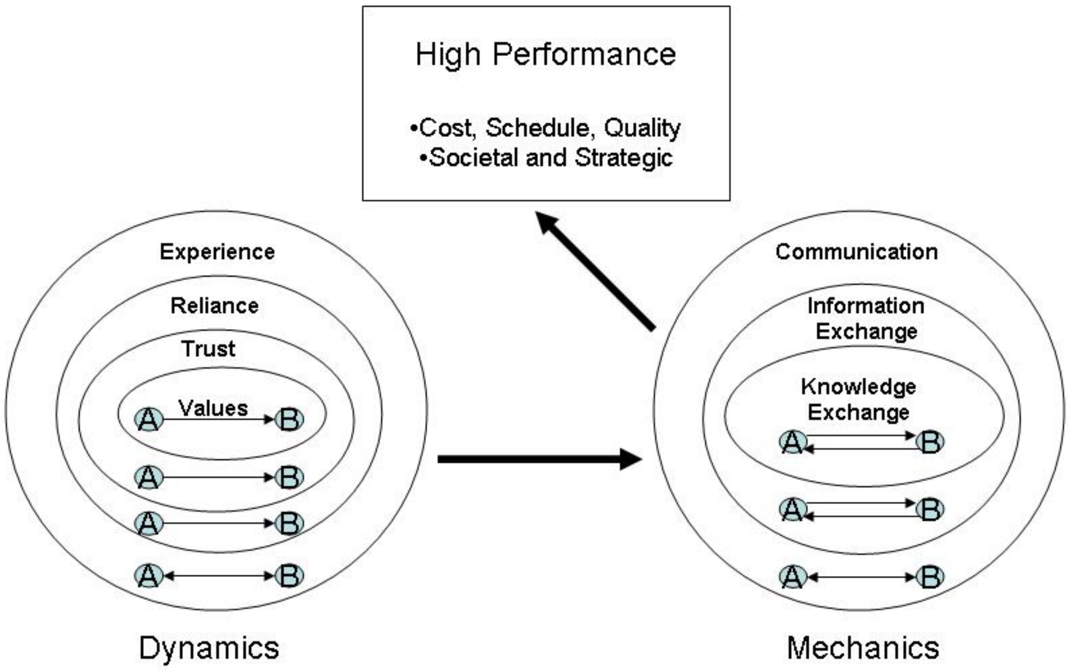

Figure 3.5: The Social Network Model for Engineering and Construction

The overall Social Network Model is illustrated in Figure 3.5. As illustrated, the model contains two basic components, dynamics and mechanics. The latter of these components, mechanics, are the items that are exchanged in a project. The mechanics contains both the classic emphasis on information sharing and exchange as well as an emphasis on knowledge exchange. The goal of the model is to achieve knowledge sharing as the mechanics that drives project execution. The former component, dynamics, can be viewed as the "why" in a project, or the reasons that motivate project teams to exchange items listed in the mechanics. The dynamics represents the social collaboration component within the project team. In this component, the goal of the model is to achieve shared values among the project team.

Combined within the model, the dynamics drive the success of the mechanics by serving as the motivator for the team to move past efficiency to high performance. The underlying concept of this relationship is that by achieving trust and shared values within the project network, the project team will increase the exchange of knowledge and information which will result in high performance output.

The definition of this output is defined along two dimensions, traditional and emerging measures. In the former, time, cost and quality remain as measures of success for the project. However, high performance teams will continually strive to exceed the traditional performance benchmarks to set new standards in project output. In the latter, high performance construction projects will extend the concepts of measurement to emerging issues such as societal and strategic concerns.

In these measures, the teams are working towards solutions that not only meet the needs of the client, but address societal issues such as environmental and energy concerns as well as strategic concerns such as long-term business viability and emerging markets.

The survey results will be analyzed using the UCINET Social Network Analysis software. The UCINET software provides the mathematical measurements as well as the graphical representations required for the organization analysis.

3.6 Organization Analysis

Communication

The initial focus of the social network survey will determine which managers know each other through communication of any type over the last 12 months. As seen in Figure 3.6, the individuals in charge of Accounting and Marketing as well as the President and the Senior Principals in San Francisco are already emerging as dominant in the communication structure. Although the network has sufficient density, this early indication of centrality is an indicator that the outlying individuals may not be sufficiently engaged in network collaboration. The first direct focus on organization management occurs with the second survey question that asks which individuals a manager communicates with at least once a month on organization specific topics. The results of this question provide an indication of the lack of communication that exists in the organization. A drop in the network density to 24% results in only half of the density found in the previous question. The interpretation of this result is that a significant percentage of the managers are not discussing organization issues on a regular basis.

A greater focus on this communication issue occurs with the third survey question where the frequency of communications related to organization issues is explored. In this question, the threshold of interest for the study is to find managers that communicate at least once a week on organization issues. The key here is that unless a weekly communication is sustained, other topics will begin to take precedence and the focus on the organization topic will begin to get lost. Using this threshold, the network is divided into responses that are less than once a week and responses that are at least once a week. From this division, the network is analyzed from two perspectives. First, a numeric analysis focusing on the leadership of the organization is performed. This analysis is designed to determine if the necessary leadership is being utilized to guide the teams and lead the organization in essential topics of discussions. The results of this analysis are shown in Figure 3.7.

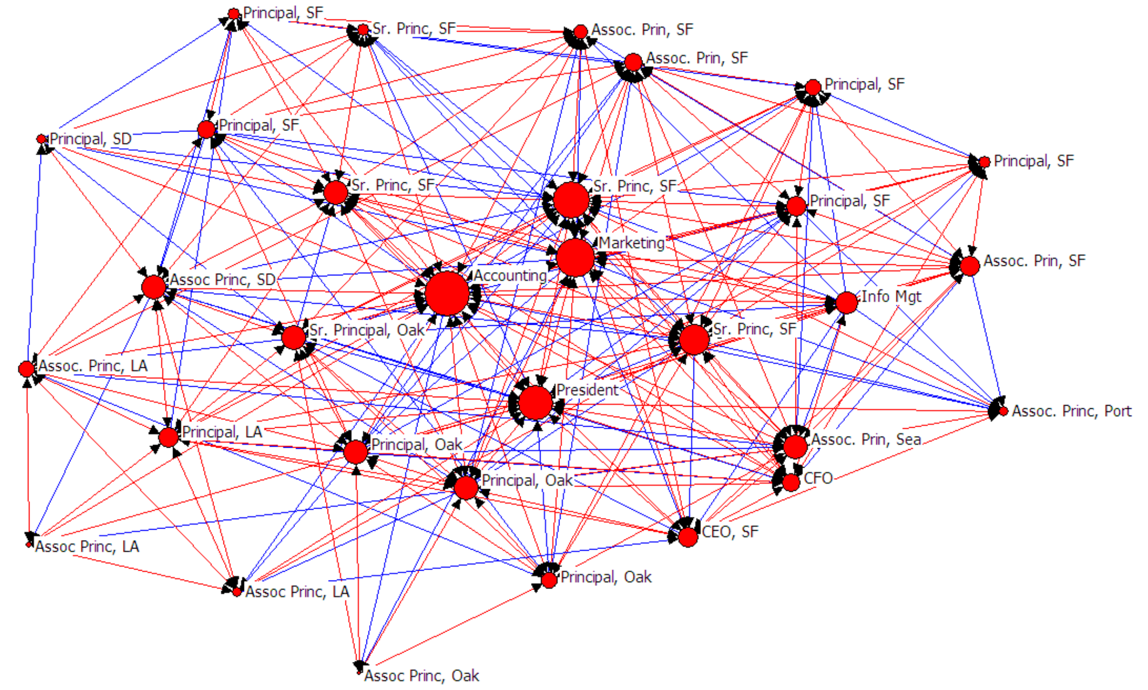

Figure 3.6: The communications network indicating any communications over the last 12 months.

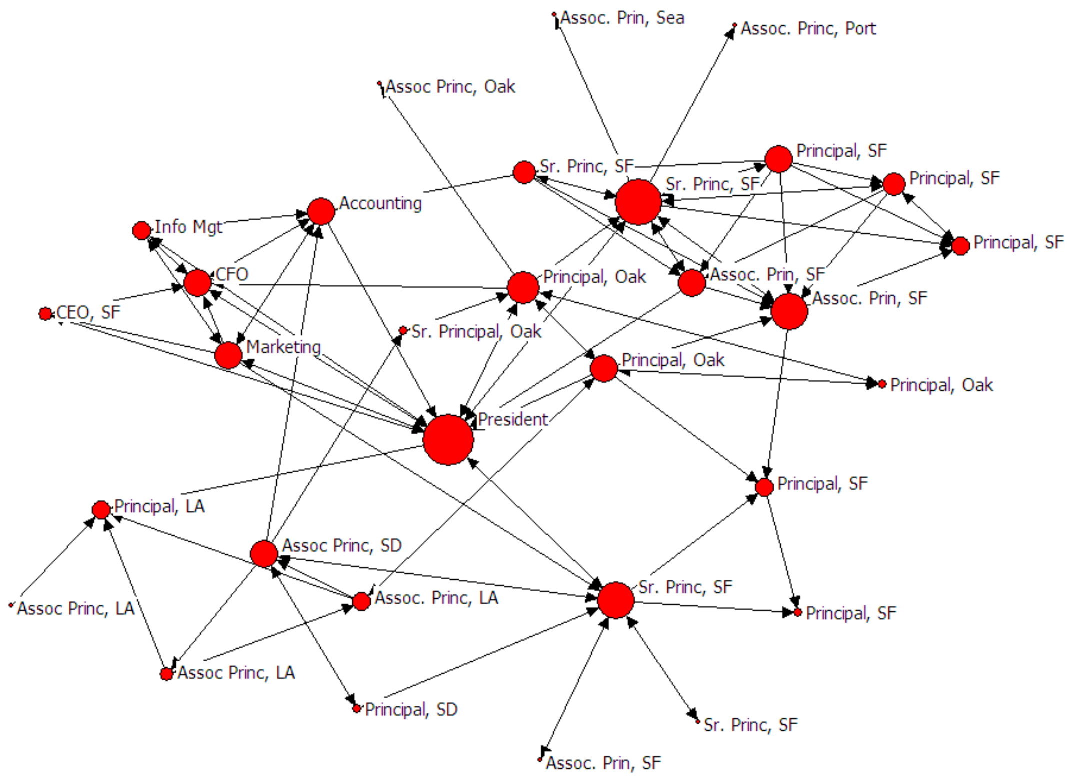

Figure 3.7: The weekly communication network for organization issues.

Dynamics

The complement to communication in supporting knowledge exchange is the social statics that exist in an organization. Specifically, the reliance that exists between individuals, the trust in the network, and the belief that values are shared are key indicators regarding how individuals are motivated to share knowledge.

Reliance

In the area of reliance, Figure 3.8 illustrates that this network has a good density with a rating of 37%. However, the network also illustrates a centralization of the reliance with the President and the office leads receiving most of the reliance indicators.
Although this could be a reflection of the move to recentralize the organization, it could also indicate a lack of interaction between managers in the offices. While the density number is good, it is somewhat cautionary in that the reliance is not equally spread throughout the network.

Trust

A direct outcome of reliance is trust. There are many forms of trust that can exist in an organization from what is referred to as blanket trust which translates to a trust of another individual in any action they take to a focused trust on a specific topic. In the context of the Social Network Model, trust is considered when an individual believes that another individual will take actions that are mutually beneficial and not solely to one's own advantage. This is a key requirement for knowledge exchange since individuals need to feel confident that knowledge that is exchanged will have a mutual benefit. In contrast, if an individual believes that exchanging knowledge can lead to a reduction in status or power, then that individual will be hesitant to release knowledge into the network.

With a density rating of 45%, it is apparent that trust is a very strong component of the network. Trust also exists between individuals in the regional offices. This is a strong foundational element that is required to build knowledge exchange in the organization.

Values

The final level of interest in Dynamics is the level of shared values in the organization. Following the pattern established with reliance and trust, there is a strong sense of shared values in the organization. The 36% density in the network indicates a good level of shared values. Although there is some centralization apparent in the network, it is not a level that would be of critical concern in addressing this issue.

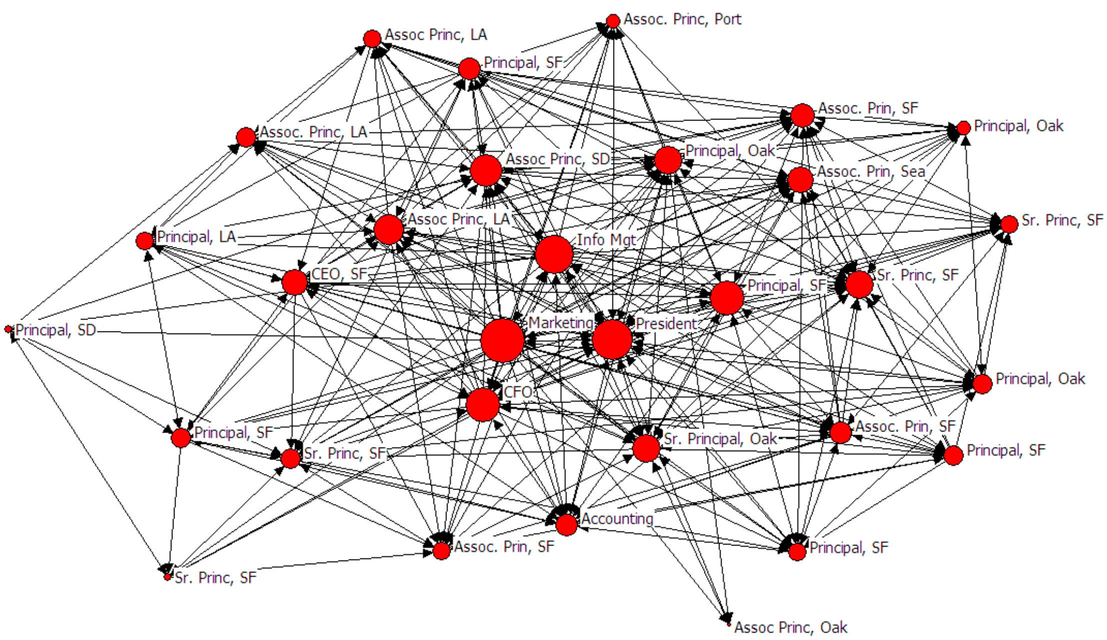

Figure 3.8: The reliance network

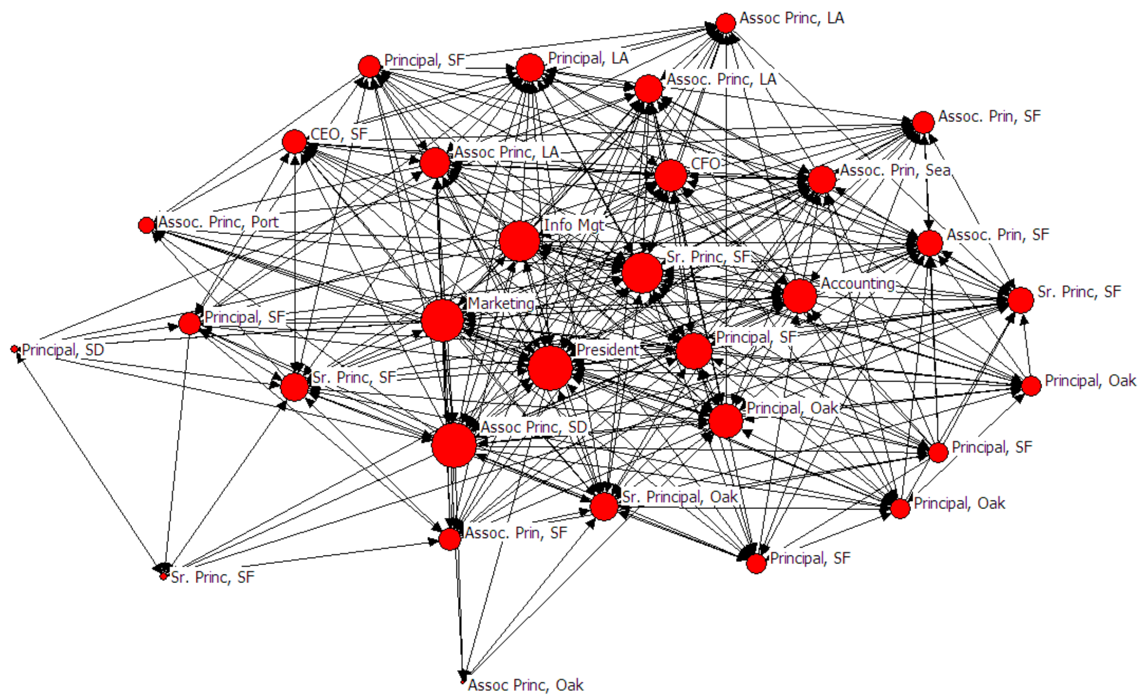

Figure 3.9: The trust network

Chapter 4 Research Methodology

4.1 Methodology Introduction

The methodology of the research involved gathering and analyzing data. All of the required data was gathered through an easy-to-use web site. Communication, knowledge exchange, experience, reliance, trust and value data was obtained.

The methodology for conducting each of the social network studies followed a three-step process adapted from the established social network protocols and put in place by the authors in the original Social Network Development phase to promote both repeatability and validity. As a foundation for the process, the authors utilized commercial software that was developed specifically for the social network data collection and analysis. As detailed, the combination of the commercial software and specific analysis provided the basis for standardizing the process among each of the testing scenarios.

The first step in the study process was the identification of the actors who would be included in the network. For this process, the Chief Executive Officer (CEO) of each participating company identified individuals who have supervisory responsibilities based on the organization chart. Using the CEO in combination with the organization chart to select the participants provided the best opportunity to enhance the consistency and reduce bias that may emerge from either self-selection by individuals who want to be part of the study, or form a single point of contact that may be biasing the sample due to selective inclusion of participants. Finally, using this criterion provided the ability to establish comparable communities within the organizations and establish defined populations for fielding the SNA study. From this selection method, the participants were identified and established as actors within the social networks. Each of the scenarios summarized in this paper represent results from these comparable networks and are consistent in their use of comparable actors and positions in the organization charts and thus provide the basis for comparing the results for each deployment.

Our initial report to the firms was based on direct measures of the observed networks using densities and visual graphs of the networks from UCINET. I expanded on the results in this thesis to examine basic statistical measures and stochastic statistical analysis of the observed networks. These statistical measures give us clues to study how networks are formed by looking at the configurations in the networks in addition to density.

4.2 Engineering Design Firms

The Participants

The participants for the Social Network Model tests each volunteered to be a part of the study. Each of the companies met a specific set of criteria including: 1) multiple offices, 2) multiple design disciplines, 3) actively participate in construction inspection and oversight, and 4) been in business for over 10 years. These criteria were set to meet two specific issues: 1) the organizations needed to be in place for a significant amount of time to have potentially developed a sense of collaboration, and 2) the offices were engaged in both the management of design and construction to enhance the potential for collaboration and integration.

The Larson Design Group formally organized under its current structure as a 100% employee-owned company in 1993. The organization is focused on turning client visions into reality with full-service design services including both architectural and engineering services. Through expansion and mergers, LDG now has six offices with headquarters in Williamsport, PA and branch offices in Bloomsburg, Selinsgrove, Ephrata, and Bethel, PA in addition to Corning, NY. The organization remains committed through its expansion to continue focusing on client satisfaction and community respect through leadership and stewardship.

Degenkolb Engineers was established in 1940 with a focus on structural engineering. The organization is based on a concept of listening to customers and providing custom structural solutions to projects of all types. The organization has grown steadily to include regional offices in Los Angeles, Oakland, Seattle, San Diego, and Portland in addition to its corporate office in San Francisco. Responding to an under performance in the organization several years ago, the organization returned to a centralized structure in late 2006.

Orchard, Hiltz & McCliment (OHM) was established in 1962, with 15 employees, as a municipal engineer for the City of Livonia, Michigan – the beginning of a four decade relationship that continues today. New partnerships were formed and the company grew to serve five major municipalities. These clients are still with OHM today. In 1984, OHM took on its first projects for the Michigan Department of Transportation. In the same year, it delved into the new world of computer-aided drafting, and launched a structural engineering group.

OHM opened a second office in Livonia to house its expanding Construction and GIS departments. They opened a new office in Auburn Hills in 1998 used by field staff to service several local municipal clients. In 2001, OHM acquired Hampton Engineering and an office in the City of Pontiac. And in 2007, they acquired a 15-person engineering and architectural firm in Houghton, Michigan.

Each of the three organizations meets the criteria set by the study. The organizations differ slightly in size, but meet the fundamental requirements. Each meets the most important criterion of delivering multiple services to support all phases of the design-construction process.

Actor Identification

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Finally, using this criterion provided the ability to establish comparable communities within the organizations and establish defined populations for fielding the SNA study. From this selection method, the participants were identified and established as actors within the social networks. Each of the scenarios summarized in this paper represent results from these comparable networks and are consistent in their use of comparable actors and positions in the organization charts and thus provide the basis for comparing the results for each deployment.

The actors were invited to participate by e-mail and given a sign-on id and password to access the questions and respond confidentially.

4.3 Data Collection Website

The second component in the study analysis was to obtain input from each of the actors in the designated network. SNA researchers focus on surveys to obtain this data and this research follows this precedent. The basis for the current survey is the Statics and Dynamics levels developed for the Social Network Model. Each level within the model required a corresponding question for the data input process. The reader is referred to the original paper introducing the Social Network Model for full definitions of each Model Component (Chinowsky, Diekmann, and Galotti, 2008). Working in conjunction with a sociologist specializing in social networks, the team developed a survey that would elicit the responses required to create a network representation of the organization. The survey questions focus on understanding relationships between each of the actors in the network for each component of the network model. The network represents a point-in-time reflection for each of the model components.

As illustrated in the survey, the questions focus on frequency of communications and knowledge transfer for the Dynamics side and on levels of experience, reliance, trust, and values for the Statics side. The focus on frequency for the Statics side is intended to provide an indication of the levels of interaction that are occurring within the organization. This focus returns to the original research question of how to increase interactions to achieve knowledge exchange and thus high performance. Each of the questions in the Dynamics side builds on the previous by first establishing a communications basis, and then using this group as a subset to determine knowledge transfer. Similarly, the Statics side uses levels of reliance or trust to determine which individuals have an above average level of reliance and subsequently trust between each other.

In each section, the questions provide a continual refinement to the population to focus the responses from the participants. The questions provide the opportunity for the actors to provide input on their relationships with each of the other actors in the network. The combination of the communication frequency, the knowledge transfer frequency, and the trust levels provides the basis for determining the degree of collaboration currently within the organizations and ultimately the potential for achieving high performance.

The delivery of the survey was completed using Network Genie, an on-line survey system designed specifically for managing social network analysis (Hansen et al 2008). The survey was distributed to the predefined list of actors in each network. The actors were individually notified to complete the survey with documentation outlining the goals of the study and the need to get 100% participation within the network. The deployment process was successful in each case, with 100% response rate achieved in each scenario.

It should be noted at this point that the focus of this survey was to obtain the perceptions of each actor in the organization. The research did not focus on the quality of communications being exchanged, nor did it focus on the mode in which communications were conducted. Addressing the quality of communications and determining how information technologies such as e-mail may affect the networks was outside the scope of this research effort. Rather, the intent of this study is to focus on the relationships between frequency of communications, levels of trust, frequency of knowledge exchange and achieving high performance. There are limitations associated with this approach such as different types of communications can require different frequencies ad different types of knowledge may require multiple contacts. These limitations are noted and are put forth as future steps in the research effort.

4.4 Initial Report

The results collected from the survey were analyzed using the UCINET Social Network Analysis software (Borgatti, Everett, and Freeman 2002). The UCINET software provides the mathematical measurements as well as the graphical representations required to conduct a Social Network Analysis. A separate analysis was completed on each of the survey questions to acquire the relationships outlined in the Social Network Model. The survey responses collected from individual questions was used to create a corresponding matrix for each question. The matrix was subsequently used to create both a graphical representation of the network as well as a set of mathematical measurements.

4.5 Statistical Analysis of the Data

The data was analyzed first by descriptive statistics, and finally by Bayesian inferential statistics. The data was prepared by calculating the densities of the social network diagrams. This provided a uniform data set of 100 participants (or Players. I will use participant, player and actors interchangeably throughout the thesis) and up to fifteen different variables to examine for a total of 1500 data points to examine. The descriptive statistics analyzes the means and the standard deviations for the different variables. Descriptive variables were the basis for my initial report to the organizations.

Together with graphics analysis, they form the basis of the quantitative analysis of data. With descriptive statistics we are simply describing what is, what the data shows. Next, simple graphic analysis was employed by creating scatter plots of the variables to analyze the patterns of the responses for two variables. Finally, inferential statistics was employed to investigate questions, models and hypotheses. Conclusions from inferential statistics extend beyond the immediate data alone. We used inferential statistics to try to infer from the sample data what the impact of communications and trust is on an organization's effectiveness. By analyzing the observed network's ERGMs, we examine what network configurations are statistically significant to the formation the observed network. We also use inferential statistics to make judgments of the probability that an observed difference between variables is a dependable one or one that might have happened by chance in this study. Thus, we used inferential statistics to make inferences from our data to more general conditions; we used descriptive statistics simply to describe what's going on in our data.

Flow of Research	Methodology of Research
Perform Initial Survey and Process the results	1. Use Network Genie to conduct the survey 2. Process the results with UCINET
Write Initial report and submit to the organization	1. Use UCINET results to analyze the network. 2. Write initial report using UCINET output.
Examine Data using basic statistics, such as density, means and deviation	1. Examine Social Network Model variables for all three organizations. 2. Examine relationship of the variables using scatterplots.
Perform diagnostics on network using inferential statistics.	1. Run PNet analysis on observed networks. 2. Examine ERGM models for observed networks for all three firms.
Examine Statistical analysis to determine if results match the social network model for engineering and construction.	1. Examine ERGM for clues to how the networks were formed. 2. Begin research to establish relationship between variables using inferential

Table 4.1: Flow Chart of Research Methodology and Table of Techniques Used to Accomplish Each Task

Densities of the Social Networks Diagrams

In order to look at the data from a statistical reference, the data was downloaded to a spreadsheet. Each answer to a question represents a matrix in a spreadsheet form (see Appendix A). Most of the questions were answered by either a 1 or a 0 depending on whether you selected another individual for the answer to the question or not. Some questions were answered by a degree of measure by answering 1 to 5. For the purpose of the analysis, these answers were converted to binary form by selecting answers greater than 2 as a 1 and answers less than or equal to 2 as a 0 (see Appendix A, figures A.3 and A.4). This is consistent with our network analysis, where we examined the communications in the organization by monthly and weekly communication.

According to the formula for density given in chapter 3, each participant's responses were added and computed as a degree for their node. This allowed us to statistically analyze networks of different number of participants. The results of these calculations are presented as Table 5.1. The top row represents the fifteen questions asked and the player column represents the individuals who responded. For example player one picked 96% of the other players for his answer to question 1 and 8% of the others for his answer to question 4, etc.

Means for the Social Network Variables

Table 5.2 summarizes the descriptive statistics for the social networks. The 100 respondents are indicated as N. The ranges for the variables are almost completely over all 100 respondents. The minimum responses were 0 and the maximums were nearly all (100% density). The means for the social network variables range from 8% for Knowledge Exchange to 56% for Communication. This represents on average 56% of respondents indicate they communicate with each other at least weekly, while only 7.6% indicated they shared knowledge with each other on average.

Referring back to the social network model for engineering and construction, we indicated that as the players in a high performing organization become more experienced with each other they will begin to rely more on each other. And as they begin to rely on each other they will build trust. This reliance and trust are the drivers for communication and knowledge exchange as demonstrated in the literature for high performance teams (Bodwell). So, what can the descriptive statistics tell us about what is happing in the social networks? The most striking statistic is the low density measures for knowledge exchange. The most any player shares his or her knowledge with other players is about one third of them.

The level of reliance is only moderate at about a third indicating that each player only relies on about a third of the others to perform his tasks.
Communications is the highest density at 56%. We dichotomized the data to include only weekly communication in our analysis.

Scatter Plots of Social Network Data

The social network data we collected from the three organizations can be plotted using scatterplots of the individual densities to observe the relationship between the variables in the social network model for engineering and construction. In Chapter 5 I examine the trust communication relationship and provide scatterplots of the other variables in Appendix B.

Some features of the plot indicate that parties must have some experience with each other before they begin to build reliance. This is demonstrated by the trend line up on the experience axis at zero reliance (This result may have happened by accident). Another feature of the plot is the distinct line of data at about equal experience and reliance. There are no points below this line. This indicates that individuals in the organization have to build experience with each other before they begin to rely on each other and vice versa. They never have high reliance on each other prior to having experience.

Another interesting feature is the points of high trust and low to moderate experience, which indicates our organization is performing at a high level. The points of low trust even at a high level of experience are areas of concern for the organization, since those players are not indicating trust in each other.

The foundation of the social network is, as you build trust in the organization, you will increase the flow of information, or knowledge transfer. A convenient measure for flow of information is communication. Trust is dependent on experience and reliance on other individuals in the organization.

We stated in the social network model that the basis for a highly effective organization was good communication and trust. Figure 5. represents a scatter plot of the communication trust relationship for the three companies surveyed. Each point represents the density for that individuals answer to the survey question and using the data for all three firms allows us to examine one hundred points all together.

4.6 Exponential Random graph Models

Introduction

Exponential Random Graph Models (ERGMs) are the most promising method of modeling observed social networks (Snijders et al 2005: 1). ERGMs are a relatively new methodology whose use is not yet widely understood in the broader academic community. This paper is written to provide an introduction to ERGMs and their application to observed networks in a survey conducted to assess an organization’s performance within the outline of the social network model for engineering and construction. We will look at why ERGMs are potentially useful for studying an organization’s networks; estimating ERGMs for observed data and the role of configurations and parameters in these estimations; simulating networks and testing the 'goodness of fit' of ERGMs; recent developments in ERGMs and the 'new specifications' and application of ERGMs to the survey results for three design firms based on the social network model for engineering and construction.

Background

Social Network Analysis (SNA) has been an instrumental tool for researchers focusing on the interactions of groups since the concept was introduced by Moreno in 1934 (Moreno 1960). Exponential Random Graph Models (ERGMs) have been developed over the last 20 years as a method of directly modeling the underlying forces which create social networks (Robins, Pattison, Kalish and Lusher 2005: 6-8). ERGMs form a statistical measurement of network properties rather than a direct measurement of the properties of a network.

To illustrate the difference between the direct measurements and statistical measurements we will look at the results of our survey for engineering design firms. I analyzed the networks based on network density, centrality and power values calculated from software designed for SNA (Chinowsky, O'Brien 2008). I looked at the attributes of the actors, such as their location in the organization chart, and evaluated the organizations performance based on these values. In the case of ERGMs I can measure the probability of a networks density and the potential for forming configurations such as reciprocity, stars and triangles. These measurements are in the form of a parameter value and standard error of the parameter value. If the parameter value is positive and statistically significant, then I can be reasonably certain that there is a higher chance probability that actors who are tied to a common actor will themselves be tied to each other. Notice the different characteristics of these measures. The characteristics of network density, centrality and power are direct measures of the properties of a network, whereas the configurations are a statistical measurement, providing us with a measure of the level of confidence that what we are observing did not happen by chance, and allowing us to control for other affects. More importantly, the configurations are conceptualized as a force which drives the formation of the network itself, whereas, network density, centrality and power are properties of the network. There is no way of knowing from the measurement of these properties whether it is the outcome of some other underlying process (most likely), or if it is actually one of the forces driving network formation.

There are two classes of ERGMs based on what they are trying to explain: 'social selection models' and 'social influence models' (Robbins, Elliott and Pattison: 2001; Robins, Pattison and Elliott: 2001). In 'social selection models' the characteristics they are trying to explain is the formation of ties between actors. The name 'social selection' comes from the idea that actors 'select' their tie partners. In the 'social influence models' the characteristics we are aiming to explain is one of the attributes of the actors in the network. The aim is to explain the formation of a particular attribute on the basis of the distribution of ties and other attributes in the network. The main strength of both classes of ERGMs is their ability to evaluate the effect of the ties and the attributes of an actor's neighbor on either the ties or attributes of that actor.

The problem with applying ERGMs to social networks is that the computer programs for estimating ERGMs for social influence have not yet been proven for analysis of a substantial data set. Thus, at the moment social influence models will have to be run on classical statistical models, and the social network effects will have to be individually measured and inputted into these models as independent variables. Such models do reveal much about the nature of networks and the forces driving actor attributes. However, given that variables in networks are inherently not 'independent' observations, classical statistical models are limited in the extent which they can accurately model social networks.

ERGMs for social selection are much more advanced. The problem for engineering design firm analysis is that the questions we can answer with social selection models are not as important as those we can answer with social influence models. However such questions are not totally without merit. We can use social selection models to ask questions such as: How are actors tied together based on the organization chart? What effect does a tie between actors adjacent to each other on the organization chart have on knowledge exchange in the network? We will focus on social selection networks because the state of ERGMs for social selection is advanced.

Exponential Random Graph Models

Exponential random graph models, also called (p*) models[2] (Frank & Strauss, 1986; Pattison & Wasserman, 1999; Robins, Pattison & Wasserman, 1999; Wasserman & Pattison, 1996) are a class of stochastic models which use network local structures to model the formation of network ties for a network with a fixed number of nodes. Stochastic models allow us to capture both the regularities in the processes giving rise to network ties while at the same time recognizing that there is variability that we are unlikely to be able to model in detail (Snijders, Pattison, Robins and Handcock, 2006). Adding a small amount of randomness to an otherwise regular process can dramatically alter the properties of the possible outcomes of that process. It is important to allow for stochasticity if we believe that it best reflects the processes we aim to model. A well-specified stochastic model allows us to understand the uncertainty associated with observed outcomes (such as an on-line survey of engineering organizations): we can learn about the *distribution* of possible outcomes for a given specification of a model, or we can estimate, for given observed data, parameters of the hypothesized model from which the data may have been generated. The parameters are constants that give us a unique picture, or "fingerprint" of an observed network. These constants can be used to evaluate the network and compare it to subsequent networks or other networks.

Statistical models also allow inferences about whether certain network (substructures or configurations) are more commonly observed in the network than might be expected by chance. In my initial report to the surveyed organizations, I used density extensively to analyze how the organization's actors were collaborating with each other. Density is one of the parameters in the p* model. We can then develop hypotheses about the social processes that might produce these structural properties. Sometimes, different social processes may make similar qualitative

[2] For other introductions to the logic of *p** modeling, see Monge and Contractor (2003), and Contractor, Wasserman and Faust (in press)

predictions about network structures and it is only through careful quantitative modeling that the differences in predictions can be evaluated.

Several longstanding questions in social network analysis relate to the puzzle of how localized social processes and structures combine to form global network patterns, and of whether such localized processes are sufficient to explain global network properties. The principal goal is to estimate model parameters from data and then evaluate how adequately the model represents the data.

We define a network space which contains all networks with a given number of nodes n. The network with n nodes can then be represented by a random variable X, which itself is a set of (n(n − 1)) tie variables X_{ij} , or $X = \{X_{ij}\}$. A realization of X is denoted by $\mathbf{x} = \{x_{ij}\}$(an observed network). Given the values of all other tie variables, two network tie variables are defined as neighbors if they are conditionally dependent, i.e. one tie's existence depends on the other tie's existence. These ties are connected to each other by a node.

A neighborhood of mutually, conditionally dependent, tie variables then forms a local network configuration. Various local interaction processes can be represented by these network configurations based on different tie dependency, or neighborhood assumptions. From the Hammersley-Clifford theorem (Besag, 1974), a model for X has a form determined by its neighborhood. This approach leads to ERGMs, or p* models, introduced by Frank and Strauss (1986), and Wasserman and Pattison (1996). Depending on the underlying neighborhood assumptions, ERGM assigns probabilities to X based on a set of counts of regular local configurations which are sufficient statistics for their parameters.

ERGMs have the following general form

$$\Pr(\mathbf{X} = \mathbf{x}) = \boldsymbol{\kappa} \exp \sum\nolimits_p \boldsymbol{\theta}_p \, z_p(\mathbf{x}) \ . \tag{1}$$

Where:

$\Pr(\mathbf{X} = \mathbf{x})$ is the probability that the ERGM generated graph is identical to the observed graph.

$\boldsymbol{\kappa}$ = is a normalizing constant, which ensures that the equation is a proper probability distribution (that is it sums to 1). For all but the very smallest networks the value of $\boldsymbol{\kappa}$ is intractable to calculate.

$z_p(\mathbf{x})$ is the network statistic of a configuration of type p.

$\boldsymbol{\theta}_p$ is the parameter associated with the statistic $z_p(\mathbf{x})$ for that configuration.

The normalizing constant **κ** is generated over the entire graph space X with $2^{n(n-1)}$ possible graphs. Without Monte Carlo simulations, the intractable normalizing constant κ makes maximum likelihood estimation of the model very difficult, even for networks with a small number of nodes.

The probability that an ERGM generated graph is identical to an observed graph is equal to a (generally very small but intractable to calculate) constant multiplied by the exponent of the sum of the parameters multiplied by the graph statistics (count) of all the components in the model (Robins, Lusher, Pattison and Kramer 2006: 10; Snijders, et. Al. 2005: 10). The aim when attempting to generate an ERGM is to find the set of parameters which maximize the probability that any random graph generated by simulating the ERGM will be identical to the observed network.

In practice, the solution for the ERGM for any observed network with more than a few actors is actually impossible to calculate directly as it is intractable to calculate the normalizing constant. Instead the equation must be solved – and the parameters determined – through estimation and simulation. The most advanced method used to estimate the parameters of an ERGM in current software is the Markov Chain Monte Carlo Maximum Likelihood Estimation (MCMCMLE) procedure. The basic method of the MCMCML estimation of parameters for ERGMs involves the simulation of a set of random graphs from a starting set of estimated parameter values, and then the refinement of the parameter values by comparing the simulated graphs with the observed graph (the reason for doing this is to eliminate the intractable normalizing constant). A computer program using MCMCMLE procedure repeats this process until the parameter estimates stabilize (Robins, Pattison, Kalish & Lusher 2005: 24). In other words the program starts with a set of parameter values, simulates a set of graphs, measures how closely these match the observed graph, refines the parameter values, simulates a further set of graphs, measures how closely these new graphs match the observed graph, and repeats this process until an adequate set of parameter values is found.

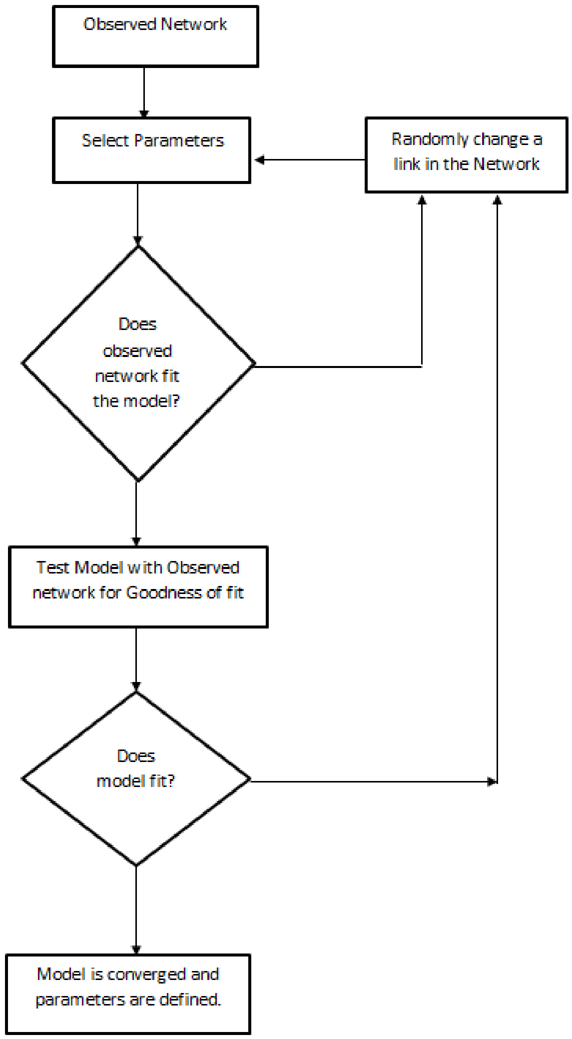

Figure 4.1: Flow chart of Simulation Process

Estimation

Maximum likelihood estimation is difficult for exponential random graph models as calculation of the normalizing constant is intractable. To avoid the need to calculate the constant, a pseudo likelihood estimation method was proposed by Strauss and Ikeda (1990). Instead of maximizing the original likelihood function, a logit model can be fitted conditioning on the rest of the network, using standard logistic regression methods. The maximum pseudolikelihood estimator (MPE) is the value of θ that maximizes the pseudo likelihood function.

By changing each dyad x_{ij} to $(1 - x_{ij})$ from the given network, the logistic regression is performed based on the change statistics of various local configurations included in the model. If our observed graph has size n, we will have $n(n - 1)$ sets of change statistics.
Maximum likelihood estimation procedures for exponential random graph (p*) models were proposed by Snijders (2002) based on the stochastic approximation method proposed by Robbins and Monro (1951). The maximum likelihood estimate (MLE) will generate a graph distribution with expected values of the graph statistics equal to the observed graph statistics. Both the graph distribution and the moment equation are intractable for big networks, hence the means of sample statistics from Monte Carlo simulations are used to approximate these values.

The overall estimation algorithm consists of three phases. Starting with an initial guess for the density parameter, the first phase simulates a small number of sample graphs. The second phase contains sub phases. Within each sub phase, parameter values are updated.
At the end of each sub phase, the mean of all updated parameter values are taken as the starting parameter values for the next sub phase. The newer sub phase will simulate more samples. The third phase repeats simulations as in phase one but based on the final estimated parameters from the second phase, and a large number of simulation iterations are carried out to check whether the parameters can generate the expected graph distribution that is centered at the observed network.

For each of the statistics, a t-ratio is calculated. If the absolute value of the t-statistic is less than 0.1, then the approximation may be considered as having converged.
This estimation algorithm has been implemented in the program SIENA (Snijders, Steglich, Schweinberger and Huisman 2005), and the program PNet (Wang, Robins and Pattison (2006)). Another program called statnet (Handcock, Butts, Hunter, Goodreau and Morris (2006)) is implemented under the R environment, and used a different algorithm based on Geyer and Thompson (1992) to estimate similar models.

Simulation

The method used to simulate is: (1) to start by choosing a tie at random, (2) calculate the probability of that tie forming (or disappearing) – given the ties around it and the parameter values of the various configurations in the model, (3) determine whether the tie is formed or not, and then (4) repeat this process hundreds or thousands of times. So, for example, if the formation of a tie will complete a 2-star (see the chart of configurations in Appendix C) , and 2-stars have a positive parameter, then this tie will normally have higher than chance probability of forming. If the tie will form both a 2-star and 3-star (as the formation of all 3-stars do) then the probability of the tie forming will be based on the net probability given the values of the 2-star and 3-star parameters. The result of the MCMCMLE procedure is a set of ‘parameter values’ and ‘standard errors of parameter values’ for the ERGM. These values are reported in the results of the ERGM model. A positive parameter value means that this configuration has a higher than random chance of being present in the graph. A negative parameter value means that this configuration has a lower than random chance of being present in the graph. The standard error measures the degree to which the estimated parameter value is likely to be an accurate measure of the actual parameter value we are trying to estimate. The standard error can be used as a measure of the significance of the parameter value. From standard statistics we know that if the parameter value is normally distributed (that is, its values are distributed with the same frequency as the normal curve) then 95% of the time, the actual parameter value will be within two (or actually 1.96) standard errors of either side of the parameter estimated by our model. Thus, the simple rule of thumb of interpreting the significance of a parameter value given the standard error applies to the parameter estimates of ERGMs: if the parameter value is greater than 1.96 times larger than the standard error, then we can assume that it is statistically significant (at the $p < 0.05$ level).

In the case of table 3, we can see that Bernoulli parameters for all the questions except questions 1, 9, 10 and 15 are statistically significant symbolized by the asterisk (*) character at the end of the rows.

OHM

	Question	Arcs	Graph Density	θ	Bernoulli Estimation Std Dev	t-value	
Q1	Communication Any Topic once 3 mo	486	0.75	1.0881	0.0928	-0.0553	
Q2	Specific Org Issues once 3 mo	392	0.60	1.0881	0.0928	-0.0553	*
Q3	Specific Communication Org Issues	155	0.24	-1.1540	0.0903	-0.0273	*
Q4	Know Exchange Org Issues	67	0.10	-2.1704	0.1339	0.0410	*
Q5	Receive Information	238	0.37	-0.5501	0.0822	-0.0046	*
Q6	Give Information	234	0.36	-0.5721	0.0815	-0.0303	*
Q7	Discuss Specific Issues Client Project	239	0.37	-0.5444	0.0780	0.0825	*
Q8	Comm. Client Project Issues	74	0.11	-2.0590	0.1280	0.0832	*
Q9	Knowledge Exchange Client Project Issues	44	0.07	-2.6289	0.1608	0.1203	
Q10	Receive Information Client Project Tasks	149	0.23	-1.2118	0.0921	-0.1345	
Q11	Give Information Client Project Tasks	165	0.25	-1.0764	0.0901	-0.0137	*
Q12	Experience Org Initiatives/Client Issues past 12 mo	393	0.60	0.4235	0.0855	-0.0195	*
Q13	Reliance	279	0.43	-0.2873	0.0786	0.0917	*
Q14	Mutually Beneficial Trust	375	0.58	0.3128	0.0787	0.0190	*
Q15	Share Similar Values	300	0.46	0.1550	0.0792	-0.0336	

* $p < 0.05$

Table 4.1: Example of ERGM results for Bernoulli Configuration Parameter Standard Error of Parameter t-statistic Significance

Simulating Networks and Testing Goodness of Fit

The parameter values estimated by MCMCMLE procedure need to be tested for their adequacy as a model for the observed network. The process for testing the adequacy of parameter values involves, first, simulation of the model through the generation of simulated graphs based on the parameter values, and the second, the comparing of simulated graphs with the observed graph through the calculation of goodness of fit statistics. In Table 4.2, I presented the goodness of fit statistics for the OHM knowledge exchange network. The simulation of graphs from the parameter values of the model is generally done in a similar way to the simulation of graphs for the MCMCMLE procedure: a tie is selected at random, its probability calculated, it is generated or not generated, and the procedure repeated hundreds, thousands or millions of times. Each repetition of the process for a new tie is called an iteration. For testing goodness of fit, generally 500 or 1000 sample graphs need to be generated. Sample graphs are normally selected at set intervals, such as one every 1000 iterations.

The sample graphs are analyzed as a distribution of possible graphs. The sample graphs are characterized by the mean and standard error of the mean of the graph statistics (counts) for each configuration. By comparing the graphs statistics of the original observed graph with the mean and standard error of the mean of the graph statistics of the simulated graphs it is possible to assess the goodness of fit of the ERGM.

The goodness of fit of an ERGM can be assessed by simulation, where various statistics from the observed network are compared with the statistics collected from the simulated network distribution to see whether the simulated graph distribution is “centered” at the observed network. The various statistics should not be limited to the ones that are being modeled in the given ERGM, as they should have been considered as very well fitted during the third phase of the MCMCMLE algorithm where model convergence is tested. Instead they should include all possible network statistics and other local and global network measurements like the ones described above.

A simple goodness of fit statistic is the t-ratio. Small t-ratios indicate good model fit. For statistics that are modeled in a given ERGM, the absolute value of the t-ratios should be less than 0.1 to prove that the model has converged. For other network statistics, t-ratios that are smaller than 2.0 are considered as indicating a good fit.

The t-ratios assess goodness of fit on each network statistic independently. To test the overall fit of the model, we need to take into account correlations among these statistics. The *Mahalanobis distance*, introduced by P. C. Mahalanobis in 1936, gives us a way of testing how similar the observed network is compared with a distribution of networks generated by a p* model.

The t-statistic is the number of standard errors that the mean of the graph statistic of the simulated graphs is away from the graph statistics of the observed graph. The aim of the researcher is to get a model where the t-statistic for all configurations is as low as possible. This t- statistic is generally reported in ERGM results, as in Table 3. It is important to note that the t-statistic reported in ERGM results is this t-statistic (a comparison of the observed and simulated graph statistics) and not a t-statistic for the parameter value. Because of this, the t-statistic has no bearing on the significance of the parameter value. For those more familiar with standard statistics, the juxtaposition of this t-statistic next to the parameter value and standard error in a results table (such as Table 3) can be misleading.

It is important to note that there are two types of goodness of fit (GoF) statistics in most ERGM programs. In PNet, there are (1) GoF statistics (t-statistics for each configuration) included in the results of each estimation of parameter values. These are generally not referred to as GoF statistics but rather as 'convergence statistics for effects in the model'. There are also (2) GoF statistics in a separate GoF procedure in Pnet, which includes both 'convergence statistics'/GoF statistics for effects in the model as well as GoF statistics for effects not in the model. The difference between these is largely just a difference of in the comprehensiveness of the GoF test. The first set of GoF statistics are more rudimentary. They are designed to give the researcher an immediate sense of the adequacy of the parameter estimates they have derived from the estimation. They include t-statistics for the configurations in the model, but are generally based on a much smaller number of iterations in the simulation procedure and a smaller sample of simulated graphs. The second set of GoF statistics are designed for comprehensive testing of an ERGM, and is only used once a researcher believes that their model is likely to fit the observed data. This set of GoF statistics generally includes t-statistics for all measurable configurations contained in the observed and/or simulated graphs. This means that configurations that are not included in the ERGM (that is, there is no parameter estimate for the configurations) are actually still tested to see if they are similar in the observed and simulated graphs. For example, a ERGM may not have a parameter estimate for 4-cliques (that is, when four actors are all tied to each other), but when calculating GoF statistics the number of 4-clique configurations in the model would still be 'counted' in the observed graph and in the simulated graphs, and a t-statistic calculated for this configuration. In addition to t-statistics for all configurations, the more comprehensive GoF procedure includes a range of other GoF statistics (for example, the mean geodesic, global clustering coefficients, triad census and skewness of in degree and out degree) which test the degree to which the simulated graphs fit the observed graph.

The more comprehensive GoF procedure has slightly different protocols for interpreting the t-statistics of different configurations (Robins, Pattison and Wang2006: 2-13). Configurations that are included in the ERGM require t-statistics of 0.1 or lower to be said to be a good fit. Other configurations and statistics not directly modeled in the ERGM require t-statistics of 1 or less to be said to be a 'good fit', and if they are above 2 they are said to be a 'bad fit'. Robins, Pattison and Wang (2006: 12-14) provide an array of 51 configurations and statistics that they recommend using to test the GoF of an ERGM.

Goodness of Fit for OHM knowledge exchange network for Markov selected parameters. The t-ratios are good for the Markov configurations; however, they are not good for the triangle configurations.

effects	observed	mean	stddev	t-ratio
arc	67	67.000	0.000	
reciprocity	15	14.978	1.890	0.012
2-in-star	86	85.725	8.395	0.033
2-out-star	141	140.731	17.011	0.016
3-in-star	71	70.796	21.312	0.010
3-out-star	257	254.218	72.643	0.038
path2	203	196.643	18.555	0.343
T1	0	0.769	0.932	-0.825
T2	5	8.628	6.161	-0.589
T3	13	15.527	7.446	-0.339
T4	9	7.870	3.768	0.300

T5	13	9.885	4.152	0.750
T6	21	23.538	7.976	-0.318
T7	82	83.327	17.538	-0.076
T8	119	118.753	20.954	0.012
T9(030T)	44	33.912	9.973	1.012
T10(030C)	8	8.959	3.436	-0.279
Sink 5	4.367	1.517	0.417	
Source 2	1.224	0.975	0.796	
Isolates	0	0.904	0.854	-1.058
AinS(2.00)	58.563	58.801	2.768	-0.086
AoutS(2.00)	70.137	70.453	3.556	-0.089
AinS(2.00)	58.563	58.801	2.768	-0.086
AoutS(2.00)	70.137	70.453	3.556	-0.089
Ain1out-star(2.00)	99.906	103.557	4.271	-0.855
1inAout-star(2.00)	83.482	86.670	5.254	-0.607
AinAout-star(2.00)	44.801	47.163	2.784	-0.848
AT-T(2.00)	38.750	29.513	7.497	1.232
AT-C(2.00)	21.500	23.712	8.090	-0.273
AT-D(2.00)	40.000	30.566	7.956	1.186
AT-U(2.00)	36.250	27.520	6.684	1.306
AT-TD(2.00)	39.375	30.039	7.694	1.213
AT-TU(2.00)	37.500	28.516	7.022	1.279
AT-DU(2.00)	38.125	29.043	7.227	1.257
AT-TDU(2.00)	38.333	29.199	7.293	1.252
A2P-T(2.00)	187.250	177.657	14.888	0.644
A2P-D(2.00)	130.000	128.588	14.598	0.097
A2P-U(2.00)	75.375	74.656	7.218	0.100
A2P-TD(2.00)	158.625	153.123	12.156	0.453
A2P-TU(2.00)	131.313	126.157	9.569	0.539
A2P-DU(2.00)	102.688	101.622	7.161	0.149
A2P-TDU(2.00)	130.875	126.967	8.664	0.451

Second form of goodness of fit statistics for degree distribution and clustering configurations:

Std Dev in-degree dist	1.629	1.609	0.207	0.097
Skew in-degree dist	0.455	0.400	0.371	0.150
Std Dev out-degree dist	2.656	2.639	0.258	0.064
Skew out-degree dist	1.328	1.244	0.307	0.273
CorrCoef in-out-degree dists	0.536	0.480	0.142	0.397
Global Clustering Cto	0.156	0.120	0.030	1.214
Global Clustering Cti	0.256	0.197	0.052	1.142
Global Clustering Ctm	0.217	0.171	0.042	1.079
Global Clustering Ccm	0.118	0.134	0.044	-0.368
Global Clustering AKC-T	0.207	0.165	0.037	1.113

Global Clustering AKC-D	0.154	0.119	0.027	1.304
Global Clustering AKC-U	0.240	0.184	0.042	1.318
Global Clustering AKC-C	0.115	0.132	0.040	-0.432

GOF on Triad Census

Triad	observed	mean	stddev	t-ratio
300	0	0.769	0.932	-0.825
210	5	4.014	2.106	0.468
120C	3	2.885	1.756	0.065
120D	4	1.549	1.267	1.935
120U	8	3.564	1.975	2.246
201	16	17.217	6.127	-0.199
111D	24	26.254	5.562	-0.405
111U	53	57.650	7.855	-0.592
030T	2	4.145	2.430	-0.883
030C	0	0.522	0.740	-0.705
102	226	222.801	33.041	0.097
021D	37	39.822	11.151	-0.253
021C	39	33.043	9.406	0.633
021U	15	18.227	5.930	-0.544

Mahalanobis distance =-21.179025
35% simulated samples have smaller Mahalanobis distances than the observed network.

Table 4.2: Goodness of Fit for OHM Network

The New Specifications

Until recently, the most common form of the ERGM was that of Frank and Strauss (1986). Also called the 'Markov parameters', these were based on the idea that edges of a graph were independent unless they potentially shared a node. This is called the Markov dependence assumption (Snijders et al 2005: 7). In effect, this dependence assumption meant that the types of configurations were limited to those configurations where all edges were potentially adjacent to all other edges, or to put it in another way, "two possible social ties are dependent only if a common actor is involved in both" (Snijders et al. 2005: 7). The standard Markov parameters/configurations for directed and non-directed graphs are listed in Appendix C, along with the symbol for the parameter.

The problem with the higher order parameters is obtaining convergence of the ERGM model. The new specifications attempt to address this issue by introducing the lambda conditioning parameter to dampen the effects of the higher order parameters on the iterations during simulation.

There are three major configurations in the new specifications: alternating- triangles; alternating-k-stars and alternating-k-two-paths (for a more complete overview of the new specifications see Snidjers et al 2005 and Robins, Pattison and Wang 2006). I summarized the new specifications in Appendix D. I was unable to get the OHM full networks to converge for the higher order parameters. In the Appendix I divided the network into a sub-network and was able to obtain parameters for the sub-network.

4.7 Conclusion

In this chapter I examined how to generate a social network and how to generate an Exponential Random Graph Model (ERGM) of an observed network. The social network was generated from an on line survey questionnaire. I reported back to the organization with an initial report based on the density, betweeness and power positions a player plays in the network. I also generated an ERGM from an observed network. The ERGM gives us important clues to how the network was generated by the individual players in the organization based on configurations in the network. The ERGM was achieved by a method of simulation and tested with a goodness of fit to determine that the parameters actually represent the observed network.

In the next chapter we will analyze all the data obtained from the on line survey using basic statistics and inferential statistics. This opens up a new path of research on organizations based on the collaboration of the individuals in the organization. It looks at how effective an organization is instead of looking at the traditional measures of performance such as time, cost and schedule.

Chapter 5 Data Analysis

5.1 Introduction

The data was analyzed three different ways. First, by descriptive statistics which was used in our initial reports to the organizations. The data was prepared by calculating densities for the organization for each of the answers to questions generated by the social network model. With descriptive statistics we are simply describing what is, what the data shows. I calculated the densities of each individual in the organizations and compared the variables using scatter plots to analyze the patterns of the responses for two variables. Finally, Bayesian inferential statistics was employed to investigate questions, models and hypotheses. Conclusions from inferential statistics extend beyond the immediate data alone. We use inferential statistics to infer from the sample data what the impact of communications and trust is on an organization's effectiveness. We also use inferential statistics to make judgments of the probability that an observed difference between variables is a dependable one or one that might have happened by chance in this study. Thus, we used inferential statistics to make inferences from our data to more general conditions; we used descriptive statistics simply to describe what's going on in our data.

5.1 Descriptive Statistics

Densities of the Social Networks Diagrams

In order to look at the data from a statistical reference, the data was downloaded to a spreadsheet. Each answer to a question represents a matrix in a spreadsheet form as shown in Table 5.3. As previously described in Chapter 3, Densities of Graphs; each participant's responses were added and computed as a percent of the total available players to choose from. This allowed us to statistically analyze the responses for individuals for all three organizations.

Player	Communication	Discuss Specific Org Issues	Specific Comm Org issues	Knowledge Exchange	Receive Info	Give Info	Discuss Specific Client Issues	Freq Specific Client issues	Fre Know Exch Client Issues	Recieve info Client Issues	Give Info Client Tasks	Experience	Reliance	Trust	Values
1	100%	100%	28%	8%	40%	44%	40%	12%	4%	8%	16%	72%	60%	72%	40%
2	56%	40%	12%	4%	24%	24%	56%	4%	0%	24%	16%	72%	68%	68%	72%
3	84%	72%	32%	12%	72%	72%	48%	0%	0%	20%	48%	64%	64%	60%	56%
4	84%	64%	44%	8%	4%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
5	92%	92%	60%	36%	68%	60%	68%	40%	32%	36%	36%	92%	92%	92%	48%
.	…	…	…	…	…	…	…	…	...	…	…	…	…	…	…

.	…	…	…	…	…	…	…	…	...	…	…	…	…	…	…
96	69%	57%	24%	10%	33%	57%	21%	12%	21%	10%	79%	40%	40%	57%	79%
97	62%	38%	7%	0%	7%	5%	10%	0%	5%	2%	24%	17%	24%	24%	24%
98	38%	19%	5%	2%	12%	10%	10%	5%	7%	10%	12%	12%	7%	5%	7%
99	60%	60%	31%	17%	24%	48%	50%	17%	29%	24%	64%	64%	62%	60%	64%
100	45%	45%	10%	7%	21%	17%	19%	5%	7%	19%	48%	31%	0%	40%	48%

Table 5.1: Densities for Individuals Responses to Questions Generated from the Social Network Model for Engineering and Construction

The top row represents the fifteen questions asked and the player column represents the individuals who responded. For example player one picked 96% of the other players for his answer to question 1 and 8% of the others for his answer to question 4, etc.

Means for the Social Network Variables

Table 5.4 summarizes the descriptive statistics for the social networks. The 100 respondents are indicated as N. The ranges for the variables are almost completely over all 100 respondents. The minimum responses were 0 and the maximums were nearly all (100% density). The means for the social network variables range from 8% for Knowledge Exchange to 56% for Communication. This represents on average 56% of respondents indicate they have any communicate with each other while only 7.6% indicated they shared knowledge weekly with each other.

Variables	N	Range	Min	Max	Mean	Std. Deviation
Experience	100	97%	0%	97%	43%	27%
Reliance	100	97%	0%	97%	37%	25%
Trust	100	90%	0%	90%	44%	25%
Values	100	97%	0%	97%	39%	26%
Communications	100	98%	0%	98%	56%	26%
Give Information	100	98%	0%	98%	25%	23%
Receive Information	100	93%	0%	93%	26%	22%
Knowledge Exchange	100	33%	0%	33%	8%	9%

Table 5.2: Descriptive Statistics for Social Network Model Variables

Referring back to the social network model for engineering and construction, we indicated that as players in a highly effective organization become more experienced with each other they will begin to rely more on each other. And as they begin to rely on each other they will build trust. This reliance and trust are the drivers for communication and knowledge exchange (see the Social Network Model for Engineering and Construction). So, what can the descriptive statistics tell us about what is happing in the social networks? The most striking statistic is the low percent measures for knowledge exchange. The most any player shares his or her knowledge with other players is about one third of them.

The level of reliance is only moderate at about a third indicating that each player only relies on about a third of the others to perform his tasks. Communications is the highest density at 56%. We dichotomized the data to include only weekly communication in our analysis.

Scatter Plots of Social Network Data

In developing the Social network Model, we emphasize how members of the organization interact with regards to experience, reliance and trust. As the parties gain experience with each other they will begin to rely on each other. This is the first step leading to trust and communication and ultimately to obtaining knowledge exchange.

The experience trust relationship is the most correlated relationship in the social network model followed by reliance and trust. If we plot a trend line through the data, we can see that most of the points in the scatterplot group around it. This would insinuate correlation (which may have happened by chance).

The next step in the social network model is, as you build reliance on each other you begin to build trust. The trust reliance relationship also clusters around a trend line indicating correlation may also exist between these variables.

Some features of the experience reliance plot, in Appendix B, indicate that parties must have some experience with each other before they begin to build reliance. This is demonstrated by the trend line up on the experience axis at zero reliance. Another feature of the plot is the distinct line of data at about equal experience and reliance. There are no points below this line. This indicates that individuals in the organization have to build experience with each other before they begin to rely on each other and vice versa. They never have high reliance on each other prior to having experience.

Another interesting feature is the points of high trust and low to moderate experience, which indicates our organization is performing at a high level. The points of low trust even at a high level of experience are areas of concern for the organization, since those players are not indicating trust n each other.

Communication and Trust

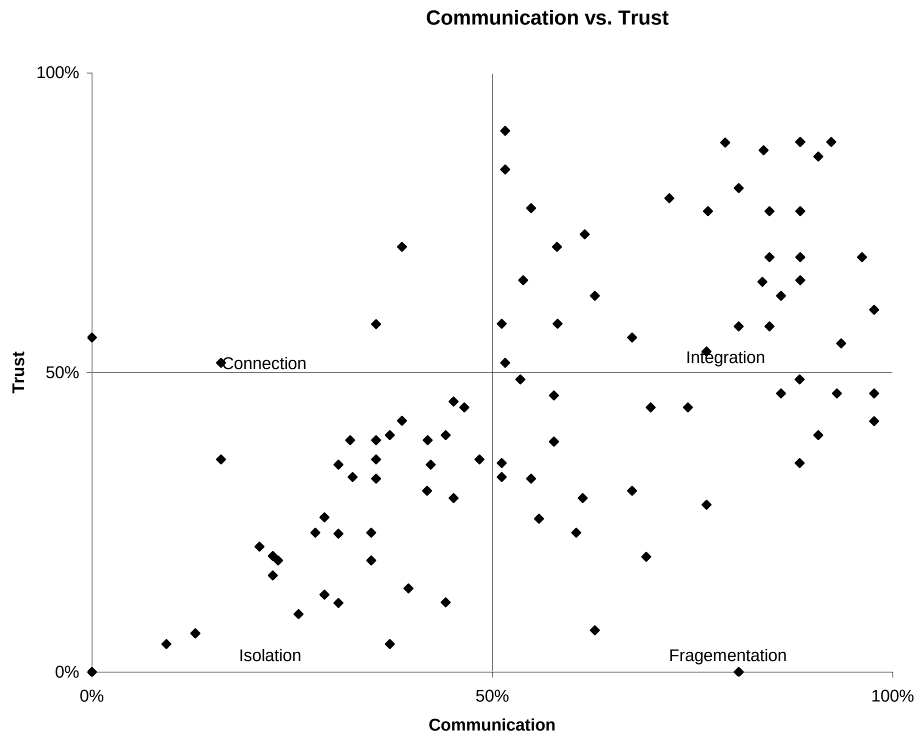

Figure 5.1: Scatter plot of Communication versus Trust for Individuals All Three Firms

The foundation of the social network is, as you build trust in the organization, you will increase the flow of information, or knowledge transfer. A convenient measure for flow of information is communication. Trust is dependent on experience and reliance on other individuals in the organization.

We stated in the social network model that the basis for an effective organization was good communication and trust. Figure 5.1 represents a scatter plot of the communication trust relationship of individuals for the three companies surveyed.

We divided the diagram into four regions as shown. Integration region represents a high percentage of trust and communication. In this state, both professional trust and communication indicate high density levels that translate into the requirements to achieve collaboration. In this state, the network individuals indicate that they both trust the other team members and have a high level of communication within the team. This integrative state is the fundamental requirement for transforming the team from individual stakeholders to a collaborative group that can effectively deliver a constructed project. This region is very populated in our results. That would be a preliminary indicator that the organizations are effective.

Low communication and low trust densities represents a state of isolation. The players show they trust only a few others in the organization and are not communicating with each other. This region will not allow the team to perform effectively. The amount of players in this region leaves the organizations room for improvement to reach their high performance goals.

When communication is increased within a team, but trust remains low, a state of fragmentation emerges within the organization. In this state, groups of individuals communicate information, but the lack of trust inhibits this information flow from developing into collaboration. This is the most common of the project states as it reflects the fragmentation within the AEC industry where contractual and professional issues contribute to individual specialties and lack of trust between project stakeholders.

The opposite of the Fragmentation state is the Connection state. In this state, trust is evident within the team, but communication density is low. The impact of this combination is to create a team where enthusiasm and interest may exist to collaborate, but the communication links are not established to put in place the interaction. Thus, the intent exists, but organizational barriers inhibit the intent from becoming realized.

In our paper, "*Project Organizations As Social Networks*," Chinowsky, Diekmann and O'Brien, we looked at the descriptive statistics for professional trust and communication and developed the following scatterplot:

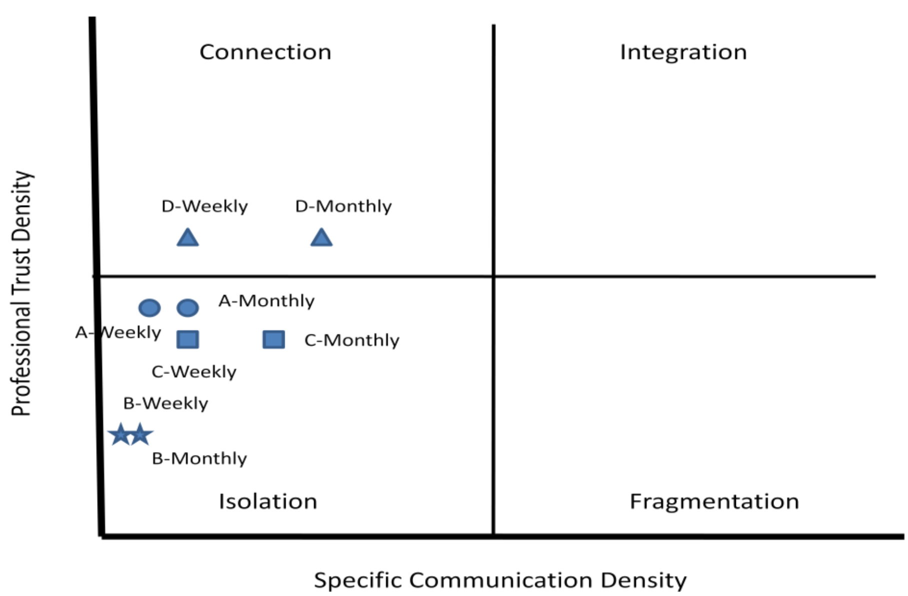

Figure 5.2 Descriptive Statistics for Professional Trust and Communication

With professional trust and client-specific information as the key measurement factors, the Scatterplot is divided into four quadrants based on the density measurement each organization. The density of the professional trust network together with the density of the specific information exchange network places an organization into one of the four states of the plot. The desired state for an organization pursuing collaboration is the upper right of the matrix, integration. The relationship between the Integration State and collaboration is based on the need to move toward an effective, trust-based environment in which a team operates. If a team has low trust within the network, then two critical barriers emerge within the team environment. First, the lack of trust creates a contentious rather than a collaborative environment. In this environment, legal, functional, and contractual roles supersede integration as the guiding principles in team operation. Second, the lack of trust places an overemphasis on information transfer within the operating environment. In this environment, individuals focus extensively on information transfer guidelines from items such as schedules or work breakdown structures. This emphasis leads to a focus on efficiency of information transfer rather than effectiveness of team interaction.

The four organizations in this study are strategically focused on enhancing collaboration. However, when the social network analysis results for each organization are placed in the context of the Integration Matrix, the capacity of the organizations to deliver on the strategic objective at this time is seen to be in question (Figure 2). As illustrated, only Company D emerges from the Isolation quadrant into the Connection Quadrant. However, both Companies A and C are close to the desired trust threshold to emerge into the Connection quadrant. Company B, due to the size and distribution of the network, is faced with a much more difficult task if the goal is to enhance collaboration throughout the network.

In each scenario, the challenge for the organizations is to enhance the communications aspect within the networks. Although the trust elements are present, a significant increase in communication is required to achieve collaboration. This will require a focused effort by the appropriate leaders to encourage collaborative efforts and to create the environment where individuals are encouraged to look beyond their local environment to interact with others throughout the organization.

5.2 Exponential Random Graph Models

Introduction

The scatterplots use direct measures to examine social network analysis based on densities of the observed networks. They give us little clues about what is going on in the network with other than players adjacent to each other. If we look at the organization chart we can use descriptive statistics to examine an observed network. Now, we can move on to another technique to analyze networks that looks at them form an inferential standpoint and can give us valuable clues as to how the network was formed and what impact an actor has on other actors than one adjacent to them in the organization chart. The program I used to perform this analysis was PNet.

Using PNet

PNet is a program for statistical analysis of exponential random graph models. It has three major functions; simulation, estimation and goodness of fit. Simulating network distributions with specified model parameter values. Estimating specified ERGM parameters for a given network. Testing the goodness of fit of a specified model to a given network with a particular set of parameters.

To setup a simulation, estimation or goodness of fit, you will need to choose the relevant options from the user interface and specify several program settings. The program requires input files, and produces text files as output. A session name is used for naming the output files. A session folder was set up for storing the output files.

There are four tabs for simulation, estimation, goodness of fit and approximate Bayesian goodness of fit with similar format. Under each tab, several settings need to be specified to configure a p* model.

To correctly configure simulation, you need to specify the number of actors, a starting graph density, we chose the actual density of the observed network, select the network type, and choose the structural parameters you are interested in modeling. There are other settings available such as attributes for nodes or arcs, however, they are not in the scope of this paper.

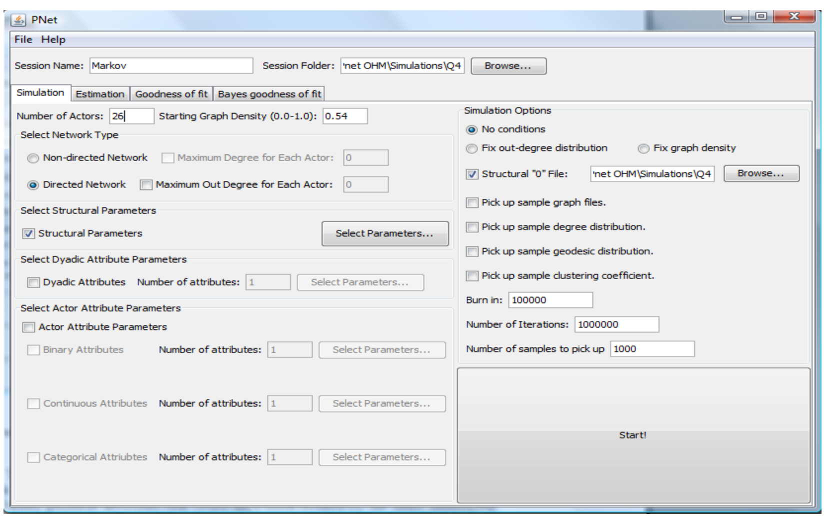

Figure 5.3: Windows Screen for PNet Simulation Setup

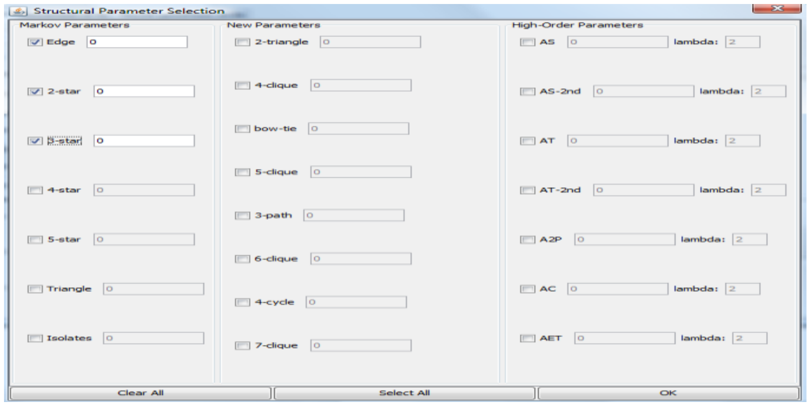

Figure 5.4: Windows Screen for Selection of Parameters

Simulation options allow you to fix the out-degree distribution, fix the graph density and input a structural file that specifies whether an arc is formed or not. The out-degree option will make simulated samples have identical out-degree distributions. Fixing the graph density fixes the number of arcs through the entire simulation. Since the density is fixed, the arc parameters were note selected for the simulation.

The structural "0" file allows you to generate a file that specifies when an arc is generated by the program. By generating a spreadsheet where a 0 or a 1 is entered, determines whether the program fixes or allows the formation of an arc. In our study, we entered a structural "0" file to reflect the organization chart of the company. These simulation options helped obtain convergence on the networks. This structural file allowed the arcs between players that are not adjacent to each other in the organization chart to vary and fixed the arcs between actors that are adjacent to each other in the organization chart, whether it exists or not.

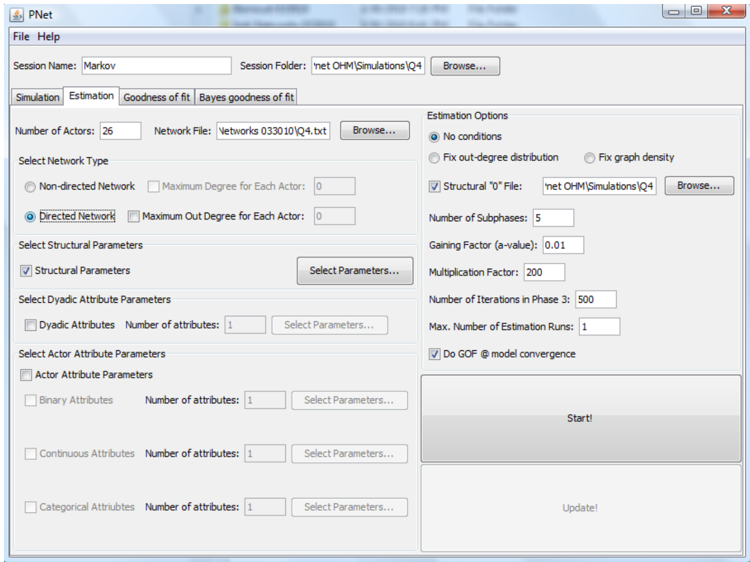

Figure 5.5: Windows Screen for Set Up of PNet Estimation

Estimation setup is similar to simulation regarding session names, session folders, number of actors, the initial network file, and specifications for the estimation. We were also able to fix the graph density to the observed graph, and use a structural “0” file. The same structural parameters were selected as the simulation. Some of the settings we used for our estimation varied from the default values, such as the multiplication factor was reset to 200 and we checked the box for do GOF @ model convergence. The last step automatically generates a goodness of fit analysis upon network convergence.

Observed Networks

The process of estimating a model starts with an observed network. This observed network is assumed, for the purposes of modeling the network, to be just one instance of a set of many possible networks that could have been formed by the same underlying structural processes that formed the observed network (Robins, Pattison, Kalish and Lusher 2005: 7). The structural processes which formed this observed network are assumed to be based on sub-graph interactions which are called 'configurations'. For an observed graph, each configuration is conceptualized as having had a particular probability of occurring. The probability of each configuration is incorporated into an ERG model as a 'parameter'. The aim of the ERG model estimation is to as accurately as possible estimate the parameters of a set of configurations, so that the observed graph has the highest possible likelihood of being replicated by the given model when the model is used to simulate a network (Robins, Pattison, Kalish and Lusher 2005: 7). An observed graph which had a high likelihood of being been replicated by a given set of ERG model parameters is said to be a 'good fit'. The first step of producing an estimation is to measure the observed network. It is these measurements that an ERGM aims to be able to replicate in simulations. In simpler (Markov) versions of ERG models, an observed network is measured by 'counting' the number of occurrences of each configuration to be included in the model.

ERGM Bernoulli and Markov Study Results for OHM

Below are PNet simulation results for OHM on their complete 15 questionnaire for the social network model for engineering and construction. The results are sorted by the levels in the social network model. The dynamic variables (experience, reliance and trust) are on top and the mechanic variables (communication and knowledge exchange) are below them.

University of Colorado
John O'Brien
Research Assistant

Exponential Random Graph Models
Survey Results
OHM

7/17/2010

OHM Parameter Estimates Summary

					Bernouli	Markov					New Specifications			
Q		Question	Arcs	Graph Density	Density	Reciprocity	in-2star	out-2star	in-3star	out-3star	ATT-T(2)	AT-C(2)	AT-D(2)	AT-U(2)
12	1	Experience Org Initiatives/	393	0.60	0.42	1.42	0.34	0.22						
13	2	Reliance	279	0.43	-0.29	1.16	0.40	0.27						
14	3	Mutually Beneficial Trust	375	0.58		1.17	0.40	0.24	-0.02					
15	4	Share Similar Values	300	0.46	0.15	0.77	0.45	0.19	-0.03					
1	5	Communication Any Topic	486	0.75	1.09	1.12	0.31			0.02				
3	5	Communication Org Issue:	155	0.24	-1.15	2.07		0.36						
8	5	Comm Client Project Issue	74	0.11	-2.06	3.12		0.28						
6	5	Give Information	234	0.36	-0.57	1.09	0.37	0.27						
5	5	Receive Information	238	0.37	-0.55	0.88	0.38	0.33	-0.02					
11	5	Give Information Client Prc	165	0.25	-1.08	1.44	0.42	0.31						
10	5	Receive Information Client	149	0.23		1.58	0.46	0.28						
2	5	Discuss Specific Org Issue	392	0.60	1.09	1.16	0.31	0.15	-0.01	0.00				
7	5	Discuss Specific Client Prc	239	0.37	-0.54	1.31	0.30	0.26						
4	6	Know Exchange Org Issue	67	0.10	-2.17	2.30		0.47			1.33 *	0.02	0.29	-0.46
9	6	Knowledge Exchange Clie	44	0.07				0.62						

Table 5.3: Exponential Random Graph Models for OHM Survey Results

Parameter Analysis

A positive parameter for graph density indicates a tendency for that configuration to exist in the network. A negative parameter as shown above indicates a weak tendency for the configuration to exist in the network and therefore a negative parameter has a negative impact on the formation of the network. Based on Table 5.3, most of the parameters for the dynamics side of the social network model are positive for OHM. The mechanics side of the model has mostly negative parameters.

A positive parameter for reciprocity indicates knowledge exchange between actors is flowing both ways. Large positive parameters, as seen above, for reciprocity demonstrates that most of the actors that are exchanging knowledge are receiving knowledge in return.

Parameters for the Markov configurations 2-star and 3-star are still positive, however, they are an order of magnitude smaller than density or reciprocity.

In my research, I did not achieve convergence on OHM networks for triangle configurations due to limitations on the software and the size of the network. Therefore, the table only reports to the 3-star configuration. I did analyze the knowledge exchange network for k-triangles by subdividing the network to contain specific configurations. I examined the relationships between the architect and the executive vice president for convenience and the sub-network contained the configurations available in PNet. This study results are reported as new specifications in Appendix E. These results indicate positive parameters for three of the k-triangle configurations. This would indicate that knowledge exchange between the architect and the executive vice president will be transferred to other actor in the organization not directly connected by the organization chart. These results coupled with the reciprocity results indicate good knowledge exchange for the OHM organization issues.

5.3 Data Analysis Summary

The following tables summarize the ERGM results using PNet for all three organizations. The questions are organized according to the social network model for engineering and construction in the left had column. The parameter values are shown under the configurations.

I highlighted the diagrams with yellow to indicate the statistically significant parameters (including 0s) and highlighted the key parameters of communication, trust and knowledge exchange in green. Networks with positive larger parameter values for density and reciprocity and lower values for higher order configurations are said to have a solid core, with looser periphery configurations. Networks with positive larger parameters for higher order configurations and small or negative parameters for density and reciprocity, are said to have a loose core-periphery makeup. This would indicate that actors will have less impact on other actors in the network other than actors directly adjacent to themselves in the organization chart.

Due to heterogeneity of individual organizations, it is difficult to compare the results of exponential random graph models with each other. In my initial research, I looked at comparing the three organizations relative to each other in the trust communication scatterplot and individually in other scatterplots. Depending on how an organization views their effectiveness will dictate how they want their parameters to look. The chart of parameters gives us a fingerprint of each organization and shows us how unique they are.

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Exponential Random Graph Models
Survey Results

4/3/2011

Q		Question	Graph Density	Bemouli Density	Reciprocity	Markov in-2star	out-2star	in-3star	out-3star
			OHM	OHM	OHM	OHM	OHM	OHM	OHM
12	1	Experience Org Initiatives/Client Issu	60%	0.42	1.42	0.34	0.22		
13	2	Reliance	43%	-0.29	1.16	0.40	0.27		
14	3	Mutually Beneficial Trust	58%		1.17	0.40	0.24	-0.02	
15	4	Share Similar Values	46%	0.15	0.77	0.45	0.19	-0.03	
1	5	Communication Any Topic once 3 mo	75%	1.09	1.12	0.31			0.02
2	5	Discuss Specific Org Issues	60%	1.09	1.16	0.31	0.15	-0.01	0.00
3	5	Communication Org Issues	24%	-1.15	2.07		0.36		
5	5	Receive Information	37%	-0.55	0.88	0.38	0.33	-0.02	
6	5	Give Information	36%	-0.57	1.09	0.37	0.27		
7	5	Discuss Specific Client Project Issues	37%	-0.54	1.31	0.30	0.26		
8	5	Comm Client Project Issues	11%	-2.06	3.12		0.28		
10	5	Receive Information Client Project Ta	23%		1.58	0.46	0.28		
11	5	Give Information Client Project Tasks	25%	-1.08	1.44	0.42	0.31		
4	6	Know Exchange Org Issues	10%	-2.17	2.30		0.47		
9	6	Knowledge Exchange Client Project I	7%				0.62		

Figure 5.6: Exponential Random Graph Models for OHM

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Exponential Random Graph Models
Survey Results

4/6/2011

Q		Question	Graph Density	Bernouli Density	Reciprocity	Markov in-2star	out-2star	in-3star	out-3star
			Degen	Degen	Degen	Degen	Degen	Degen	Degen
12	1	Experience Org Initiatives/Client Issu	43%	-0.28	0.65	0.22	0.15		
13	2	Reliance	34%	-0.68	0.48	0.19	0.18		
14	3	Mutually Beneficial Trust	41%	-0.37	0.61	0.20	0.18		
15	4	Share Similar Values	35%	-0.64	0.69		0.20		
1	5	Communication Any Topic once 3 mo	39%	-0.43	2.73		0.19		
2	5	Discuss Specific Org Issues	22%	-1.24	1.57	0.16	0.24		
3	5	Communication Org Issues	10%	-2.25	3.20		0.64		
5	5	Receive Information	17%	-1.56	1.55	0.18	0.28		-0.01
6	5	Give Information	14%	-1.81	2.54		0.43		-0.03
7	5	Discuss Specific Client Project Issue:	18%	-1.53	2.44		0.11		
8	5	Comm Client Project Issues	6%	-2.67	3.79				
10	5	Receive Information Client Project Ta	12%	-2.04	1.10		0.20		
11	5	Give Information Client Project Tasks	11%	-2.12	2.75	0.94	0.41	-0.43	
4	6	Know Exchange Org Issues	5%	-3.03	3.35				
9	6	Knowledge Exchange Client Project I	4%	-3.07	4.17				

Figure 5.7: Exponential Random Graph Models for Degenkolb

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Exponential Random Graph Models
Survey Results

4/3/2011

Q		Question	Graph Density	Bemouli		Markov			
				Density	Reciprocity	in-2star	out-2star	in-3star	out-3star
			LDG	LDG	LDG	LDG	LDG	LDG	LDG
12	1	Experience Org Initiatives/Client Issu	35%	-0.62	1.43	0.13			
13	2	Reliance	39%	0.06	1.83	0.23	0.07	-0.01	0.00
14	3	Mutually Beneficial Trust	89%	0.10	1.96	0.21	0.06	-0.01	0.00
15	4	Share Similar Values	41%	-0.37	1.19	0.21	0.09	-0.01	
1	5	Communication Any Topic once 3 mc	61%	0.45	1.27	0.10	0.07		0.00
2	5	Discuss Specific Org Issues	49%	-0.03	1.05	0.13	0.12		
3	5	Communication Org Issues	18%	-1.51	2.43		0.27		-0.01
5	5	Receive Information	28%	-0.93	0.73	0.23	0.15	-0.01	
6	5	Give Information	29%	-0.92	1.05	0.23	0.13	-0.01	
7	5	Discuss Specific Client Project Issues	30%	-0.86	2.41	0.21	0.08	-0.01	
8	5	Comm Client Project Issues	13%		3.29	0.23	0.25		
10	5	Receive Information Client Project Ta	22%	-1.26		0.30	0.13	-0.03	
11	5	Give Information Client Project Tasks	54%	0.17	1.93	0.13	0.12		
4	6	Know Exchange Org Issues	9%	-2.37	3.09		0.41		-0.03
9	6	Knowledge Exchange Client Project I	23%	-1.22	2.13	0.23	0.14	-0.02	

Figure 5.8: Exponential Random Graph models for LDG

Chapter 6 Discussion of Results

6.1 Discussion of what analysis means

Review Types of ERGMs

The results of the ERGM models allows us to look at the 'social selection' characteristics of the networks for engineering design firms (Robbins, Elliott and Pattison: 2001; Robins, Pattison and Elliott: 2001). We can look at, and have analyzed in our initial report, how the actors interact with each other based on their position in the organization chart. We can also look at how the networks are formed based on their configurations by examining the ERGM parameters.

We can use social selection models to ask questions such as: How are actors tied together based on the organization chart? What effect does a tie between actors adjacent to each other on the organization chart have on knowledge exchange in the network?

Analysis of Parameters

A positive parameter indicates a high probability that the configuration will be present in the network. A negative parameter indicates that it is less likely that the configuration will be in the network. As we look at the initial analysis we performed on the three design firms we can demonstrate the conclusions using EGM analysis.

A positive parameter for reciprocity indicates knowledge exchange between actors is flowing both ways. Large positive parameters, as seen above, for reciprocity demonstrates that most of the actors that are exchanging knowledge are receiving knowledge in return.

From figures 5.6, 5.7 and 5.8, we can see that more parameters are significant for knowledge exchange for Degen and LDG than for OHM. Also, OHM has a more dense distribution of significant parameters for the less complex configurations than Degen and LDG. The conclusion from this analysis if OHM is performing at a significant difference than Degen or LDG (I hesitate to say performing less than).

Discussion of initial report analysis and ERGM results

LDG

In our initial report for LDG (Chinowsky, Paul S. 2008) we discussed organization-based communication issues and how certain groups were separate from the overall network. The interpretation of this result was that a percentage of the LDG managers were discussing organization issues within their own discipline area at a greater rate than with the overall organization. Additionally, a geographic effect was taking place within the network. The newer regional offices were not yet integrated fully into the network and thus have less communication on organization issues.

Similar to the communication side, the Dynamics side of the LDG organization appeared to reflect the greater discipline and regional emphasis in the network. Although an above average feeling of trust exists between the managers, there is room for improvement. It is strongly recommended that the organization focus on greater interaction possibilities between the offices to improve this metric.

The lower communication and trust scores are reflected in the poor knowledge exchange results in relation to organization issues. The knowledge exchange network has a minimal density at 9% and is divided into a series of clusters around the disciplines and regional offices. There is a strong focus on providing knowledge to the Chief Operating Officer and the Human Resource Director. However, there is a significant lack of knowledge exchange between the disciplines and between the spoke offices.

Similar to the organization-based analysis, the client project analysis found results that indicate communication barriers in the organization. Communication is focused heavily on the regional offices and minimal density is found in the network. The result of these barriers is a placement of the LDG organization in the Isolation quadrant of the integration matrix. However, it is believed the organization has significant potential to improve this rating.

Overall, the low density and clustering found in the networks indicates that the organization is performing like knowledge islands with the knowledge isolated in a combination of the disciplines and the regional offices. However, a change in this situation can occur through strong leadership. It is recommended that LDG analyze the roles that the leaders are playing in the organization and improve the level of interaction between the leadership and the regional and discipline-based employees.

The ERGM parameters have to be evaluated carefully. In our analysis we examine density as a basis for our conclusions for the organization. The parameter for density can be interpreted the same as a percentage for density. We cannot say absolutely that a certain number is better than another for density, however, we can say that a higher density indicates collusion between the players and good communication and trust exists between the players. We can also say that too high of a density is not very good since there is redundancy in the communication and trust. Too low of a density means that not enough players are communicating with each other and, therefore, knowledge exchange will not be occurring.

ERGMs are a probability distribution defined by parameters indicating how the observed networks were formed based on the configurations present in the network. Examining the ERGM models for LDG social network results reflects the conclusions from our initial report. The statistically significant parameters are high throughout the communication questions. However, parameters for the higher order configurations fall off as the complexity of the configuration increases. This means it is less likely that that configuration will be present in the network. As LDG reconfigures their network to changes in leadership as recommended in the initial report, these parameters will probably increase in value.

Degenkolb

In our initial report for Degenkolb (Chinowsky, Paul S. 2008) we discussed the lack of density in communications makes it evident that the individual offices were performing in a decentralized manner with communication clusters. The network also indicated that actors were assuming a central position in the clusters. This clustering effect was creating a hindrance to potential knowledge sharing.

In contrast to the communication side, the Dynamics side of the Degenkolb organization appeared to reflect a feeling of trust between the managers. However, based on the low communication numbers evident in the Mechanics side of the analysis, this trust could be based more on team building than in actual work processes. If the trust was based in collaboration, then knowledge sharing should be evident. If the trust is based more on social interaction, then a lack of knowledge sharing may be evident.

This divided basis is reflected in poor knowledge exchange results in relation to organization issues. The knowledge exchange network has a minimal density at 5% and is divided into a series of clusters around the regional offices. The only connection between the offices is through the President. The Los Angeles office is completely separated from the remainder of the organization. Of greater concern, four managers do not have any weekly conversations related to knowledge exchange with other managers.

Similar to the organization-based analysis, the client project analysis found results that indicate communication and knowledge sharing barriers in the organization. Communication is focused heavily on the regional offices and minimal density is found in the network. Although the trust remains as a basis for the organization, there is a concern that this trust could be based more on social factors than work process collaboration.

Overall, the low density and clustering found in the networks indicates that the organization is performing like knowledge islands with the knowledge isolated in regional offices. However, the lack of density within each regional office illustrates that the knowledge islands themselves are weak in knowledge exchange and require a change in the approach to collaboration.

An examination of the ERGMs reflects the low densities (the parameters are negative) and on the Dynamics side of the Social Network Model the higher order configurations cease to be statistically significant (the only statistically significant parameters are the negative density, reciprocity and out 2-stars). This reinforces our conclusions using classical statistical measures for the social network model.

OHM

In our initial report for OHM (O'Brien, John 2008), in terms of organization issues, the OHM leadership appeared strong in supporting organization communication. They had high densities in their communications networks. However, the communication densities fall off dramatically between infrequent communication and weekly communication. The organization demonstrates centrality in their network with very little evidence of clustering. This indicates the organization is working closely together in terms of communicating on project and organization issues.

On the dynamics side of the social network model, OHM demonstrates a high level of trust for each other. This is reflected in the strong communication networks. This level of trust and communication indicates collaboration among the managers. However, the weekly knowledge exchange network indicates a potential problem due to a select group of power brokers controlling the flow of knowledge in the organization. The network density drops off dramatically, between infrequent knowledge exchange and weekly knowledge exchange.

The client project analysis indicates that power brokers are similarly controlling the information related to client projects. The lower density that appears in the reliance networks for client related issues reflects the reduced number of individuals involved with these discussions.

Overall, OHM demonstrates a high density and centrality in the networks. Some power brokering is occurring in control of the client-focused information and there may be a minor issue with trust among some individuals. The network analysis indicates an organization that is prepared to function at a high performance level based on trust factors within the management team. However, to achieve this performance level, increased communications are required to enable a greater level of knowledge sharing to occur.

The power brokers in our initial report are demonstrated in the ERGMs by higher order parameters falling off and becoming statistically insignificant as the order increases. This indicates a strong core loose-periphery structure to the networks. As OHM works to decrease their centrality in their networks more higher order parameters in the ERGM should become statistically significant.

Chapter 7 Conclusions

7.1 Benefits of the Research

The first objective was to develop a social network model for engineering and construction that identifies significant variables in an organization's performance other than profit, schedule or rate of returns. Three design engineering firms with similar characteristics were selected to perform an on-line survey using Network Genie software. Write a report using network statistics such as density, centrality and betweeness as measures of trust, communication and knowledge exchange according to the social network model for engineering and construction.
The focus of the research is to expand on the network statistics using exponential random graph models to measure an organization's effectiveness by analyzing the configurations within the network to assess collaboration through connectivity. Due to the heterogeneity of organizations, we cannot compare the organizations with each other, rather we can look at the distribution of the configurations to assess the effectiveness of groups in the organization as well as individuals.

7.2 Future Research

Exponential Random Graph Models can be used to describe collaboration among groups as well as individuals in the context of social networks based on the model of communication, trust and knowledge exchange. By stochastically fitting our observed networks to a theoretical model, we are able to obtain a set of parameter constants that describes how network configurations contribute to collaboration in the networks through connectivity. Using the parameter constants in conjunction with the social network model for engineering and construction we are able to quantitatively describe an organization.

7.3 Conclusion Summary

In the traditional perspective, project management is increasingly focused on the use of tools to preplan tasks and develop schedules that are as detailed as possible. The concept behind this perspective is that a majority of issues can be identified and engineered prior to the start of the project. Additionally, this emphasis is intended to enhance effectiveness of the process by identifying information that is required to be exchanged between participants during project execution. Research in critical success factors has identified the effectiveness of information exchange as a key element in producing projects that achieve benchmarks in time, cost and quality.

The Social Network Model for Engineering and Construction defines the relationships between static and dynamic variables crucial to an organizations effectiveness. Even though the organization is functioning as a high performance organization, social network analysis can identify the level of experience and trust the actors have in each other. An organization that has a high level of trust and shares values with each other has a greater chance of higher levels of communication and knowledge exchange.

Three organizations underwent Social Network Analysis and the authors delivered a unique perspective on their organizations they never had before. They saw through graph theory how their organizations actors collaborate with each other and how the leaders of the organization interacted with the team. They can evaluate the strength of their leadership and weaknesses that are causing bottlenecks in their communications and knowledge transfer.

The social network model can be verified by statistical inference methods using exponential random graph models. The results of the analysis provide parameter values that indicate the formation of a network based on the configurations of the static variables. It is important for the organization to stress to achieve greater than 50% of the individuals trusting each other and sharing social values for effective communication to take place. Knowledge exchange parameters are scarce and difficult to analyze due to the low density in the network. The goal of the research is to develop a method to ascertain the knowledge exchange by analyzing the trust and communication and the other dynamic variables. The relationship between trust and communication is critical for the parties to be collaborating with each other in an effective organization

Research is ongoing with more organizations and we intend to research networks for project with different organizations interacting as a project organization. We want to analyze a very large program with multiple projects at different levels of planning, design and construction.

As we fine tune the questions for response we will still find improvements to the model. More research is needed to assess the statistical parameters between the variables and study the patterns of responses to our survey questions.

Organizational Efficiency is not a Strategy argues Porter in his now famous essay on “What is Strategy?” A unique set of activities is what will set your organization apart. An organizations willingness to undergo Social Network Analysis is the first indicator of an organization willing to define those activities and test them to achieve an effective strategy.

The social network model can be analyzed statistically using ERGMs to evaluate relationships between networks. ERGMs identify configurations in the network that can provide a measure of what is happing in the networks and can verify that our organizations are acting as an effective team. Statistical constants calculated as parameters in a probability distribution function demonstrate how the players build reliance and trust in each other as they increase their experiences with each other.

The relationship between trust and communication is critical for the parties to be collaborating with each other to achieve effectiveness. The trust communication relationship is special in the social network model for engineering and construction. An ERGM of trust and communication demonstrate a strong dependency on 2-stars and reciprocity.

We experimented with k-triangles on the knowledge network for OHM for organizational issues. The alternating k-triangle statistic is a measure of clustering based on the dependency between the formation of a tie between two nodes and whether they share multiple partners. A positive value for the alternating k-triangle parameter indicates that people sharing multiple partners are likely to be connected. All our results for AT-Cs were positive including an analysis for a sub network with all the triangles included.

The goodness of fit of an ERGM was assessed by simulation. Although the goodness of fit provided t-ratios very low for the k-triangles, the goodness of fit for the other parameters was not very good based on the t-values for other parameters than the triangles. For these parameters we need to refer to the previous study of the network parameters using Bernoulli and Markov.

The Mahalanobis distance results show 95% simulated samples have smaller Mahalanobis distances than the observed network. The observed network is not very similar compared with a distribution of networks generated by a p* model.

Further research is needed to collect enough ERGM data to plot the relationship between the static and dynamic variables of the social network model for engineering and construction. We want to analyze a very large program with multiple projects at different levels of planning, design and construction.

As we fine tune the questions for response we will still find improvements to the model. More research is needed to assess the statistical relationships between the variables and study the patterns of responses to our survey questions.

Bibliography

1. Arbuckle, James L., *Amos 17.0 User's Guide* (1995-2009), Amos Development Corporation.
2. Barrie, Donald S. and Bod C. Paulson, Jr., *Professional Construction Management*, McGraw-Hill Book Company, 2nd Ed., 1984.
3. Bodwell, Donald J., www.highperformanceteams.org. Copyright (C) 1996, 1997, 1998, 1999 Donald J. Bodwell. All rights reserved.
4. Borgatti, S.P., Everett, M.G. and Freeman, L.C. 2002. Ucinet for Windows: Software for Social Network Analysis. Harvard, MA: Analytic Technologies.
5. Chinowsky, Paul S. (November 2008), *A Social Network Model Analysis of Larson Design Group*
6. Chinowsky, Paul S. Diekmann, James, and Galotti, Victor (2008). "The Social Network Model of Construction," *Journal of Construction Engineering and Management*, 134(10), 804-810.
7. Chinowsky, Paul S.; Diekmann, James and O'Brien, John; *Project Organizations as Social Networks*
8. Chinowsky, Paul S.; O'Brien, John (October 2008); *A Social Network Model Analysis of Orchard, Hiltz, McCliment*
9. C. J. Geyer and E. A. Thompson. Constrained Monte Carlo maximum likelihood for dependent data. *Journal of the Royal Statistical Society*. Series B (Methodological), 54(3):657– 699, 1992.
10. Congdon, Peter; *Introduction to Bayesian Statistical Modeling*, John Wiley & Sons Ltd, 2001. Reprinted January 2002
11. C. Steglich and T. A. Snijders. Dynamic networks and behavior: Separating selection from influence. In Press.
12. Contractor, N., Wasserman, S. & Faust, K. (in press). Testing multi-theoretical multilevel hypotheses about organizational networks: An analytic framework and empirical example. *Academy of Management Journal.*
13. *Dependence Graphs, and p*.* In P. Carrington, J. Scott & S. Wasserman (Eds.) *Models and Methods in Social Network Analysis* (pp.148-161). New York: Cambridge University Press.
14. D. R. Hunter. Curved exponential family models for social networks. Social Networks (Special Edition), In Press.
15. D. Strauss and M. Ikeda. Pseudo likelihood estimation for social networks. Journal of the American Statistical Association, 85(409):204–212, Mar. 1990.Halpin, Daniel W. and Ronald W. Woodhead, *Construction Management*, John Wiley and Sons, 1980.
16. Erdös, P., & Renyi, A. (1959). On random graphs. I. *Publicationes Mathematicae (Debrecen), 6*, 290-297.
17. Feld, S., (1981). The focused organization of social ties. *American Journal of Sociology, 86*, 1015-1035.

18. F. Agneessens, H. Roose, and H. Waege. Choices of theatre events: p_ model for affiliation networks with attributes. Metodoloˇski zvezki, 1(2):419–439, 2004.
19. Frank, O., & Nowicki, K. (1993). Exploratory statistical analysis of networks. In J. Gimbel, J.W. Kennedy & L.V. Quintas (Eds.), *Quo Vadis, Graph Theory? Annals of Discrete Mathematics, 55,* 349-366.
20. G. L. Robins, P. Elliott, and P. E. Pattison. Network models for social selection processes. Social Networks, 23:1–30, 2001.
21. G. L. Robins and P. E. Pattison. Models and Methods in Social Network Analysis. Interdependencies and Social Processes: Generalized Dependence Structures. Cambridge University Press, 2005.
22. G. L. Robins, P. E. Pattison, Y. Kalish, and D. Lusher. An introduction to exponential random graph (p*) models for social networks. Social Networks (Special Edition). In Press.
23. G. L. Robins, T. A. Snijders, P. Wang, M. Handcock, and P. E. Pattison. *Recent developments in exponential random graph (p*) models for social networks. Social Networks* (Special Edition), In Press.
24. G. L. Robins, P. E. Pattison, and S. Wasserman. Logit models and logistic regression for social networks, iii. valued relations. Psychometrika, 64(3):371–394, Sep. 1999.
25. G. L. Robins, P. E. Pattison, and J. Woolcock. Small and other worlds: Global network structures from local processes. American Journal of Sociology, 110(4):894–936, Jan. 2005.
26. Halpin, Daniel W. and Ronald W. Woodhead, *Construction Management*, John Wiley and Sons, 1980.
27. Handcock, M.S. (2003). Statistical models for social networks: Degeneracy and inference. In Breiger, R., Carley, K., & Pattison, P. (eds.). *Dynamic social network modeling and analysis* (pp. 229-240). Washington DC: National Academies Press.
28. Handcock, M., Hunter, D., Butts, C., Goodreau, S., & Morris, M. (2004). *Statnet: An R package for the statistical modeling of social networks.* Manual, University of Washington, URL: http://www.csde.washington.edu/statnet
29. Hansen, William B., Reese, Eric, Bryant, Kelvin S., Bishop, Dana, Wyrick, Cheryl H., and Dyreng, Douglas I. (2008). *Network Genie User's Manual*, Tanglewood Research, Inc.
30. Haythornwaite, C. (1996). Social network analysis: an approach and technique for the study of information exchange. *Library and Information Science Research*, **18**(4), 323-342.
31. Hendrickson, Chris and Tung Au, *Project Management for Construction,* Prentice Hall, 2nd Edition, Version 2.1, 2003
32. Hodgetts, R.M., *Management: Theory, Process and Practice,* W.B. Saunders Co., Philadelphia, PA, 1979.
33. Holland, P.W., & Leinhardt, S. (1981). An exponential family of probability distributions for directed graphs (with discussion). *Journal of the American Statistical Association*, *76*, 33-65.
34. Hunter, D. & Handcock, M. (2006). Inference in curved exponential family models for networks. *Journal of Computational and Graphical Statistics*.

35. Hendrickson, Chris and Tung Au, *Project Management for Construction*, Prentice Hall, 2nd Edition, Version 2.1, 2003
36. Hodgetts, R.M., *Management: Theory, Process and Practice*, W.B. Saunders Co., Philadelphia, PA, 1979.
37. H. Robbins and S. Monro. A stochastic approximation method. The Annals of Mathematical Statistics, 22(3):400–407, Sep. 1951
38. Kerzner, H. *Project Management: A Systems Approach to Planning, Scheduling and Controlling.* 2nd. Ed., Van Nostrand Reinhold, New York, 1984.
39. Lazega, E.,& Pattison, P. E. (1999). Multiplexity, generalized exchange and cooperation in organizations. *Social Networks, 21*, 67-90.
40. Lazega, E., & van Duijn, M. (1997). Position in formal structure, personal characteristics and choices of advisors in a law firm: A logistic regression model for dyadic network data. *Social Networks, 19*, 375-397.
41. Levitt, R.E., R.D. Logcher and N.H. Quaddumi, "Impact of Owner-Engineer Risk Sharing on Design Conservatism," *ASCE Journal of Professional Issues in Engineering*, Vol. 110, 1984, pp. 157-167.
42. M. S. Handcock. Assessing degeneracy in statistical models of social networks, working paper no.39. 2003.
43. Microsoft Windows Excel.
44. (Eds.). *Models and Methods in Social Network Analysis* (pp.192-214). New York: Cambridge University Press.
45. Monge, P.R., & Contractor, N.S. (2003). *Theories of communication networks.* NY: Oxford University Press.
46. Moolin, F.P., Jr., and F.A. McCoy: "Managing the Alaska Pipeline Project," *Civil Engineering*, November 1981, pp. 51-54.
47. Moreno, J. L., & Jennings, H. H. (1938). Statistics of social configurations. *Sociometry*. *1*, 342-374.
48. Murray, L., E. Gallardo, S. Aggarwal and R. Waywitka, "Marketing Construction Management Services," *ASCE Journal of Construction Division*, Vol. 107, 1981, pp. 665-677.
49. Newman, M. (2003). The structure and function of complex networks. *SIAM Review, 45*, 167-256.
50. O. Frank and D. Strauss. Markov graphs. Journal of the American Statistical Association, 81:832–842, Sep. 1986.
51. Padgett, J.F., & Ansell, C.K. (1993). Robust Action and the Rise of the Medici, 1400-1434. *American Journal of Sociology, 98*, 1259-1319.
52. Pattison, P. E., & Robins, G. L. (2002). Neighbourhood-based models for social networks. *Sociological Methodology, 32*, 301-337.
53. Pattison, P., & Robins, G.L. (2004). Building models for social space: Neighborhood based models for social networks and affiliation structures. *Mathematiques des science humaines, 168,* 11-29.
54. Pattison, P. E., & Wasserman, S. (1999). Logit models and logistic regressions for social networks, II. Multivariate relations. *British Journal of Mathematical and Statistical Psychology, 52*, 169-194.

55. P. W. Holland and S. Leinhardt. An exponential family of probability distributions for directed graphs. Journal of the American Statistical Association, 76(373):33–50, Mar. 1981.
56. Project Management Institute, *A Guide to the Project Management Body of Knowledge*, Newtown Square, Pennsylvania, 2000.
57. Ramsey, Fred L. and Schafer, Daniel W., *The Statistical Sleuth: a course in methods of data analysis*, Wadsworth Group, 2002, 2nd Edition.
58. Richard, Pierre J., Devinney, Timothy M., Yip, George S., Johnson, Gerry; Measuring Organizational Performance as a Dependent Variable: Towards Methodological Best Practice
59. Robins, G. L., & Pattison, P. E. (2005). *Interdependencies and social processes: Generalized dependence structures.* In P. Carrington, J. Scott & S. Wasserman
60. Robins, G. L., Elliott, P., & Pattison, P. E. (2001). Network models for social selection processes. *Social Networks, 23,* 1-30S. M. Goodreau. *Advances in exponential random graph (p*) models applied to a large social network*. Social Networks (Special Edition). In Press.
61. Robins, G., Snijders, T., Wang , P., Handcock, M., Philippa Pattison, P.. *Recent developments in exponential random graph (p*) models for social networks*, Elsevier Science Direct Social Networks © 2006 Elsevier B.V. All rights reserved.
62. Scott, John (1991). *Social network Analysis: A Handbook*, Sage: London.
63. Schweinberger, M, & Snijders, T.A.B. (2003). *Settings in social networks: A measurement model.* Sociological Methodology, 33, 307-341.
64. Skvoretz, J., & Faust, K. (1999). Logit models for affiliation networks. In Michael
65. Snijders, T.A.B. (2001). *The statistical evaluation of social network dynamics*. In M.E.
66. Sobel and M.P. Becker (eds.), *Sociological Methodology-2001*, 361-395. Boston and London: Basil Blackwell.
67. Snijders, T.A.B. (2002). *Markov chain Monte Carlo estimation of exponential random graph models.* Journal of Social Structure, 3, 2.
68. Snijders, T.A.B., Pattison, P., Robins, G.L., & Handock, M. (2006). New specifications for exponential random graph models. *Sociological Methodology.*
69. Strauss, D. (1986). On a general class of models for interaction. *SIAM Review, 28,* 513-527.
70. Strauss, D., & Ikeda, (1990). Pseudo-likelihood estimation for social networks. *Journal of the American Statistical Association, 85,* 204-212.
71. T. A. Snijders. *Markov chain monte carlo estimation of exponential random graph models.* Journal of Social Structure, 3:2, 2002.
72. T. A. Snijders, P. Boer, E. Zeggelink, M. Huisman, and C. Steglich. Siena: Simulation investigation for empirical network analysis. 2001.
73. T. A. Snijders, P. E. Pattison, G. L. Robins, and M. Handcock. *New specifications for exponential random graph models*. Sociological Methodology., In Press.
74. Van Duijn, M.A.J., Snijders, T.A.B., & Zijlstra, B.J.H. (2004). *p*2: a random effects model with covariates for directed graphs. *Statistica Neerlandica, 58,* 234-254.

75. P. Wang, G. L. Robins, and P. E. Pattison. Pnet: A program for the simulation and estimation of exponential random graph models. 2006.
76. S. Wasserman and G. L. Robins. Models and Methods in Social Network Analysis. An Introduction to Random Graphs, Dependence Graphs, and p_. Cambridge University Press, 2005.
77. Wasserman, Stanley, & Faust, Katherine. (1994). *Social network analysis.* Cambridge, MA: Cambridge University Press.
78. Wasserman, S., & Robins, G. L. (2005). *An Introduction to Random Graphs,*
79. Watts, D.J. (1999). *Small worlds: The dynamics of networks between order and randomness.* Princeton, NJ: Princeton University Press.

Appendix A – Spreadsheet printout for Network Genie responses

	A	B	C
1	Begin Legend		
2	Item I	Item Text	
3	1	What individuals do you communicate with on any topic, work related or not, at least once every three months?	
4	{Responses are binary. '1' for the alters included in subgroup; '0' for the alters not included in subgroup}		
5	Item I	Item Text	
6	2	Which of the following individuals do you discuss issues that are SPECIFIC to the organization at least once every three months?	
7	{Responses are binary. '1' for the alters included in subgroup; '0' for the alters not included in subgroup}		
8	Item I	Item Text	
9	3	How often do you have specific communications with {name} about organization issues?	
10	Resp	Resp	Response Text
11	1	1	Rarely - Less than once a month
12	2	2	Infrequently - Less then once a week
13	3	3	Weekly - 1-2 times per week
14	4	4	Frequently - Several times per week
15	5	5	Daily - At least once per day
16	Item I	Item Text	
17	4	How often do you exchange KNOWLEDGE with {name} to develop new solutions or approaches to organization issues.	
18	Resp	Resp	Response Text
19	1	0	Never
20	2	1	Rarely - Less than once a month
21	3	2	Infrequently - Less than once a week
22	4	3	Weekly - 1-2 times per week
23	5	5	Daily - AT least once per day
24	Item I	Item Text	
25	5	Who do you RECEIVE information from that is necessary for you to perform/complete your organization-related initiatives? Select indviduals you receive information from.	
26	{Responses are binary. '1' for the alters included in subgroup; '0' for the alters not included in subgroup}		
27	Item I	Item Text	
28	6	Who do you GIVE information to that is necessary for them to perform/complete their organization-related initiatives?Select individuals that you give information to	
29	{Responses are binary. '1' for the alters included in subgroup; '0' for the alters not included in subgroup}		
30	Item I	Item Text	
31	7	Which of the following individuals do you discuss issues that are SPECIFIC to a Client Project at least once every three months?	
32	{Responses are binary. '1' for the alters included in subgroup; '0' for the alters not included in subgroup}		
33	Item I	Item Text	

Figure Appendix A.1: Spreadsheet printout of Network Genie Results

156	Item Number: 2																													
157	Resp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
158	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
159	2	1	0	1	0	0	1	0	1	1	0	1	0	0	0	0	1	1	0	0	1	0	0	0	0	0	1	0	0	0
160	3	1	1	0	1	1	1	0	1	1	0	1	1	0	1	0	1	1	1	0	1	1	0	1	1	0	1	0	0	1
161	4	1	0	1	0	1	0	1	1	1	0	1	1	1	1	1	1	0	1	1	0	1	0	0	0	0	1	0	1	1
162	5	1	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	0
163	6	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	0
164	7	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
165	8	1	1	0	0	1	1	0	0	1	0	0	1	1	0	0	1	1	0	0	1	1	1	1	1	0	0	0	0	1
166	9	1	0	1	0	0	1	0	1	0	0	0	1	1	1	0	1	0	0	0	1	0	0	0	0	1	1	0	0	0
167	10	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0
168	11	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
169	12	1	0	1	0	1	1	0	0	1	0	0	0	1	0	0	1	1	0	0	0	1	1	1	0	1	1	0	0	0
170	13	1	1	1	0	0	1	0	0	1	0	0	1	0	1	0	1	1	0	0	1	1	0	1	1	0	1	0	0	0
171	14	1	1	1	1	1	1	0	1	1	0	1	1	1	0	1	1	1	1	0	1	1	1	1	1	0	1	0	0	0
172	15	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	1	1	1	1	0	0	0
173	16	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	0	0	0
174	17	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	0	1	0	0	0
175	18	0	1	0	0	1	1	0	1	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0
176	19	1	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
177	20	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	0	0	1	0	1	1	0	1	0	0	0
178	21	1	0	1	1	1	1	0	1	1	0	0	1	1	1	1	1	1	0	0	1	0	0	0	1	1	0	0	0	0
179	22	1	1	0	1	1	1	1	1	0	0	0	1	1	0	1	1	1	1	0	1	0	0	1	0	0	1	0	0	0
180	23	1	1	1	1	1	1	0	1	1	0	0	0	1	0	1	1	1	0	0	1	0	0	0	1	1	0	0	0	0
181	24	1	1	1	1	1	1	0	1	1	0	0	0	1	0	1	1	1	0	0	1	1	0	1	0	0	1	0	0	0
182	25	1	1	1	0	0	1	1	1	1	1	1	1	0	0	1	0	0	0	1	0	1	0	1	1	0	0	0	0	0
183	26	1	1	1	0	1	1	0	1	1	0	0	1	1	1	1	1	1	1	0	1	0	0	1	1	0	0	0	0	1
184	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
185	28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
186	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure Appendix A.2: Spreadsheet printout of responses to question 2

Dichotomizing data: converting answers given as weighted from 1-5 to binary 0 or 1.

187	Item Number: 3																													
188	Respo	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
189	1	na	5	2	2	2	3	1	2	3	1	1	2	2	2	1	3	3	1	1	3	2	1	1	2	4	1	1	1	4
190	2	4	na	1	na	na	2	na	1	2	na	1	na	na	na	na	2	3	na	na	3	na	na	na	na	na	2	na	na	na
191	3	3	2	na	2	2	5	na	2	3	na	3	4	na	2	na	3	2	1	na	5	3	na	2	2	na	2	na	na	3
192	4	3	na	2	na	5	na	5	3	3	na	3	1	3	3	3	3	na	2	2	na	3	na	na	na	na	2	na	2	2
193	5	2	1	3	5	na	3	5	4	2	na	3	2	2	3	3	4	3	2	na	3	3	4	2	3	1	3	na	na	na
194	6	3	2	4	3	3	na	2	2	5	na	4	4	4	4	3	4	3	3	na	4	3	2	3	2	3	4	na	na	na
195	7	na	na	na	na	1	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
196	8	2	2	na	na	4	2	na	na	2	na	na	2	2	na	na	3	3	na	na	2	3	3	3	2	na	na	na	na	1
197	9	4	na	4	na	na	5	na	4	na	na	na	3	4	4	na	3	na	na	na	4	na	na	na	na	3	4	na	na	na
198	10	2	na	na	na	na	na	na	na	1	na	na	1	na	na	na	na	2	na	na	na	na	na	na	na	3	na	na	3	na
199	11	na	na	2	na	na	3	na	na	na	na	na	na	na	na	3	na	na	na	na	na	na	na	na	na	3	na	na	na	na
200	12	2	na	2	na	2	3	na	na	1	na	na	na	1	na	na	2	2	na	na	na	2	1	1	na	1	2	na	na	na
201	13	3	3	2	na	na	5	na	na	4	na	na	1	na	2	na	2	2	na	na	2	2	na	2	2	na	2	na	na	na
202	14	2	2	1	2	2	3	na	1	3	na	2	1	2	na	1	2	2	1	na	2	5	1	1	1	na	2	na	na	na
203	15	2	2	na	3	2	3	4	2	1	1	4	2	2	1	na	3	4	1	na	na	1	2	5	2	1	1	na	na	na
204	16	3	2	2	2	4	4	2	4	2	na	2	2	2	3	3	na	3	2	na	2	3	2	2	2	1	2	na	na	na
205	17	4	3	na	2	2	2	na	3	2	2	2	2	4	2	4	3	na	3	na	2	2	5	4	2	na	3	na	na	na
206	18	na	1	na	na	2	4	na	1	na	na	na	na	1	na	na	1	2	na	na	na	na	na	na	na	na	5	na	na	na
207	19	1	na	na	1	na	na	na	na	1	na	2	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	4	na	1
208	20	4	3	4	3	3	3	na	2	3	na	1	1	3	2	1	3	2	2	na	na	3	na	2	4	na	2	na	na	na
209	21	2	na	2	1	3	2	na	2	1	na	na	3	2	4	2	3	2	na	na	1	na	na	na	1	1	na	na	na	na
210	22	1	1	na	2	3	1	1	1	na	na	na	2	1	na	2	2	5	2	na	1	na	na	1	na	na	2	na	na	na
211	23	1	1	2	1	1	3	na	2	1	na	na	na	2	na	4	2	3	na	na	1	na	na	na	1	1	na	na	na	na
212	24	4	2	3	1	4	3	na	3	2	na	na	na	2	na	2	3	3	na	na	3	3	na	2	na	na	2	na	na	na
213	25	3	1	1	na	na	2	1	1	1	3	4	2	na	na	1	na	na	na	4	na	1	na	1	1	na	na	na	na	na
214	26	2	2	2	na	2	4	na	2	2	na	na	2	2	1	2	3	2	4	na	2	na	na	1	2	na	na	na	na	1
215	27	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
216	28	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
217	29	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na

Figure Appendix A.3: Question 3 responses prior to dichotomizing

0	1	0	0	0	1	0	0	1	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	1	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
1	0	0	0	0	1	0	0	1	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0	0	0
1	0	0	0	1	0	1	1	1	0	1	0	1	1	1	1	0	0	0	0	1	0	0	0	0	0
0	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	1	0	0	1	1	1	0	1	0	1
1	0	1	1	1	0	0	0	1	0	1	1	1	1	1	1	1	1	0	1	1	0	1	0	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	1	1	0	0	0
1	0	1	0	0	1	0	1	0	0	0	1	1	1	0	1	0	0	0	1	0	0	0	0	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	1	0	1	1	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0
1	0	0	0	1	1	0	1	0	0	0	0	0	1	1	0	1	0	0	0	1	0	0	0	0	0
1	1	0	0	0	0	0	1	0	0	0	0	1	0	1	1	0	1	0	0	0	1	1	0	0	1
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	0	0	1	0	0	0	1	0	0	1	0	0	0	0	1	0	0	1	0	0
0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0
1	0	1	0	1	1	0	1	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	0	0
1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0

Figure Appendix A.4: Question 3 responses after dichotomizing

APPENDIX B – Additional Scatterplots of Densities for all individuals of all three firms.

Tables of Densities

The following tables summarize all the actors (players) responses expressed as a density percent. We can plot the results as scatter plots to examine the relationships between the variables in the Social Network Model For engineering and Construction.

SNA Statistical Data Engineering Design Firms

	OHM		Degenkolb		LDG	
Player	Communication	Trust	Communication	Trust	Communication	Trust
1	100%	72%	37%	40%	79%	29%
2	56%	68%	57%	80%	64%	7%
3	84%	60%	37%	60%	52%	60%
4	84%	0%	97%	57%	88%	64%
5	92%	92%	53%	87%	40%	14%
6	92%	92%	87%	90%	64%	64%
7	32%	36%	60%	73%	93%	88%
8	80%	80%	37%	37%	55%	50%
9	84%	0%	47%	30%	90%	50%
10	32%	12%	13%	7%	33%	33%
11	60%	40%	63%	30%	90%	36%
12	72%	20%	30%	27%	43%	31%
13	88%	60%	40%	73%	93%	40%
14	88%	80%	33%	40%	38%	40%
15	96%	92%	50%	37%	57%	26%
16	92%	92%	53%	53%	10%	5%
17	84%	84%	40%	43%	36%	24%
18	32%	24%	23%	17%	79%	55%
19	44%	36%	30%	13%	45%	12%
20	92%	72%	17%	37%	86%	67%
21	92%	80%	27%	10%	52%	36%
22	88%	72%	53%	93%	36%	19%
23	60%	48%	0%	0%	88%	48%
24	64%	76%	57%	33%	71%	45%
25	60%	40%	43%	40%	74%	81%
26	92%	68%	0%	0%	100%	48%
27			13%	7%	0%	57%
28			47%	47%	29%	24%
29			37%	33%	21%	21%
30			17%	53%	81%	90%
31			23%	20%	95%	48%
32					76%	45%
33					69%	31%
34					100%	62%
35					48%	45%
36					24%	19%
37					100%	43%
38					52%	33%
39					69%	57%
40					62%	24%
41					38%	5%
42					60%	60%
43					45%	40%

Table Appendix 1.1: Densities of Individual Responses for Questions on Communication and Trust

SNA Statistical Data Engineering Design Firms

Player	OHM Experience	OHM Trust	Degenkolb Experience	Degenkolb Trust	LDG Experience	LDG Trust
1	72%	72%	47%	40%	62%	29%
2	72%	68%	87%	80%	21%	7%
3	64%	60%	70%	60%	60%	60%
4	0%	0%	63%	57%	95%	64%
5	92%	92%	93%	87%	14%	14%
6	96%	92%	100%	90%	93%	64%
7	36%	36%	77%	73%	93%	88%
8	84%	80%	37%	37%	52%	50%
9	0%	0%	30%	30%	64%	50%
10	12%	12%	7%	7%	33%	33%
11	40%	40%	33%	30%	67%	36%
12	20%	20%	27%	27%	31%	31%
13	60%	60%	73%	73%	40%	40%
14	80%	80%	40%	40%	45%	40%
15	100%	92%	43%	37%	38%	26%
16	92%	92%	53%	53%	5%	5%
17	96%	84%	43%	43%	26%	24%
18	24%	24%	17%	17%	55%	55%
19	36%	36%	13%	13%	26%	12%
20	84%	72%	37%	37%	95%	67%
21	80%	80%	10%	10%	36%	36%
22	80%	72%	100%	93%	19%	19%
23	56%	48%	0%	0%	95%	48%
24	76%	76%	33%	33%	62%	45%
25	44%	40%	40%	40%	81%	81%
26	72%	68%	0%	0%	74%	48%
27			7%	7%	93%	57%
28			47%	47%	26%	24%
29			33%	33%	50%	21%
30			53%	53%	93%	90%
31			23%	20%	88%	48%
32					67%	45%
33					43%	31%
34					62%	62%
35					57%	45%
36					19%	19%
37					98%	43%
38					33%	33%
39					79%	57%
40					24%	24%
41					12%	5%
42					64%	60%
43					48%	40%

Table Appendix 1.2: Densities of Individual Responses for Questions on Experience and Trust

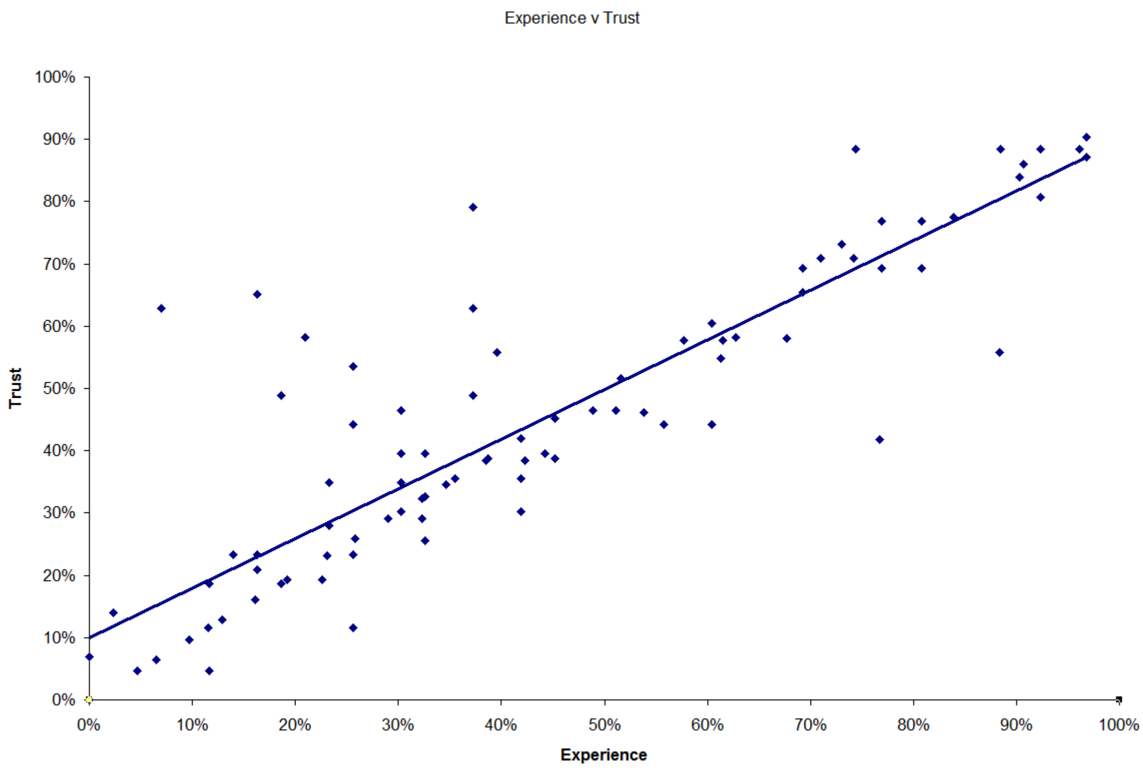
SNA Statistical Data Engineering Design Firms

Player	OHM Trust	OHM Values	Degenkolb Trust	Degenkolb Values	LDG Trust	LDG Values
1	72%	40%	40%	17%	29%	26%
2	68%	72%	80%	87%	7%	21%
3	60%	56%	60%	57%	60%	60%
4	0%	0%	57%	60%	64%	64%
5	92%	48%	87%	53%	14%	10%
6	92%	92%	90%	80%	64%	71%
7	36%	36%	73%	67%	88%	93%
8	80%	48%	37%	13%	50%	48%
9	0%	0%	30%	23%	50%	52%
10	12%	12%	7%	7%	33%	33%
11	40%	24%	30%	33%	36%	45%
12	20%	20%	27%	10%	31%	17%
13	60%	60%	73%	73%	40%	31%
14	80%	80%	40%	27%	40%	33%
15	92%	52%	37%	37%	26%	14%
16	92%	92%	53%	53%	5%	5%
17	84%	96%	43%	27%	24%	24%
18	24%	24%	17%	3%	55%	55%
19	36%	36%	13%	13%	12%	7%
20	72%	44%	37%	20%	67%	95%
21	80%	68%	10%	10%	36%	36%
22	72%	52%	93%	100%	19%	10%
23	48%	24%	0%	0%	48%	40%
24	76%	76%	33%	33%	45%	62%
25	40%	28%	40%	20%	81%	21%
26	68%	16%	0%	0%	48%	43%
27			7%	7%	57%	62%
28			47%	43%	24%	19%
29			33%	30%	21%	12%
30			53%	53%	90%	93%
31			20%	17%	48%	76%
32					45%	26%
33					31%	43%
34					62%	62%
35					45%	24%
36					19%	19%
37					43%	48%
38					33%	33%
39					57%	79%
40					24%	24%
41					5%	7%
42					60%	64%
43					40%	48%

Table Appendix 1.3: Densities of Individual Responses for Questions on Trust and Values

Experience and Trust

If we take a scatter plot of the data for experience and trust, we can make some interesting observations of the data. The players who have a higher density of other players they consider to have experience with, have a tendency to have a higher density of trust in other players in the social network. In other words, as experience goes up so does trust in terms of network density.



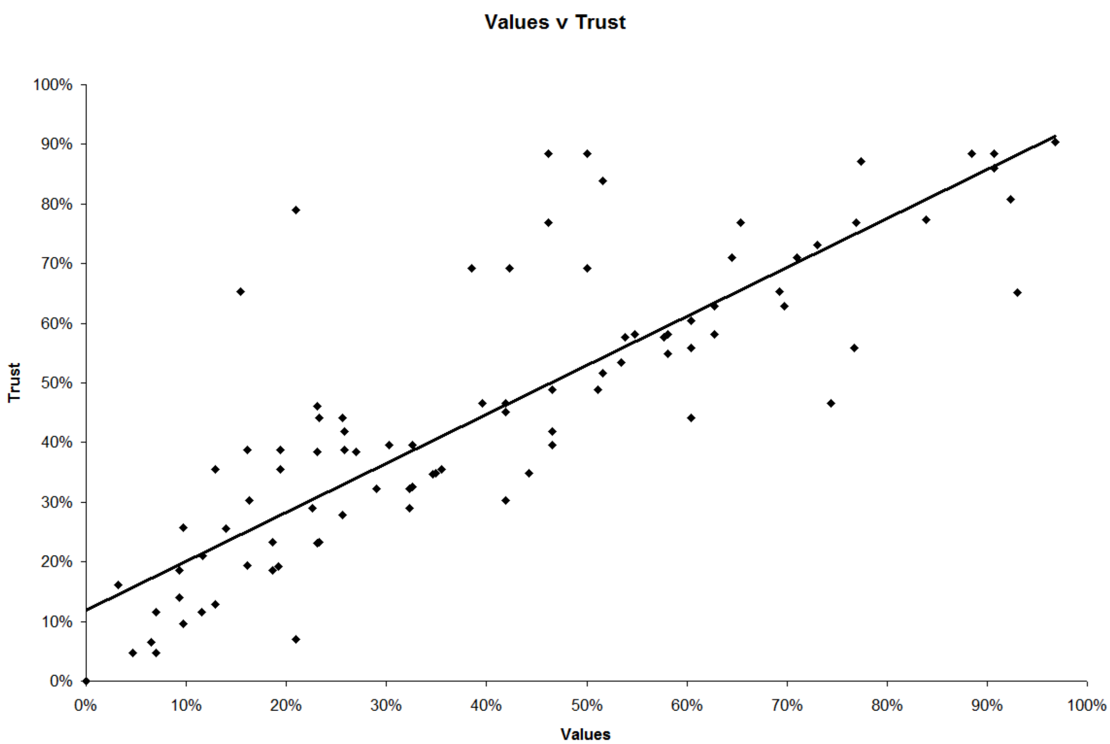
Appendix B Figure 1: Scatter Plot of Experience versus Trust All Three firms

In developing the Social network Model, we emphasize how members of the organization interact with regards to experience, reliance and trust. As the parties gain experience with each other they will begin to rely on each other. This is the first step leading to trust and communication and ultimately to obtaining knowledge exchange.

Another interesting feature is the points of high trust and low to moderate experience, which indicates our organization is a high effective group. The points of low trust even at a high level of experience are areas of concern for the organizations, since those players are not indicating trust in each other.

Trust and Values

A direct outcome of reliance is trust. There are many forms of trust that can exist in an organization from what is referred to as blanket trust which translates to a trust of another individual in any action they take to a focused trust on a specific topic. In the context of the Social Network Model, trust is considered when an individual believes that another individual will take actions that are mutually beneficial and not solely to one's advantage. This is a key requirement for knowledge exchange since individuals need to feel confident that knowledge that is exchanged will have a mutual benefit. In contrast, if an individual believes that exchanging knowledge can lead to a reduction in status or power, then that individual will be hesitant to release knowledge into the network.

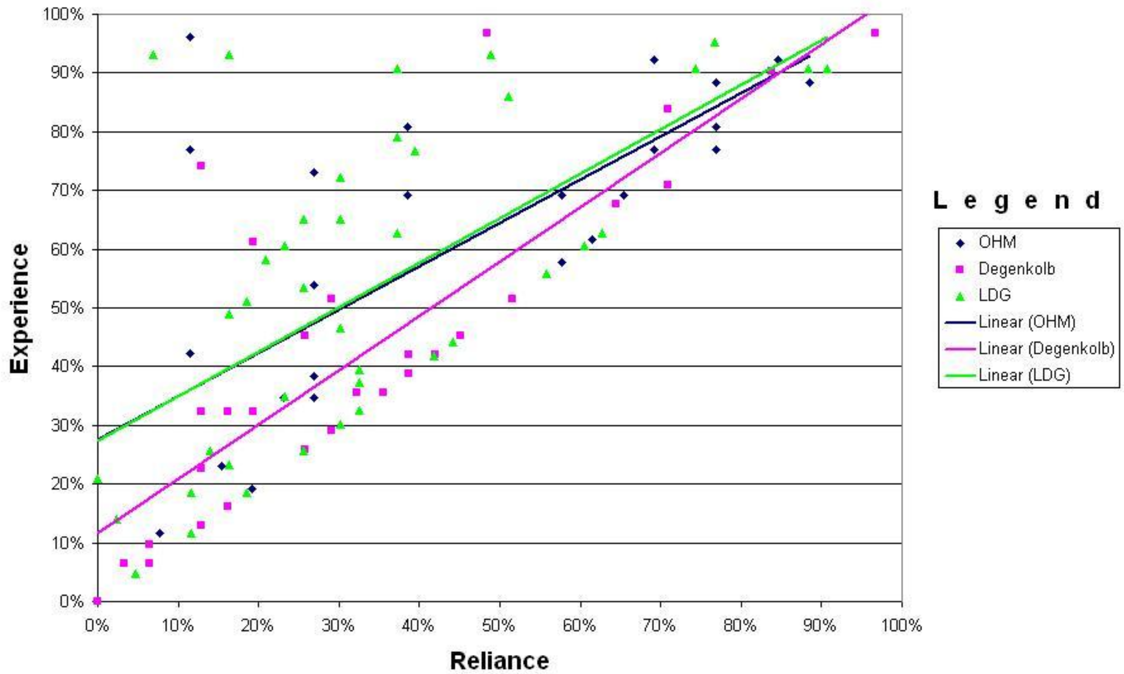


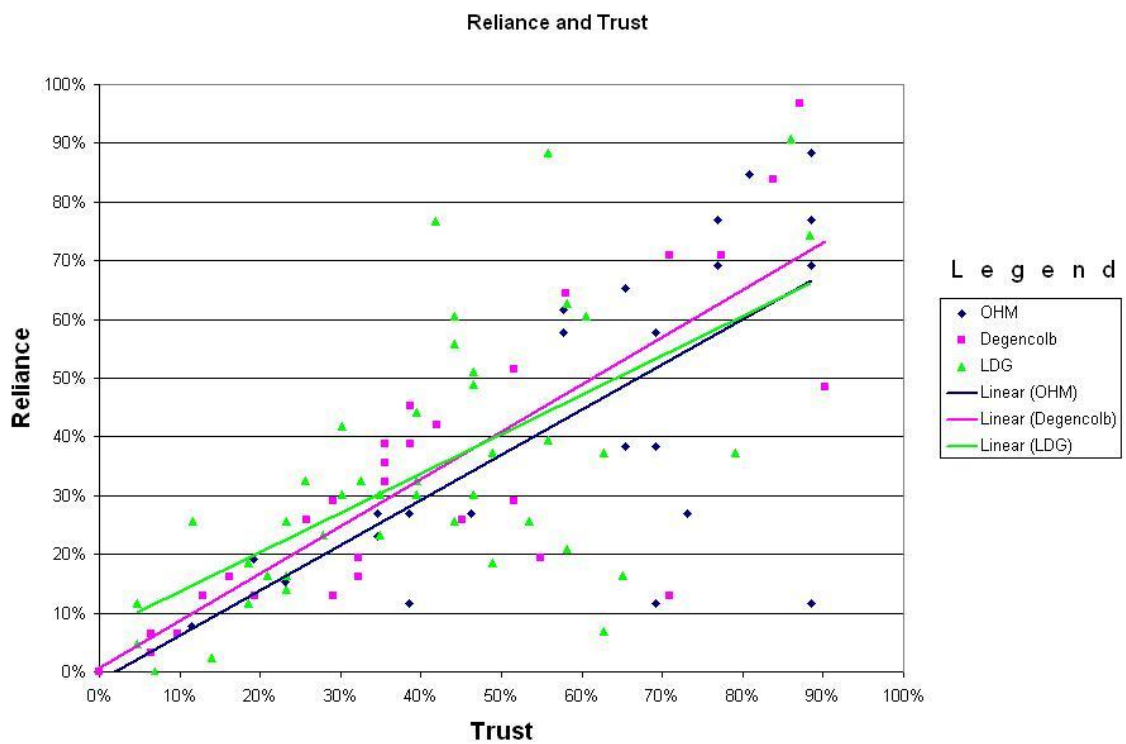
Appendix B Figure 2: Scatter Plot of Value versus Trust All Three Firms

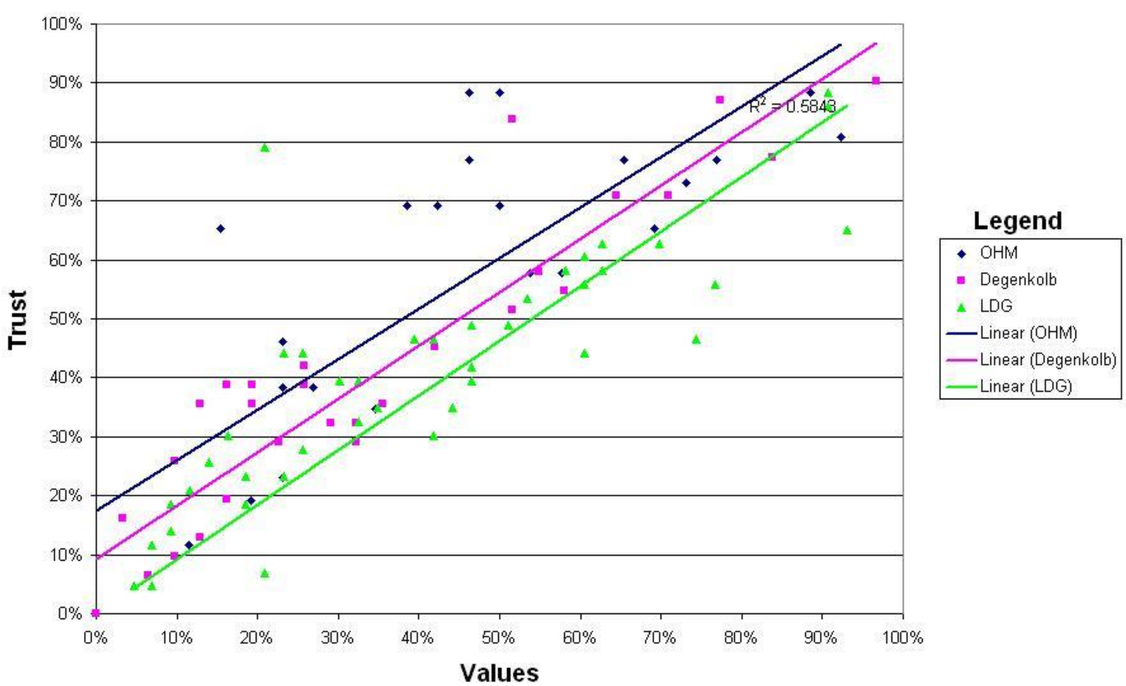
The final level of interest in the social network model on the statics side is the level of shared values in the organization. As can be seen in Figure 2, players with a high sense of trust in each other demonstrate a high sense of shared values, and people with a low trust in each other tend to demonstrate a low level of shared values with each other. Highly Effective Organizations demonstrate a high level of trust and shared values.

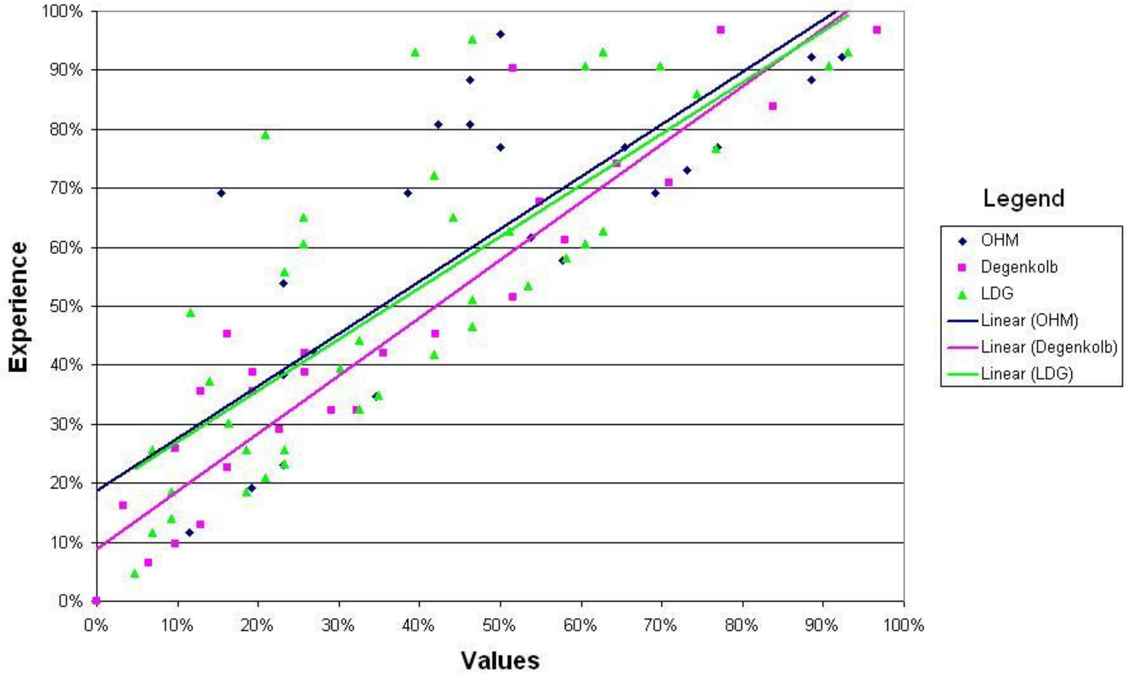
Our results show a wide spread over trust and values as can be seen on the graph. The outlier players seen to have a high sense of trust in each other even though they share values with less than half the organization. This would indicate that shared values are not necessarily required for a high level of trust in each other.

Other variable scatterplots of the Social Network Model for Engineering and Construction

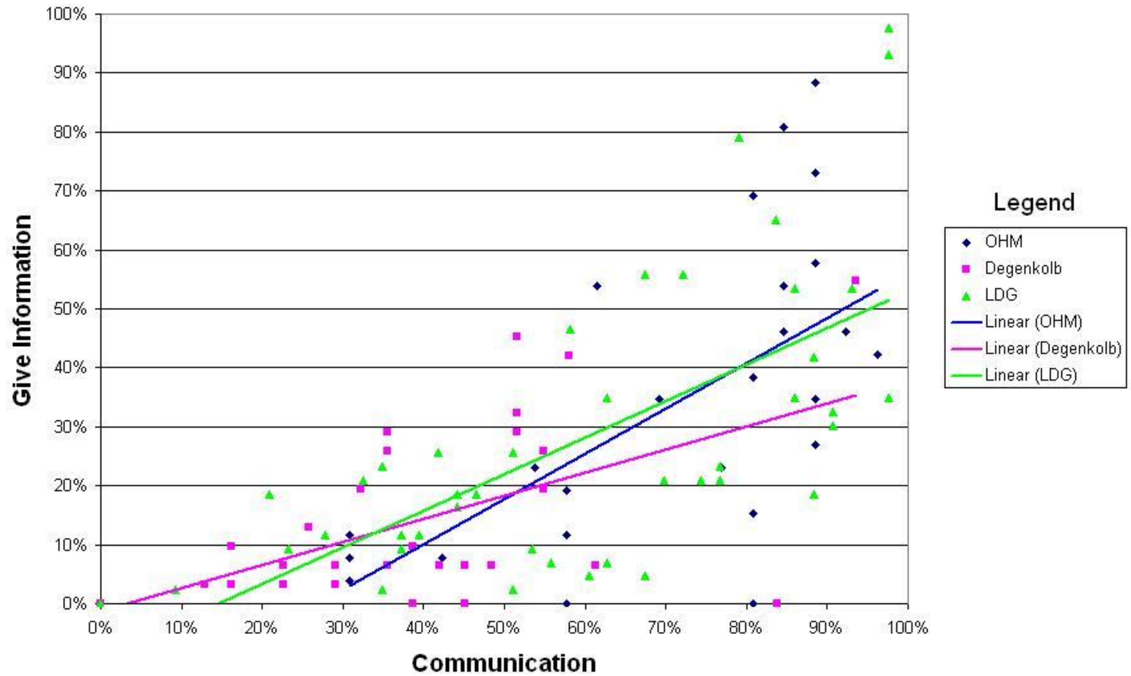


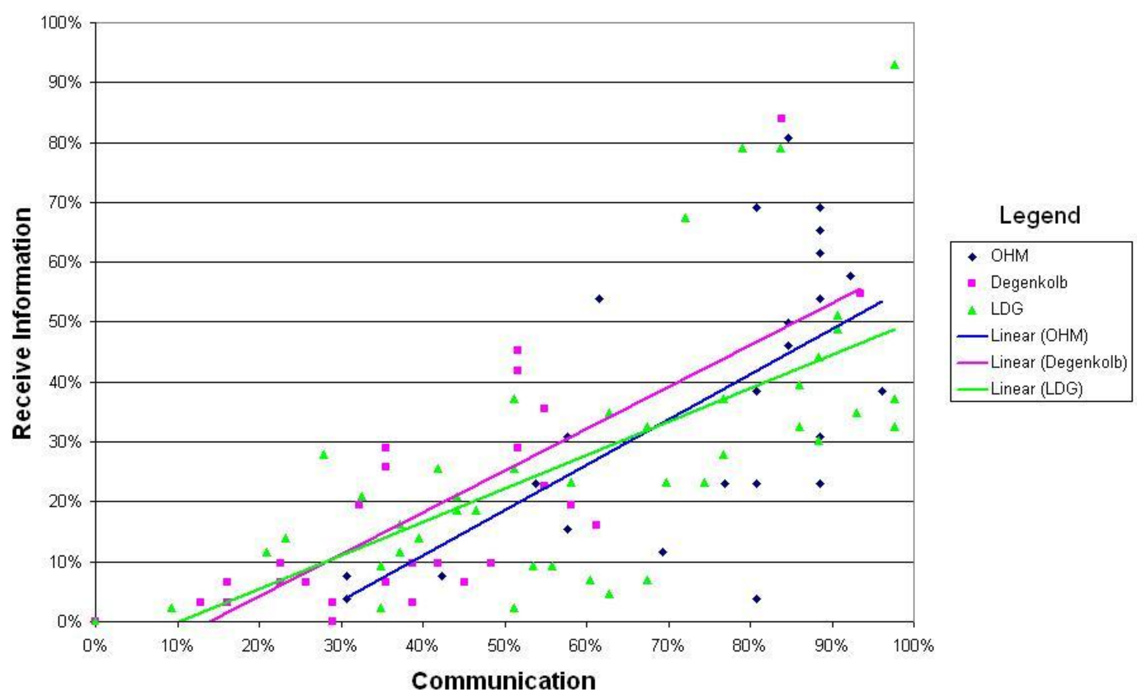

Reliance and Trust
Reliance
Trust
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
L e g e n d
OHM
Degencolb
LDG
Linear (OHM)
Linear (Degencolb)
Linear (LDG)

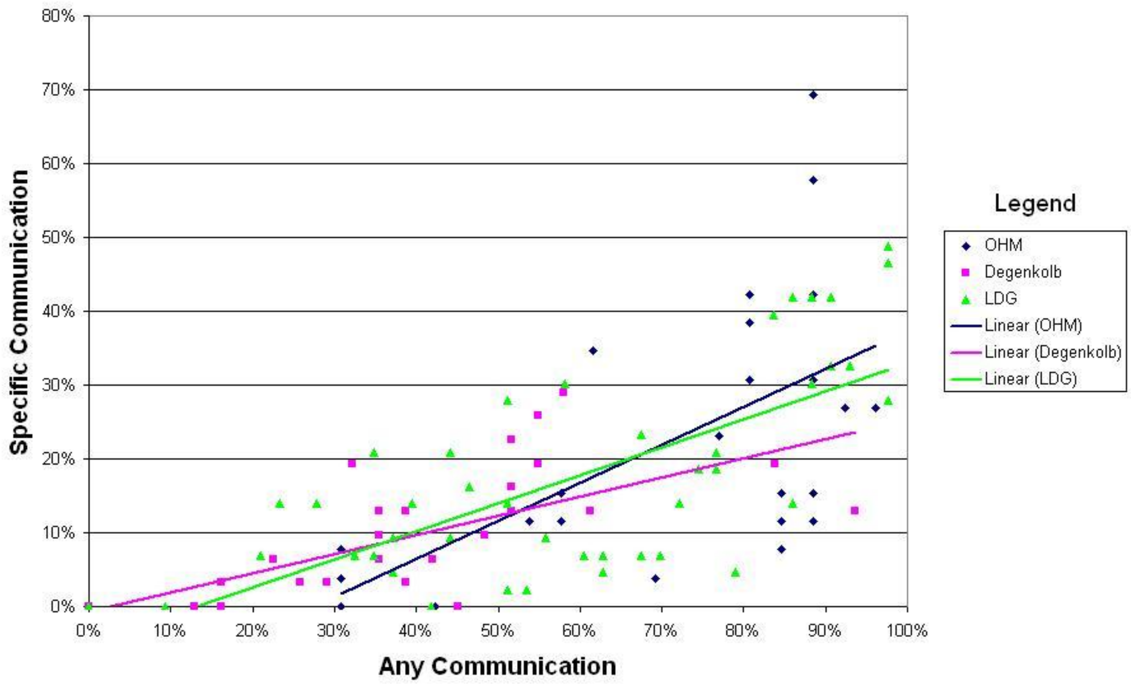

Trust
Values
$R^2 = 0.5848$
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Legend
OHM
Degenkolb
LDG
Linear (OHM)
Linear (Degenkolb)
Linear (LDG)

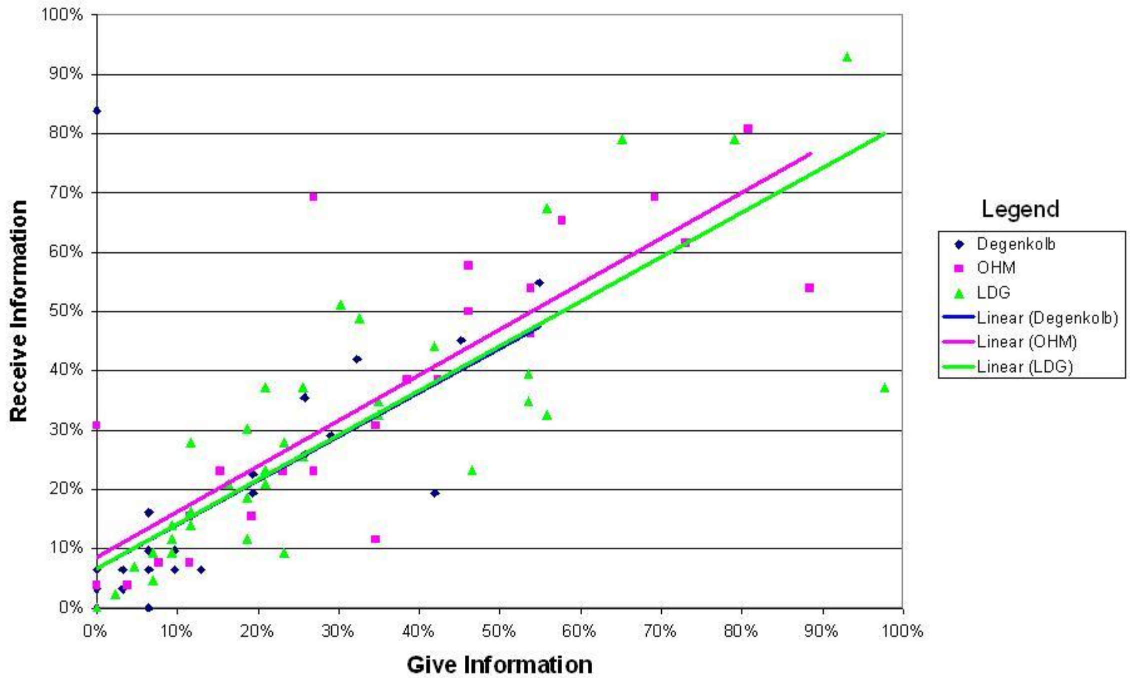


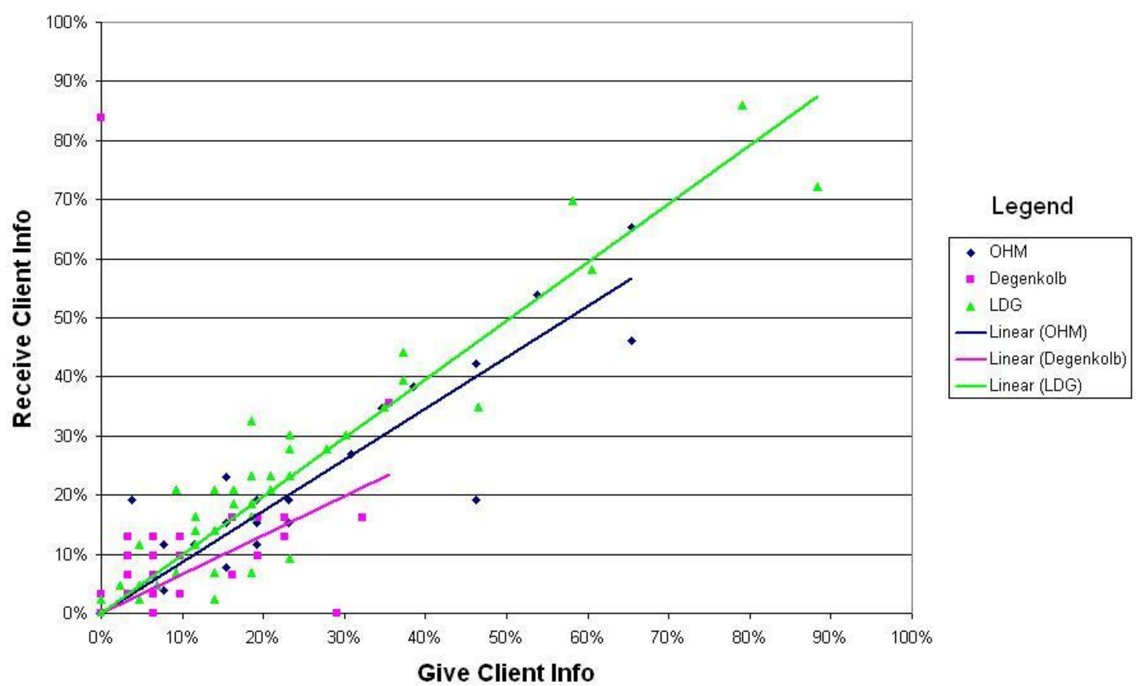
Experience
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Values
Legend
OHM
Degenkolb
LDG
Linear (OHM)
Linear (Degenkolb)
Linear (LDG)

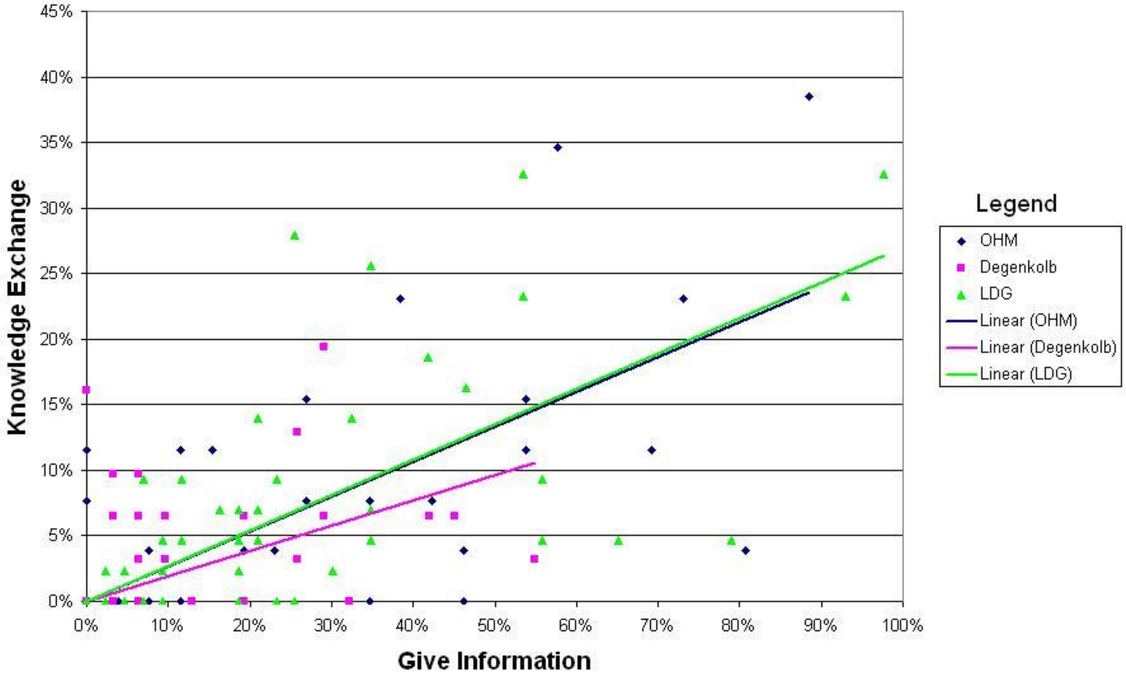

100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Give Information
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Communication
Legend
OHM
Degenkolb
LDG
Linear (OHM)
Linear (Degenkolb)
Linear (LDG)


100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Receive Information
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Communication
Legend
OHM
Degenkolb
LDG
Linear (OHM)
Linear (Degenkolb)
Linear (LDG)


80%
70%
60%
50%
40%
30%
20%
10%
0%
Specific Communication
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Any Communication
Legend
OHM
Degenkolb
LDG
Linear (OHM)
Linear (Degenkolb)
Linear (LDG)

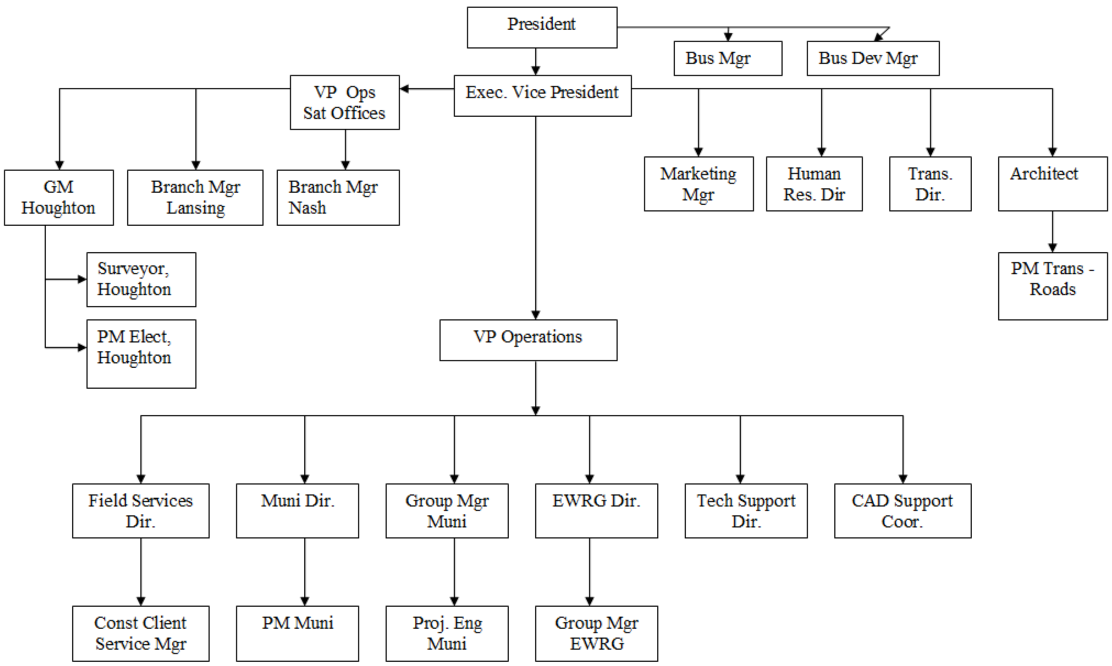

Receive Information
Give Information
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Legend
Degenkolb
OHM
LDG
Linear (Degenkolb)
Linear (OHM)
Linear (LDG)

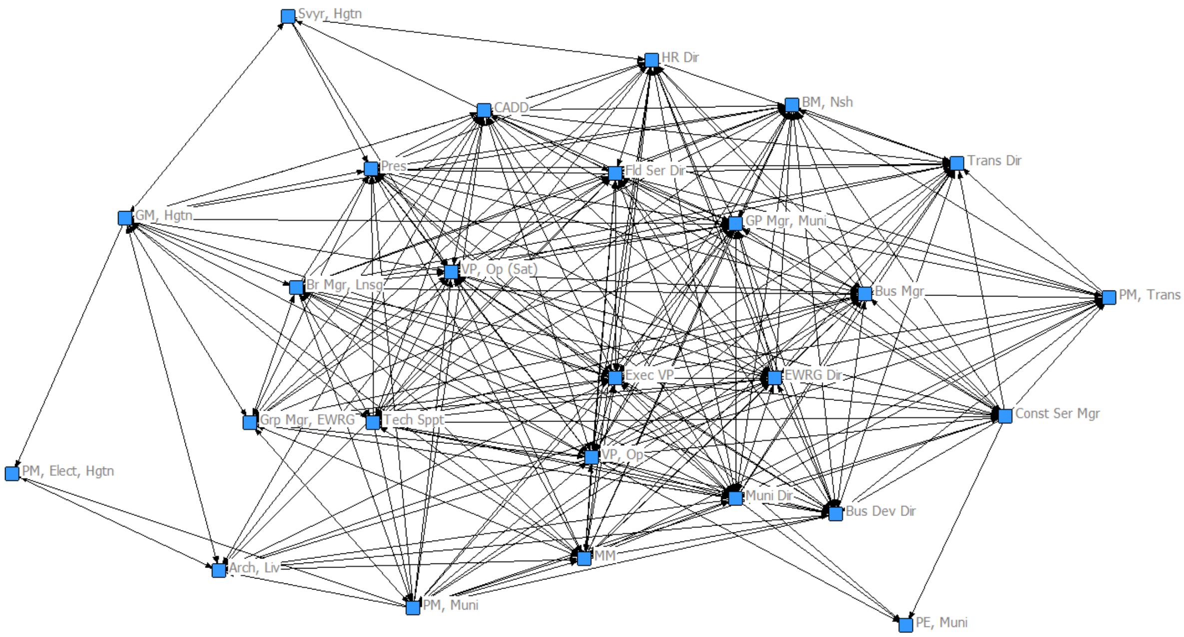

Receive Client Info
Give Client Info
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Legend
OHM
Degenkolb
LDG
Linear (OHM)
Linear (Degenkolb)
Linear (LDG)


45%
40%
35%
30%
25%
20%
15%
10%
5%
0%
Knowledge Exchange
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Give Information
Legend
OHM
Degenkolb
LDG
Linear (OHM)
Linear (Degenkolb)
Linear (LDG)

APPENDIX C

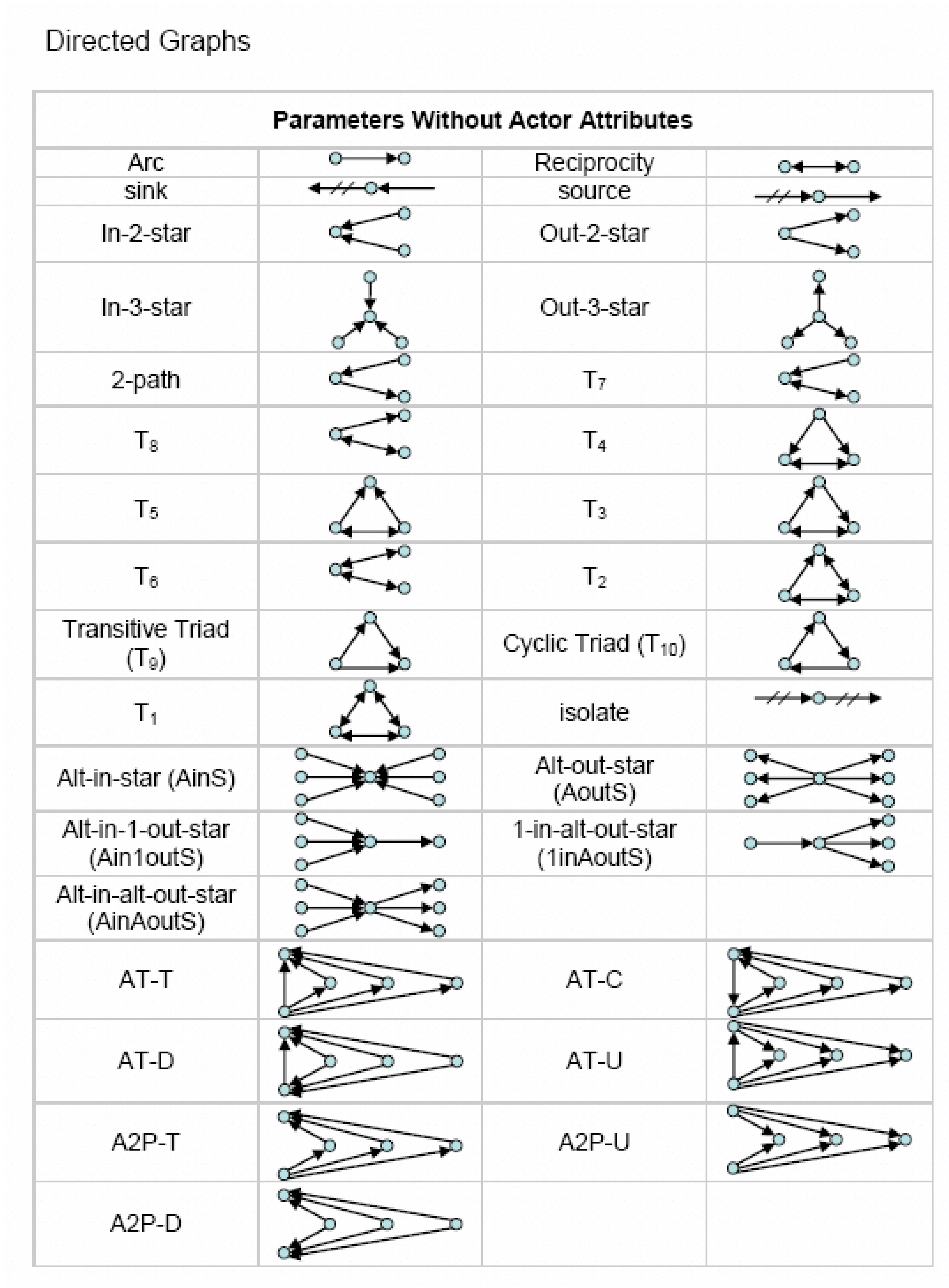
OHM ORGANIZATION CHART





Knowledge Exchange Network (Org Issues)

Appendix D – Available Parameters Estimated Using PNet



Directed Graphs

Parameters Without Actor Attributes			
Arc		Reciprocity	
sink		source	
In-2-star		Out-2-star	
In-3-star		Out-3-star	
2-path		T_7	
T_8		T_4	
T_5		T_3	
T_6		T_2	
Transitive Triad (T_9)		Cyclic Triad (T_{10})	
T_1		isolate	
Alt-in-star (AinS)		Alt-out-star (AoutS)	
Alt-in-1-out-star (Ain1outS)		1-in-alt-out-star (1inAoutS)	
Alt-in-alt-out-star (AinAoutS)			
AT-T		AT-C	
AT-D		AT-U	
A2P-T		A2P-U	
A2P-D			

Appendix E – ERGM Higher Order Parameters

The New Specifications

Until recently, the most common form of the ERGM was that of Frank and Strauss (1986). Also called the 'Markov parameters', these were based on the idea that edges of a graph were independent unless they potentially shared a node. This is called the Markov dependence assumption (Snijders et al 2005: 7). In effect, this dependence assumption meant that the types of configurations were limited to those configurations where all edges were potentially adjacent to all other edges, or to put it in another way, "two possible social ties are dependent only if a common actor is involved in both" (Snijders et al. 2005: 7). The standard Markov parameters/configurations for directed and on-directed graphs are listed in Figure 2, along with the symbol for the parameter (in brackets).

There are three major configurations in the new specifications: alternating- triangles; alternating-k-stars and alternating-k-two-paths (for a more complete overview of the new specifications see Snidjers et al 2005 and Robins, Pattison and Wang 2006). The meaning of the new specifications can be best understood by exploring an example: the alternating-k-stars configuration (in a non-directed network).

Methodology

Alternating-k-stars

A diagram of the alternating-k-star (non-directed) can be seen in Figure 4. There are three main features of the alternating-k-star configuration: First, all star effects within the model are incorporated within the one configuration/parameter (Snijders 2005: 21). In the Markov parameters it was generally the case that 2-stars were one configuration, 3- tars another configuration, and 4-stars another. In the new specifications, the propensity to form stars is incorporated into one configuration – the alternating-k-stars configuration. Second, there is a special weighting of the probabilities of each 'order' of star ('order' referring to the number of partners: that is, 2-stars are nodes with two partners, 3-stars nodes with three partners, etc. Each being one order higher than the last.). The weighting specifies that there is a lower likelihood of higher order stars (which means that there is, for example, a lower likelihood of 4-stars than 2-stars for any positive parameter value for the alternating k-star parameter). The probability of a star of a particular order is approximately inversely proportional to its order. However, to understand this weighting it is important to note that 'the lower likelihood of 4-stars' refers to the lower 'additional' likelihood contributed by the 4-star parameter itself to the formation of a 4-star. In a simulation, the likelihood of a tie forming to create a 4-star is determined not only by the 4-star parameter, but also by the 3-star parameter (since a tie forming a 4-star also forms three 3-star configurations, and three 2-star configurations and an edge).

Thus, the probability of forming a tie to form a four star is actually dependent on the parameter values for at least three other configurations, and because higher order stars include multiple lower order stars, this actually makes ties that form a higher order star generally more likely to form than other ties in the network (in the presence of a positive parameter value for an alternating-k-star effect).

The third feature of the alternating-k-star configuration is that the configuration has a special 'alternating' aspect of its weighting of different orders of stars: the sign (positive (+) or negative (-)) of the probability for higher order stars is sequentially alternated for each higher order star. So 2-star configurations have a positive probability, 3-stars have a negative probability, 4-stars a positive probability, 5-stars a negative probability, and so on. This alternating characteristic of the new specifications adds a further tendency against large numbers of higher-order configurations (stars, triangles, etcetera). The combined effect of the three features of the alternating-k-star configuration is to create a parameter that, if positive, can be interpreted as a tendency towards a large number of small stars, and over and above this a more moderate, but nonetheless positive, tendency towards higher order stars.

From the Markov model, one can model stars up to size (n − 1). The model puts large weights on big stars, or nodes with high degree, which causes the degeneracy problem. The new specification uses a single parameter for the entire degree distribution by introducing a weight parameter λ_s, $\lambda_s \geq 1$, which dampens the effect of large changes in the statistics of large stars. The weights of stars also have alternating signs, so that the even-k-stars' positive weights are balanced by the odd-k-stars' negative weight. The new statistic, known as alternating k-stars with parameter λ_s, can be expressed as,

$$\boldsymbol{z_s(\lambda_s, x)} = z_{s2}(\mathrm{x}) - \frac{z_{s_3}(x)}{\lambda s} + \frac{z_{s_4}(x)}{\lambda_s^2} - \cdot\cdot\cdot + (-1)^{n-2}\,\frac{z_{s_{n-1}}(\mathrm{x})}{\boldsymbol{\lambda}_s^{n-3}}$$

$$= \sum_{k=2}^{n-1}(-1)^k\,\frac{\mathrm{z}_{\mathrm{s_k}}(\mathrm{x})}{\boldsymbol{\lambda}_s^{k-2}}$$

Where:

$\boldsymbol{z_s(\lambda_s, x)}$ = the graph statistic for the alternating-k-star configuration.

k = the order of the star configuration in the equation (so a 2-star is order 2 and k = 2; a 3-star is order 3 and k = 3; etcetera).

$\sum_{k=2}^{n-1}(-1)^k\,\frac{\mathrm{z}_{\mathrm{s_k}}(\mathrm{x})}{\boldsymbol{\lambda}_s^{k-2}}$ = the sum of the equation for all values of k greater than 2. In other words, repeat the calculation of the equation for each star configuration with an order equal to 2 or greater, and then add together the values for all orders of stars.

$(-1)^k$ = minus one to the power of k. For even values of k (2, 4, 6…) this will equal 1, for odd values of k (3, 5, 7…) this will be negative. This gives rise to the 'alternating' character of the statistic.

z_{s_k} (x) = Graph statistic for star configuration of order k. This is a 'count' of the number of stars of order k in the graph.

$\lambda_s = \lambda$ is a constant, typically set to $\lambda = 2$ (Robins, Pattison and Wang 2006). λ_{k-2} increases at an increasing rate for higher order stars. Since λ_{k-2} is a denominator in the equation, higher order stars have much lower impact on the graph statistic $z_s(\lambda_s, x)$. This has the effect of producing fewer higher order stars in simulations.

Alternating-k-triangles

The non-directed version of the alternating-k-triangle configuration is illustrated in Figure 3. The alternating-k-triangle has a similar logic to the alternating-k-star configuration. Note, however, that the alternating-k-triangle includes four-cycles, whereas the alternating-k-star did not, and thus the alternating-k-triangle is reliant on the development of partial conditional independence while the alternating-k-star was not. The k refers to the number of triangles which share the same base, so for example a 2-triangle is comprised of two triangles which share the same base. Like the alternating-k-star configuration, the alternating-k-triangle has three major properties:

- All triangle effects in the model are incorporated within one statistic in the case of a non-directed graph, or in a directed graph are grouped into sets of statistics that incorporate all orders of the one type of triangle into one statistic (see Robins, Pattison and Wang (2006) for examples of the specifications for alternating-k-star configurations for directed networks).
- The contribution of higher order triangle configurations to the probability of a tie that forms a higher order triangle is approximately inverse proportion to its order (actually in proportion to $\frac{1}{2k-2}$).
- The sign of the contribution of higher order triangles to the likelihood of ties to form that triangle is sequentially alternated for each higher order triangle.

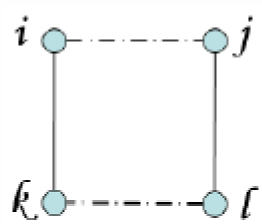
The effect of these three properties is a configuration (or set of configurations for directed graphs), which, if the parameter is positive, can be interpreted as a tendency towards forming a large number of lower-order triangles (for example, 2-triangles), and a smaller, but still significantly more than chance, number of higher-order triangles.

The Markov assumption models network transitivity by a single triangle parameter. The previous simulations show that the Markov edge and triangle model has the problem of degeneracy, since it only covers the near empty or near complete region of the network space. The Markov assumption restricts the tie dependence structure such that tie variables must share a node to be considered as conditionally dependent. However, according to the realization dependent assumption described below, ties in a network may well be conditionally dependent even if they do not share a node. The Markov assumption is too restrictive, and a simple single triangle is not sufficient to capture all completed structures involved in human social networks.

The realization dependence assumption expands the dependency structure to sub graphs of four nodes. The assumption states that two edge variables are conditionally dependent, given the rest of the network, only if one of two conditions is met: The arcs share a node which is the condition needed to satisfy the Markov assumption. Or, two ties exist, then the two arcs would be part of a four-cycle as shown in Figure 1.

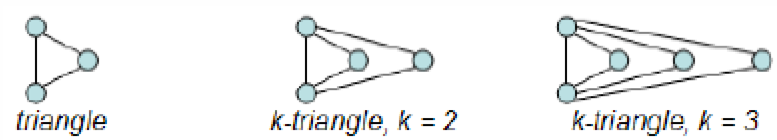
Based on the realization dependence, the formation of a tie is not only affected by other ties that two nodes have, but also other ties that do not directly involve those two nodes, so that the probability of forming a tie is assumed to depend on whether the arc is part of a social circuit (four-cycle). Graphs generated from a realization dependence model are called realization dependent graphs.

From experience, triangles in social networks tends to form clique-like structures (a clique is a completed sub graph), where many triangles are formed within a small group of nodes. The new specification proposed a new graph statistic called *k-triangles* which is defined as *k* triangles sharing a common edge, as shown in Figure 2. A k-triangle is a further specification that satisfies the realization dependent assumption; it represents connected dyads having multiple shared partners.



Appendix D Figure 1: Realization dependence assumption when a four-cycle is created

To avoid the problem that the model puts large weight on large sized triangles, in analogy to alternating k-stars, the parameters for all $(n-2)$ k-triangles are modeled as a function of a single parameter τ . The k-triangles also have a weight parameter λ_t and alternating signs such that $\tau_k = -\frac{\tau_{k-1}}{\lambda_t}$, which leads to the *alternating k-triangle* statistic which can be simplified by the binomial formula. When $\lambda_t > 1$,



Appendix D Figure 2: K-triangles

$$z_t(\lambda_t,\mathrm{x}) = 3z_{t_1}(\mathrm{x}) - \frac{z_{t_2}(\mathrm{x})}{\lambda_t} + \frac{z_{t_3}(\mathrm{x})}{\lambda_t^2} - \cdot\cdot\cdot + (-1)^{n-3}\frac{z_{t_{n-2}}(\mathrm{x})}{\lambda_t^{n-3}}$$

$$= \sum_{i=1}^{n}\sum_{j=i+1}^{n} x_{ij} \ \sum_{k=1}^{n-2}\left(\frac{-1}{\lambda_t}\right)^{k-1}\binom{L_{2ij}(\mathrm{x})}{k}$$

$$= \sum_{i=1}^{n} \sum_{j=i+1}^{n} x_{ij} \sum_{k=0}^{n-2} \left\{ (-\lambda_t) \left(\frac{-1}{\lambda^t} \right)^k \binom{L_{2ij}(\mathrm{x})}{k} + \lambda_t \right\}$$

$$= \lambda_t \sum_{i=1}^{n} \sum_{j=i+1}^{n} x_{ij} \left\{ 1 - \left(1 - \frac{1}{\lambda_t} \right)^{L_{2ij}(\mathrm{x})} \right\}$$

Where:

$z_t(\lambda_t,\mathrm{x})$ = the graph statistic for the alternating-k-triangle configuration

k = the order of the triangle configuration in the equation (so a 2-triangle is order 2 and k = 2; a 3-triangle is order 3 and k = 3; etcetera).

$\sum_{i=1}^{n} \sum_{j=i+1}^{n} x_{ij}$ = the sum of the equation for all values of k greater than 2. In other words, repeat the calculation of the equation for each triangle configuration with an order equal to 2 or greater, and then add together the values for all orders of triangles.

$\left(\frac{-1}{\lambda_t} \right)^k$ = minus one to the power of k. For even values of k (2, 4, 6…) this will equal 1, for odd values of k (3, 5, 7…) this will be negative. This gives rise to the 'alternating' character of the statistic.

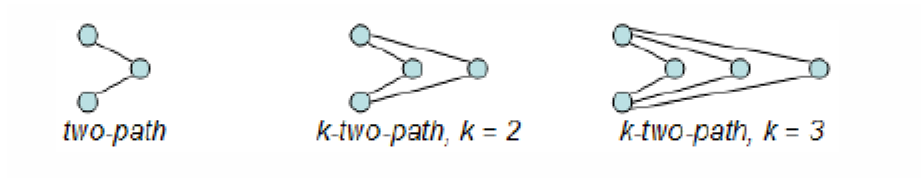
T_k = Graph statistic for triangle configuration of order k. This is a 'count' of the number of triangles of order k in the graph.

λ_t = λ is a constant, typically set to λ = 2 (Robins, Pattison and Wang 2006). λ_{k-2} increases at an increasing rate for higher order triangles. Since λ_{k-2} is a denominator in the equation, higher order triangles have much lower impact on the graph statistic S. This has the effect of producing fewer higher order triangles in simulations.

Alternating-k-two-paths

The alternating-k-two-path configuration is almost identical to the alternating-k triangle configuration, except that the edge at the base of the k-triangle is optional in the alternating-k-two-path. The alternating-k-two-path (non-directed network) is represented in Figure 6. The mathematics for calculating the graph statistic for alternating-k-two-path parameter is almost identical to that of the other two alternating-k parameters presented, and thus will not be repeated. The main way this parameter is interpreted is when it is combined with the k-triangle parameter: if the alternating-k-triangle parameter is positive in models that include the alternating-k-two-path parameter, then it means that the transitivity (triangulation) in the network occurs because of the formation of the base of the triangles, and not because of the formation of the sides (Robins, Pattison and Wang 2006). To express the same idea more simply: if the alternating-k-triangle parameter is positive in the presence of the alternating-k-two-path parameter, then it means that the formation of multiple paths between two nodes increases the likelihood that those two nodes will themselves be connected.

A two-path is the same as a two-star, four nodes with two two-paths forms a four-cycle or a 2-two-path. We define a k-two-path as a structure such that two nodes are connected by k two paths, as shown in Figure 3. The k-two-path structure also satisfies the realization dependence assumption.



Appendix D Figure 3: K-two-paths

For ties to be part of a k-triangle, it can either be the base that makes the closure of the k-two-paths, or be the side as part of a two-path. Inclusion of the k-two-path in the model will distinguish between the effect of closure and the effect of forming prerequisites for closure.

Applying a weight parameter λ_v, and alternating signs as for k-stars and k-triangles, we form the alternating k-two-path statistic, when $\lambda_v > 1$,

$$z_v(\lambda_v,\mathrm{x}) = z_{v1}(\mathrm{x}) - 2\frac{z_{v2}(\mathrm{x})}{\lambda_v} + \sum_{k=3}^{n-2}\left(\frac{-1}{\lambda_y}\right)^{k-1} z_{vk}(\mathrm{x})$$

$$= \lambda_v \sum_{i=1}^{n}\sum_{j=i+1}^{n}\left\{1-\left(1-\frac{1}{\lambda_v}\right)^{L_{2ij}(\mathrm{x})}\right\}$$

where $L_{2ij}(\mathrm{x})$ is the number of two paths in the network.

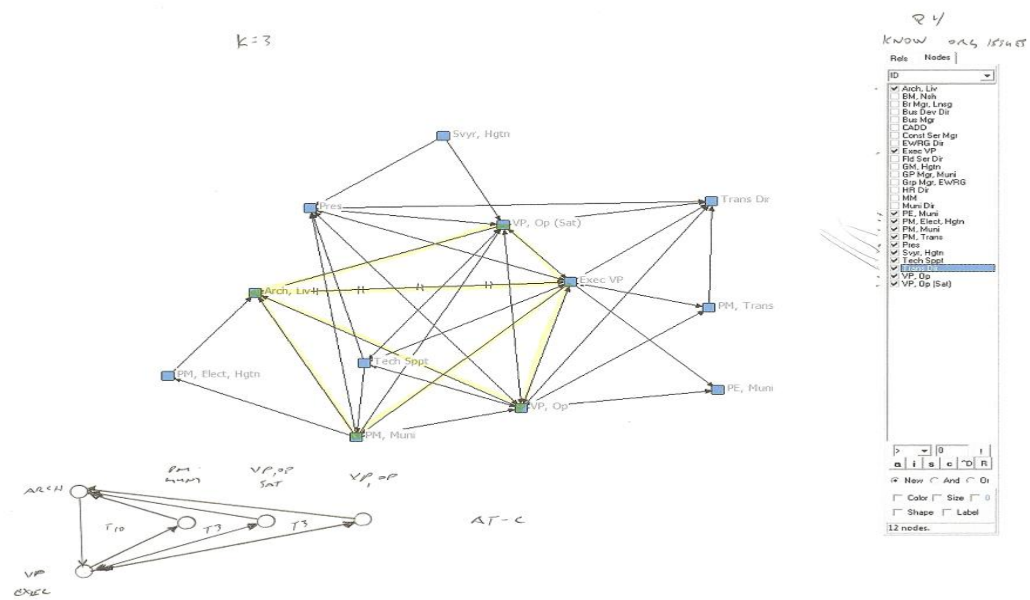
K Triangles and OHM Knowledge Network

This study examines K triangles in the OHM knowledge exchange network. I took the network for knowledge exchange related to organizational issues and subdivided it into smaller networks so I could examine the k-plexes in the network. I subdivided the network to contain the specified configurations and examined the relationships between the architect and the executive vice president for analysis. I chose to look at the relationship between the Architect and the Executive Vice President as the common tie and analyzed the AT-C, AT-CU and the remaining 4-triangle that completes all the triangles associated with the common arc.

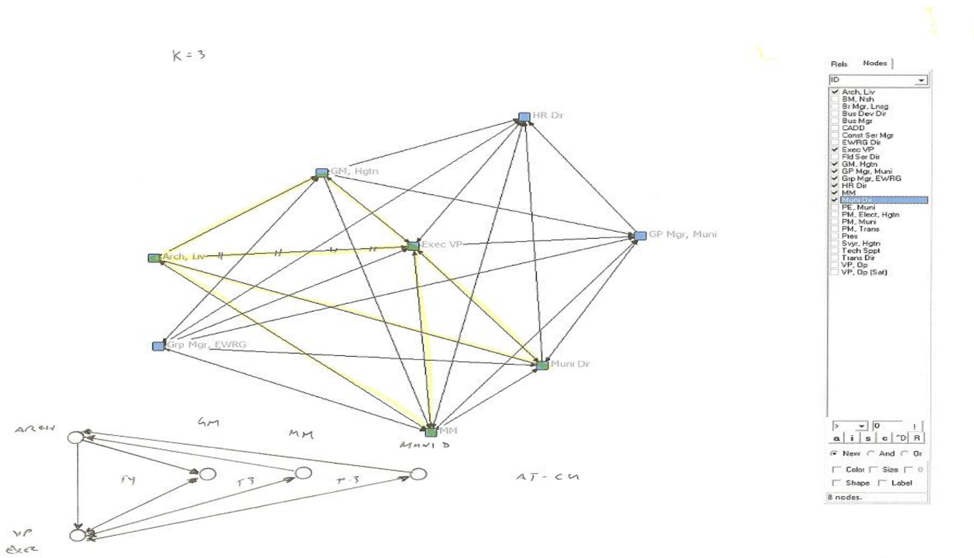
I ran the sub networks through the PNet analysis to obtain the parameter constants for the subject triangle configurations and interpreted the results. I also ran a network with all the triangles in one sub network to examine the parameters. Subsequently, I looked at the goodness of fit for the parameters with the observed network.

The results indicate positive parameters for three of the k-triangle configurations. This would indicate that knowledge exchange between the architect and the executive vice president will be transferred to another actor in the organization. These results coupled with the reciprocity results indicate good knowledge exchange for OHM organization issues.

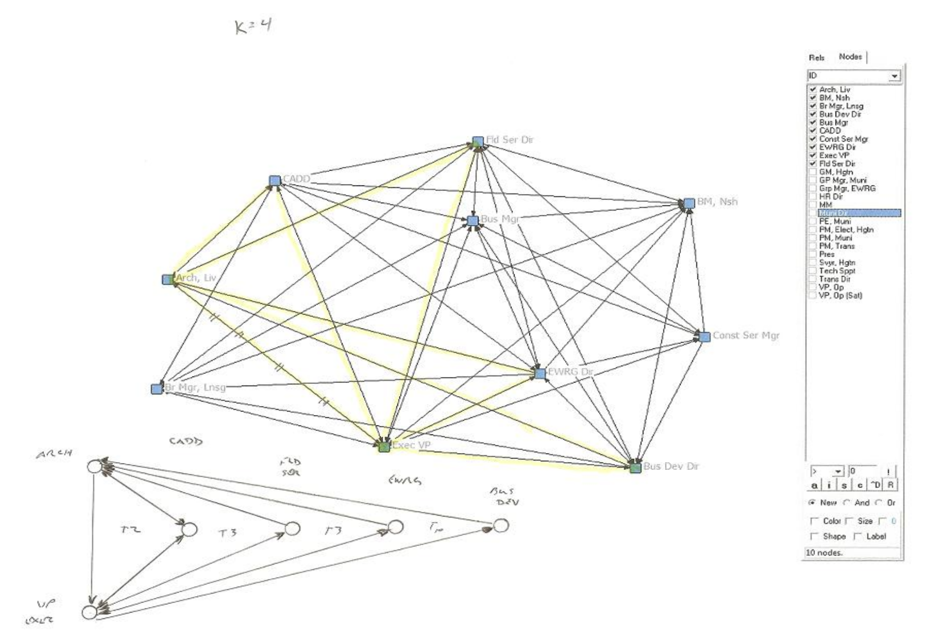
The following figures show the sub networks with the k-triangle complexes highlighted for emphasis and readability.



Appendix D Figure 4: Knowledge Exchange Organizational Issues – OHM Question 4. Relationship between Exec. VP and Arch. Livonia. Sub network with AT-C K-Triangle configuration.



Appendix D Figure 5: Knowledge Exchange Organizational Issues – OHM Question 4. Relationship between Exec. VP and Arch. Livonia. Sub network with AT-CU K-Triangle configuration.



Appendix D Figure 6: Knowledge Exchange Organizational Issues – OHM Question 4. Relationship between Exec. VP and Arch. Livonia. Sub network with 4-Triangle configuration.

Results of the PNet estimation for AT-C, AT-CU, 4-Triangle and K-Triangles All

The OHM knowledge exchange network for organizational issues was divided into sub-networks each containing the configuration of focus. One had an AT-C configuration, one had an AT-CU configuration and one had a 4-plex triangle configuration. This is a summary of the results from PNet for all the AT configurations for each sub-network. Notice only the AT-T configuration is statistically significant for any of the sub-networks. Also note the AT-T configuration has a large and significantly larger positive parameter than the other configurations for k-triangles. AT-D and AT-U parameters tend toward the negative side meaning there are less of them and they are not statistically significant to the formation of the network.

Estimation K-Triangles AT-C

effects	estimates	stderr	t-ratio	
AT-T(2.00)	1.331904	0.57310	0.00202	*
AT-C(2.00)	0.018915	0.27001	-0.00797	
AT-D(2.00)	0.289982	0.50041	-0.02562	
AT-U(2.00)	-0.458383	0.41729	-0.02258	

Estimation K-Triangles AT-CU

effects	estimates	stderr	t-ratio
AT-T(2.00)	2.270859	1.36737	0.07588
AT-C(2.00)	0.501507	0.77969	0.03583
AT-D(2.00)	-0.783431	0.83865	-0.01434
AT-U(2.00)	-0.811085	0.80946	-0.02545

Estimation K-Triangles 4-Triangles

effects	estimates	stderr	t-ratio
AT-T(2.00)	1.107236	1.01426	0.05307
AT-C(2.00)	-0.524259	0.50385	-0.09845
AT-D(2.00)	1.146934	1.03596	0.01650
AT-U(2.00)	0.572258	0.80982	0.00168

Estimation K-Triangles All

effects	estimates	stderr	t-ratio
AT-T(2.00)	1.294256	1.55918	0.03134
AT-C(2.00)	0.413871	0.89060	-0.03206
AT-D(2.00)	0.931424	1.64160	-0.06315
AT-U(2.00)	-1.000078	0.95894	-0.01338

The following PNet results for goodness of fit for the OHM knowledge exchange network for organization issues including all the k-triangle configurations shows us a good fit for the k-plexes, however, the goodness of fit for the Markov parameters is not very good. The OHM networks show a poor goodness of fit for Markov triangles (in fact we could not get a convergence for them).

GOF K-Triangles All

effects	observed	mean	stddev	t-ratio
arc	99	99.000	0.000	
reciprocity	41	36.981	1.525	2.636
2-in-star	376	366.133	2.975	3.317
2-out-star	384	378.652	10.860	0.492
3-in-star	869	799.867	21.090	3.278
3-out-star	919	877.946	58.473	0.702
path2	743	743.109	6.572	-0.017
T1	62	40.355	6.900	3.137
T2	427	318.514	34.860	3.112
T3	491	420.881	23.577	2.974
T4	244	207.389	12.356	2.963
T5	261	215.117	15.848	2.895
T6	261	209.288	18.585	2.783
T7	612	547.391	25.100	2.574
T8	638	566.974	27.729	2.561
T9(030T)	596	561.606	16.648	2.066
T10(030C)	188	186.205	5.190	0.346
AinS(2.00)	150.314	150.213	0.032	3.217
AoutS(2.00)	150.484	150.677	0.990	-0.195
AinS(2.00)	150.314	150.213	0.032	3.217
AoutS(2.00)	150.484	150.677	0.990	-0.195
Ain1out-star(2.00)	196.078	196.544	0.184	-2.530
1inAout-star(2.00)	194.799	194.286	4.570	0.112
AinAout-star(2.00)	47.201	47.111	0.987	0.092
AT-T(2.00)	191.402	191.352	0.845	0.059
AT-C(2.00)	189.650	189.838	4.423	-0.042
AT-D(2.00)	192.490	192.488	0.785	0.003
AT-U(2.00)	188.121	188.272	4.202	-0.036
AT-TD(2.00)	191.946	191.920	0.659	0.040
AT-TU(2.00)	189.762	189.812	2.062	-0.025
AT-DU(2.00)	190.306	190.380	1.890	-0.039
AT-TDU(2.00)	190.671	190.704	1.249	-0.026
A2P-T(2.00)	252.668	253.189	5.043	-0.103
A2P-D(2.00)	127.314	128.449	0.555	-2.042
A2P-U(2.00)	124.803	124.420	5.162	0.074

A2P-TD(2.00)	189.991	190.819	2.376	-0.348
A2P-TU(2.00)	188.735	188.804	5.079	-0.014
A2P-DU(2.00)	126.059	126.434	2.416	-0.156
A2P-TDU(2.00)	168.262	168.686	3.278	-0.129
Global Clustering AKC-T	0.758	0.756	0.018	0.080
Global Clustering AKC-D	0.756	0.749	0.001	6.046
Global Clustering AKC-U	0.754	0.757	0.018	-0.206
Global Clustering AKC-C	0.751	0.750	0.004	0.207

Mahalanobis distance =81.707219 (6676.069648)

95% simulated samples have smaller Mahalanobis distances than the observed network.

PNet ANALYSIS RESULTS FOR OHM NETWORKS

The following PNet results are for the OHM knowledge exchange network for organizational issues, bifurcated to knowledge exchange weekly. Notice none of the parameters are statistically significant for this simulation. This model contains significant negative parameters indicating less of a tendency for triangulation in the graph. These results suggest a tendency for a loose a core periphery structure and a degree distribution with a tendency against particularly high degree nodes.

Estimation effects	Knowledge Exchange		
	estimates	stderr	t-ratio
arc	-2.93273	0.66808	-0.02609
reciprocity	1.05384	0.68416	-0.07296
2-in-star	1.03302	1.5141	-0.00652
3-in-star	-0.45958	0.57209	-0.01384
AinS(2.00)	-0.40514	1.72061	-0.00318
AT-T(2.00)	-0.11544	2.08386	-0.01921
AT-C(2.00)	0.10527	0.35308	-0.08756
AT-D(2.00)	-0.06027	1.93469	-0.00855
AT-U(2.00)	-0.13911	2.63083	-0.00608
A2P-T(2.00)	-0.15792	0.14687	-0.06358

K Stars and K Triangle Relationships

Recent research suggests a relationship between k-star parameters and k-triangle configurations. Positive k-star parameters suggests a degree distribution containing some higher degree nodes, and a resulting "loose" core-periphery structure; whereas a negative parameter suggests a truncated degree distribution with a tendency against particularly high degree nodes. A positive k-triangle parameter estimate suggests a tendency for triangulation in the graph, with the triangle tending to form together into "clumps" (Robins, Snijders, Wang, Handcock, & Pattison).

For the higher order models, it is important to interpret the combination in the one model of alternating k-stars and alternating k-triangle parameters. A pattern of negative k-star and positive k-triangle estimates is not uncommon. Here there are two countervailing tendencies: one towards a triangulated core–periphery structure, and one against a degree-based core–periphery structure. So a range of models with a fixed positive k-triangle parameter, but with k-star parameters ranging from 0 to increasingly negative values, sees a move from centralization to segmentation in the network.

The table below sums up the k-star parameters for the OHM knowledge exchange sub networks. The results show all positive parameter estimates for k-stars and mostly negative parameter estimates for k-star one in/out configurations. The out stars are mostly statistically significant forming the graph. These results with the previous results for k-triangles suggests the OHM knowledge exchange network tends toward a centralized clustered network, where triangulation plays a significant role in the formation of knowledge exchange in the organization.

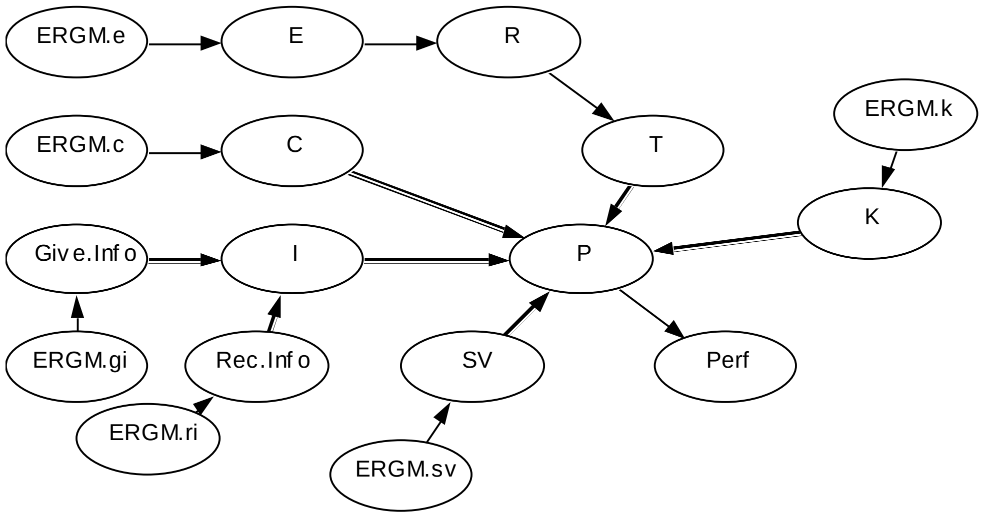
K-Star analysis for the OHM Knowledge Exchange Networks

	AinS Star			AoutS Star			Atin 1 out Star			AinAout Star		
	Estimate	Std Err	t-ratio	Estimate	Std Err	t-ratio	Estimate	Std Err	t-ratio	Estimate	Std Err	t-ratio
4-Triangle	0.745338	1.17035	0.04673	2.718717	0.4146	0.03035 *	-2.125976	0.34496	-0.04121 *	-2.125976	0.34496	-0.04121 *
12 Node	-0.109053	0.66345	-0.0097	0.602249	0.56226	0.02881	-0.478701	0.4856	-0.03451	-0.478701	0.4856	-0.03451
AT-C	0.941276	0.53033	-0.04018	1.778149	0.37257	-0.03431 *	-1.543052	0.33351	0.07515 *	-1.543052	0.33351	0.07515 *
AT-CU	0.032191	1.06751	0.02721	2.988191	0.45651	-0.00934 *	-1.795944	0.31215	-0.01507 *	-1.795944	0.31215	-0.01507 *
K-Triangle	2.436244	2.21244	-0.025	2.912808	1.30706	0.0444 *	-2.745588	1.08467	-0.03973 *	-2.745588	1.08467	-0.03973 *

We have been researching the Social Network Model for engineering and construction for a couple of years now. We developed the model to assess the relationship between variables associated with high performance teams. We conducted a survey with three design engineering firms to develop their social networks and reported on their organizations based on the survey results.

We developed Exponential Random Graph Models (ERGM) from the networks to assess the characteristics of the networks from a stochastic point to evaluate the effects different configurations in the observed networks have on the formation of the network.   Several questions arose as to the significance of the ERGMs, their parameters and how they relate to the Social Network Model. These questions can be answered by application of Markov Chain Monte Carlo techniques to the social network model itself as it relates to the ERGM models of the networks.

Appendix F – Bayesian Statistical Modeling



Open bugs model for Performance based on one parameter for each variable of the social network model. In this model we used density as the parameter.

ERGM.# are ERGM Parameters inputted into the model.

E, R, T, C, K, SV, K are variables from the social network model. They are configured as exponential variables and their parameters are the density parameters from the ERGM results.

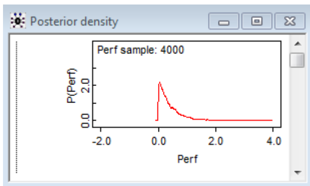
I is the sum of **Give.Info** and **Rec.Info** representing a total of information transferred. This node is logical.

P is a logical node representing a cumulative parameter of the **Perf** variable. The **Perf** variable is an exponential probability distribution representing a company's performance curve.

OHM

Node statistics

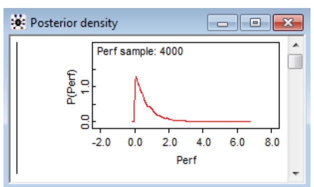
	mean	sd	MC_error	val2.5pc	median	val97.5pc	start	sample
Perf	0.3987	0.4069	0.006401	0.01048	0.2723	1.511	1	4000



Degenkolb

Node statistics

	mean	sd	MC_error	val2.5pc	median	val97.5pc	start	sample
Perf	0.678	0.692	0.01089	0.01782	0.4631	2.57	1	4000



LDG

Node statistics

	mean	sd	MC_error	val2.5pc	median	val97.5pc	start	sample
Perf	0.3971	0.4053	0.006376	0.01044	0.2712	1.505	1	4000

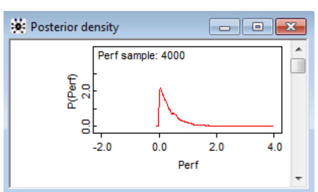
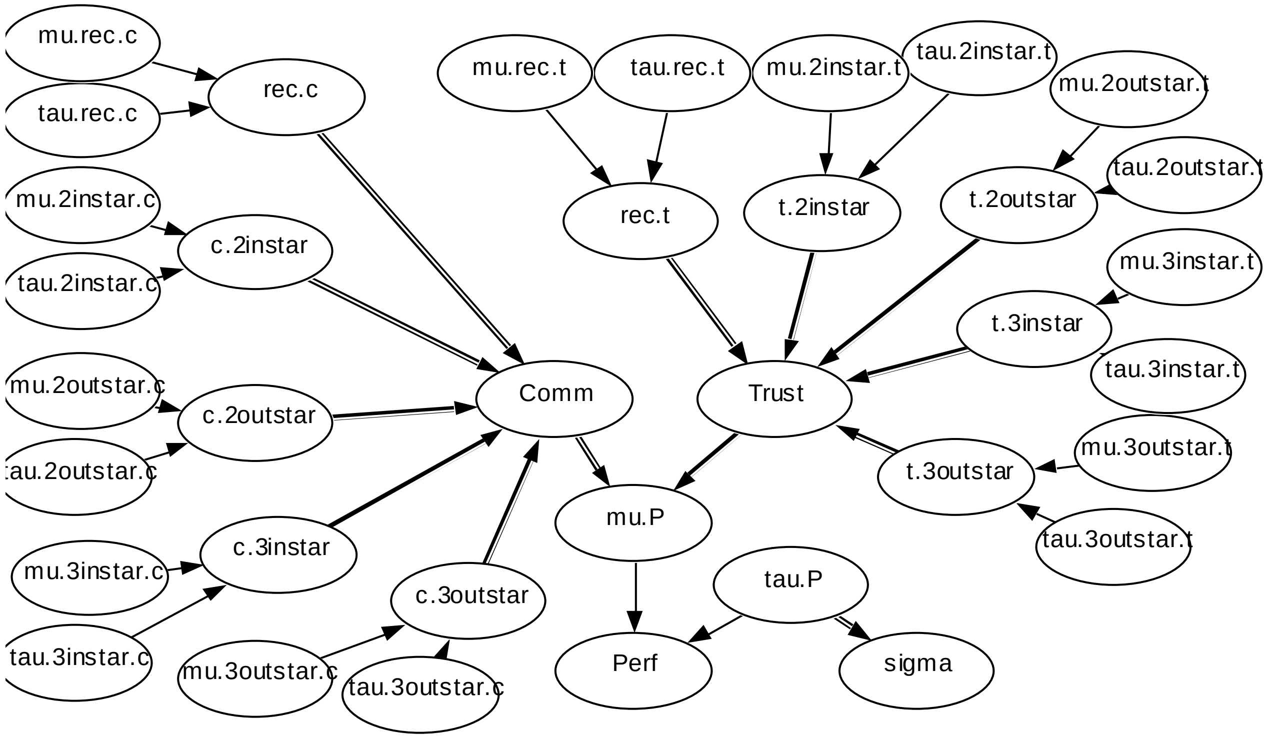


Table of MCMC Simulation Statistics and Probability Distribution



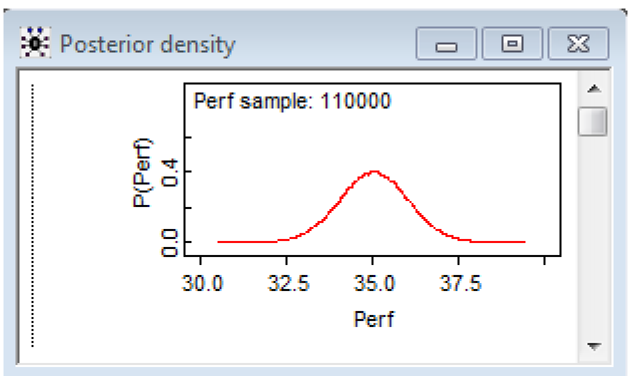
OpenBUGS Model

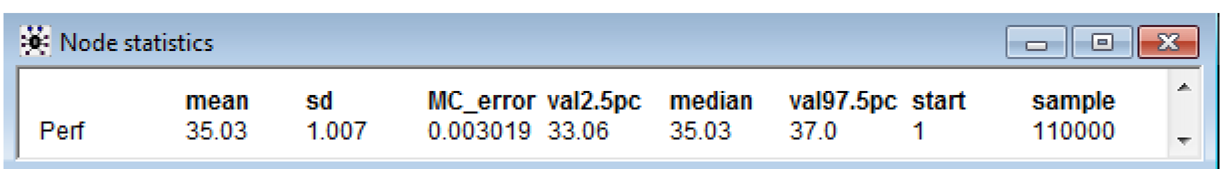
This model represents a normal performance posterior or predictive distribution based on the Communication and Trust ERGM results. The nodes rec.c, c.2instar, c.2outstar, c.3instar and c.3outstar represent configurations distributions from the ERGM results for the Communication network. The node names are similar for the Trust network. Mu and tau represent the means and precision of the corresponding ERGM nodes, respectively.

Below is the data table from the ERGM results followed by the Performance posterior distribution and statistics.

OHM ERGM Results

Configuration	**Communication (Q1)**				**Trust (Q14)**			
Effects	observed	mean	stddev	t-ratio	observed	mean	stddev	t-ratio
arc	486	486	0		375	375	0	
reciprocity	206	206.036	4.629	-0.008	139	139.19	5.305	-0.036
in-2star	4581	4581.206	95.104	-0.002	2741	2740.655	65.89	0.005
out-2star	4646	4648.098	74.491	-0.028	3169	3175.187	94.392	-0.066
in-3star	28171	28169.61	1218.469	0.001	12993	12993.04	666.103	0
out-3star	29523	29548.57	1196.171	-0.021	18216	18302.59	1177.4	-0.074

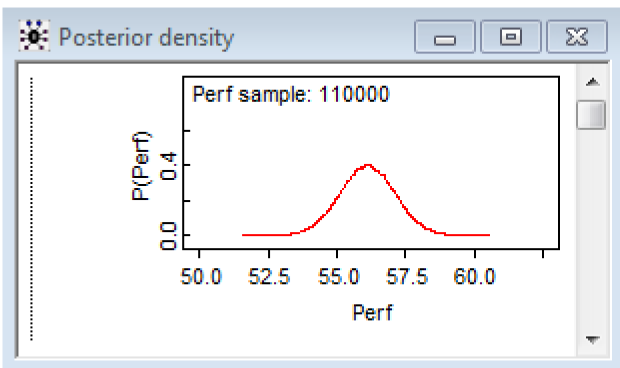



Node statistics

	mean	sd	MC_error	val2.5pc	median	val97.5pc	start	sample
Perf	35.03	1.007	0.003019	33.06	35.03	37.0	1	110000

LDG ERGM Results

Configuration	Communication (Q1)				Trust (Q14)			
Effects	observed	mean	stddev	t-ratio	observed	mean	stddev	t-ratio
Arc	1103	1103	0		949	949	0	
reciprocity	440	439.466	7.817	0.068	358	358.165	7.078	-0.023
in-2star	14855	14838.29	191.728	0.087	10741	10752.92	115.206	-0.103
out-2star	16102	16104.49	274.672	0.009	12515	12503.82	253.977	0.044
in-3star	137249	136898.1	4389.044	0.08	81863	82102.78	2122.305	-0.113
out-3star	166430	166447.4	6423.749	-0.003	120605	120350.7	5813.312	0.044

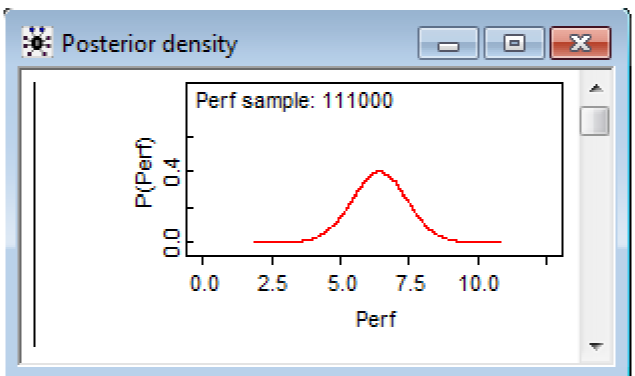


Node statistics

	mean	sd	MC_error	val2.5pc	median	val97.5pc	start	sample
Perf	56.11	1.007	0.003019	54.14	56.11	58.08	1	110000

Degen ERGM Results

Configuration	**Communication (Q1)**				**Trust (Q14)**			
Effects	Observed	mean	stddev	t-ratio	observed	mean	stddev	t-ratio
arc	366	366	0		380	380	0	
reciprocity	137	137.017	4.451	-0.004	102	102.145	6.976	-0.021
in-2star	2239	2240.652	57.392	-0.029	2468	2469.506	91.201	-0.017
out-2star	2623	2625.164	100.01	-0.022	3079	3060.938	167.351	0.108
in-3star	9586	9600.521	796.263	-0.018	11106	11118.29	1095.648	-0.011
out-3star	14090	14106.61	1298.269	-0.013	18825	18604.24	2190.604	0.101



Node statistics

	mean	sd	MC_error	val2.5pc	median	val97.5pc	start	sample
Perf	6.422	1.007	0.003125	4.448	6.423	8.392	1	111000

Appendix G - Initial Report

A
Social network Model Analysis
of
Orchard, Hiltz, McCliment

September 2008

Paul Chinowsky, PhD

And

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OHM
Advancing Communities

Executive Summary

Orchard, Hiltz & McCliment was established in 1962, with 15 employees, as a municipal engineer for the City of Livonia, Michigan – the beginning of a four decade relationship that continues today. New partnerships were formed and the company grew to serve five major municipalities. These clients are still with OHM today. In 1984, OHM took on its first projects for the Michigan Department of Transportation. IN the same year, it delved into the new world of computer-aided drafting, and launched a structural engineering group.

OHM opened a second office in Livonia to house its expanding Construction and GIS departments. They opened a new office in Auburn Hills in 1998 used by field staff to service several local municipal clients. In 2001, OHM acquired Hampton Engineering and an office in the City of Pontiac. And in 2007, they acquired a 15-person engineering and architectural firm in Houghton, Michigan.

The focus of this study is to determine the current state of knowledge sharing in the organization and where the organization can improve to achieve high performance. Twenty six managers were given the opportunity to confidentially complete the social network survey focusing on both organization-based and client-based communication issues. A 100% response rate was achieved, with each of the managers completing the survey in its entirety. The analysis results in this report reflect the complete set of data provided by the managers.

In terms of organization issues, the OHM leadership appears strong in supporting organization communication. They have high densities in their communications networks. However, the communication densities fall off dramatically between infrequent communication and weekly communication. They demonstrate exceptional centrality in their network with very little evidence of clustering. This indicates the organization is performing as a high performance team.

On the dynamics side of the social network model, OHM demonstrates a high level of trust for each other. This is reflected in the strong communication networks. This level of trust and communication indicates collaboration among the managers. If the trust is based on collaboration, then knowledge sharing should be evident.

The weekly knowledge exchange network indicates some power brokers are controlling the flow of information in the organization. The density drops of dramatically, between infrequent knowledge exchange and weekly knowledge exchange.

The client project analysis indicates the power brokers are controlling the information to and from clients. The lower density in the reliance networks for the client related issues reflects this.

Overall, OHM demonstrates a high density and centrality in their networks. Some power brokering is occurring in control of the information to and from clients and there may be a minor issue with some little or no trust. However, their network analysis indicates an organization that is function at a high performance level based on communications and trust among the managers.

Table of Contents

Introduction

The focus of this analysis is to assist the OHM organization in determining how to achieve high performance in both organization and client project collaboration. Using a Social Network Model as a basis for the analysis, this report details how the organization is performing based on a concept of social collaboration and knowledge sharing. The analysis is not intended to evaluate individual performance, but rather is intended to evaluate the organization as a whole. Where individual performance in terms of collaboration is affecting the organization network, the individual will be highlighted. However, the social network analysis should be interpreted from a collective collaboration perspective and not as a critical evaluation of individuals.

Current Status

OHM was established in 1962 as a municipal engineering firm for a major metropolitan area that was experiencing rapid growth. The organization has grown steadily to now include a diverse range of products and several offices throughout the state of Michigan. The organization is recognized as an outstanding member of the community and the principals and managers have been recognized for their experience and well-respected for their expertise.

The company has acquired companies and opened several offices in recent years.

Analysis Motivation

The motivation for this study is to assess the communications and the collaborative effort of the organization. The focus of the study is to determine the current state of knowledge sharing in the organization and where the organization can improve to achieve high performance.

This study is one component in the author’s doctoral thesis, which is to study the trends in the Social Network data from three different design engineering organizations. The results of this study will be assessed against the results of the other organizations to validate the social network model, the results and recommendations.

Study Methodology

The Social Network Model

The current study is based on the Social Network Model of performance developed at the University of Colorado. The focus of the model is to alter an organization's perspective from efficiency of projects to high performance projects. However, as documented in high performance research, the requirement for creating this change is a greater focus on the individuals within the team and their ability to collaborate to create a higher standard of success for the entire team. In the Social Network Model, the underlying concept is that teams need to be managed as social collaborations to achieve results that exceed traditional expectations. If organizations can be viewed from a social collaboration perspective, then an increased emphasis will be placed on developing teams that have shared values and trust among the participants. As demonstrated in the high performance research, teams that have this as a basis will focus on sharing knowledge to produce high performance results. Additionally, these teams will work in a proactive mode that is motivated to excel and encourages the identification and resolution of project or organization issues prior to the issues being discovered as a reaction to negative results.

The overall Social Network Model is illustrated in Figure 1. As illustrated, the model contains two basic components, the dynamics and the mechanics. The latter of these components, the mechanics, can be viewed as the "what" in a network, or the items that are exchanged to execute a project or address organization issues. The mechanics contains both the classic emphasis on information sharing and exchange as well as an emphasis on knowledge exchange. The goal of the model is to achieve knowledge sharing as the mechanics that drives collaboration. The former of these components, the dynamics, can be viewed as the "why" in a network, or the reasons that motivate teams to exchange items listed in the mechanics. The dynamics represents the social collaboration component within the network. In this component, the goal of the model is to enhance knowledge exchange by achieving a greater level of trust and shared values between the network members.

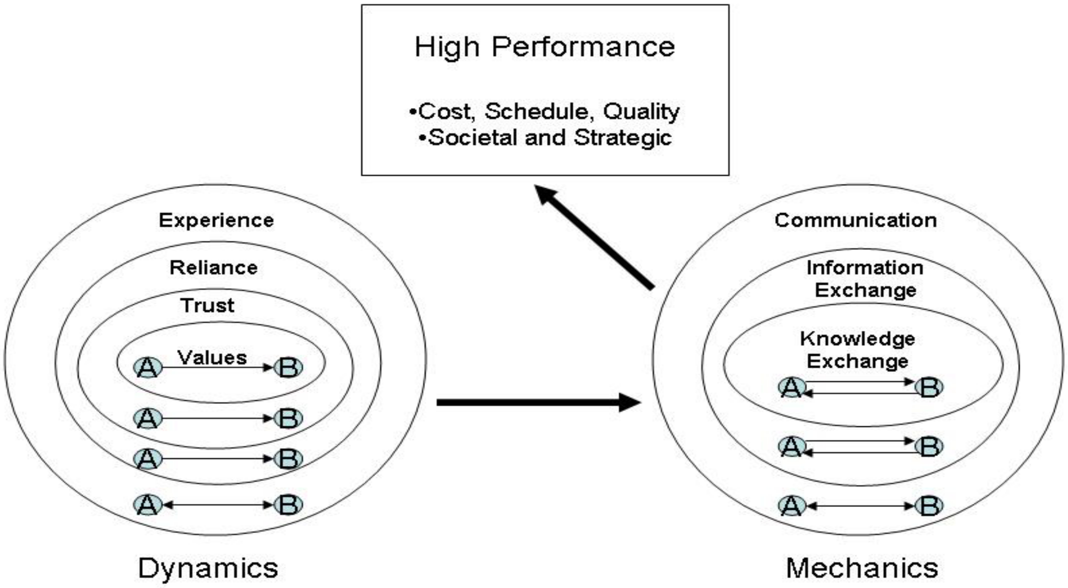

Figure 1. The Social Network Model

The Social Network Survey

The organization study was deployed to the OHM organization through an electronic, web-based format. The survey contains questions that map to the levels in the Social Network Model. The intent of the survey is to obtain data that corresponds to the perspectives of each individual in regards to all areas of the model. The 26 managers provided by the organization were each notified of the survey and were given the opportunity to confidentially complete the survey. A 100% response rate was achieved, with each of the 26 managers completing the survey in its entirety. The analysis results in this report reflect the complete set of data provided by the managers.

The survey results were analyzed using the UCINET Social Network Analysis software. The UCINET software provides the mathematical measurements as well as the graphical representations required for the organization analysis. A separate analysis is completed on each of the variables to acquire the relationships outlined in the Social Network Model. The analysis in this report utilizes four key measurements for evaluating the organization network as follows:

• Network density – A measure to indicate the amount of interaction that exists between the network members. Density reflects the number of actual links that exist between members in comparison to the number of potential links that exist if all members were connected through relationship links. The larger the density number that is calculated, the greater the number of relationships that actually exist in the network.

• Centrality – A key measure that reflects the distribution of relationships through the network. In a highly centralized network, a small percentage of the members will have a high percentage of relationships with other members in the network. In contrast, a network with low centrality will have relatively equal distribution of relationships through the network. An example of a highly centralized network is one where an individual such as the project manager serves as a filter for a high percentage of communications rather than communications being distributed throughout the network.

• Power – The power variable works in conjunction with centrality. Whereas centrality measures the total number of relationships that an individual may have, power reflects the influence of an individual in the network. Individuals who are giving information to others in the network, who are in turn passing along that information to others, has a high degree of influence or power. Individuals, who are mainly on the receiving end of communications may be central in the network, but have little power as they do not influence the actions taken by others.

• Betweenness - This variable measures the amount of information that is routed through an individual to distribute to the team. This rating indicates which individuals are involved in discussions that are occurring within the network.

These measurements will be referred to throughout the study as foundational analysis components used to review the collaboration occurring in the network.

Analysis

The analysis of the OHM findings is presented in this section using the Social Network Model as the base element. These findings reflect the underlying premise of the model that high performance is a direct result of knowledge exchange, which in turn is based on a combination of trust and communication.

Organizational Analysis

Communication

The initial focus of the social network survey determined which managers knew each other through communication of any type on a monthly basis. This analysis found that there is a high level of familiarity in the organization between the managers with a network density of 75%. There is balance among the leadership (shown by the consistent size of the nodes), and significant reciprocity (actors that choose each other in their responses). Figure 2

The first direct focus on organization management occurs with the second survey question that asks which individuals a manager communicates with at least once a month on organization specific topics. Even though the density drops off slightly, this network still shows a high level of centrality and a density of 60%.

A greater focus on the communication issue occurs with the third survey question where the frequency of communications related to organization issues is explored. In this question, the threshold of interest for the study is to find managers that communicate at least once a week on organization issues. The key here is that unless a weekly communication is sustained, other topics will begin to take precedence and the focus on the organization topic will begin to get lost. Using this threshold, the network is divided into responses that are less than once a week and responses that are at least once a week.

The results of the OHM survey reflect a significant drop off in the density from weekly to more frequent communication. The weekly communication network, Figure 3, reflects some brokering beginning to occur among the leadership managers. This is reflected in a drop off of density in the knowledge exchange network.

From this division, the network is analyzed from two perspectives. First, a numeric analysis focusing on the leadership of the organization is performed. This analysis is designed to determine if the necessary leadership is being utilized to guide the teams and lead the organization in essential topics of discussions. The results of this analysis are shown in Figure 4.

The OHM leadership analysis reflects the organization's centralization. The leadership is central to all communications in regarding organization issues. The leadership is also influencing organization issues through the power analysis and is engaged in organization discussions based on the betweenness factor.

A final focus on communication is reflected in the question of who an individual receives, and gives, information from, and to, in order to do their job related to organization issues. This network has a density of 36%. Improvements in the density of the receives and gives information networks increase communications and knowledge exchange for the organization.

Dynamics

The complement to communication in supporting knowledge exchange is the social dynamics that exist in an organization. Specifically, the reliance that exists between individuals, the trust in the network, and the belief that values are shared are key indicators regarding how individuals are motivated to share knowledge. Overall, the OHM organization has a strong Dynamics side within its networks.

Reliance

In the area of reliance, Figure 5 illustrates that OHM's management network has a good density with a rating of 61%.

Trust

A direct outcome of reliance is trust. There are many forms of trust that can exist in an organization from what is referred to as blanket trust which translates to a trust of another individual in any action they take to a focused trust on a specific topic. In the context of the Social Network Model, trust is considered when an individual believes that another individual will take actions that are mutually beneficial and not solely to one's own advantage. This is a key requirement for knowledge exchange since individuals need to feel confident that knowledge that is exchanged will have a mutual benefit. In contrast, if an individual believes that exchanging knowledge can lead to a reduction in status or power, then that individual will be hesitant to release knowledge into the network.

In the case of the OHM organization, trust is evident throughout the network. With a density rating of 68%, it is apparent that trust is a very strong component of the OHM network. The only apparent exceptions to this are a low trust numbers of the Business Development Director. It is also clear that although there remains a focus on trust with the central corporate positions, trust also exists between individuals. This is a strong foundational element that is required to build knowledge exchange in the organization.

Values

The final level of interest in Dynamics is the level of shared values in the organization. In the case of the OHM network, these values are the values established for the organization. Following the pattern established with reliance and trust, there is a strong sense of shared values in the organization. The 46% density in the network indicates a good level of shared values.

In summary, the Dynamics side of the OHM organization appears to reflect a feeling of trust between the managers. However, based on the low communication numbers evident in the Mechanics side of the analysis, this trust could be based more on team building than in actual work processes. If the trust is based in collaboration, then knowledge sharing should be evident. If the trust is based more on social interaction, then a lack of knowledge sharing may be evident. This question is explored in the following section.

Knowledge Exchange

The basis for achieving high performance in an organization is the free exchange of knowledge. The previous sections have detailed how OHM exhibits a split foundation for achieving knowledge exchange. On the negative side, the organization is underperforming in terms of communication patterns. However, on the positive side, the organization displays a significant level of trust and shared values.

The result of this split foundation is illustrated in the knowledge exchange network in Figure 6. Once again, the threshold of a minimum of a weekly exchange of knowledge is used to divide the survey responses. As illustrated in the network, the organization is failing to achieve knowledge exchange using this threshold. The network has a minimal density at 10% and shows some power brokering. It is clear from the network that the company leadership forms the hubs of the knowledge exchange clusters.

Client Focus Analysis

The second major focus of this analysis was the network communication related to client projects. In this analysis, the same approach was taken as for the organization analysis with the same questions being asked in relation to client project issues. Similar to the organization analysis, the following sections highlight the communication, the trust, and the knowledge exchange results.

Communication

Similar to the initial focus in the organization analysis, the initial focus in the client project survey was a focus on communication frequency. The first question for client project communication was to determine which managers communicated at least once a month on client project issues. As a baseline measurement, this question provides an indication of which managers have a working relationship on client projects. The focus of the result is to determine if there is centralization or clustering at the broadest communication level.

Figure 7 illustrates the result of this question for the OHM organization. With a density of 37%, the monthly communication network indicates two potentially significant issues. First, the density is lower for client communication than the network for organizational issues. This indicates that the organization managers are not using collaboration as a primary approach to client solutions. Second, the density of client communications drops off with increased frequency demonstrates a bias towards internal communications.

The survey next focused on weekly client-focused communications. Once again, the weekly communication indicator serves as a threshold to determine which managers are actively collaborating on client issues. Using the numeric leadership indicators as a first analysis, the client project network is analyzed for the role that the leadership team is playing in directing collaboration. Based on the measurements illustrated in Figure 8, it is apparent that the majority of the leadership team is performing as expected, leading the organization in centrality, power, and betweenness.

In contrast to the positive ratings, the density rating for the weekly communications is very low at 12%. As with the organization communications, this low density is indicating a lack of collaboration in the network concerning client project issues. When combined with the high leadership values, the low density is indicating a centralized communication that includes a minimum of managers.

Dynamics

The dynamics of an organization are only measured once. The concepts of reliance, trust, and values change very little between specific topics, so the questions are not repeated. This is in contrast to the mechanics where different focal areas can have very different results in terms of communication. Given this basis, the previously addressed findings will remain as the focus on dynamics for the OHM organization.

In summary, the dynamics illustrate that the managers within the organization indicate a strong amount of reliance and trust within the network. In addition, there is a belief that the majority of individuals share the same corporate values. However, as said previously, this trust could be a social trust and not a result of collaboration. This was seen in the organization analysis where less knowledge exchange was occurring despite the strong levels of trust and reliance.

Knowledge Exchange

The knowledge exchange for client project issues is illustrated in Figure 9. Once again, the network uses a requirement of weekly exchanges of knowledge as the threshold for dividing the responses. The network clearly illustrates that using this threshold, there is less knowledge exchange occurring in the organization.

In summary, the OHM network is exhibiting the same difficulties in client-based knowledge exchange as existed in the organization-based knowledge exchange. The network is not exhibiting collaboration despite the indication that trust exists between the individuals. As with the organization knowledge, the trust appears to be based in social communication and is not a reflection of trust built on collaborative processes.

Recommendations

The focus of the following recommendations is on the results obtained from the network analysis. The intent of the recommendations is to provide possible enhancements to the current state of the OHM network.

Organization Issues

• Frequency of Communication Meetings – One method to increase communications and knowledge exchange is to apply an external force. Specifically, have a weekly meeting where organizational issues are discussed. Although people do not appreciate having more meetings, the lack of interaction displayed in the network, as frequency of communications increases, indicates a need for an external force.

• Face-to-Face Opportunities – A central force in starting collaboration is to have individuals participate in face-to-face meetings. Given the relatively close geographic distance between the offices, it is reasonable to have the leadership and other principal managers meet on a quarterly basis to build greater collaboration.

• Individual Motivation – It is clear from the organization networks that not all individuals in the organization are embracing collaboration. It is time to meet with the individuals who are consistently on the outer edge of the network and determine what their motivations are in terms of the company.

• Trust Redefinition – The significant levels of trust that are evident in the OHM network indicate a strong social trust between organization employees. However, this trust must be redefined to focus on collaboration and work processes. The basis for trust is in place; however this trust needs to be reinforced through collaboration on projects and then tested again to see if the high level remains in effect.

Client Project Issues

• Recognition – Although it appears that OHM does a good job in recognizing efforts in the organization on projects, a greater amount of recognition could be given to collaborative efforts. If collaboration and knowledge exchange is the goal, then it needs to be recognized when it occurs.

• Infrastructure – Knowledge exchange and trust require an infrastructure to be in place that facilitates knowledge exchange. Although knowledge exchange is not an information technology problem, it does require an IT infrastructure to facilitate exchange. The IT infrastructure of OHM should be examined to determine if it is providing the support that is required.

• Trust Redefinition – Similar to the organization issue recommendation, trust must be refocused from a social basis to work process basis. Overall, the OHM organization has a strong history and foundation to build on. This will require a strong example by the leadership team. A concerted effort to apply external pressures that enable collaboration is a requirement. Additionally, altering processes to obtain greater interaction will be required. The strong social trust that is evident in the organization is a good first step to build on. However, to achieve high performance, a rapid move toward building collaborative trust is required. When this trust is established and individuals begin to identify with the organization, OHM will be on the path toward achieving the high performance it desires to achieve.