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Modeling and Analysis of Social Networks

Robert S. Renfro II

MODELING AND ANALYSIS

OF SOCIAL NETWORKS

DISSERTATION

Robert S. Renfro, II, Captain, USAF

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Abstract
This dissertation develops new methods for the modeling and analysis of social networks. Social networks describe the complex relationships of individuals and groups in multiple overlapping contexts. Influence in a social network impacts behavior and decision making in every setting in which individuals participate. This study defines a methodology for modeling and analyzing this complex behavior using a Flow-Model representation. Multiple objectives in an influencing effort targeted at a social network are modeled using Goal Programming. Value Focused Thinking is applied to model influence and predict decisions based on the reaction of the psychological state of individuals to environmental stimuli. This research advances the science of Operations Research and its application to broad classes of problems dealing with social networks. Application areas span academic, private sector, and government analysis. Sample cases are used in this research from the private sector and government. Specifically, influencing foreign government decision making is demonstrated for the case of Iran. Counter-terrosim applications are demonstrated for a sample case using Usama Bin Ladin. The contributions of this research serve private and public sector users.

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Robert S. Renfro, II, B.S., M.S., PGIP

Captain, USAF

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Robert S. Renfro, II, B.S., M.S., PGIP
Captain, USAF

Approved:

Date

Richard F. Deckro (Chairman)

William E. Wiesel (Dean's Representative)

James W. Chrissis (Member)

Ernest P. Smith (Member)

Stephen P. Chambal (Member)

Accepted:

Robert A. Calico, Jr.
Dean, Graduate School of Engineering and Management

Date

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Rob Renfro

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Abstract

This dissertation develops new methods for the modeling and analysis of social networks. Social networks depict the complex relationships of individuals and groups in multiple overlapping contexts. Influence in a social network impacts behavior and decision making in every setting in which individuals participate. This study defines a methodology for modeling and analyzing this complex behavior using a Flow Model representation. Multiple objectives in an influencing effort targeted at a social network are modeled using Goal Programming. Value Focused Thinking is applied to model influence and predict decisions based on the reaction of the psychological state of individuals to environmental stimuli.

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MODELING AND ANALYSIS OF SOCIAL NETWORKS

Chapter 1. Introduction

The ability to understand and predict human behavior and decision making is an age old problem. Fundamentally, every aspect of our existence, access to resources, and ability to exceed or fail in our endeavors are predicated on interaction with those who, directly or indirectly, make up our environment. To a greater or lesser degree all people have the ability to influence aspects of their environment and others within that environment.

This research synergistically combines existing techniques from the Social Sciences developed to support understanding, predicting, and influencing human behavior with the robust analytical modeling capabilities found in Operations Research methods. Operations Research methods extend and refine the analytical capabilities of Social Science theories and methods with results that are measurable, quantifiable, and organized in a manner that allows specific courses of action to be evaluated and ranked.

This study is focused on the complex interaction of people and organizations (*i.e.*, groupings of people) within specific contexts of interaction. These contexts are both formal (workplace hierarchies, for example) and informal (recreational and religious, for example). For a given person or group of people, membership in these contexts naturally overlaps. While membership in various contexts intersects in daily life, relative power, influence, and cultural norms may vary tremendously across these contexts.

Most people exist in, and make decisions based on, the influence of many social networks, many of which coincide (*i.e.*, members share more than one social context). Therefore, decisions made in one context (work, for example) are potentially not only influenced by those in the social network for the formal workplace, but the greater social network(s) spanning multiple contexts in the informal structure. The key point is that to analyze behavior in a social network requires understanding of both the formal and informal social networks and sub-elements for the scenario under consideration.

The people and groups operating in this multi-context environment define a *social network*. A social network is an abstract representation in which individuals are represented as *nodes* and their interrelations are represented by *edges* (Krackhardt, 1996:166). These nodes and edges are arranged in such a way as to form a network, or graph. Measures of the strength of connectivity between individuals are termed *social closeness* where a greater social closeness indicates a stronger influence in the relationship between the individuals. Social closeness is represented as a weight on the edges in a social network graph.

Correctly interpreting a social network assists in predicting behavior in terms of decision making within the social network. This ability to understand and predict behavior within a social network allows the analyst to better evaluate specific courses of action that will influence a social network or its subelements. For example, a decision-maker may seek to gain more power in the social network or a specific context(s), influence the selection of a particular alternative by other decision makers in the network, create a more (or less) cooperative environment, weaken (or strengthen) individual's positions within a social environment of interest, or exclude (or include) people or ideas in the environment of the social network.

Specific applications of this research are widely found in the private sector and public sector. The Social Sciences have considered these problems for some time. Private sector applications include: advertising, market research, organizational theory, organizational development, behavioral science, and human resource management. In the government and military sector additional applications include predicting or influencing the behavior of terrorists, computer hackers, or the leadership of adversarial powers. Social Science applications of social network analysis are those found in Psychology, Sociology, Anthropology, Political Science, and Communications, including the study of both individual and group behavior. Relevant contexts include peer group interaction and affiliation, political cliques, clan or tribal affiliation, friendship relationships, family associations, and many others.

While the Social Sciences have long recognized the need for understanding and modeling of social networks, Operations Research and other analytical sciences have shown limited interest in this problem. From an Operations Research perspective, there are many difficulties in such *soft* modeling. However, existing optimization techniques may be expanded to consider social networks. Operations Research methods have long been applied to other network structures such as roadways, telecommunications, and problem classes easily mapped to a network structure (Evans, 1992:1). The data available for analysis is often sparse, subjective, and uncertain. Available data that is quantifiable is often ordinal or nominal in nature. Such data significantly limits the proper use of appropriate existing analysis methods. In addition, the data is often proprietary, sensitive, or classified.

Theoretical gaps within existing Social Sciences and Operations Research theory have also impeded previous efforts to provide a robust implementation of a social network model. An interdisciplinary model of a cross-cultural, single-criteria, single-context social network is developed in this study, and is then extended to include multi-criteria, multi-context scenarios. In this study, criteria are social closeness measures, and contexts are the various settings, both formal and informal, in which individuals may be connected to each other.

For the purposes of this research, analysis of social networks describes the interactions between various formal and informal groups, as well as the individuals in those groups. It is important, at a minimum, to be cognizant of the nature of a social network for a given situation. Understanding a social network includes determining connections in the formal and informal structures. Once the structure is modeled, analysis is conducted to determine the nature of the relationships and investigate their estimated cultural effects. Ultimately, this work serves as a basis for predictive modeling. With such a predictive model, it is possible to investigate how to influence the social network through *pressure points* (*i.e.*, susceptible points of influence).

The ability to understand and predict behavior is valuable in itself; however, evaluating courses of action that influence future behavior is an even more critical concern, whether applied to government decisions, military actions, or the private sector. Such models could be used to determine courses actions that prevent wars, deter terrorists, influence legislation, promote worker harmony, increase market share, or analyze many other settings where human decisions and behavior drive the course of events.

The concept of social networks has been studied in different contexts from a Social Science perspective. Although these studies have had limited focus on developing analytical methods and techniques, the legacy of the Social Science effort is essential in developing Operations Research based analytical methods. Specific Social Science disciplines of interest include: Psychology, Behavioral Science, Sociology, Anthropology, Organizational Behavior, and Organizational Theory. Areas of Cognitive Science such as Semeiotics and Reflexive Control are also discussed. The nexus of these disinclines and associated theories and methods forms the core of any cross-cultural analytical model of social networks.

It is a tenant of this study that existing optimization techniques may be extended to consider social networks. In this dissertation, social network modeling and analysis is first mapped to a flow problem. Goal Programming is then applied for multi-objective analysis. Decision Analysis adds value in this research by providing a method to explicitly modeling decision making behavior within the social network. Efficient flow network algorithms and graph theoretical aggregation techniques increase the tractability of large scale problems previously thought impractical using existing Social Science analysis methods.

The focus of this research is to act in concert with the Social Sciences to consider how to expand social network modeling and analysis techniques by applying optimization techniques to Social Science based measures of human interaction. It is not the intent of this effort to redefine existing Social Science based measures to form new

Social Science theory. Rather, a goal of this research is to make existing single dimensional graph based social network analysis more robust by considering multiple dimensions of human interaction in a single graph and appropriately contracting nodes and edges in social network graphs to increase tractability using existing theory as a foundation. The study of these problems is the core of the theoretical contribution of this research.

Before considering a methodology applicable to solving these problems, it is first necessary to consider the foundation of Social Science theory on social network analysis. A review of traditional Operations Research techniques that are relevant to the research will then be considered. From this foundation, violations of model assumptions are examined. Mitigating methods are developed as expansions of existing Operations Research theory.

This dissertation includes a review of Social Science and Operations Research literature related to social networks. Chapter 2 describes in detail many models, concepts, techniques, and methods which play a critical role in defining a starting point for this research and identifies theoretical gaps to the development of a profile-based, multi-criteria, multi-context, cross-cultural social network model. The methodology to be undertaken in this research is described in Chapter 3.

Chapter 3 includes discussion of the proposed methods to overcome specific theoretical gaps and the experimental design to be applied and a description of the theoretical and practical contributions of this research. The methodology described in Chapter 3 is explored in Chapters 4, 5, and 6. Chapter 4 discusses, proves, and demonstrates the flow model representation and the use of Goal Programming for social network analysis. Chapter 5 details a mathematically consistent aggregation method applicable to social networks. Chapter 6 extends this research to include Decision Analysis methods.

This research provides a complete methodology for the analysis of a multi-criteria, multi-context, cross-cultural social network. There remains a number of areas for continued research and refinement. Overall conclusions of this effort and recommended areas for future research are the subject of Chapter 7.

Chapter 2. Literature Review

This chapter reviews the literature on both the existing Social Science and Operations Research theories and methods applicable to modeling and analysis of social networks. A fundamental tenant of this effort is that with detailed knowledge of interrelations and influences (or motivators), one can begin to postulate reactions to specific environmental and situational stimuli. This leads directly to a need to understand individual personality and behavior from a Psychology and Behavioral Science perspective. From an understanding of individual behavior, attention is given to social behavior of networks of individuals. Following an examination of social behavior from a Social Science perspective, Operations Research methods relevant to modeling Social Science theories must be understood in detail. The first step then is to investigate individual personality in a formal context.

Personality Assessment

One way to consider personality is as:

> … an abstraction of hypothetical construction from or about behavior, whereas behavior itself consists of observable events. Statements that deal with personality describe inferred, hypothesized, mediating internal states, structure, and organization of individuals (Mischel, 1968:4).

This hints at elements of personality that are critical in the foundation of the analytical model: personality is linked to behavior, personality is specific to individuals, and personality must be assessed (by appropriate experts and means).

There are many existing theories and models proffered for assessing personality, some for general purpose uses and some with very specific applications (Mischel, 1968:1-2). What is required for this study is an accepted theory that can be mapped to an analytical model. Mischel suggests that approaches to personality assessment can be organized into two main categories: Trait (Psychometric) Theory and State (Psychodynamic) Theory (Mischel, 1968:4).

Trait Theory (Psychometric). "At the simplest level a trait refers to the differences between the directly observable behavior or characteristics of two or more individuals on a defined dimension" (Mischel, 1968:5). A useful property in assessing traits is that assessments are based on observing behavior of an individual and comparing that observed behavior to the behavior of another individual(s) to categorize an aspect of both individuals' personalities. Trait Theory "maintains [that] behavior reflects an interaction between a person's traits and various situational factors" (Curphy, 1993:147). Further, it should be noted that traits (and their measures) are stable and do not change based on the environment (Mischel, 1968:5). It is these measurable traits that determine behavior given specific environmental stimuli (Curphy, 1993:148).

Since individual traits are stable, traits may be measured by observing behavior and, once assessed, can be used to reliably predict future behavior. Reliably predicting future behavior implies that a person may or may not take the exact same action given the same environment, but would feel the same about the environment each time, as a result of a stable psychological state. This stability feature is what suggests that an analytical model can be constructed to predict changes in psychological state given changing environmental stimuli. A remaining open question, however, is whether there is an analytical solution to the question of reliably predicting overt, specific behaviors resulting from this changed psychological state (Mischel, 1968:41).

Another feature of trait theory that makes it even more attractive to use in formulating an analytical model is that past research has concluded that "cumulative model trait indicators are related additively to the inferred underlying disposition" (Mischel, 1968:6). This feature suggests that a linear additive-weighted analytical model based on Trait Theory may be formulated.

The Psychological and Social Science theories that form the foundation of an analytical model of individual and social behavior come from many sources. In this research these theories are organized into three categories (or *pillars*):

- Traits common to all people
- Traits unique to a culture
- Traits specific to an individual

State Theory (Psychodynamic). State (or Psychodynamic) Theory was also reviewed. This review suggests that a model based on State Theory is likely non-linear. One of the key reasons is that "psychodynamic theory posits highly indirect, nonadditive relations between behavior and hypothesized underlying states" (Mischel, 1968:6). In addition, state theory asserts that unstructured, ambiguous, or projective situations are necessary for the assessment process (not just observing behavioral responses to environmental stimuli) (Mischel, 1968:7). State theory claims that:

> Major determinants of human behavior are not only unconscious but also irrational, and that individuals are driven by persistent, illogical demands … chiefly sexual and aggressive … from within (Mischel, 1968:7).

Modern psychologists practice both Trait and State Theory of Psychology. An important criterion for the underlying theory used in this research is an ability to map the theory to an analytical model. Trait Theory seems naturally more amenable in this sense. State Theory, while not ruled out for inclusion in this type of research, will, however, require a much greater degree of domain expert input in any analysis effort.

Criminal (Antisocial) Personality. One of the main objectives of this study is to incorporate into any model an ability to assess both rational and *criminal* personalities. Adopting Dr. Stanton Samenow's definition, criminal or antisocial personality has little to do with a given set of laws or culture, but rather with how a person is influenced by external stimuli (Samenow, 1998:90). As Samenow states in *Straight Talk About Criminals*, "There are people who would be criminals, regardless of when or where they exist on this planet" (Samenow, 1998:18). He adds, "unprincipled, predatory human beings [criminals] have existed throughout the ages in a variety of cultures and societies" (Samenow, 1998:89).

Criminal personalities are important to this study since traditional rational actor models track poorly when applied to such individuals. For example, in considering a geopolitical application, it is clear that there are certain national leaders who do not fit a *Western* view of a rational actor. It is hypothesized that such leaders might have included Hitler, Stalin, Iddi Amin, and Genghis Khan as historic examples and Saddam Hussein, Slobedon Milosavic, and Usama Bin Ladin from present day.

Some traits that are specific to a criminal personality are:

- Moral relativism (Samenow, 1998:44)
- Choosing to annihilate ones enemy as a first option (Samenow, 1998:90)

- Little or no fear of consequences (Samenow, 1998:162)
- Internally motivated (Samenow, 1998:190)
- Shallow time horizon (Samenow, 1998:193)
- Engaging in self-grandeur and self-righteousness (Samenow, 1998:201)

Criminality is a matter of degree just like any other trait theoretical assessment of personality. Thus, criminality must consider the underlying stable tendencies of an individual personality toward criminality and environmental factors. This is consistent with the assertion that certain environments offer greater opportunities for criminals to engage in victimizing behavior (Samenow, 1998:90-96). One use of a criminality measure is to determine appropriate engagement strategies (for example, relying on a rational reaction from an individual with a criminal personality would not be a wise business, diplomatic, or military strategy).

Cross-Cultural Considerations. As described in the previous section, Dr. Samenow has high confidence that his understanding of a criminal personality holds cross-culturally; however, for use in this research, high confidence that the greater body of Trait Theory holds cross-culturally is required. In this vein, Dr. Walter Mischel in his text *Personality and Assessment* gives a lengthy discussion of this exact question, citing a number of studies (Mischel, 1968:47-72). The essence of Mischel's discussion is that the constructs of a trait model hold cross-culturally; however, the assessment across cultures varies. In other words, people with a common culture are better assessors of other members of their own culture (Dasen, 2000:430). According to Mischel, "members of the same culture often learn similar constructs or interpretations about the meaning of particular behaviors and events" (Mischel, 1968:65).

Mischel notes that, "trait theories that have guided most psychometric personality research are not dissimilar from the common trait concepts [colloquially] found in the Western cultures in which the theories arose" (Mischel, 1968:65). What Mischel suggests is that when assessed by a person with the same cultural understanding as the subject, modern trait theory holds up consistently; however, it may be forcing people to categorize personality in terms of a Western framework.

Dr. Jeffery White takes this idea further in his white paper "A Different Kind of Threat: Some Thoughts on Irregular Warfare." Dr. White develops the concept of "microclimates," saying:

> These [operational environments] have to be seen in a detailed and nuanced context. … Arab history is one thing, the history of the Christian-Druze conflict in Lebanon is another, and the role of specific families and family members yet another (White, 1998:2).

He goes on to say, "[c]ultural geography also needs to be understood in the micro sense" (White, 1998:3). White points out that when it comes to politics, intelligence, warfare, and so forth, an analyst often may not have the luxury of having individuals from other cultures available to do the analysis or assessments, particularly in conflict situations. An educated cadre of personnel who are both subject matter experts and cultural experts in one or more cultures is an essential requirement for detailed analysis and insight.

In the context of this research, these domain experts would prove valuable in validation of models developed and case study analysis. When available, the inclusion of such experts should be highly sought for any analysis effort. Dr. Mischel's comments on trait model frameworks themselves are a more involved problem requiring further research.

Traits Common to All People. A theoretical foundation of the values common to all people may be based on Maslow's *Hierarchy of Needs* (Maslow, 1954:80-92) as extended by Alderfer's *Existence, Relatedness, and Growth (ERG) Theory* (Alderfer, 1972:25). Maslow's Hierarchy of Needs asserts that human motivations are in response to satisfying needs in the following order: Physiological, Security, Belongingness, Self-Esteem, and Self-Actualization (Maslow, 1954:80-92). Formal definitions of these terms may be found in the Glossary (Appendix A); however, as Mischel points out, the colloquial understanding of these terms is sufficiently close to their formal definition for most uses (Mischel, 1968:65). Relying solely on Maslow's theory would suggest that these needs form successive tiers of a hierarchy. However, Alderfer's ERG Theory suggests that this may not necessarily be the case.

Alderfer groups Maslow's *Physiological* and *Security* needs into a category of needs called *Existence* (Alderfer, 1972:25). He groups *Belongingness* and *Self-Esteem* into the *Relatedness* category and *Self-Actualization* in to the *Growth* category (Alderfer, 1972:25). Alderfer originally split aspects of esteem into *Relatedness* ("interpersonal" esteem) and *Growth* ("self-confirmed" esteem) (Alderfer, 1972:25); however, later work included esteem entirely under *Relatedness* (Curphy, 1993:263). This later research described the broad concept of esteem in terms of *Self-Esteem* using the definition that *Self-Esteem* "refers to the overall positiveness or negativeness of a person's feelings about … experiences and roles [self-concept]." (Curphy, 1993:175). This definition includes what Alderfer called "interpersonal esteem" and "self-confirmed esteem" and is consistent with Maslow's original definition (Maslow, 1954:92).

ERG theory also adds two other important concepts in determining the structure of values common to all people. First, ERG Theory maintains that people often satisfy more than one of these needs at the same time (Curphy, 1993:263). This means that needs are not strictly hierarchical, as Maslow had originally postulated. Alderfer goes further in developing a similar concept called Frustration Regression (Alderfer, 1972:16-17). This concept holds that frustration (or inability) with satisfying a higher-level need can lead to efforts to satisfy a lower-level need (Alderfer, 1972:17). Although not necessarily a unique representation, Maslow and Alderfer's theories form a comprehensive representation of the needs common to all people.

Independence of measures is one of the desirable characteristics of any analytical model to be built (Kirkwood, 1997:17). In reviewing the literature, it was found that *Self-Actualization* is best determined in relation to *Physiological*, *Security*, *Belongingness*, and *Self-Esteem* needs creating a dependency (Maslow, 1954:92). As Maslow indicates, "the clear emergence of these needs [self-actualization] usually rests upon prior satisfaction of the physiological, safety [security], love [belongingness], and esteem [self-esteem] needs" (Maslow, 1954:92).

Another important theory regarding traits common to all people is Herzberg's *Two-Factor Theory*. Two-Factor Theory divides traits into two categories: *motivators* and *hygiene factors* (Herzberg, 1959:113). Motivators are those traits that lead to increased satisfaction. Hygiene Factors have limited impact on overall satisfaction, but lead to dissatisfaction when not achieved to some level.

There are aspects of human psychology and behavior that are influenced more specifically by factors other than those common to all people, as described by Maslow and Alderfer, in most trait theory models. These influences make up *Cultural Effects* and *Individual Traits*. Cultural Effects are discussed in the next section, followed by a discussion of Individual Traits.

Cultural Effects. Any understanding of culture carries with it the idea that across a common grouping (or culture) there are certain shared traits (Soukhanov, 1984:335; Dasen, 2000:429). By inference this indicates that there are additive traits, at least when considered as a whole, that have not been addressed in the pillar *Common to All People*. It can also be inferred that traits not common to all people or to a particular culture, must be those unique to the individual. A necessary question to ask is: "To what culture does a person belong?" The answer to this question is not simple. The most definitive answer would be to consider the culture that is most relevant to the psychology of the individual under consideration. This problem is moderated by the fact that some traits may be common across all the cultures to which the individual belongs.

The primary underlying theory used in examining this pillar is *Value Programming* (Curphy, 1993:169). Value Programming is founded on the idea that in addition to genetic factors, "forces outside the individual shape and mold personal values" (Curphy, 1993:169). This theory speaks broadly of religion, technology, media, education, parents, peers, and other societal factors (Curphy, 1993:163).

The traits common to all people and those traits specific to a given culture have been proposed, but there are still a plethora of relevant psychological factors that must be considered. These factors are those that are specific to an individual. *Individual Traits* are considered in the next section.

Individual Traits. There are many trait-based assessment tools available for the identification of individual personality. The Myers-Briggs Type Indicator (MBTI) is a well-known example of such a comprehensive assessment tool (Myers, 1998:1). The MBTI and other recognized psychological measures are discussed in detail below. The MBTI serves only as an example and is not the only tool for use in this type of study to measure individual traits. The MBTI includes measures of tendency toward extroversion versus introversion, sensing versus intuition, thinking versus feeling, and judging versus perceiving. The MBTI classifies people into 16 different types. This level of differentiation between individuals is not sufficient for all cases.

Particular areas not specifically identified in the MBTI that are necessary to complete a formulation of a psychological model are *Achievement Orientation*, *Stress Tolerance*, and *Risk Needs* (Curphy, 1993:264). These values and their measures are very specific to individuals and do not rely directly on culture or the human condition.

Achievement Orientation is the "tendency to exert effort toward task accomplishment" (Curphy, 1993:264). Alderfer adds that:

> The achievement-oriented personality is generally attracted to activities which require the successful exercise of skill … Whatever the level of challenge to achieve, he will strive more persistently than others when confronted with an opportunity to quit and undertake some different kind of activity instead (Alderfer, 1972:368).

To measure *Achievement Orientation*, it may be further broken down into *Power Needs* and *Motivation*. Power Needs describes the nature of achievement orientation, either personalized or socialized. Personalized power is "selfish, impulsive, uninhibited, and lacking self-control. These individuals exercise power for their own self-centered needs, not for the good of the group or the organization" (Curphy, 1993:122). Socialized power "implies a more emotionally mature expression of the motive. Socialized power is exercised in the service of higher goals to others or organizations and often involves self-sacrifice toward those ends" (Curphy, 1993:122). An individual whose *Achievement Orientation* leans towards high personalized *Power Needs* is more susceptible to psychological influence than someone who leans toward socialized *Power Needs* (Curphy, 1993:122).

Motivation "is anything that provides direction, intensity, and persistence to behavior … a sort of shorthand to describe choosing an activity or task to engage in, establishing the level of effort to put forth on it, and determining the degree of persistence in it over time" (Curphy, 1993:257). Motivation may be internal or external (Maslow, 1954:176; Atkinson, 166:118-119). Internal motivation is "behavior seemingly motivated for its own sake, for the personal satisfaction and increased feelings of competence or control one gets from it" (Curphy, 1993:264). External motivation is the exact opposite; behavior motivated only due to factors outside the individual (Curphy, 1993:274).

Stress also influences individual behavior. *Stress Tolerance* represents the amount of negative psychological and environmental factors one can handle prior to entering a dysfunctional psychological state (or inferior functioning). To measure Stress Tolerance, the concept of the *Inferior Function* from MBTI theory may be applied. An individual's Inferior Function is defined by the individual's MBTI type. Entering inferior functioning (termed "The Grip") is the weakest psychological functioning possible for a given personality (Quenk, 1996:4). "The smallest share of conscious psychic energy goes to the inferior function, so it is essentially unconscious" (Quenk, 1996:4).

> The inferior function appears in a specific and predictable form. The form is similar to the qualities that would describe a person who has that dominant function, but compared to the dominant form of the function the inferior will be: exaggerated or extreme – like a caricature of that type; inexperienced or immature – the person will come across childish, touchy, easily angered; undifferentiated or categorical – perceptions and judgments will be black and white, all or none (Quenk, 1996:6-7).

Common triggers include:

- Fatigue
- Illness
- Stress
- Alcohol or mind-altering drugs

Each MBTI has its own additional and specific triggers and propensity for entering The Grip (Quenk, 1996:7).

Including *Risk Needs* as a trait supports developing a collectively exhaustive model of personality, as does *Activity Preference* aspects of motivation neglected under the measures of *Achievement Orientation*. According to Atkinson, a problem "of behavior which any theory of motivation must come to grip with … is to account for an individual's selection of one path of action among a set of possible alternatives" (Atkinson, 1976:11). The constant cause of these differences is related to risk-taking behavior defined as the "the relationship of strength of motive, as inferred from thematic apprehension, to overt goal-directed performance" (Atkinson, 1976:11).

Activity Preference is defined as the amount of risk the target individual prefers in activity choices, where risk could be of life, money, freedom, or other valuable resources. *Fear of Consequences* acts as a deterrent to participating in certain activities even if the person has a high preference for that activity (Samenow, 1998:5). *Time Horizon* is the length of time in the future that the target individual considers relevant when making plans or decisions (Clemen, 1991:21).

Underlying theories derived from Psychology and Behavioral Science have been discussed. Next consideration is given to how individuals interact in a social network. It is necessary, therefore, to consider theories from the fields of Sociology, Organizational Behavior, Organizational Theory, and Anthropology that are relevant to this study of social network modeling. Each of these fields offers important theories that serve as the foundation for the development of an analytical model for social networks. Several key Social Science constructs for representing and categorizing social networks are examined in detail in this section. As will be seen, all of these constructs leave considerable room for a more analytical implementation. The most analytical techniques employed in these approaches focus on Least Squares Regression, developing pairwise correlations, or other multivariate techniques, generally using data collected through a survey, poll, or other similar device.

Sociology and Social Network Analysis (SNA)

Social Network Analysis (SNA) offers a good starting point for the development of an analytical model of a social network as it is an accepted methodology applied by Sociologists. This theory comes from Sociology, but has been applied across other domains including Organizational Development, Biology, Anthropology, and others (Krackhardt, 1996:161; Brennan, 1999:356). The goal of SNA is to identify "who the key actors are and what positions and actions they are likely to take" (Krackhardt, 1996:161). SNA has been applied to networks of individuals (Krackhardt, 1996:162-172) as well as networks of organizations (Brennan, 1999:355-375).

In SNA, interrelations and connections are represented as networks where the nodes are either individuals or organizations with arcs representing associations (Krackhardt, 1996:166). The arcs may be directed or undirected; undirected arcs indicate a mutual relationship. The actual relationships are traditionally determined through the use of surveys which ask questions such as: "Who among your co-workers do you typically go to for help or advice when you encounter a problem or have a question at work?" or "Check the names of all those who you talk to virtually every day about work-related matters" (Krackhardt, 1996:165, 170).

Once all of these surveys are collected, the relationships revealed are plotted on either directed or undirected graphs based on the type of study under consideration (Krackhardt, 1996:165). The resulting graph allows one to make certain observations about the given social network. For example, the number of arcs (representing the relationship elicited in the survey tool) incident to a node (representing a person or group) indicates the relative importance of that node in the social network (Krackhardt, 1996:166). This relative importance may be far different than that node's (person's) formal position in the given organization under consideration. In fact, one cannot directly infer from a formal organizational chart the underlying social network (Krackhardt, 1996:171). Nor can one "infer from the network pictures how to solve their particular problems … [unless] accompanied by a local sense of the problems" (Krackhardt, 1996:172).

For example, consider the organizational line chart in Figure 1, where Tom is the senior manger, Joe, Mike, and Bob are functional area managers subordinate to Tom, and Ann is the office secretary.

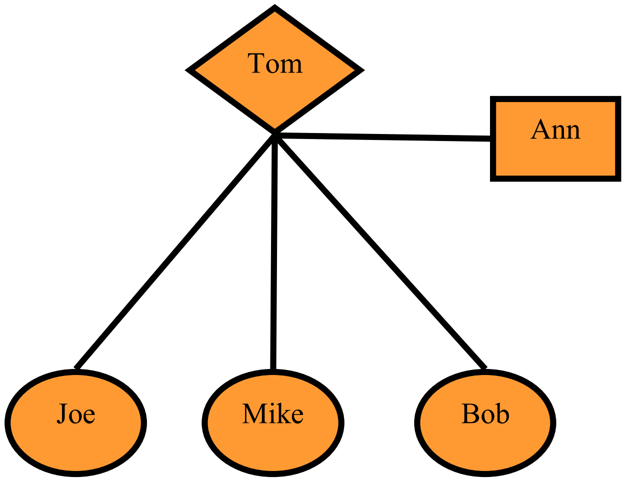

Figure 1. Sample Organizational Line Chart (Formal Network)

In the sample SNA graph shown in Figure 2, it is clear to see that Ann, the secretary, is a key to interoffice communication, not Tom the senior manager or Joe, Mike, and Bob who are subordinate to Tom. Ann is in essence a gatekeeper for information passing to the senior management. Such a directed graph would result from a survey asking: "Who do you most often seek advice from at work?".

Relationships in a SNA network can be quantified in several ways, allowing further analysis. As previously noted, one measure of strength is counting the number of arcs incident to the individuals involved. Depending on the survey tool used, other countings may also be possible, such as counting the number of times pairs of individuals communicate in a fixed time period. For cases where these measures exist, they can be used to weight the arcs in the SNA graph.

Using a weighted SNA graph, there are existing techniques available to Sociologists to conduct further analysis. These techniques include Hierarchical

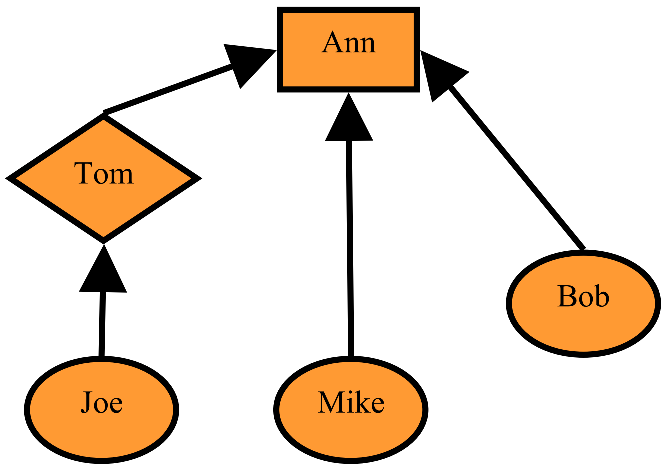

Figure 2. Sample Social Network Analysis (SNA) Graph (Informal Network)

Clustering, Multidimensional Scaling, and Ego Network analysis. Each of these techniques is described below. These techniques are implemented in several commonly available software packages such as UCINET 5 and Anthropac (Borgatti, 1996:1).

Hierarchical Clustering is a classic multivariate analysis technique that clusters (*i.e.*, groups individuals or objects) in descending order of the strength of the connections in each cluster based on the measure applied (Borgatti, 1994:78). An example of a clustering algorithm is provided for illustration. Note, however, a number of other clustering approaches and distance measures exist. As can be seen in the following algorithm, the bottom of the hierarchy (least strength tier) includes everyone in the social network under analysis (cluster of 1) (Borgatti, 1994:78).

Prior to applying a Hierarchical Clustering algorithm, it is necessary to construct a matrix (A, with elements a_{ij}) such that an organization of N people forms an NxN matrix where each person i=1,..., N has $a_{ij} = d_{ij}$ $\forall j$=1,…, N and d_{ij} is the measure being applied (Borgatti, HC, 78). This matrix is called the *similarity matrix* (Borgatti, 78). If

a_{ij} were binary {0,1} where 1 represents a connection and 0 otherwise, this matrix is an adjacency matrix. Borgatti uses the d_{ij} notation to reinforce the distinction between an adjacency matrix and a similarity matrix. Borgatti applies the following algorithm:

1. Start by assigning each item to its own cluster, so that if you have *N* items [people], you now have *N* clusters, each containing just one item [person]. Let the distances (similarities) between the clusters equal the distances between the items they contain [a_{ii} often equals 0 depending on the measure applied].

2. Find the closest (most similar) pair of clusters [closest in terms of a_{ij}] and merge them into a single cluster, so that now you have one less cluster.

3. Compute distances (similarities) between the new cluster and each of the old clusters [based on the closest, greatest, mean, or median a_{ij} in the cluster to the old clusters using the rule selected by the analyst], so that you now have one less cluster.

4. Repeat steps 2 and 3 until all items are clustered into a single cluster of size *N* (Borgatti, 1994:78).

Inferences drawn from Hierarchical Clustering must be based on the measure applied. For example, if one used the measure of number communications then the closest people are those who communicate most frequently and the resulting clusters are those containing people who communicate with each other frequently. This type of analysis does not directly imply why these people communicate. Further, Hierarchical Clustering is restricted to the context of the measure applied. A matrix of measures with the opposite monotonicity of similarity is called a *difference matrix* and similar methods can be applied to this matrix.

It is important to note that the Hierarchical Clustering as defined above is only one example of clustering methods applicable to social networks. The aim of cluster analysis procedures is to "classify *n* objects or individuals, upon which *t* measurements have been taken, into *m* clusters" (Godehardt, 1990:29). Godehardt notes that there are four broad types of clustering procedures: (1) *disjoint clustering* where *n* objects are split into a *m* non-overlapping, disjoint clusters, (2) *non-disjoint clustering* where objects may belong to more than one cluster at the same time, (3) *hierarchical clustering* where objects and groups of objects are arranged in the form of a tree representing the hierarchy, or (4) *quasi-hierarchical clustering* where clusters at each level of the hierarchy may overlap (Godehardt, 1990:42-43). Note that the "*t* measurements" described, may be multiple measures of social closeness.

Multidimensional Scaling (MDS) "provides a visual representation of the pattern of proximities (*i.e.*, similarities or distances) among a set of objects [or people]" (Borgatti, 1996:29). MDS requires the same *N*x*N* matrix defined above for Hierarchical Clustering and a stress function that measures "the degree of correspondence between distances [or similarities]" (Borgatti, 1996:32). Borgatti suggests the use of the metric Kruskal stress function defined as: $((\Sigma_i\Sigma_j\, a_{ij} - d_{ij})/(\Sigma_i\Sigma_j\, d_{ij}^2))^{1/2}$ where d_{ij} is the Euclidean distance between points *i* and *j* based on the coordinates assigned in the following algorithm (Borgatti, 32). The MDS algorithm as defined by Borgatti follows:

1. Assign points [people] to arbitrary coordinates in *p*-dimensional space [often MDS is applied in two dimensional space].

2. Compute the Euclidean distances among all pairs of points, to form what is called the *D* matrix.

3. Compare the *D* matrix with a monotonic function [$f(a_{ij})$] of the input data [the metric *Kruskal stress function* defines $f(a_{ij}) = a_{ij}$], called *DHAT*, by evaluating the stress function. The smaller the value, the greater the correspondence between the two.

4. Adjust coordinates of each point in the direction that best maximally reduces stress [requiring the use of non-linear optimization].

5. Repeat step 2 through 4 until stress [will not] get any lower (Borgatti, 1996:30).

Using the above MDS algorithm, particularly when two-dimensional spaces are used, it is possible to plot the coordinates of people in the social network where those people who are closer to each other are, based on the theory of this technique, closer socially in the context of the measure applied. Borgatti notes that, "the best possible configuration in two dimensions may be a very poor, highly distorted, representation of your data. If so, this will be reflected in a high stress value" (Borgatti, 1996:31). Any stress value greater than zero indicates that the representation of relationships is distorted. Borgatti suggests that even in the presence of stress, "you can rely on the larger distances as being accurate" (Borgatti, 1996:35).

Borgatti further notes that, "four or more dimensions render MDS virtually useless as a method of making complex data more accessible to the human mind" as there is no way to visually observe the results in a single graph (Borgatti, 1996:31). Borgatti also maintains that the axes and the orientation of the MDS plot are "meaningless" as there may be multiple orientations that have the same minimum stress and the axes are only proportional in nature (Borgatti, 1996:35). In addition, since MDS is based on the same *N*x*N* matrix of data as Hierarchical Clustering, MDS has all the problems inherent to making inferences based on such data. These problems do not make MDS unusable; however, results must be considered in light of these limitations.

Correspondence Analysis is a technique very similar to Multi-Dimensional Scaling for cases where data is non-metric (Anderson, 1992:340). Correspondence analysis, however, only preserves ordinal relationships of ordinal data and provides no order relationships when nominal (categorical) data is used (Anderson, 1992:340). Correspondence Analysis is of little interest in this research, where the fundamental objective is to develop analysis methods that allow one to observe, measure, and interpret detailed relationships in a social network quantitatively. Correspondence Analysis is basically a qualitative technique that uses similar methods as those of MDS with all of the same mathematical problems and additional problems associated with the non-metric data.

Ego Networks "consist of a focal node ('ego') and the nodes to whom the ego is directly connected to (these are called 'alters') plus the ties, if any, among the alters" (Borgatti, 2000:1). Note that in Graph Theory an Ego Network without any ties between the alters exactly defines a "star" graph (West, 1996:70). Each alter in a given Ego Network can be thought of as the Ego of its own Ego Network. Thus, a social network can be defined as a set of interlocking Ego Networks (Borgatti, 2000:1). Borgatti notes that an Ego Network can be constructed from a single-context relationship basis, as in SNA, or a multi-context basis where the Ego Network represents all the connections of any nature to others in the network. "A standing hypothesis about ego networks is that strong ties are homophilous. That is, people have the strongest ties with people who [are] similar to themselves" (Borgatti, 2000:3). Another hypothesis about Ego Networks is that "heterogeneous networks are 'better off' … [as] the greater the diversity of their network, the more chance that someone in the network has something the ego needs" (Borgatti, 2000:3). Thus, Ego Network analysis is less of an analysis technique itself, but primarily a framework for understanding a social network where other analysis techniques may be applied in terms of the homophily and heterogeneity of the network.

SNA and related analysis techniques provide a strong foundation for building an analytical model; however, has many areas where significant improvement must be made in order create a robust model. The survey-based approach to collecting data is not possible in all situations. The questions asked are fairly simple and are only taken in one context (problems at work, for example). Further, these questions themselves may lead to bounding the number of connections (for example, if one is asked to check up to three names of co-workers with whom they associate). In addition, these questions do not capture the relative weight of the relationship. Although SNA can be used to consider either individuals or groups, it is not intended to consider both individuals and groups in the same graph. Further, the analysis techniques for SNA graphs described have the noted mathematical problems. The problems inherent to analysis techniques such as MDS, the most robust of the methods discussed, stem in part from a lack of advantageous properties of the measures applied (may lack additivity, for example), the dimensionality of the space may be ill defined, and a lack of multi-context data may lead to higher stress as significant social connections may be neglected (Borgatti, 1996:36).

These problems can, in part, be answered by including other disciplines of the Social Sciences. This research considers each of the theoretical limitations above by examining theories from these other disciplines. First, Organizational Behavior and Organizational Theory are used to address the question of why the social network (informal structure) of an organization may differ drastically from its formal organizational structure. Psychology and Behavior Science are use to move beyond SNA's single context, survey-based nature to a multi-objective, value-based representation of individuals and organizations. Anthropology serves as a foundation to help explain how to combine individuals and groups into a single graph using culturally specific criteria. Later sections of this dissertation are devoted to analytical methods to address the questions of weighting and cardinality as well as other properties that allow for exploitation of the graphical structure introduced by SNA.

Explaining Informal Structure in Organizations

By observation, most modern organizations have a formal, in some cases hierarchical, structure. This structure is based on a division of labor between functional areas, production areas, or a matrix across both functional and production areas. Such structures are usually shown in organizational line charts that depict the given structure. Unfortunately, formal organizational networks such as those described by line charts offer limited help in predicting the underlying informal social network except in the most rigid of societies. "Individuals create their reality and attitudes … through interaction with others and through membership in a common social context" (Aydin, 1991:120).

Aydin goes on to observe that people identify with more than one "subculture" within an organization, citing at a minimum "occupational" and "departmental" groupings (Aydin, 1991:120). For example, a secretary from a given department participates in a subculture amongst secretaries as well as a subculture within his or her assigned department. This particular secretary may be, for example, the most senior secretary and a leader in the subculture of secretaries, but be new to his or her current department and not yet fully trusted or proficient at his or her duties in the departmental subculture. These organizational subcultures, combined with "personal networks" (Brennan, 1999:358) of friends, leads quickly to the conclusion that "many factors are naturally confounded" in cross-cultural situations, particularly in more open societies (Hsee, 1999:176).

These complicated underpinnings to organizational structures do not mean that there is no way to consider interactions in the organization, however. Organizational theorists have posited the idea of Organizational Development (OD). OD takes as a given the complicated social system that hides behind the formal organizational chart and tries to find ways to shape that system so that organizational goals can be achieved.

Organizational Development (OD)

Organizational Development (OD), Management Development (MD), Organizational Transformation (OT), and Human Systems Development (HSM) are related theories of organizational change, growth, and creation (Pilarz, 1990;166). According to Pilarz, these techniques all share the following fundamental process (Pilarz, 1990:167-168):

1. Characterize the situation in terms of identifiable objects with well-defined properties.
2. Find general rules that apply to situations in terms of those objects and properties.
3. Apply the rules logically to the situation of concern, drawing conclusions about what should be done.

Pilarz states, "different organizations require new orientations and new basic assumptions. They require that we identify new organizational features and actions which increase our options dealing with social systems" (Pilarz, 1990:168). The search for these assumptions and how to use them to create desirable organizational change is Organizational Development (OD) (Schein, 1990:14). OD is not a "set of techniques at all, but a philosophy" (Schein, 1990:13).

OD practitioners have an array of tools available to them including:

- Surveys
- Meetings with employees, managers, or both
- SNA type graphs of different organizational systems
- Statistics (Schein, 1990:13)

Pilarz maintains this open methodology is necessary as organizations are non-trivial entities characterized by being analytically unpredictable, history dependent, synthetically deterministic (*i.e.*, approximating a stochastic process using a deterministic model), and analytically indeterminable (Pilarz, 1990:171). This complexity is what leads many to consider Chaos and Complexity Theory as the best model of organizational behavior (Massarik, 1990:8). For these reasons, Chaos and Complexity Theory have not been ruled out as methodologies for this class of research; however, if organizations are "history dependent" then future behavior may be predicted to some degree (at least bounded) until a turning point, or radical change, occurs. Further, even if organizational models are "synthetically deterministic," it is likewise observed that at least a model could be analytically determinable. Stochastic and deterministic methods are both considered relevant to social network analysis in this research and may in part be determined by the data available and objectives of a particular application.

OD and the other related disciplines attempt to move understanding organizations beyond the trivial machine model: predictable, history independent, synthetically deterministic, analytically determinable (Pilarz, 1990:170-171). The elements of trivial machine organizational models include: motivation to work, roles and interactions, leadership, power and influence, and culture (Handy, 1993:29, 60, 96, 123, 180). By observation, many of the elements of a trivial machine model are represented by aspects of Trait Theory described previously. As in Trait Theory, these trivial machine elements are the foundation for more robust models.

Trait Theory goes beyond these few elements in terms of traits, interactions, and implications for personality. OD goes beyond these elements in terms of describing non-trivial organizational characteristics. The noted frustration with traditional methods that has led some OD practitioners to consider Chaos and Complexity Theory a preferred tool for representing organizational behavior may be similar to those Psychologists who find Trait Theory inadequate and consider the more abstract State Theory a better representation of the complexities of personal and social interaction.

Although OD, MD, OT, and HSM have found only philosophical ways of dealing with complexity and chaos, other theories provide more analytical representations. Reflexive Control (also known as Situational Control, Feedback Control, or Cybernetics) models these situations with an "object," "analyzer," and "object of control" (Pospelov, 1986:13). In such a model, decisions are made based on feedback from past decisions as interpreted by the analyzer.

Reflexive Control and Semiotics

Reflexive Control is a promising, evolving science, initially developed to support artificial intelligence applications (Pospelov, 1986:vi). At the core of the Reflexive Control methods employed by Pospelov are Semiotic Models, which have long been posited as a model for human processes (Pospelov, 1986:35).

The formal representation of these methods is a Model, M = (T, P, A, n) where T is the set of basic elements of the system, P is the syntactic rules, A is a system of axioms, and n are semantic rules (Pospelov, 1986:36). The set T of basic elements is a finite set of elements of any nature (Pospelov, 1986:36). The syntactic rules, P, are used to construct "syntactically correct combinations" of the basic elements in T (Pospelov, 1986:36). Any set of syntactically correct combinations forms the system of axioms, A (Pospelov, 1986:36). The semantic rules, n, are rules for expanding the syntactically correct combinations (Pospelov, 1986:36).

In a Semiotic Model, once the model, M, has been defined and the rules and axioms, T, P, and A, are defined, a definition of the current operations of the system has been stated. When the semantic rules, n, are learned and applied analysts are able to advance the system to new functionality or understanding. In the general case of Reflexive Control these rules are learned through interpreting feedback (*i.e.*, trial and error).

Semiotic models offer theory necessary for creating machines that can learn from feedback. What has been outlined above just touches on the significant amount of analytical work that has been done in developing these models; however, in terms of developing causal models for human behavior, Reflexive Control models and, hence, Semiotic Models provide limited insight. Further, their short-term state-based nature (*i.e.*, the next state is dependent only on the current state of the system) is inadequate for forecasting long-term behavior. Feedback control systems only utilize the current state to determine what action to take leading to the next state.

This section has reviewed several ways in which past researchers have attempted to explain and model formal and informal structure. Organizational Development and Reflexive Control have been reviewed as means of dealing with highly complex organizational structures (whether formal or informal in nature). Traditional organizational models closely parallel those developed from a basis in Psychology and Behavioral Science described in the next section.

Moving Away from Single Context Graphs

SNA and the other techniques discussed thus far are focused on understanding a social network within a single context. This is in part a result of the survey tools used to collect data. To truly understand a social network requires more detail than that captured in a single context. For example, some individuals employed in the same formal organization likely share membership in other informal organizations such as churches, sports teams, and other activities external to the formal organization. Some individuals likely share ties from attending the same schools, previous employment, or other past experiences as well. Small World theory serves as an example of how to model the interconnectedness of all people outside of a particular context (Watts, xi).

Duncan Watts, in his 1999 book *Small Worlds*, makes significant progress in advancing the idea of a graphical representation of a generalized (non-contextual) social network. Watts' work demonstrates some of the same Psychological and Behavioral Science theories used in the past works already discussed. However, Watts reverts to an unweighted, single-criteria representation for relationships. Watts' representation of Small World theory is discussed in the next section. It should also be noted that Watts' work is the first of the theories presented that uses Graph Theory in its formal mathematical context.

Small World Theory

Small World Theory essentially states that "any two people, selected randomly from almost anywhere on the planet, are 'connected' via a chain of only a few intermediate acquaintances" (Watts, 1999:xi). Progress has been made since the 1960's toward realistic representations of social networks and the introduction of specific concepts, such as:

1. The restriction to a finite subpopulation from which *k* acquaintances can be chosen and a corresponding strong overlap of friendship circles.
2. The introduction of structural biases, specifically, homophily (the tendency to associate with people "like" yourself), symmetry of edges (which implies undirected instead of directed edges), and triad closure (the tendency of one's acquaintances to also be acquainted with each other).
3. Social differentiation of a population into heterogeneous subgroups (Watts, 1999:13).

"Strong" and "weak" ties are not defined in terms of psychological factors, but rather as cardinality in the graph structure. Specifically, "the stronger the ties between *A* and *B*, the larger the proportion of individuals in *S* [population] to whom they will both be tied…" (Watts, 1999:14). This sense of stronger and weaker ties is shown in Figure 3.

Figure 3. Strength of Ties in Small World Theory (Watts, 14)

Watts also stresses that weak ties can be critical and very powerful (Watts, 1999:15). Weak ties serve as a bridge between non-overlapping strongly connected friendship groups. The strength (*i.e.*, cardinality) of these weak ties between non-overlapping groups, or clusters, defines the density of a social network (Watts, 1999:15).

Throughout his book, Watts describes in detail the theoretical space in which Small World graphs exist and defines a number of formal terms and measures, most of which are found in any standard text on Graph Theory. More importantly, Watts identifies three areas which "appear to remain open" for research:

1. Social networks exhibit structural characteristics that are inherently nonlocal.

2. Analytical difficulties increase with the size of the network, and almost none of the work has been tested for large population size (*n*) with sparse connectivity.

3. It is unknown where on the structural spectrum real social networks lie, but no treatment has been given to the properties of continuous families of networks, whose structural properties vary all the way from one extreme to the other, with the intention of determining the location and nature of any transitions that occur in between (Watts, 1999:21).

Watts examines social networks from a Small World, graph theoretic approach by looking at the types of graphs that exemplify Small World properties. Specific cases Watts considers are: the spread of infectious disease (Watts, 1999:163), cellular automata (Watts, 1999:181), game theory and cooperation (Watts, 1999:199), and coupled phased oscillators (Watts, 1999:223).

Watts leaves open the listed theoretical gaps and does little to attempt to develop a key measure to understanding social networks, social closeness, where social closeness is a consistent measure of how strong ties are between people in a psychological sense, beyond just the cardinality of their common connectedness (Watts, 1999:21). Watts does say that this "distance [or closeness]" is likely "multivalued" (Watts, 1999:22). His treatment of social networks in terms of graphs neglects to consider weighting arcs with a social closeness value or vector. Instead, Watts focuses on cardinality based measures.

It is hypothesized in this research that using measures such as those found in Psychology and Sociology a vector measure of social closeness based on networks of individuals may constructed. This hypothesis is further explored in Chapter 6. A solution to the problem that Watts describes in terms of the large scale of social networks may lie in contracting the social network graph once it has been constructed. Applicable contractions, in terms of aggregation, are explored in Chapter 5. This idea is examined from a mathematical standpoint in this dissertation based on Graph Theory; however, prior to looking at the mathematics of contracting and expanding graphs, it necessary to understand how to create groups from a collection of individuals conceptually. This is the subject of the next section.

Combining Groups and Individuals

All of the theories and methods previously described treat groups and individuals separately. For a model of social networks to be truly robust, it should be able to accommodate both individuals and groups in the same model. Clearly, one way to approach this problem is to consider a group as the aggregation of individuals. Although most would agree with this proposition, the concept neglects the detail to implement it analytically without a more refined theoretical foundation. To understand the aggregate behavior of people in groups it is necessary to consider the culture of those involved.

In the 1998 anthology *Kinship, Networks, and Exchange*, a number of modern anthropologists give insight into the problem of understanding this aggregate behavior cross-culturally. Unfortunately, Anthropology does not offer simple rules for how people form groups that applies across cultures. It is therefore understood that even before considering a mathematical context for contracting a social network of individuals into a graph of groups or, more likely, a graph of both groups and individuals, unique cultural aspects of the social network must be considered.

Per Hage and Frank Harary, describe how anthropologists have used Minimum Spanning Trees (discussed in detail in the later section on Graph Theory) to help determine the origin of how people "cluster" into groups (Hage, 1998:251). Unfortunately, this work has all been descriptive, not predictive, in nature (*i.e.*, given a cluster of people, determining how that cluster occurred). Without some kind of general systematic rules, the predictive problem is left to considering the culture of the people involved. Attempts have been made to build models of the path a specific culture will take using hypothesized cultural conventions, rules for behavior in a given culture (*Kinship, Networks, and Exchange*, 1998:11-12).

Consider, for example, the simple clustering of two individuals into a marriage. In the United States, sharing relationships where both the man and woman contribute equally is a cultural norm; however, in the United States and abroad there are a variety of cultures where this equation is not balanced. One approach used by anthropologists is to view balance in terms of "corporate groups" where a "corporate group" is a "set of individuals who have socially recognized claims – rights – to consume or use a specific resource or set of resources" (Bell, 1998:188). In combining individuals into groups, identifying the "corporate groups" within the network identifies the decisions-maker(s).

It is important to note that even within a cultural framework, "corporate groups" and kinship, a familial or familial-like relationship, generally have constraints. Reciprocity, a perceived give-and-take, "determines to a significant extent who is regarded as kin. Without kinship, reciprocity is hard to realize, without reciprocity, a sense of kinship fades" (Tumu, 1998:275). Although marriage produces "instant kinship" (Tumu, 1998:275), "for most nonstratified societies, … such primary kin ties have their limits – they cannot be expanded quickly or easily by cultural conventions because their effectiveness depends on a history of mutual trust or deeply rooted common interest" (Tumu, 1998:278).

Anthropology provides insight into conceptually determining how to contract a graph of individuals into groups. First, it may be possible to identify clusters within the known cultural context. Second, one can identify the decision-makers in any such grouping by finding the corporate group. Third, in a stratified society an analyst may be able to identify cultural conventions for such groups and in a nonstratified society an analyst should consider relationships formed through family, history, and mutual interest. Further, it is possible to break the bonds of kinship if one member of the cluster does not feel they are receiving reciprocity. These concepts will be essential in contracting or expanding social networks and a strong cultural (perhaps sub-cultural) understanding is essential to the success of such endeavors.

The foundation provided by relevant and complementary theories taken from the Social Sciences is a starting point for developing an analytical, cross-cultural, multi-criteria, multi-context, mixed (individuals and groups) model of social networks. To construct such a model analytically, it is necessary to look at existing analytical methods and identify where existing methods are sufficient and where new theory must be developed and proven. The next section of this chapter describes relevant existing analytical methods that are likely to support the construction of the desired type of model already described. Where existing theory seems insufficient, hypotheses are made as to how to expand existing theory. Developing, testing, and proving these theoretical expansions serves as the subject of this research.

Before a methodology to extend existing Operations Research techniques can be discussed, it is first necessary to understand Operations Research domains that are relevant to social network modeling as well as the theoretical gaps that exist in these techniques when attempts are made to integrate models, measures, and data from the Social Science methods described. Specifically, attention is given to Graph Theory, Optimization for Network Problems, and Decision Analysis.

Graph Theoretic Framework

Graph Theory is a discipline within Discrete Mathematics (West, 1996:xi). Abstract understandings of a graphical network have already been introduced (such as that described in SNA). Graph Theory provides a formal definition as follows:

> A *graph G* with *n vertices* and *m edges* consists of a *vertex set* $V(G)=\{v_1,\ldots,v_n\}$ and *edge set* $E(G)=\{e_1,\ldots,e_m\}$, where each edge consists of two (possibly equal) vertices called its *endpoints* (West, 1996:1).

Graph Theory provides a variety of formal ways to understand, classify, and manipulate graphs. In this section definitions of graph theoretical concepts have been taken primarily from the text *Introduction to Graph Theory* by Douglas West, however, similar definitions may be found in any collegiate level text on Graph Theory.

In this study, no attempt is made to review all of Graph Theory; rather key concepts that are expected to prove fruitful in the development of a social network model are reviewed. It has already been informally noted that the individuals and organizations in a social network are represented as vertices (or nodes) and social connections are represented by edges (or arcs). Watts notes that "symmetry of relationships" implies an undirected graph (Watts, 1999:13); however, if the edges are weighted with social closeness then a directed graph (or digraph) is required if any of these weights are not symmetric. The anthropological understanding of "reciprocity" indicates there may be a threshold on these weights occurring when "kinship fades" (Tumu, 1998:275). If the difference between the out-going weight is significantly out of balance with the in-coming weight, then the relationship may be weakened, may be truly only a one way relationship, subservient in nature, or a result of a dominate culture. It may also be necessary to have a minimal level of influence (meet or exceed a threshold) before a individual or group is influenced.

The case described by Watts is defined as a *simple graph*. "A *simple graph* is a graph having no loops or multiple edges" (West, 1996:1). In general, a social network would have no loops, since a loop would imply a social closeness to oneself (exceptions might include certain cases of aggregation). A multiple edge would imply multiple social closeness values to the same person or organization at the same time. This might occur if one were to model formal and informal structures in the same graph, for example.

The case where directed edges are required is defined as a *digraph*. A *digraph* is a graph "where each edge is an ordered pair of vertices … in which each ordered pair of vertices occurs at most once as an edge" (West, 1996:2). Assigning weights to either a simple graph or digraph results in a *weighted graph*. "A *weighted graph* is a graph with numerical values assigned to the edges (West, 1996:73)."

When observing a graph there are certain properties one may wish to examine to better classify the graph. These include (but are not limited to): *eccentricity*, *diameter*, *radius*, *center, circumference,* and *chromatic number*. According to West,

> The *eccentricity* of a vertex *u*, written $\mathcal{E}$(u), is the maximum of its distances to other vertices. In a graph *G*, the *diameter* diam*G* and the *radius* rad*G* are the maximum and minimum of the vertex eccentricities, respectively. The *center* of *G* is the subgraph induced by the vertices of minimum eccentricity (West, 1996:54).

The *circumference*, c(*G*), of a graph *G* is "the length of the longest cycle in *G*" (West, 1996:394).

In a social network graph, the eccentricity of a vertex (individual) is the greatest distance that an individual is from any other individual or group in the social network. The diameter then is the greatest distance an individual is from others in the graph and the radius is the minimum of these greatest distances an individual is from others in the graph pairwise. The center of a social network is the subgraph containing those individuals who share the minimum of these greatest distances from others in the graph. The circumference is the longest (greatest number of edges) cycle in a social network and is the largest clustering of individuals who are connected such that each member of the cluster knows exactly two others in the cluster.

The *chromatic number* relates to the "coloring" problem, as follows "A *k-coloring* of *G* is a labeling $f : V(G) \rightarrow \{1,\ldots,k\}$. The labels are *colors*; the vertices with color *i* (where $i \in \{1,\ldots,k\}$) are a *color class*. The *chromatic number* $\mathcal{X}(G)$ is the minimum *k* such that *G* is *k-colorable*" where *G* is *k-colorable* if vertex *x* is adjacent (shares a common edge) to vertex *y*, then $f(x)$ and $f(y)$ are not equal for all *x* and *y* in V(*G*) (West, 1996:173). A social network graph with a larger *chromatic number* has more strongly tied clusters than a social network graph with a smaller *chromatic number*. This relates directly to the Small World strength measure of social closeness discussed earlier. In an aggregate sense a graph with a large *chromatic number* contains stronger (socially closer) ties.

"A graph G is *bipartite* if V(G) is the union of two disjoint sets such that each edge consists of one vertex from each set" (West, 1996:3). A *star* is a bipartite graph where the cardinality of the vertices in one of the two disjoint sets is 1 and the cardinality of the vertices in other set is n-1 (denoted $K_{1,n-1}$) where n is the total number of vertices in G (West, 1996:70). Stars minimize the diameter of a graph (West, 1996:70). If e is an edge between vertices u and v in G, then the "*contraction* of e is the operation of replacing u and v by a single vertex whose incident edges are the edges other than e that were incident to u or v" (West, 1996:65). The resulting graph is denoted $G \bullet e$. $G \bullet e$ has exactly one less edge and node than G . To handle the large scale problem noted by Watts, one could *contract* the edges in the social network into a graph as close to a *star* centered at a particular target individual or group as possible, while maintaining required fidelity for a given scenario. Contractions forming stars or stars with additional edges relate directly to Ego Network analysis, as each such contracted graph is an Ego Network.

Before shifting attention to Network Models, which will exploit Graph Theory, it is necessary to formally define several concepts that are critical to the techniques described. These include: *walk*, *trail*, *path*, *cycle*, *forest*, *tree*, *leaf, spanning subgraph*, *spanning tree*, *matching*, *flower*, and *blossom*.

- A *walk* of *length k* is a sequence $v_0, e_1, v_1, e_2, \ldots, e_k, v_k$ of vertices and edges such that $e_i = v_{i-1}v_i$ [an edge between vertices v_{i-1} and v_i] $\forall\, i$.
- A *trail* is a walk with no repeated edge.
- A *path* is a walk with no repeated vertex.

- A *u,v-walk* has first vertex *u* and last vertex *v*; these are its *endpoints*.
- A walk (or trail) is *closed* if it has length at least one and its endpoints are equal.
- A *cycle* is a closed trail in which "first=last" is the only vertex repetition.
- A *loop* is a cycle of length 1 (West, 1996:14).

Walks, *trails*, *paths*, *cycles*, and *loops* are all structures commonly found in graphs. Some graphs are more complex than others; *trees* are a simple type of graph (or subgraph) structure. A structural organizational line chart of a hierarchical organization would be a tree, for example. Related definitions include:

- A graph having no cycle is *acyclic*.
- A *forest* is an acyclic graph.
- A *tree* is a connected acyclic graph.
- A *leaf* (or *pendant vertex*) is a vertex of degree 1 [only one edge incident to the vertex].
- A *spanning subgraph* of *G* is a subgraph with vertex set V(*G*) .
- A *spanning tree* is a spanning subgraph that is a tree. (West, 1996:51).

Understanding *flower* structures is relevant as it is possible to contract the *blossom* of a *flower* into a single vertex. A *matching* of size *k* in a graph *G* is a set of *k* pairwise disjoint edges (West, 1996:98). A vertex not belonging to an edge in the matching is *unsaturated* by the matching (West, 1996:98). "Given a matching *M*, an *M-alternating path* is a path that alternates between edges in *M* and edges not in *M*" (West, 1996:99). Given the definition of a matching, it is now possible to define a *flower* and its properties.

> Let *M* be a matching in a graph *G*, and let *u* be an *M*-unsaturated vertex. A *flower* is the union of two *M*-alternating paths from *u* that reach a vertex *x* on steps of opposite parity [where edges in *M* have parity opposite those not in *M*] (having not done so earlier). The *stem* of the flower is the maximal common initial path (of nonnegative even length). The *blossom* of the flower is the odd cycle obtained by deleting the stem (West, 1996:128).

It is possible to contract the *blossom* into the vertex at the end of the *stem* by iteratively applying the contraction procedure described for developing a *star* graph. As with all contractions, re-labeling the contracted nodes adds clarity and if one wishes to expand the graph at a later date, it is necessary to record the details of the contraction.

Graph Theory lays the foundation for an analytical view of social network analysis. This dissertation extends beyond the cases already mapped to social networks and already in use for social network analysis to cases involving flow network modeling, aggregation, and extensions of these models and methods. The next section describes optimization for network problems. Many network analysis methods exploit aspects of Graph Theory. Network problems are a logical extension and application of Graph Theory.

Optimization for Network Problems

As noted, one reason that social networks may have received limited attention to date in the Operations Research/Management Science/Decision Analysis community is the lack of specific measures beyond simple connectivity. Whether as existing measures or newly developed measures, the ideal case for this research is the development of a social distance (also termed "difference") or social closeness (also termed "strength" or "similarity") metric. If a metric for social closeness could be defined, then all relevant mathematical theory related to distance in general would apply to this social closeness metric and related space (Apostol, 1974:60).

Metrics and Measures. In general, a *metric* $d(x,y)$ (such as social distance or closeness) is defined in terms of a *metric space* as follows (Apostol, 1974:60):

> A *metric space* is a nonempty set ϕ of objects (called points) together with a function d from $\phi \times \phi$ to $\mathbf{R}$ (called the *metric* of the space) satisfying the following four properties $\forall\ x, y, z \in \phi$:
>
> 1. $d(x,x) = 0$
> 2. $d(x,y) > 0$ if $x \neq y$
> 3. $d(x,y) = d(y,x)$
> 4. $d(x,y) \leq d(x,z) + d(z,y)$

When the "properties of distance are studied abstractly they lead to the concept of a *metric space*" (Apostol, 1974:60). In terms of social distance, the first property implies that people have no social distance from themselves. For social networks of individuals, this property is often assumed. This also means that in a graphical depiction of the network there are no loops. The second property (non-negative distance), may not always hold for some of the measures (especially those where negative values are assigned directly to measures or delta sender-receiver type measures). The third property (distance is the same in both directions), may often not hold in a directed representation of a social network where social closeness may not be mutual (either it is one-way or, if two-ways, is not necessarily equal). The fourth property (called the *triangle inequality*) may not hold as two people may know each other very distantly, but both may be very close to a common friend.

Erhard Godehardt, in his text *Graphs as Structural Models*, notes that in Sociology, Psychology, and other practical applications that property four, the triangle inequality, is often violated or simply neglected (Godehardt, 1990:38). Godehardt relates this lack of mathematical rigor back to the origin of the empirical classification methods used in these disciplines and indicates that for such cases validation against datasets where the correct classification is known is the only justification for using such methods (Godehardt, 1990:28).

In addition to cases where the properties of a metric may not hold, one may also observe measures that are not real valued (assumed in the definition). In these cases, measures may be binary, whole numbers, integers, or categorical.

When considering the use of a measure in a classical Operations Research flow network model, the measure should in general be proportional, additive, divisible, and certain (Winston, 1994:54). A metric that conforms to the above definition will meet these criteria if it is first-order (linear). For cases where integer, ordinal, or categorical measures are used, clearly the measure only takes on discrete values. This does not, in general, prevent the use of classical methods; however, it may require the application of Integer Programming and other methods (especially when the problem does not demonstrate total unimodularity) and care must be taken in analyzing results (Winston, 1994:512). Negativity (which violates the properties of a metric) is a problem in some network models (especially when the negativity occurs in a cycle).

Mathematical Programming and Network Models. Graph Theory provides a mathematical expression of a network. It is also possible to describe a network in terms of a mathematical programming representation (*i.e.*, a set of equations defining relationships in the network). Mathematical programming representations are used to solve optimization problems with network structures. Graph Theory is a mathematical discipline that defines the properties of graphs in general. In addition, there are a wide array of tools to help implement related algorithms for network analysis. This includes various matrix representations of adjacency and other properties. Mathematical programming and network optimization techniques often exploit these matrix representations. Since each of these representations has its merits and can be easily mapped to each other, the focus of this section is on the major classes of problems for which networks serve as a valuable representation. Descriptions of these general problem classes are stated in terms of their application to social networks.

Problem classes of particular interest to the analysis of social networks include: *minimum spanning tree, shortest-path, assignment,* and *cut-set* problems. These methods are addressed in more detail in the remainder of this section. This is not to say other, more complex network problems are of no interest to social networks, but rather that the more abstract extensions of social networks to *minimum-cost flow, maximum flow, traveling salesmen*, other *routing* problems, and *location* problems requires an understanding of these more fundamental problem classes.

A *minimum (maximum) spanning tree* is a spanning tree of minimum (maximum) weight (Evans, 51). For the case of a social network with arc weights defined in terms of social closeness, a minimum spanning tree defines the minimum social connectivity of the entire network. Conversely, a maximum spanning tree defines the maximum social connectivity of the entire network. As previously noted, anthropologists have used minimum spanning trees to help determine the origin of certain traits in a given society.

The *shortest-path* between two nodes in a graph is the path(s), directed (termed a *directed path*) or undirected (termed a *chain*), as defined in the previous section, from one of the nodes to the other such that the sum of the arc weights along the path is minimized (Evans, 1992:77). For a social network of individuals with undirected arcs all of weight equal to 1, the maximum shortest-path between any two nodes (people) in the graph equals the *K* acquaintance separation defined in Small World theory as a measure of strength. When weights represent social distance in a directed or undirected social network graph, the shortest-path between two nodes (people or groups) is the minimum social closeness separating those two nodes (assuming that the measure under consideration is additive).

A matching of degree 1 in a bipartite graph is called an *assignment* (Evans, 1992:234). Essentially, an assignment is a pairing of nodes in a graph. If a graph is bipartite, then it is possible for this matching to saturate every node in the graph. A matching which saturates every node in a graph is called a *perfect matching* or a *1-factor* (West, 1996:98). When a matching saturates as many nodes in a graph as possible it is called a *maximal* or *maximum-cardinality matching* (Evans, 1992:236). Assignment problems may occur in social networks, such as matching students to tutors, men to women in marriages, observers to oversee a set of groups, and so forth. A matching in such social networks allows an analyst to contract the nodes in each pairing into clusters reducing the number of nodes by half in the resultant graph. It is clear that a perfect matching may not always be feasible in a social network; however, a maximal matching will always exist (in the worst case the cardinality of the maximum-cardinality matching would be zero). A maximal cardinality matching in a social network represents the greatest possible number of clusters containing only two individuals in the network.

A *cutset* is a set of arcs (*arc cutset*), nodes (*node cutset*), or both (*mixed cutset*) which when removed from the graph increases the number of components, disjoint subgraphs, in the graph (Evan, 1992:9). Of particular interest are cutsets that do not contain another cutset as a subset, these cutsets are called *minimal* or *proper cutsets* (Evans, 1992:10). A minimal cutset removes the least number of arc, nodes, or both as appropriate to increase the components in the graph. An additional concept of interest is *s,t-cuts*, these are the set of arcs, nodes, or both which disconnect some node *s* from another node *t* in the same graph (West, 1996:149). In a social network, a minimal cutset would break the network into disjoint clusters of individuals or groups. It is also easy to see that a minimal cutset would contain the arcs that make up "weak" ties defined in terms of Small World theory. An *s,t-cut*, in a social network, represents a more focused effort to break the ties between two specific nodes (individuals or groups).

This section and the preceding section have discussed aspects of Graph Theory and network optimization. Another analytical framework considered relevant for social network analysis is Decision Analysis. Decision Analysis, both single and multi-criteria, is discussed in the next section of this chapter.

Decision Analysis

There are many difficult, complex, or uncertain decisions to be made in a social network context. The following discussion highlights several decisions that may be of general interest when considering social network problems. In the text *Strategic Decision Making* by Craig Kirkwood, he states that elements of a decision are: "the existence of alternatives," "various alternatives lead to differing consequences or outcomes," and may "involve uncertainty about what consequence will result from each alternative" (Kirkwood, 1997:2). Kirkwood's definition of a decision is used in this consideration of decisions involving social networks.

Looking at a social network either internally (as a member of the network) or externally (not a member of the network), there are a number of features one may be interested in observing – who is (are) the leader(s) either formal or informal, who influences whom, who are the most influential people, and so on. The following decision problems are all applicable to social network analysis:

- What is the formal and informal structure of the organization and its impact on the decision(s) process?

- Given limited resources (money, power, access, friendship, and so forth), what is the best way to influence the groups or individuals represented in the social network under consideration?

- What is the best way to restructure (strengthen or weaken) a social network such that it has certain properties (for example, everyone knows everyone else fostering an environment of friendship or only the official hierarchy is used to make decisions leading to a formal bureaucracy, and so on)?

- What is the best strategy to isolate a person or group from another person or group?

- Who are the appropriate individuals to assign a particular task, hire or not hire, or give access to (such as security clearances or admission to a particular social network)?

The general types of decision problems described above cover many problems that may be considered for specific scenarios. Each of these decision problems has multiple alternatives, each alternative may have differing consequences or outcomes depending on the scenario, and uncertainty is likely to exist in most social network models – with respect to behavior over time even if all initial values were known (an unlikely case in itself). Based on Kirkwood's definition of a decision, each of these problems represents a decision. For non-trivial scenarios (a trivial scenario would be one where all of the alternatives result in the same exact outcome, for example) these decisions are difficult, complex, and uncertain.

Robert Clemen, in his text *Making Hard Decisions*, further notes that decisions may be hard due to: complexity, inherent uncertainties, multiple objectives, and different perspectives leading to different conclusions (Clemen, 1991:2-3). Clemen defines complexity as a combination of the following: number of alternatives, number of factors influencing outcomes, number of uncertain factors, amount of uncertainty, and number of possible outcomes (Clemen, 1991:2). It is clear for decision problems involving social networks that there may be multiple alternatives, many ways in which social networks are influenced, potential for great uncertainty (especially for non-cooperative scenarios such as modeling political or corporate adversaries), and several possible outcomes.

A decision-maker may consider an array of decisions simultaneously (for example, minimizing the cost of resources while maximizing closeness to the desired structure and minimizing cascading effects). Different perspectives may lead to very different outcomes. A classical example is mirror imaging, modeling one's adversary who has a different culture based on the norms of the modeler's culture. If the two cultures do not share the same norms, the resulting representation of social behavior is likely to be very different than if a person from the culture being modeled were to build the model, assign values to its properties, and so on.

Clemen defines a "*requisite* decision model" as a model that "contains everything that is essential for solving the problem" (Clemen, 1991:9). He adds that, "a model is requisite when the decision maker's thoughts about the problem, beliefs regarding uncertainty, and preferences are fully developed" (Clemen, 1991:9). It is clear that in building a decision model for a social network, a requisite model is desired – in that, an analyst would not want to neglect any factors that are essential for solving the problem at hand. In the next few sections of this chapter elements of Single and Multi-Criteria Decision Analysis are discussed in terms of building a social network model.

Overview of Decision Analysis. A *decision* is a choice that must be made between two or more *alternative* courses of action, where only one alternative can be selected (Kirkwood, 1997:2). Most often alternatives will result in different *outcomes* and these different outcomes may have different *values* in terms of dollars, distance, time, or some other measure which could even be unitless (Kirkwood, 1997:2). Aspects, called *uncertainties*, of a decision may be uncertain or unknown at the time the decision must be made (Clement, 1991:2). Uncertainties are often the result of imperfect information on all the requisite details of the given decision problem (Clement, 1991:37-38). Other factors that may complicate a decision problem include the decision-maker's *time horizon*, the time to realize the value of a specific outcome (Clement, 1991:21), and attitudes about *risk* in terms of money, physical safety, or other consequences (Clement, 1991:6).

Decision Analysis (DA) methods can be broken down into two broad categories: single-criteria and multi-criteria models. This section first reviews single-criteria models and their representation, including decision trees and influence diagrams. After reviewing single-criteria models, multi-criteria models are then addressed with an emphasis on Value Focus Thinking (VFT). As in past sections of this paper, the goal is not to make the reader an expert on Decision Analysis, but rather to describe some areas where DA may be of use in developing a social network model.

Single-Criteria Decision Analysis. Single-Criteria Decision Analysis is a key starting point in an examination of DA. Multi-Criteria Decision Analysis (MCDA) will build on this foundation. A single-criteria decision problem is one in which the decision-maker(s) is only trying to maximize or minimize the value of a single measure or criteria (for example, profit, weight, or fuel consumption). Two related representations of these types of problems, Influence Diagrams and Decision Trees, are described in this section.

An Influence Diagram, as shown in Figure 4, represents all the aspects thought relevant to a decision problem and their affinities to each other in a picture (Kirkwood, 1997:326). Different shapes are used to represent the nature of elements of the problem (Kirkwood, 1997:326). As an example, using the definitions found in the software package Decision Programming Language (DPL), decisions are represented as rectangles, known values and functional relationships are depicted as rounded rectangles, and uncertainties are represented as ovals (DPL, 1995:27). Arrows, directed arcs, are used to show how the various elements are related (DPL, 1995:27). An influence diagram could be used to represent the influence between individuals and groups in a social network, as shown in Figure 4. Associated with the arcs in the influence diagram are probabilities or functional relationships of the data provided. Uncertainty nodes represent probability distributions. The influence diagram is used to calculate the expected value of the single criteria of concern in the problem (denoted *value* in Figure 4).

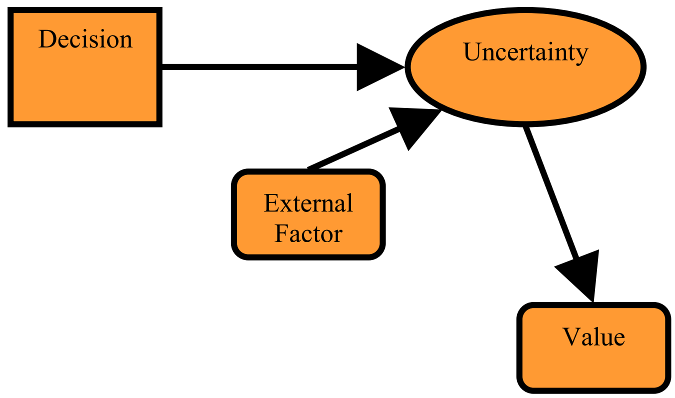

Figure 4. Example Influence Diagram

A Decision Tree represents the same type of information as found in an Influence Diagram, but in a different pictorial representation. Influence Diagrams are an excellent tool for visualizing the complex connections between elements, both known and uncertain, in a decision problem; however, Influence Diagrams alone mask much of the underlying information about the problem (Clement, 1991:49). A Decision Tree overcomes this problem by starting at the root node (the decision) and exploring branches (edges of the graph) for every alternative and every probabilistic outcome (continuous probabilities are most often discretized for this type of analysis) resulting from uncertainties (Kirkwood, 1997:326).

At the end of each path through a decision tree's edges and nodes (representing known values and uncertainties), are values for each outcome (Kirkwood, 1997:326-327). This approach results in the complete enumeration of every possible known outcome. Using these values it is possible to calculate the *expected value* by summing the value of each possible outcome multiplied by the probability that the outcome occurs for each alternative (Clement, 1991:68-70). Neglecting risk preference (termed *risk neutral*) the best choice is the alternative that minimizes or maximizes, as appropriate, the expected value (Clement, 1991:367). Theory also exists to consider decision-makers who are *risk seeking* or *risk averse* (Clement, 1991:367).

Figure 5 gives an example of a Decision Tree representing two successive coin flips. Each coin flip has a 50% probability of either resulting in a "Head" or "Tail." There are three possible outcomes: 2 Heads, 1 Head and 1 Tail, or 2 Tails. The outcome with 1 Head and 1 Tail is found by following two different paths through the decision tree. If one wants to know the expected value (EV) for the number of heads, following each path through the tree derives the following formula:

$$EV[Heads] = 0.50(0.50(2)+0.50(1))+0.50(0.50(1)+0.05(0)) = 1 \text{ Head} \qquad (1)$$

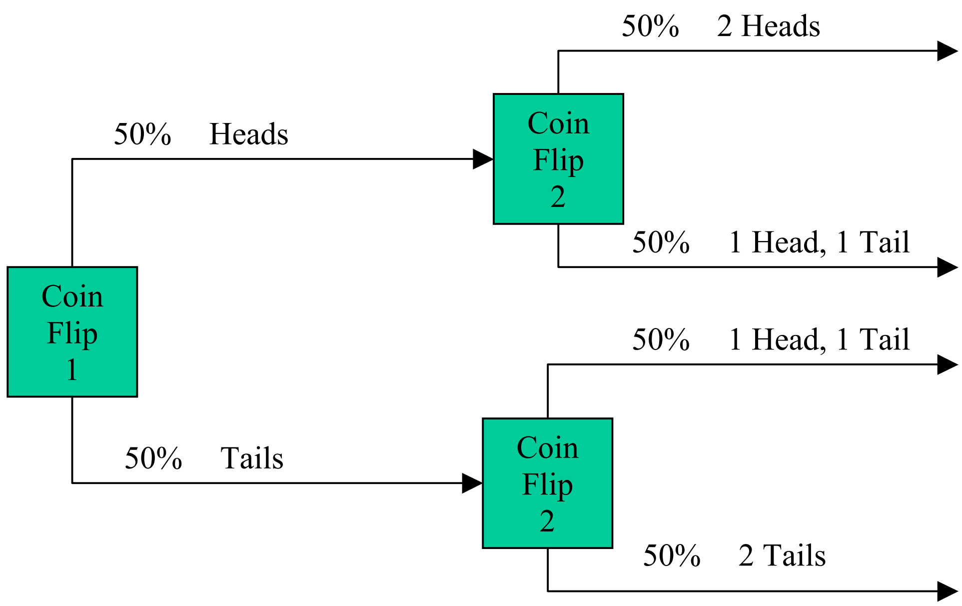

Figure 5. Example Decision Tree

Influence Diagrams and Decision Trees are valuable analytical tools for representing and analyzing single-criteria decisions; however, do not readily support a multi-context, multi-criteria, cross-cultural social network model. Clearly, Single-Criteria Decision Analysis would force the analysis back to a single-criteria social closeness framework. In addition, a social network is made up of many decision-makers, found in what has already been defined as corporate groups, who make many decisions with various degrees of imperfect information. This situation requires separate models for each corporate group. The thought of complete enumeration in such a framework, even when probabilities are all discretized, is not appealing. The next section of this paper discusses the Situational Influence Assessment Module (SIAM). SIAM attempts to address some of the problems found in using Single-Criteria Decision Analysis by using Bayesian Influence Nets.

Situational Influence Assessment Module (SIAM). The Situational Influence Assessment Module (SIAM) is a tool designed to support analysis of complex problems across many domains by building an analytical model describing the "impact of all issues, events, perceptions, and other factors which are believed to be of some significance" to the problem under consideration (SIAM, 1998:1). This analytical model is termed an *Influence Net*. An *Influence Net* is a graph where the nodes represent events and the edges represent causal relationships (SIAM, 1998:9).

Each node is a statement of some aspect of the problem (for example, "Company X is on the verge of collapse"). Associated with each node is a *belief value* indicating the degree to which the user thinks this statement is true or false (SIAM, 1998:9). Edges are directed and weighted in an *Influence Net*. The weight of an edge represents the *strength* of the connection, where *strength* is the "degree the parent [node from which the directed edge originates] will help or hinder the occurrence of the child node" (SIAM, 1998:10). Nodes that have no parents are called *initial nodes* (SIAM, 1998:10). Nodes that have no children are called *root nodes* (SIAM, 1998:10). SIAM requires that an Influence Net contain only one *root node* (SIAM, 1998:112). Nodes that fall on any path from an initial node to a root node comprise the root node's *ancestry* (SIAM, 1998:10). SIAM requires that every node in an *Influence Net* be *connected*, exist somewhere in the ancestry of the root (SIAM, 1998:113).

Once the user has defined the nodes (statements about the environment) and edges (including weight and direction) in the *Influence Net*, belief values can be manually entered or calculated automatically from the belief values associated with the initial nodes (SIAM, 1998:12). Automatic calculations are made through the successive application of *Bayes' Rule* (SIAM, 1998:116). *Bayes' Rule* can be understood as follows: given k mutually exclusive, collectively exhaustive states, $(B_1, B_2, \ldots, B_k)$ of a space, S, such that $S = B_1 \cup B_2 \cup \ldots \cup B_k$. $P(B_i)$ is then the prior probability of B_i where $P(B_i) > 0$ $\forall\, i = 1, \ldots, k$. For each possible outcome A_j of an experiment or observation for each possible state B_i, $P(A_j|B_i)$ is defined as the likelihood of the outcome A_j given state B_i. Bayes' rule defines the posterior probability, $P(B_i|A_j)$. Using this definition, Bayes' Rule states that (Mendenhall, 1990:64):

$$P(B_i|A_j) = P(A_j|B_i)*P(B_i) \,/\, \Sigma_i\, P(A_j|B_i)*P(B_i) \qquad (2)$$

The fundamental output of SIAM is an estimated posterior probability of truth (or falsity) of the statement represented by the root node of the Influence Net (SIAM, 1998:116). SIAM can also "identify those nodes with the greatest impact on or potential for change of a selected node" (SIAM, 1998:118). Nodes with a high potential to change the root node's probability are termed *pressure points* (SIAM, 1998:122). SIAM has automated sensitivity analysis of three types of *pressure node* belief values: *pressure* *points*, *pressure parents* (parent nodes of *pressure points*), and *highlighted pressure nodes* (a user selected set of *pressure points* or *pressure parents*) (SIAM, 1998:122-123).

As can be seen from this brief description, SIAM is a powerful tool with many favorable implementation and analysis features. Considering SIAM from the standpoint of social network modeling, however, reveals some areas of weakness. First, by allowing only one root node, SIAM forces the user into a single context framework similar to Single-Criteria Decision Analysis. Second, SIAM is primarily designed to focus on changes in the environment surrounding a decision by modeling events rather than specific individuals and their perceptions about the environment. Third, SIAM relies heavily on (and is held hostage to) user defined continuous quantification of belief from true to false (which is later discretized) and the strength of ties between events in the *Influence Net*. If the user overrides the automatic Bayesian expansion of the belief structure, it is easy to introduce inconsistencies deviating from the underlying statistical theory. Fortunately, SIAM has a mechanism for testing for such inconsistencies (SIAM, 1998:110). Unfortunately, the only solutions to inconsistencies offered are: for users to manually alter their evaluation, for SIAM to apply its automated Bayesian approach, or, in some cases, to continue the analysis with these known inconsistencies.

Despite these problems for implementing a multi-criteria social network in SIAM, SIAM is a possible tool to support the continuation of this research. Altering SIAM to overcome the above stated problems is a possibility, particularly if a Bayesian approach is ultimately selected as the most appropriate framework for a given analysis effort. Multi-Criteria Decision Analysis (MCDA) is discussed in the next section. Multi-Criteria Decision Analysis and particularly Value Focused Thinking offers a means of overcoming some of the problems found with single-criteria methods for application to social network analysis.

Multi-Criteria Decision Analysis: Value Focused Thinking. Value Focused Thinking (VFT) is a methodology that accommodates decisions where the desire is to satisfy many, possibly competing, criteria (Kirkwood, 1997:11-13). Other Multi-Criteria Decision Analysis techniques, such as Goal Programming (Rao, 1996:782) and Multiattribute Utility Functions (Rao, 1996:780), are also possible frameworks and are discussed in subsequent chapters of this dissertation. Focus has been placed on VFT for reasons made clear in this section and further explored in Chapter 6. The basic idea behind VFT is to first define in a weighted, measurable, hierarchical manner the values of the decision maker(s). Such a model can be depicted as a *value hierarchy*, a type of graph where the nodes are *values* (or criteria to satisfy) and the edges connect and define the hierarchical structure. Once the value hierarchy is fully developed, it is then possible to evaluate how each alternative satisfies this value structure (Kirkwood, 1997:12). In a social network, a value hierarchy may be used to represent the values held by individuals and groups within the network. The next section describes how to build a value hierarchy.

Building a Value Hierarchy. One type of analytical model selected for study in this research is a "value hierarchy," which will be shown to have a natural fit to Trait Theory. A value hierarchy is a "value structure with a hierarchical or 'treelike' structure" (Kirkwood, 1997:12). A value structure is:

> The entire set of evaluation considerations [traits], objectives [preferred direction of movement], and evaluation measures [measures of traits] for a particular decision analysis (Kirkwood, 1997:12).

A correctly specified value hierarchy has several desirable characteristics. These characteristics guide the selection of specific theories to include in a value model. Desirable characteristics are the properties of completeness, nonredundancy, independence, operability, and small size (Kirkwood, 1997:17-18).

Completeness means that the value hierarchy should include all relevant factors involved in the given decision analysis (*i.e.*, the model should be requisite). Nonredundant indicates that the same value is not included in more than one part of the hierarchy. Independent, a broader concept than nonredundant, states that no values should be directly correlated to each other. Operable is defined as a representation that is helpful to the user. Small size implies that a smaller model is preferred to a larger model, if the results are similar.

Associated with every tier of the hierarchy are weights. Each value is weighted relative to the other values in its tier that share the same parent in the hierarchy. Within a given tier of the value hierarchy, all weights are on a [0,1] scale and sum to 1. Values are propagated up the hierarchy often in a linear weighted manner (requires that measures, or traits, modeled be additive). Thus, it is possible to observe the value of each alternative at any given tier in the hierarchy (*i.e.*, any level of aggregation).

A common, cross-cultural value hierarchy may be constructed from the foundation of the pillars of personality already described in this research: *Common to All People*, *Cultural Effects*, and *Individual Traits*. This application of VFT overcomes many of the problems described with Single-Criteria Decision Analysis, but at the same time is a very non-traditional use of VFT. The proposed VFT approach uses the same value hierarchy for every person, but with different weights and scores for the values (or traits) measured. It may be possible to use a value hierarchy, again with different weights and scores for the values measured, for each corporate group at an aggregated level. The significant problem to such a method is populating the model with the necessary weights and scores for the values measured. Most often these weights and scores are gathered from direct interaction (termed *elicitation*) with decision makers (Kirkwood, 1997:23) or at minimum from written doctrine (Kerchner, 1999:1, Kerchner, *et. al.*, 2001:45).

At best this process would be time consuming, possibly to the point of intractability, and may even be impossible for non-cooperative situations (for example, analyzing the social network of a political or business adversary). For these reasons, psychological profile based assessments are considered as a source of data for this research. Clearly using psychological profiles for cases where decision makers are not accessible, value functions developed may be inherently flawed or at least uncertain, if constructed in a traditional manner. Random Utility Models (RUM) offer a solution for dealing with especially uncertain data, whereas, sensitivity analysis may be appropriate for cases with less uncertainty.

Random Utility Models. For the purpose of this discussion, the proposition that value functions are utility functions or at least can be treated as such is accepted. Random Utility Models (RUM) are not a defined set of models, but rather a broad set of techniques for handling cases in which utility is stochastic. The *Handbook of Utility Theory* states:

> Traditional utility theories assume that preferences are deterministic, that their utility representations use nonrandom, real-valued functions determined up to a group of order-preserving transformations, and that choices from feasible sets [of alternatives] maximize utility or expected utility and are unique except when two or more alternatives have equal maximizing utilities (Barbera, 275).

Stochastic utility "refers to theories of preference or choice that violate one or more these assumptions" (Barbera, 1998:275). For the case of psychological profile based assessment, traditional utility functions may exist for the traits and individuals being modeled; however, may only be estimated or bounded by a psychological profile based assessment. For this reason, a *stochastic utility* approach seems naturally appropriate when uncertainty is exceptionally high and the nature of that uncertainty is known or may be estimated.

Other theoretical problems exist in the development of a VFT based social network model as well. For example, human psychology contains dependencies as noted earlier. Further, predicting changes in psychological state does not necessarily imply a specific overt behavior will result. As noted, these complexities have encouraged some researchers to consider Chaos and Complexity Theory as a framework. One tool for this type of modeling is Swarm.

Swarm. Before the details of Swarm can be addressed, it is necessary to add more terms to our vocabulary. "An *agent* is any actor in a system, any entity that can generate events that affect itself and other agents" (Askenazi, 1996:3). Typically an agent is defined by a "set of rules" to describe the agent's reaction to stimuli (Askenazi, 1996:4). A chronological list of *discrete events* impacting agents over time (*i.e.*, time advances only by the occurrence of events) is a *schedule* (Askenazi, 1996:3). "A *swarm* is a collection of agents with a schedule of events over those agents" (Askenazi, 1996:4). A swarm may be a collection of agents, other swarms (called *embedded swarms*), or a mix of both (Askenazi, 1996:4). The *environment*, the world as known to the swarm, surrounding the behavior of agents and embedded swarms is also modeled as an agent in Swarm (Askenazi, 1996:6).

Swarm is a multi-agent, discrete-event simulation software tool (Askenazi, 1996:1). Swarm offers a very flexible modeling environment, but is most applicable to highly complex models of behavior that emerges over time based on the interaction of some abstract type of agent(s) and embedded swarms with each other and their environment (Askenazi, 1996:2). In Swarm, "there are no domain specific requirements such as particular spatial environments, physical phenomena, agent representations, or interaction patterns" (Askenazi, 1996:3). This high degree of flexibility makes Swarm a candidate for implementing a social network model.

Swarm allows an agent to have a "cognitive component" defining a set of rules for "an agent's own beliefs about its world [or environment]" (Askenazi, 1996:4). Swarm would definitely be a tool to consider when looking at how a social network changes over time. In this context, *agents* could represent individuals and *embedded swarms* could represent clusters or corporate groups at any degree of aggregation. The *environment* agent could represent a single-context of interaction or a complex, even emergent, type of interaction. These properties suggest that *Swarm* offers a modeling environment appropriate for analysis based on a Chaos or Complexity Theory representation of social networks.

This chapter has reviewed literature and techniques from the Social Sciences and Operations Research in order to establish a foundation on which to build a methodology that bridges the gaps between these two domains in terms of social network analysis. A number of theoretical gaps have been identified. In addition, a wide array of applications have been described. The next chapter of this dissertation presents the methodology to be implemented in this research focused at filling specific theoretical gaps and demonstrating techniques applicable to multiple applications for business, government, military, and other relevant fields.

Chapter 3. Overview of Methodology

The methodology to be applied in this research has three main aspects: (1) mapping social network analysis to a classic Operations Research optimization framework, (2) aggregation and disaggregation based on Graph Theory, and (3) Decision Analysis applications exploiting Value Focused Thinking. Each of these aspects is outlined in this chapter.

Mapping Social Network Analysis to Operations Research

Developing an analytical model for social network analysis requires a mapping of the aspects of social networks to an existing Operations Research problem class. This study maps social networks to a classic Operations Research network flow model. Chapter 4 demonstrates that flow models are an appropriate and useful means of analyzing social networks.

Specifically, the properties of measures applicable to the use of network flow models in a social network context are defined and their mathematical properties proven in this research. This definition accommodates measures of social closeness that are at least ratio in nature. The definition established in this research provides for non-metric measures and is proven to meet the assumptions of mathematical programming. The properties of the metric subset of social closeness measures is also defined and proven. When metric measures are used, other techniques such Multi-Dimensional Scaling (which requires metric measures) are applicable to the analysis in addition to the optimization techniques developed in this study.

The mapping of social network analysis terms to mathematical programming, and specifically flow modeling, is non-trivial. The taxonomy of this mapping is developed, defining specifically how Social Science theory aligns with the optimization implementation of social network analysis.

Social network analysis using a flow model representation is demonstrated by starting with a single criteria (social closeness measure) for a single context. This class of problem maps to the classic single-commodity flow problem. This discussion extends directly to the development of the multi-criteria case. Two problem classes are demonstrated. The first class being that of independent measures across multiple contexts, denoted *multi-criteria*. The second case discussed is for cases where multiple measures of social closeness share capacity across multiple contexts, denoted *multi-commodity*. The first case maps to multiple independent single-commodity flow models and the second case to classic multi-commodity flow problems.

Gains and losses are next considered. In a social network context, gains and losses represent predispositions, communication problems, and other similar factors based on the specific scenario under consideration. Thresholds can also be set for cases where individuals or groups require a minimum level of influence before they take a specific course of action.

The flow model framework sets the stage for the consideration of multiple objectives with respect to the influencing effort(s) under consideration. These multiple objectives are analyzed using Goal Programming. Partial Lagrangian Duality is demonstrated as an efficient solution technique for Goal Programming for problems with an underlying flow network structure. The Partial Lagrangian Duality method allows for increased efficiency by maintaining the underlying network structure (*i.e.*, unimodularity) of subproblems.

Chapter 4 concludes with a discussion of how to deal with measures and models that violate the assumptions of mathematical programming. Sensitivity analysis is demonstrated for the flow modeling and goal programming cases. Examples used in Chapter 4 are hypothetical, randomly generated using computer code developed for the purpose of this research to test analysis methods, and from actual case study data from publicly available sources. Large scale examples are included to demonstrate the capability of these methods to solved real-world scale problems for business and geopolitical case studies in Chapters 4 and 5.

The methods described in Chapter 4 are extended in Chapter 5 in terms of defining consistent aggregation and disaggregation techniques for social networks. Aggregation allows for faster analysis of large problems by reducing the number of nodes and edges to the fidelity required for a given analysis effort. Disaggregation allows the analyst to increase the fidelity of an analysis effort when required for additional detail based on the aggregated network solution or refinement of the problem statement. Large scale case study examples are considered, directly addressing a theoretical gap noted in Chapter 2 with respect to considering large scale problems.

The concept of psychological-profile based measures of social closeness is developed in Chapter 6. Decision Analysis, and specifically Value Focused Thinking (VFT), is used to develop a Trait Theory based cross-cultural model of individual behavior. The VFT measures are then used to generate social closeness values based on Social Science theory. This technique adds a great deal of capability for the analysis of non-cooperative social networks or network were little data is known apriori on the social closeness of individuals. This psychological profile based measure may also be used as one of several measures, including those demonstrated and discussed in Chapter 4, in a multi-criteria analysis.

A social network may be aggregated into a corporate group of one or more decision makers. The aggregation of the psychological profile based social closeness measure then becomes a weighting scheme for a single combined aggregated value hierarchy. This aggregate value hierarchy may then be used to evaluate alternatives or predict courses of action from a discrete set of alternatives using VFT analysis.

Chapter 6 discusses and proves necessary theoretical expansions to VFT. Sensitivity analysis using a sample case analysis is also demonstrated. VFT methods are demonstrated with respect to limiting uncertainty in otherwise subjective data by properly using elicitation for data collection.

These methods require less data collection, fewer mathematical assumptions, produce more detailed results, and accommodate more problem classes than traditional Social Science methods. Comparisons are made between these methods and Social Science methods with a focus on Multi-Dimensional Scaling, as Multi-Dimensional Scaling is the current leading analysis technique for social network analysis, as described in Chapter 2. The methods developed in this dissertation are based on existing Social Science theory, the legacy of social network analysis methods, and well-founded Operations Research methods. Theoretical developments presented are with respect to extending Operations Research methods. The remaining sections of this chapter discuss some of the theoretical gaps encountered and the theoretical contributions made in this research beginning with a discussion of the measurement theory problems encountered.

Measurement Theory Implementation Problems

The problems in the Measurement Theory domain to operationalize this study are multi-fold. The first step is to classify the measures collected and reported by the Social Science methods currently in use. Measures meeting the definition provided for social closeness in Chapter 4 are applicable to all of the methods developed in this research. Those not meeting this definition *may* be considered, but in the context of the discussion dealing with violation of assumptions. It has been noted in Chapter 2 that many existing measures are non-metric. Several existing social network analysis methods, such as MDS, require metric measures or use an approximation. As noted, many analysts simply accept these violations of assumptions in part because of a lack of a robust non-metric analysis capability such as that provided by this research.

As an example, the MBTI assigns binary, nominal categories to four measures of personality; however, underlying this categorical system are the results of a survey that counts answers to survey questions and groups them into eight bins (one for each of the four binary, categorical measures). The tallies in these bins are integers (a counting of answers which place a given response in a particular bin). Measures such as these integer valued countings may be used directly rather than the binary, nominal categories in social network analysis. Chapter 4 discusses cases of measures applicable to social network analysis based on existing data collection and analysis techniques found in the Social Sciences. Chapter 6 describes the use of psychological-profile data to construct measures of social closeness.

As already discussed, it is unlikely that any of the measures considered meet all of the properties of a metric. Likewise, the advantages of a metric measure have also been discussed in Chapter 2. Chapter 4 defines and proves the properties of the subset of social closeness that does conform to a metric. Metric measures are particularly useful when found, as they may be used in existing Social Science methods requiring a metric measure such as Multi-Dimensional Scaling (MDS). Chapter 4 discusses in detail the advantages of flow model analysis, including the fact that metric data is not required. Flow model analysis is compared in detail to MDS and its extensions to non-metric data.

A further problem exists, particularly for measures that are not known with certainty. As noted, certainty is an underlying assumption of mathematical programming techniques. There are probabilistic ways of handling uncertainty. Decision Analysis, as previously discussed in this methodology, is an excellent method for handling decision making under uncertainty. This research will identify the limits of models with uncertain measures and establish bounds on their use. Uncertainty is discussed in Chapter 4 with respect to violating this assumption in mathematical programming. Chapter 6 discusses the use of Decision Analysis methods to handle uncertainty.

It has also been noted that some of the Social Science measures will have dependency on other measures. Most of the modeling techniques considered, other than those specifically for dealing with non-linearities, assume that measures are independent. This problem will be handled by careful selection of measures and models in Chapter 4 and theoretical expansion of Decision Analysis in Chapter 6.

Besides not being real or integer valued, often having significant uncertainty, and inherent dependency, some measures are expected to be non-linear and non-additive. It has been noted that Trait Theory is fundamentally linear and additive; however, State Theory is non-linear and non-additive. Mathematical programming techniques for non-linear optimization exist and are discussed in Chapter 4, however, non-linear Social Science measures are likely to have some or all of the other problems noted above (some of which violate the assumptions of linear programming, including being dependent, not necessarily proportional, and uncertain). For these reasons, the advantageous properties of Trait Theory discussed in Chapter 2 and the existence of publicly available datasets, Trait Theory serves as the foundation for the models developed in Chapter 6.

Recall that it is not a focus of this research effort to develop new Social Science measures that meet all the assumptions of a metric or even those of mathematical programming. Rather, this effort is focused on developing valid Operations Research models that build on existing Social Science theory in defining the model formulation. For this reason, the core of this research is on Operations Research methods and theory to model social networks and provide a wide variety of options to analyze social networks.

Theoretical difficulties with Social Science measures impact on their use in Optimization and Network Models as well as aspects of Decision Analysis. Other theoretical questions for using these Operations Research methods are discussed in the next sections of this chapter.

Optimization and Network Model Implementation Problems

Social closeness as a measure of potential influence is represented as a capacity of an edge rather than a weight or cost for problems mapped to a flow problem or multi-commodity flow problem. In this mapping, social closeness represents a capacity on an edge. Such a mapping is interesting as it implies that social closeness may not always be fully exploited to influence others in every case.

Representing vector-valued social closeness as a capacity implies a multi-commodity flow formulation must be considered. A multi-commodity flow problem is one in which individual commodities share capacity on edges in the network (Ahuja, 1993:649). Sharing capacity on the edges in a social network implies that either capacity of the edge is an aggregate of multiple contexts, or based on a known sociological or psychological property of the measured influence where one context directly manifests itself in another context. For example, a person may be influenced in a business decision by others not in the network associated with business decision making. True multi-commodity models, where capacity of influence is shared between contexts, as well as multi-criteria models, where more than one commodity flows between individuals without sharing capacity are discussed in Chapter 4.

Chapter 6 defines applications of Decision Analysis and describes approaches where shared capacity across multiple contexts may be quantitatively measured. Using these Decision Analysis methods it is possible, given appropriate data, to model how much religion, for example, impacts an individual's or group's decision making in other contexts.

To use the Value Focused Thinking model for prediction of decision making, it is essential to know every significant alternative available. Unlike the case of influencing, where the user makes environmental changes, the case of predicting must consider future decisions that are entirely up to the target person or group. For a mathematical solution to be found, the set of possible alternatives, called the decision space, must be finite. In addition, for a solution to be found in a reasonable amount of time the *decision space* must contain a discrete number of alternatives and not a continuous spectrum of alternatives. Sample cases will, thus, be restricted in this manner.

No assumption is made that all of the nodes influenced must be influenced the same way, by a single change to the environment, or even that the nodes involved exist in the same context. Mathematical programming and Decision Analysis are viable frameworks on which to build social network analysis applications with an ability to represent the underlying Social Science theories. Therefore, the methodology described represents a starting point believed to lead to significant results that will help to elucidate an operable approach and add insight to areas where other techniques may be applicable.

The size of a social network has been noted in Chapter 2 as an existing problem for the Social Science methods currently in use. As demonstrated in Chapter 4, optimization methods exploiting network structures can accommodate large scale problems. For problems that do not require the fidelity of a large social network, an analyst would desire to aggregate the network to increase the efficiency of the analysis. Chapter 5 discusses aggregation and disaggregation and demonstrates cases where single and multi-context graphs are aggregated.

Graph Theory Implementation Problems

The contraction procedures involved, in general, offers multiple combinations of the iterative application of pairwise contractions leading to the same aggregated graph. This alone is not a problem. A problem occurs if these multiple solutions do not result in the same values for social closeness in the same aggregated graph. Contraction procedures are developed in Chapter 5 to achieve this necessary consistency and include properties defined by the Social Sciences and cluster analysis to insure repeatability.

Identification of Measurement System

The first step to developing the psychological profile based measures in Chapter 6 is the identification of a model of individual personality. This will be accomplished by reviewing accepted trait theoretical measurement systems and selecting a measurement system(s) that best demonstrates the properties of additivity, independence, completeness, nonredundancy, operability, and small size as well as acceptance and credibility among Social Scientists. These properties were selected because they are requisite to a Value Focused Thinking model, as noted in Chapter 2. The Myers-Briggs Type Indicator (MBTI), Alderfer's Existence, Relatedness, and Growth (ERG) Theory, and the complementary work of others described in Chapter 2, are implemented in a Value Focused Thinking model in Chapter 6 due to their characteristics relative to the above criteria and current use across many domains. This approach presents several theoretical challenges in terms of Value Focused Thinking described in the next section.

Modeling Individual Behavior

A Value Focused Thinking (VFT) value hierarchy of individual behavior will be constructed based on traits, rules, and assumptions of the selected measurement system. It is known that this model will contain dependencies, violating an underlying assumption of VFT. These dependencies are modeled in the value hierarchy based on their proper assumptions under the measurement system applied. Theoretical extensions to VFT are described and proven mathematically to deal with this violation of assumptions for a specific class of linear transformations of measures. The essence of the proof is that certain transformations of measures do not contradict an additive, weighted, linear model of preference consistent with VFT, in general.

Chapter 6 discusses how to use the psychological profile data in the VFT model to build measures of social closeness that may then be used in the flow modeling methods developed in Chapter 4, either as single commodities (criteria) or as part of a multi-criteria analysis. The next section outlines this methodology.

Measuring Social Closeness

The results of the VFT model will be used to develop delta sender-receiver measures (*i.e.*, calculating the difference between preferences in directed, pairwise relationships) of social closeness using results from various tiers in the value hierarchy based on behavior already described that applies generally (homophily, for example) and specifically based on culture (kinship, for example). This measure of social closeness will then be used to create and weight a single-criteria social network graph demonstrating additional behavioral phenomena (triad closure, for example). The resulting graph will be a digraph since multiple edges or loops will not exist; however, weight between individuals may differ greatly. From the single-criteria (single-commodity) case, the model is extended to a multiple-criteria, multiple-context case using the VFT based social closeness measure or other existing measures.

Multiple Context Model

The transition to a multi-context model starts from the observation that if the data used to develop social closeness measures had been collected for contexts other than that modeled in a given analysis, that the resulting model would carry with it the validity that has already been tested. The mathematics applied in traditional social network analysis techniques and the models postulated in this research would not change based on the data set under analysis, as the techniques are not dependent on the data set. It is transparently possible to construct multiple models involving the same people for different contexts simply by changing the context in which the data is collected. Likewise, additional individuals can be added to various contexts without any additional theory required to use the model. The multi-criteria case has a similar theoretic foundation.

Multiple-Criteria Model

To extend this work to a multi-criteria methodology, a vector social closeness weight on edges, that includes other measures of social closeness, is developed in Chapter 4. These additional measures may include the cardinality type measures already discussed (the Small World strength measure, for example). Other measures could be included for specific scenarios, such as the number of communications in a specified time period. However, to retain independence and nonredundancy, these additional measures should not rely on any data used to create other measures already incorporated in the optimization. If the use of dependent measures is required for a specific application, one of the dependent measures should be modeled as fixed and the others as functions of this dependent measure. Dependencies can be avoided through diligent selection of measures and, often, dependent measures could simply be excluded from the optimization (and tested separately for inclusion, if desired and when appropriate).

Conducting Analysis

Using this methodology, a multi-context, multi-criteria social network is developed, tested, verified, and validated. The existence of such a network does not, however, provide all that is necessary to correctly conduct further analysis.

The delta sender-receiver psychological profile based measure may in general take on negative values. As already noted, this is a problem in some network optimization methods. This problem, unlike the others to be discussed, is relatively easy to handle by rescaling the data such that all of the values are positive. Rescaling of data is discussed and demonstrated in Chapter 4 for all measures used in a multi-criteria model.

Using Trait Theory as a foundation for the psychological profile based measure and restricting other measures to only those which are proportional, additive, divisible, and certain in nature, provides enough mathematical foundation to proceed with the analysis techniques developed in this dissertation. This research explores the theoretical metric limitations of the measures used in this methodology by defining the properties of a metric over the space represented by the measures modeled. Even if no existing measures conform to a metric in the space under consideration, the properties of such a metric are defined and proven. For non-metric measures, the limitations of the modeling approach are clearly delineated.

Previous discussion, in Chapter 2, has already established that a Trait Theory based model is linear and additive. Restricting other measures included to those that are linear allows for the application of most traditional network optimization techniques for each measure in a single-criteria analysis. Allowing non-linear measures requires the use of non-linear optimization techniques.

Using the above methodology, it possible to model a social network across multiple contexts and using multiple criteria. It is further possible to analyze and understand the behavior of this network for both the single criteria cases and multiple criteria cases. This methodology is extended to predicting behavior using psychological profile data and Decision Analysis methods. Together these techniques form a robust methodology for the analysis of social networks.

This chapter has described the approach taken in this research. Chapters 4, 5, and 6 implement this methodology, proves the necessary theoretical extensions, demonstrates sample cases, and describes the results. This methodology develops better tools for social network analysis than existing techniques.

Chapter 4. Network Optimization Implementation and Results

This chapter describes in detail the implementation of network optimization techniques applied to social networks. In addition, sample cases are used to illustrate these techniques. Two mappings to optimization problem classes are examined in detail. The first mapping is to network flow modeling and the second uses goal programming to perform multiple objective analysis. Both of these models offer significant results useful for the analysis of social networks.

As noted in Chapter 2, measures must be proportional, additive, divisible, and certain to meet the necessary conditions of the linear optimization techniques applied. This chapter concludes with an analysis of the sensitivity of the optimization methods to these assumptions and discusses the consequences of violating one or more of these assumptions. While measures are not required to be metric in nature, this chapter defines the nature of a metric space under conditions commonly found in measuring social closeness. Before considering the impact of measures that violate key assumptions, it is first necessary to consider instances of social networks where the assumptions hold.

Social Network Analysis Mapped to Flow Problems

The fundamental theory of mapping social network analysis to a classic network flow problem is that pairwise measures of social closeness represent the capacity of the potential influence between individuals (Borgatti: 1999, 59). This means that social closeness, distance, similarities, or differences can be represented as capacities on the influence between individuals. Influence, measured by social closeness, distance, similarities, or differences, is, thus, the commodity(s) flowing over the network where the magnitude of the flow is the relative influence. Social closeness and similarities are defined in this study to be strictly positive monotonic (greater magnitude implies greater influence). Likewise social distance and differences are defined to be strictly negative monotonic (greater magnitude implies less influence) (Apostol, 1974:94).

These strictly monotonic functions are related as follows. If x and y are both measures of social closeness, and if $x < y$, then $f(x) < f(y)$ where the function f is the relative influence in a particular context. If x and y are both measures of social distance, and if $x < y$, then $g(x) > g(y)$ where the function g is the relative influence in a particular context. Within the same context, then, $f(x) = -g(x)$; that is within the same context, g is the inverse function of f (Apostol, 1974:94). If $f(x) \neq -g(x)$, then $f(x)$ and $g(x)$ do not measure the same influence (*i.e.*, one or both of $f(x)$ and $g(x)$ are incomplete measures). It is possible for different single-criteria measures, even within the same context, that $f(x) \neq -g(x)$; however, for any $f(x)$ or $g(x)$ an inverse function will exist for all of the ratio type measures used in this study.

For the purpose of this analysis, only social closeness measures are considered and are assumed to have positive monotonicity, on a positive-valued scale. Zero represents the absence of social closeness (or no relationship whatsoever) and in the related social network graph no edge will exist. For measures not defined on this scale, the stated conditions may be achieved through a simple mathematical transformation without loss of detail or generality. For example, under the necessary conditions, social distance (with negative monotonicity) may be converted to social closeness (with positive monotonicity) by multiplying all values by –1. Measures that take on negative values may be rescaled to a positive scale. For example, any number greater than the absolute value of the smallest-valued measure may be added to all measures. For measures where zero does not represent the absence of social closeness, it is also possible to rescale in a similar manner. Such linear transformations are admissible for measures that are at least ratio in nature (Knuze, 1971:67-68).

When considering multiple measures of social closeness it is necessary that all of the data used in a particular study be on the same scale, if they will be weighted against each other in a model (as in weighted Goal Programming, for example). Normalization is only necessary in such models when the various measures are on different scales. If such measures were not normalized, the relative magnitude of their different scales could introducing biasing error, impacting the solution. Normalization is possible since the scale for the normalized data is not important except to the degree that it maintain positive monotonicity, take on only positive values, and zero continues to represent the absence of social closeness. One possible approach is the following transformation:

$$d_i' = f(d_i) = \frac{d_i}{Max_j(d_j)} \qquad (3)$$

d_i is the original social distance value for some edge i, where i is an edge in the social network under analysis with e edges. d_i' is then the normalized social closeness calculated using the function $f(d_i)$ where $Max_j(d_j)$ is maximum valued edge in the set of edges $j = 1, \ldots, m$. This transformation normalizes all of the edge weights to a [0,1] real valued scale, where $d_i' = 0$ if and only if $d_i = 0$. If the measures are update they must be mapped into the existing scale. Note that $Max_j(d_j)$ must be non-zero. If this mapping introduces values less than 0, then it is necessary to rescale.

A social network where edges are weighted with a measure having the specified properties may be mapped to a single-commodity flow problem. A social network with multiple measures as edge weights having these conditions may be mapped to a multi-commodity flow problem or multiple single-commodity flow problems, as demonstrated in this chapter.

Maximum flow problems, with both single and multiple sources and sinks, are useful for the analysis of several problem classes related to the social networks. Maximum flow problems address questions such as: "How much may A sources influence B sinks?" where sets A and B exist in the set of all nodes in the social network N $(A, B \in N)$. The case where A and B have cardinality of 1 is the situation where one person influences only one other person. The case where A has cardinality of 1 and $B = N - A$ indicates that one person, A in this case, attempts to influence an entire network, $N - A$. A may also attempt to influence any subset of $N - A$. Cases where the cardinality of A is greater than 1 represents a combination of people attempting to influence one or more individual in a network. When data is available, achieving specified threshold levels of influence, the effects of predispositions, misunderstanding the message, and other such problems of interest may also be modeled in the flow network representation.

Minimum-cost flow models are applicable to problems of how to influence a network where cost, monetary or otherwise, is associated with influencing individuals. The objective of a minimum-cost flow analysis would be to find the least cost in terms of some predefined resource(s) to generate a desirable flow pattern. A desirable flow pattern may be one where everyone in the network is influenced some specified amount (equally, at least to a threshold level, or other similar conditions), where particular individuals are influenced, certain paths are taken or avoided, or any other similar situation. The minimum-cost flow representation is not needed for cases where the cost is only associated with influencing sources, which may be handled using a maximum flow representation. Minimum-cost flow is applicable to cases where there is a variable cost associated with flow across the network (for example, means of transmitting the information from one individual to another has a cost associated).

Further, the solution to these problems, subject to the accuracy and fidelity of the network representation, provides detailed information as to the number, strength, and path of the influence flowing over the network achieving the optimal solution. This allows the analyst to consider the unintended side-effects of the optimal solution. If undesirable side-effects occur, the problem may be constrained to avoid the conditions associated with the undesirable effect(s). Further, multiple optimal solutions may exist, offering a choice of courses of action of equal value (*i.e.*, equal maximum flow in the case of a maximum flow mapping). These additional problem constraints are a sample of the many possible scenarios that may be easily modeled for an analysis of a social network and its behavior given an influencing stimulus.

This level of detailed analysis is not available in classic social network methods. For example, an analyst could use Multi-Dimensional Scaling (MDS) to determine the person(s) in a network with the least distance (closest) to another person(s) in a network (Borgatti, 1996:30). The MDS solution would not explain how the information would flow in the network or the potential side-effects. Further, any stress in the MDS model implies a lack of fit to the social closeness (or social distance) data (Borgatti, 1996:33). As already noted, MDS methods involve setting both upper and lower bounds on stress. These thresholds mean that unless the number of dimensions is known with certainty and data is collected without error, stress must exist in the MDS solution. In addition, MDS requires metric data or an approximation of metric data (Borgatti, 1996:32-33).

Data available for classic MDS applications for social network analysis is derived from self-reporting cooperative survey tools, polling, or other similar methods. Data appropriate for analysis methods discussed in this dissertation may be derived from many other sources. These sources could include countings of communications across multiple types of media independently or as an aggregate elicitation as described in Chapter 6 for cooperative or assessment for non-cooperative social networks, psychological profile evaluation, and other similar sources. These sources may be used to develop contextual models as well. For example, an analyst could use a history of email communications in an organization to extract the flow of messages over the formal organizational line chart to measure social closeness in the formal context. The remaining data then represents messages flowing over an unofficial (informal) context within the same organizational structure. Additionally, messages from outside unofficial channels could also be observed. These outside ties represent ties to other social networks where the strength of such weak ties, already noted as very important in terms of resources available to a particular network, could be discovered and modeled. This example could be used cooperatively or non-cooperatively relative to the target social network. Whether used for MDS type analysis, the methods defined in this dissertation, or other methods, it is important to understand whether the data is metric or not, as the mathematical nature of the data defines the set of methods applicable to the analysis.

Even when applied to metric data, and properly implemented, MDS lacks detail with respect to what the dimensions actually represented. Two approaches are suggested for labeling the resulting MDS dimensions (axes in a graphical representation): (1) "subjective" and (2) "objective" procedures (Anderson, 1992:330). Subjective procedures involve either or both the analyst and decision-maker(s) using their judgment to label dimensions by visual inspection (Anderson, 1992:330). "There is no attempt to quantitatively link the dimensions to attributes [of the data]" (Anderson, 1992:330). The objective procedure "collects attribute ratings [criteria] for each object and then finds the best correspondence [based on Principle Component analysis or other similar methods] of each attribute to the derived perceptual space [MDS coordinates]" (Anderson, 1992:330). In this approach multiple attributes are assigned to each axis based on which axis represents the greatest *weighting* of particular attributes; however, aspects of the attributes are still manifested in other dimensions as well (Anderson, 1992:330). Neither of these approaches results in a unambiguous specification of the data and attributes.

While non-metric MDS techniques exist, the results of non-metric MDS techniques only retain ordinality of the data and then only if the data were at least ordinal (Borgatti, 1996:19). When ordinality is not a property of the underlying data, Correspondence Analysis may be used; however, only affinity (or correspondence) relationships are retained (Anderson, 1992:340). Correspondence analysis only tells the analyst who communicates with whom in a social network with no indication of the magnitude of that connection in terms of influence. While these non-metric methods are applicable to non-metric data, they lack the detail provided by a flow model representation. In addition, labeling dimensions such that the axes properly represent the underlying attributes remains a problem, as in metric MDS analysis.

In contrast to MDS, a flow model representation does not require metric data (as proven later in this chapter). Flow models, depending on the model used, in general do not require linear objective functions or constraints. The solution to a flow model will include the aggregate flow as well as the flow's path information. A flow model can be modeled to account for gains and losses of flow over the edges. Flow models may be analyzed using heuristic methods to get a good, operable solution when an optimal solution cannot be attained in reasonable time. Any data that meets the underlying assumptions of MDS (*i.e.*, metric data) may be used in a flow model representation. It is shown in this chapter that, for theoretic and practical reasons, a flow representation provides a more detailed solution and has fewer necessary underlying mathematical assumptions than classic Social Network Analysis methods.

Before considering these cases in detail it is necessary to address two possible assumptions regarding the nature of the flow across a social network. First, an analyst may model flow without gains or losses (*i.e.*, conservation of flow). The maximum flow in the network is then bounded above by the sum of the capacity (representing measures of social closeness) originating from the source(s) or into the sink(s), whichever is smaller. An alternative model is to allow gains up to the capacity of each edge in the network involved in the flow. This means that the maximum flow is bounded above only by the sum of the capacity terminating in the sink(s).

The flow without gains case describes a scenario where individuals may not be influenced greater than the sum total of the social closeness of those influencing them (*i.e.*, conservation of flow). Flow with gains (losses) implies that individuals may be influenced more (less) completely by those influencing them no matter the relative social closeness. This latter case implies that those receiving influence may either add or subtract from the influence they send out due to preconceived opinions or influence from outside the network being modeled.

Specifically, gains and losses may be used to represent predispositions of individuals favoring the influence represented by the flow. Losses may also be used to represent predispositions of individuals opposed to the influence represented by the flow or communication problems such as misunderstanding the message. Implicitly, gains and losses represent strengthening or weakening of influence, respectively. These representations may make use of existing flow problem models by using a gain factor (*i.e.*, multiplier).

As discussed in Chapter 2, all of these cases are found in Social Science theory. A particular representation used for a specific analysis must consider the context of the problem under examination. If the nature of predispositions or other communication problems are unknown, flow with and without gain may still be used to bound the resulting impact on the social network of an influencing effort. For cases where the context is not clear, flow without gains represents a lower bound, assuming no losses, and flow with gains represents an upper bound (*i.e.*, it is clear that the optimal solution to the flow with gains representation must be greater than or equal to the optimal solution to the flow without gains representation which, in turn, must be greater than flow where losses may occur). Using gains and losses to represent predisposition requires apriori knowledge of such individual predispositions. Only in cases where such data is available is this representation most applicable (for example, polls or surveys taken early in a decision process would provide this type of data). The use of gains and losses in terms of social network analysis is demonstrated in the example problems to follow.

Formal Definitions and Proofs

In this section, social closeness is formally defined. Social closeness, as defined here, is proven to be a sub-field of the real numbers. Social closeness is in general a non-metric measure. Conditions under which social closeness is a metric measure are stated and proven. Further, it is proven that classic linear flow models do not require metric decision variables.

> **Definition.** *Social closeness* is defined by $s_{ij} \in \{0, \mathbf{R}^+\}$ (where $\mathbf{R}^+$ is the set of positive real numbers) and is the maximum potential influence one person or group (i) has upon another person or group (j) in a set of N people or groups in a given scenario. The set of N people or groups and their associated s_{ij} measures completely define a *social network* when $s_{ij} = a(s_{kl})$, $a \in \mathbf{R}^+$, $i \neq j, k \neq l$, $\forall\, i, j, k, l \in N$ (*i.e.*, social closeness is a ratio measure). When $s_{ij} = 0 = 0(s_{kl})$ and $s_{ii} = 0\ \forall\, i$, there exists no potential influence. Since s_{ij} is directed and the network may be asymmetric, $-s_{ij}$ denotes the inverse of flow between i and j and has the property $-s_{ij} = -a(s_{kl})$, $a > 0$, $i \neq j, k \neq l$, $\forall\, i, j, k, l \in N$. Further, s_{ji} need not equal $|-s_{ij}|$. Social closeness is therefore defined as a set denoted S, where S contains $\forall\, s_{ij}$. S is, thus, a subset of $\mathbf{R}$.
>
> **Theorem.** Social closeness, S, is a field.
>
> **Proof**. Social closeness, S, is a field iff it is (A) closed under addition and (B) closed under multiplication and (C) the following nine algebraic properties hold (Hoffman, 1971:1-2).
>
> (A) Closure under addition: $s_{ij} + s_{kl} = b(s_{kl})$, where $b = 1 + a$ for some $a, b \in \mathbf{R}^+$, $\forall\, i, j, k, l \in N$. Addition is closed since $b(s_{kl}) \in S$ by definition.
>
> (B) Closure under multiplication: $s_{ij}(s_{kl}) = a(s_{ij}) = b(s_{kl})$ where $a = s_{kl}$ and $b = s_{ij}$, for some $a, b \in \mathbf{R}^+$, $\forall\, i, j, k, l \in N$. Multiplication is closed since $a(s_{ij}), b(s_{kl}) \in S$ by definition.

(C) Algebraic properties:

(1) Addition is commutative,

$$s_{ij} + s_{kl} = a(s_{kl}) + s_{kl} \tag{5}$$
$$= (a+1)s_{kl}$$
$$s_{kl} + s_{ij} = s_{kl} + a(s_{kl}) \tag{6}$$
$$= (1+a)s_{kl}$$
$$= (a+1)s_{kl}$$

Therefore, $s_{ij} + s_{kl} = s_{kl} + s_{ij}$

(2) Addition is associative,

$$s_{ij} + (s_{kl} + s_{ab}) = a(s_{kl}) + (s_{kl} + b(s_{kl})) \tag{7}$$
$$= a(s_{kl}) + (1+b)(s_{kl})$$
$$= (a+1+b)(s_{kl})$$
$$(s_{ij} + s_{kl}) + s_{ab} = (a(s_{kl}) + s_{kl}) + b(s_{kl}) \tag{8}$$
$$= (a+1)s_{kl} + b(s_{kl})$$
$$= (a+1+b)s_{kl}$$

Therefore, $s_{ij} + (s_{kl} + s_{ab}) = (s_{ij} + s_{kl}) + s_{ab}$

(3) There is a unique element 0 such that $s_{ij} + 0 = s_{ij}$, $\forall\, s_{ij} \in S$.

$$s_{ij} + 0 = a(s_{kl}) + 0 \tag{9}$$
$$= a(s_{kl})$$
$$s_{ij} = a(s_{kl}) \tag{10}$$

Therefore, $\mathrm{s_{ij}} + 0 = \mathrm{s_{ij}}$

(4) To each s_{ij} in S there corresponds a unique element $-s_{ij}$ in S such that $s_{ij} + (-s_{ij}) = 0$.

$$-s_{ij} = a(s_{ij}), \text{ when } a = -1(b) \text{ and } a = b\ \exists\, -s_{ij} \in S \tag{11}$$
$$s_{ij} + (-s_{ij}) = s_{ij} + (-1(s_{ij})) \tag{12}$$
$$= (1-1)s_{ij}$$
$$= 0(s_{ij}) = 0$$

Therefore, $s_{ij} + (-s_{ij}) = 0$

(5) Multiplication is commutative,

$$s_{ij}(s_{kl}) = (a(s_{kl}))s_{kl} \tag{13}$$

Let $b = a(s_{kl})$, then $s_{ij}(s_{kl}) = b(s_{kl})$

$$s_{kl}(s_{ij}) = s_{kl}(a(s_{kl})) \tag{14}$$
$$= (s_{kl})b = b(s_{kl})$$

Therefore, $s_{ij}(s_{kl}) = s_{kl}(s_{ij})$

(6) Multiplication is associative,

$$s_{ij}((s_{kl})(s_{ab})) = a(s_{kl})((s_{kl})(b(s_{kl}))) \quad (15)$$
$$= a(s_{kl})^2(b(s_{kl}))$$
$$= a(b)(s_{kl})^3$$
$$(s_{ij}(s_{kl}))s_{ab} = (a(s_{kl})s_{kl})(b(s_{kl})) \quad (16)$$
$$= a(s_{kl})^2(b(s_{kl}))$$
$$= a(b)(s_{kl})^3$$

Therefore, $s_{ij}((s_{kl})(s_{ab})) = (s_{ij}(s_{kl}))s_{ab}$

(7) There is a unique identity (denoted 1) in S such that $s_{ij}(1) = s_{ij}$ $\forall\, s_{ij} \in S$.

$$s_{ij} = a(s_{kl}) \quad (17)$$

If a =1, then $s_{ij} = s_{kl}$

So, $s_{ij} = 1(s_{kl}) = s_{ij}(1)$

Therefore, $s_{ij}(1) = s_{ij}$

(8) To each non-zero s_{ij} in S there corresponds a unique element s_{ij}^{-1} in S such that $s_{ij}(s_{ij})^{-1} = 1$.

$$s_{ij}^{-1} = a(s_{ij}) \text{ when } a = s_{ij}^{-2} \;\exists\, s_{ij}^{-1} \in S \quad (18)$$
$$s_{ij}(s_{ij})^{-1} = s_{ij}(a(s_{ij})) \quad (19)$$
$$= s_{ij}(s_{ij}^{-2})(s_{ij})$$
$$= s_{ij}^{2}(s_{ij}^{-2})$$
$$= 1$$

Therefore, $s_{ij}(s_{ij})^{-1} = 1$.

(9) Multiplication distributes over addition,

$$s_{ij}(s_{kl} + s_{ab}) = a(s_{kl})(s_{kl} + b(s_{kl})) \quad (20)$$
$$= a(s_{kl})(1+b(s_{kl}))$$
$$= a(1+b)s_{kl}^{2}$$
$$s_{ij}(s_{kl}) + s_{ij}(s_{ab}) = a(s_{kl})(s_{kl}) + (a(s_{kl}))(b(s_{kl})) \quad (21)$$
$$= a(s_{kl})^2 + (a(b(s_{kl})^2))$$
$$= a(s_{kl}^{2} + b(s_{kl}^{2}))$$
$$= a(1+b)s_{kl}^{2}$$

Therefore, $s_{ij}(s_{kl} + s_{ab}) = s_{ij}(s_{kl}) + s_{ij}(s_{ab})$

$\therefore$ Therefore, since conditions (A), (B), and (C) hold $\forall\, i, j, k, l \in N$ and $\forall\, a,b \in \mathbf{R}^{+}$, social closeness, S, is a field and S is therefore a sub-field of **R**, since $s_{ij} \in \{0, \mathbf{R}^{+}\}$.

The underlying assumptions of a linear program are linearity, additivity, proportionality, divisibility, and certainty (Winston, 1994:53-54). Any mathematical program with a linear objective function, linear constraints, and social closeness measures as decision variables is a linear program as additivity, proportionality, divisibility, and certainty hold, as demonstrated, for any field.

By definition, social closeness is a capacity on potential influence by definition. Potential influence, therefore, can be considered a commodity in a flow network. As such, the flow of influence across a social network, as defined in terms of social closeness, may be appropriately modeled as a flow problem. Since social closeness meets the necessary assumptions of classic flow models, *all* such flow models are appropriate for analysis of social networks without exception.

As noted in Chapter 2 and discussed throughout this dissertation, much of the data available or that may be collected as measures are non-metric. Unlike those measures applicable to MDS, social closeness is non-metric. This adds capability to social network analysis as a whole. When an analyst uses a technique such as MDS for data that is inconsistent with the underlying assumptions of the methods, erroneous results can occur. If an analyst resorts to existing non-metric techniques, the results do not fully make use of all available information (for example, may only maintain ordinality or worse).

Theorem. Social closeness is non-metric.

Proof. Social closeness lacks symmetry, in general,

$$s_{ij} = a(s_{kl}) \tag{22}$$

$$s_{ji} = b(s_{kl}) \tag{23}$$

$$a(s_{kl}) = b(s_{kl}) \text{ iff } a = b, \tag{24}$$

$$\text{thus for } a \neq b,\ s_{ij} \neq s_{ji}$$

Further, the triangle inequality, in general, need not hold,

$$s_{ik} + s_{kl} = a(s_{kl}) + s_{kl} \tag{25}$$

$$= (a+1)s_{kl}$$

$$s_{il} = b(s_{kl}) \tag{26}$$

$$b(s_{kl}) \leq (a+1)s_{kl} \text{ iff } b \leq 1+a, \tag{27}$$

$$\text{thus, for } b > 1+a,\ s_{il} > s_{ik} + s_{kl}$$

∴ Therefore, social closeness is non-metric.

It has already been demonstrated that social closeness meets the assumptions of mathematical programming and, in cases where the objective function and constraints are linear, meets the assumptions of Linear Programming, without exception. For sub-sets of social closeness, which are metric in nature, all of the techniques applicable to non-metric measures still apply. In addition, however, other techniques are also applicable and may be used to provide additional insight to the analyst. These techniques include MDS already discussed, but also mappings to other classic network flow models such as transportation and location problems where distance is assumed to be metric (*i.e.*, such as measures of terrestrial distance). Therefore, it is necessary to rigorously define the conditions under which social closeness is metric, so as not to make the same violation of assumptions found in some classic social network analysis.

The necessary conditions to determine whether social closeness measures are metric are defined and proven in this research.

> **Definition.** A graph is *Triangular* when every node is a member of a clique of three nodes.

> **Definition.** A graph is *Prefect Triangular* if the graph is Triangular and if all edge weights conform to the *Triangle Inequality*. For unweighted graphs, all Triangular graphs are Prefect Triangular graphs, under the assertion that edges may be treated as equally weighted.

As described in the literature review, there is no existing measure of social closeness (or social distance) that conforms to the properties of a metric. However, given the known properties of any measure, it is possible to define the properties of a metric space for that measure in this domain.

> **Definition.** *Metric social closeness* is a social closeness measure(s) where all of the elements (s_{ij}) are metric measures. The space S, defined in terms of social closeness, is then a metric space.

Theorem. Social closeness is metric, denoted metric social closeness, if $s_{ij} = s_{ji}$ $\forall\, i, j \in N$ and the social network defines a graph that is Perfect Triangular.

Proof. By definition, metric space is a nonempty set ϕ of objects (called points) together with a function d from ϕ x ϕ to **R** (called the metric of the space) satisfying the following four properties for all points $x, y, z \in \phi$. If we let $S = \phi$, then $\forall\, i \in N$ are points. For any nontrivial case, S is nonempty. Then let $d = s_{ij} = a(s_{kl})$ for $a \in \mathbf{R}^+$ and $\forall\, i, j, k, l \in N$ then d is a function from ϕ x ϕ to **R**. If the following four properties hold, then S is a metric space and s_{ij} a metric of the space (Apostol, 60).

(1) $s_{ii} = 0$ $\forall\, i \in N$, by definition of social closeness

(2) $s_{ij} > 0$ $\forall\; i \neq j$, since all non-trivial (*i.e.*, non-existent) $s_{ij} \in \mathbf{R}^+$ by the definition of social closeness

(3) $s_{ij} = s_{ji}$ $\forall\, i, j \in N$ by supposition of this theorem

(4) $s_{il} \leq s_{ik} + s_{kl}$ $\forall\, i, k, l \in N$ since the social network is Perfect Triangular

$\therefore$ Therefore, social closeness is metric if $s_{ij} = s_{ji}$ $\forall\, i, j \in N$ and the social network defines a graph that is Perfect Triangular.

Based on these definitions, it is now possible to consider representative sample cases. The following cases are described below: (1) single-commodity flow, (2) multi-commodity flow, (3) single-commodity flow with gains, (4) single-commodity flow with gains and losses (predisposition). Multi-commodity flow with gains and losses follow naturally from the single-commodity flow with gains and losses.

The mapping summarized in Table 1 lays the foundation for mapping social networks to classic flow models. This mapping and its applications are described further in the next sections of this chapter.

Table 1. Taxonomy of Social Closeness Mapped to a Flow Model

Social Closeness Terms	**Flow Model Properties**
People or groups	Nodes (sinks, sources, or transshipment)
Connectivity or affinity	Capacitated arcs (or edges) between nodes
Social Closeness	Capacity
Influence	Commodity
Potential Influence	Magnitude of flow
People or groups initiating influence in the network	Source(s)
Target people or groups to be influenced	Sink(s)
People or groups involved in influencing	Transshipment node(s)
Multi-Criteria within a shared context	Multi-Commodity, where contexts share capacity
Multi-Context or Multi-Criteria in different contexts	Multiple independent single-commodity models for each context or criteria

Single-Commodity Flow

The single-commodity flow representation of a social network is defined in this section. First, it is necessary to define a notional source node (denoted s) and a notional sink node (denoted t). Node s will initially be assigned incident notional directed arcs with infinite capacity (or at least large enough capacity so as not to artificially bound the solution) terminating in the actual (or targeted) source node(s) under consideration in the problem.

An alternative representation is to capacitate the edges from node s based on the ability of the decision-maker(s) to influence the actual source nodes. This alternative representation allows for course of action analysis as part of the flow problem implementation rather than as post-processing analysis. Implementing this approach requires data on the specific means, methods, costs, and other resource limitations constraining a specific decision-maker's ability to influence the targeted source node(s) for a particular scenario. This alternative approach is described here for completeness, however, is not considered further in this study.

The actual (or targeted) source nodes are those individuals who will initiate the influence represented by the flow in the network. Node t will have notional directed arcs with infinite capacity from the actual sink nodes under consideration in the problem terminating in node t. These actual sink nodes are the individuals to be influenced.

The objective of this problem representation is to maximize the flow (*i.e.*, maximize the influence) from s to t. The capacity from node i to node j in the network is s_{ij} where s_{ij} is the monotonically increasing social closeness measure from node i to j. Note that s_{ij} need not necessarily equal s_{ji} for all cases. The actual flow from node i to j is denoted x_{ij} where $x_{ij} \leq s_{ij}$. In addition, note that $\sum_j x_{sj} = \sum_i x_{it}$ since no gains or losses are allowed in this formulation. The notation x_{ij} will be used throughout this dissertation to represent the flow of influence where s_{ij}, denoting social closeness in general is the capacity of the flow.

The related mathematical program for this problem is (Evans, 1992:178):

$$\text{Maximize} \quad z \quad \text{(where } z \text{ is the maximum flow)} \tag{28}$$

$$\begin{aligned} \text{Subject to:} \quad & \textstyle\sum_j x_{sj} - z = 0 \\ & \textstyle\sum_j x_{ij} - \sum_j x_{ji} = 0 \;\; \forall\, i \\ & z - \textstyle\sum_i x_{it} = 0 \\ & 0 \leq x_{ij} \leq s_{ij} \;\; \forall\, i, j \end{aligned}$$

This formulation is demonstrated in the following example.

Social closeness data can be countings of communications over one or means of communication (phone calls, faxes, emails, meetings, and so on), elicited from people in the social network as described in Chapter 6, or more complex psychological profile based measures also described in Chapter 6. Aggregations (summations, averages, and so on) of social closeness measures are also social closeness measures. Consider the social network depicted in Figure 6 with a hypothetical positive monotonic social closeness measure:

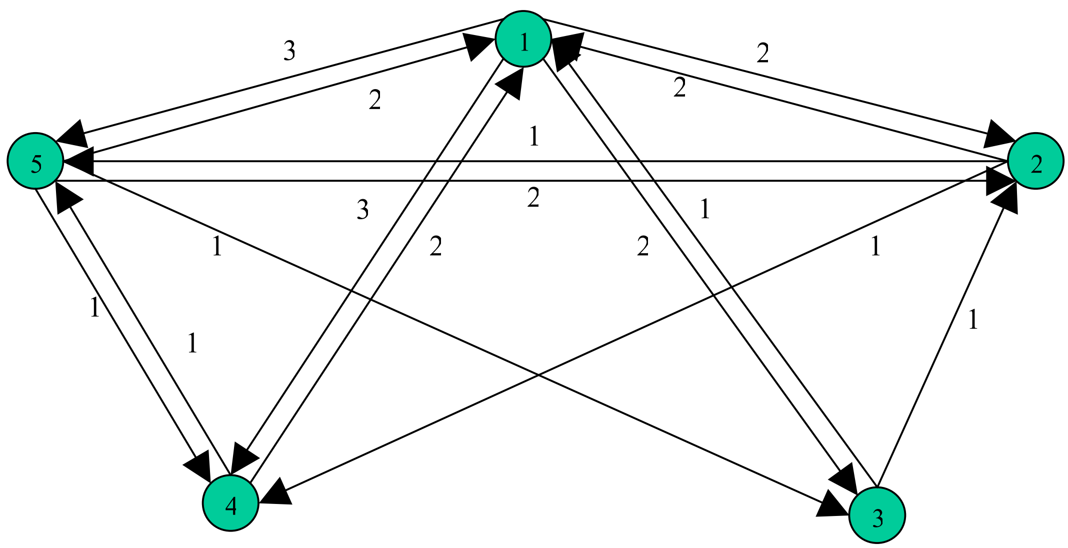

Figure 6. Sample Single-Commodity Social Network

To determine which person, represented by nodes 1 to 5 has the most potential influence on the entire network (or any of the other nodes), five separate maximum flow problems are solved. In each of these separate problems one node is the source and the sinks are all the other nodes. Once all n_1 problems, where n_1 is the number of candidate source nodes, are solved, the respective maximum flows may be compared. The greatest maximum flow out of a source node found in these problems corresponds to the person (

or group) able to exert the greatest potential influence over the other members of the network. Table 2 shows the maximum flow associated with each of these five problems.

Table 2. Maximum Flow from Each of Five Sources

Source	**Max Flow to other nodes**
1	10
2	4
3	2
4	3
5	6

Results differ depending on the source because not everyone in the social network has the ability to influence all of the others and those who influence others do not all have the same capacity on their influence. Further, since no influence is gained in this representation, if a source has relatively low capacity in its first tier of connections (*i.e.*, those paths with cardinality of one), then the resulting flow across the entire network will be relatively low. In other words, flow from a single source is bounded by the capacity in this first tier of connections.

From these results we see that the person represented by node 1 has the greatest potential to influence the entire network. Further, we know that this mathematically optimal solution is achieved by the following flows traveling over the associated edges shown in Table 3 (assuming conservation of flow):

Table 3. Flows Associated with Edges in the Optimal Solution

Edge	Flow
1,2	2
1,3	2
1,4	3
1,5	3
3,2	1
5,2	2
5,3	1

This optimal flow (greatest potential influence) pattern is shown graphically in Figure 7.

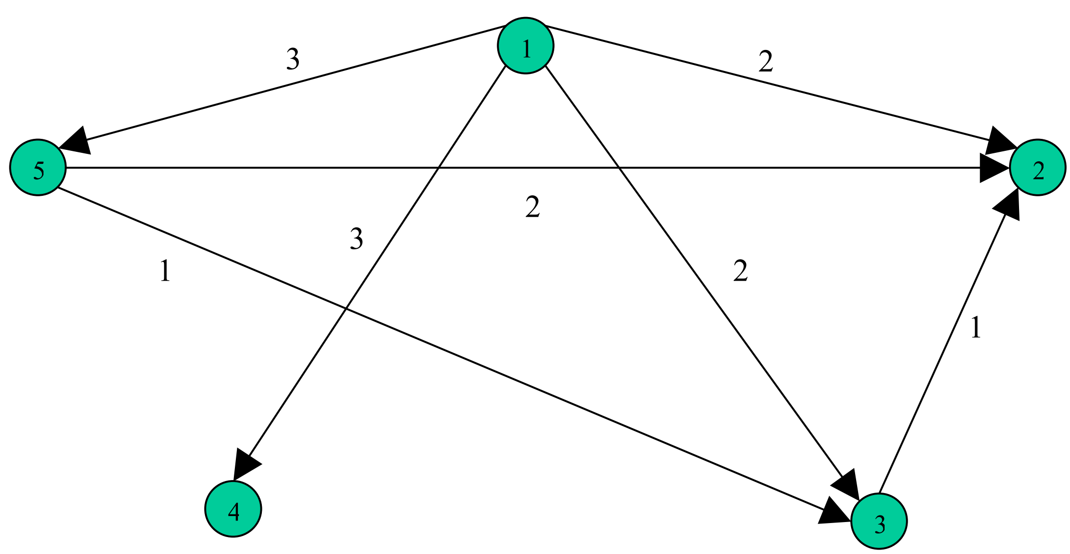

Figure 7. Graphical Depiction of Maximum Flow

In this example, node 1 exerts the greatest potential influence over nodes 5 and 4 (a value of three units) and less influence over nodes 2 and 3 (a value of two units). Node 5 is able to use two units to influence node 2 and one unit to influence node 3. Node 3 uses one unit to influence node 2. Node 2, as a sink, receives the greatest potential influence of five units. Nodes 3, 4, and 5 received three units of influence each. Even in this relatively simple example, it is observed that while the maximum flow relies heavily on the one-to-one relationships node 1 shares with others, node 5 still plays a role in adding to the total influence on node 2 and node 3 and node 3 influences node 2. On the other hand, if the ultimate goal where to exert influence on node 3, a *s,t flow analysis* would suggest node 4 might be an alternative source with a flow of three from node 4 (via nodes 1 and 5). The flow network representation allows the tailoring of analysis.

Multiple Criteria and Commodity Flow

Using the foundation established by this single-commodity flow representation it is natural to next consider a multi-commodity flow representation. Representing multiple criteria as commodities flowing in a social network is similar to the single-commodity flow in many ways. In the multiple criteria flow representation, the commodities are independent measures of social closeness. Each of these measures could be represented as capacities on different edges in the social network. This representation results in a multi-graph, in general. Multi-graphs, where there are more than one undirected or two directed edges allowed between any two nodes, have fewer graph theoretic properties than simple graphs or digraphs. It is appropriate to represent the multiple criteria capacities as a vector weighted capacity on edges. The vector weight representation results in a digraph, in general.

A digraph is preferable to a multi-graph for several reasons. First, it is easier to visualize the digraph representation. Second, digraphs have more graph theoretic properties than do multi-graphs. Using either the multiple edge or vector weight capacity representation, the mathematical programming representation for k commodities (different measures of social closeness) is simply k separate single commodity flow problems. A true multi-commodity flow problem in Operations Research occurs when one or more of the criteria share capacity over a related edge. For clarity, the case of k independent models will be referred to as *multi-criteria* and the classic case with shared edge capacity as *multi-commodity* flow, respectively. In both of these cases, criteria and commodity refer to measures of social closeness.

In a multi-commodity flow problem, some or all of the commodities share edge capacities. This model is developed for social networks by defining x_{ijk} as the flow of commodity k over the edge from i to j . The mathematical programming representation for k commodities follows. The subscript k has been added to appropriate variables to specify the k commodity case (Ahuja, 1993:650).

$$\text{Maximize} \quad \sum_k z_k \quad \text{(where } z_k \text{ is the maximum flow in context } k\text{)} \tag{29}$$

$$\begin{aligned} \text{Subject to:} \quad & \sum_j x_{sjk} - z_k = 0 \;\; \forall\, k \\ & \sum_j x_{ijk} - \sum_j x_{jik} = 0 \;\; \forall\; i, k \\ & z_k - \sum_i x_{itk} = 0 \;\; \forall\, k \\ & 0 \leq \sum_k x_{ijk} \leq s_{ij} \;\; \forall\, i, j \end{aligned}$$

Assuming that the associated data has been normalized, this representation indicates that all commodities are of equal weight.

Weighting commodities in this representation only constrains this problem if the sum of the z_k commodities is bounded (for some or all k commodities). Such a constraint would have the form:

$$\sum_k z_k \leq u \tag{30}$$

where u is the upper bound on the total flow allowed for all commodities combined. This case applies to social networks in that one may not have the time or other resources to induce flow over all of the various commodities (communication channels) available. While this case naturally bounds the optimal solution in terms of maximum flow, the optimal solution to the network flow model provides the path the flow travels to achieve the maximum flow. Clearly, a similar approach may be used to bound a subset of the k commodities.

It is possible to consider different weights on each commodity, where w_k is the weight for some commodity k. This changes the objective function of the mathematical programming representation to:

$$\text{Maximize} \qquad \sum_k w_k z_k \tag{31}$$

Weighting the various commodities differently foreshadows some of the cases to be considered using the goal programming representation. For normalized data, weighting becomes a prioritization of the commodities such that those with a greater weight are higher priority to maximize flow than those with lesser weight. Rather than further explore the weighted objective function approach here, weighting will be presented in terms of Goal Programming, which can easily accommodate this and several other problem classes discussed in the Goal Programming section. Before considering Goal Programming cases, however, flows with gains and losses are discussed next.

Both multi-criteria and multi-commodity cases are of interest to an analyst. The multi-criteria case is likely to be the one more commonly developed when data is collected independently for each context under investigation. Properly identifying and modeling the multi-criteria case allows an analyst to solve sub-problems for each context rather than one large problem and only may require re-solving sub-problems when updates occur in a specific context. The multi-commodity case occurs when there are dependences between contexts and allows the analyst to consider the impact of flow in one context on another context. This case is likely more realistic, in that people likely have difficulty totally separating work relationships from overlapping recreational relationships, for example. While the multi-commodity case is more realistic, the data is less likely to be available regarding how much such relationships overlap in terms of influence from existing survey based data collection techniques.

Single-Commodity Flow with Gains. Influence in terms of flow may be gained or lost when people or groups represented by nodes in the social network are more or less likely to support the influencing effort. This may be a result of preconceived ideas, influence from unknown sources outside of the social network represented, and other similar factors. Recall that single-commodity flow with gains and losses are defined here to represent cases where individuals may be influenced more completely by those influencing them no matter the relative social closeness of those influencing them (for example, an off hand comment from a senior leader may be interpreted as a requirement). This representation allows those being influenced to produce a flow as a percentage of the influence received and their ability to influence others (for example, influence from a very junior person may result in less influence than if the same influence originated from a senior leader). Such a case is easily modeled in the flow representation. This case is only applicable where one has some apriori knowledge that would lead to establishing either a general rule for percentage of flow produced or a person-by-person pairwise percentage of flow produced.

When a general percentage is known for the portion of influence up to full capacity, the problem then has the formulation:

$$\text{Maximize} \quad z \quad \text{(where } z \text{ is the maximum flow)} \tag{32}$$

$$\begin{aligned} \text{Subject to:} \quad & \textstyle\sum_j x_{sj} - z = 0 \\ & \textstyle\sum_j x_{ij} - \sum_j q_{ji} x_{ji} = 0 \;\; \forall\, i \\ & z - \textstyle\sum_i x_{it} = 0 \\ & 0 \le x_{ij} \le s_{ij} \;\; \forall\, i, j \end{aligned}$$

This is the classic single commodity flow with gains representation (Evans, 1992:151). The variable q_{ji} is the percentage of the flow from j to i gained by x_{ij}. In this representation q_{ji} is typically referred to as a "gain factor" (Evans, 1992:151). If $q_{ji} = 1$, then this formulation is the single-commodity flow problem without gains. If $q_{ji} > 1$, then gains are occurring. Note that the resulting flow is still bounded by s_{ij} in a later constraint. The bound on influence would be significant in cases where node i does not have the ability to influence node j to the same degree that node i has been influenced by others in the social network. When $q_{ji} < 1$, losses are occurring. Losses in this model represent cases where less than the influence sent is received. Such losses may be a result of communication problems, misunderstanding, cultural effects, and other such interpretations.

It is possible to represent requirements for meeting a specified threshold level (t_i) to influence the person or group represented by the node i, as a side constraint to the classic flow model representation. Thresholds can be implemented using a binary indicator variable ($h_{ij} = \{0,1\}$) and classic *either-or constraints* (Winston, 1994:478). Such a constraint has the form $x_{ij} = h_{ij} * \sum_k x_{ki}$ where $k \neq i, j$ and $h_{ij} = 1$, if $\sum_k x_{ki} \geq t_i$ and 0, otherwise.

The preceding sections describing flow representations have focused on solving a maximum flow problem. In addition, it is transparent to solve pairwise (or other subset) maximum flow problems by appropriately assigning source and sink representations. All of the single-commodity methods may be extended to multi-criteria or multi-commodity representations as described. Minimum-cost flow requires knowledge apriori of any costs ($0.10/minute, $3 billion in foreign aid, $2500/advertisement, and so forth) associated with influencing individuals, however, this representation follows logically from the cases discussed already.

The minimum-cost flow representation only applies where there are costs associated with flows between nodes. The case where there is costs associated with selecting or influencing a source(s) may be analyzed by determining maximum flow/cost to get a flow per unit of cost for comparison. Choosing the source(s) up to a specified budget such that flow per unit of cost is maximized is then easily found.

When data is available or may be estimated, capacitated flow, gains, and losses may be used to represent both structural elements of the social network as well as the environmental conditions of the communication(s) channels. Structural elements include thresholds required to influence individuals and groups, the maximum ability of individuals or groups to influence other individuals or groups, the capability of individuals to augment or decrease the influence (flow) based on their predisposition, influences not explicitly represented in the social network model, and other similar factors. Environmental factors include the loss of signal associated with communication systems or simply the reinterpretation and repetition of the intended message, misunderstanding including cultural effects, and other similar factors.

This section has demonstrated the value of analysis using a flow representation of a social network. The analysis has demonstrated several problem classes applicable to the flow representation. These are by no means the limits to what can be done. With the link to flow models, a rich modeling environment from Operations Research is opened up. This work can be extended to any number of modeling environments.

Goal Programming allows one to optimize multiple objectives simultaneously. This may be done without weighting, explicit weighting of objectives, or generalized prioritization of objectives. Goal Programming is discussed in the next section.

Social Network Analysis Using Goal Programming

Using the flow representation of a social network there are potentially multiple objectives one may wish to consider simultaneously. Goal Programming allows the analyst to determine the solution of multiple objectives. Goal Programming places another modeling tool in the SNA tool kit. Some of these objectives may be competing with each other.

Influence in a social network consists of subsets of people (nodes in the social network graph) who are influencers (sources) and those to be influenced (sinks) in a specific scenario. Assume there are n nodes in a social network with n_1 sources, n_2 sinks, and n_3 other nodes (possible transshipment nodes) where $n = n_1 \cup n_2 \cup n_3$. For any given problem, the influence of n_1 on n_2 defines the primary problem under consideration.

Consider more complex problem when a decision-maker desires to influence a subset of n_2 with maximum flow, by a minimum (or minimum cost) subset of n_1, with the minimum number of others (n_3) involved in the flow (*i.e.*, minimizing side-effects), and at the same time minimizing the number of n_2 members who are weakly influenced (*i.e.*, n_2 members who are effected by the influencing effort without being significantly influenced) defines the problem under investigation. In the previous example for single-commodity flow, an example was given where the desire was to choose one source from five, defined as $n_1 = 5$. In this section, examples are given that further demonstrate the importance of $n = n_1 \cup n_2 \cup n_3$ structure of social networks.

Each of the optimization problems described above may be solved as separate problems; however, this approach neglects the impact of the solution on other possibly competing objectives. Goal Programming is an approach applicable to solving these types of complex optimization problems simultaneously. Example problem classes include: (1) one of n_1 sources, one of n_2 sinks (One-Against-One), (2) m_1 of n_1 sources, 1 of n_2 sinks (Many-Against-One), (3) 1 of n_1 sources, m_2 of n_2 sinks (One-Against-Many), and (4) m_1 of n_1 sources, m_2 of n_2 sinks (Many-Against-Many).

Goal Programming is applicable to all of the situations and scenarios described above. To demonstrate the capability of Goal Programming, the remainder of this section describes and solves a sample multi-criteria, multi-context (formal and informal), directed, capacity weighted, multi-objective problem using a goal programming methodology based on the flow problem representation described in previous sections.

The case used to demonstrate capabilities of Goal Programming is the single-commodity flow example problem extended such that the hypothetical social closeness represented in that example is now considered the formal context and a hypothetical informal social closeness is added to the problem on the same 0 to 3 scale (*i.e.*, already normalized). These two contexts are represented by vector-weighted capacities in the social network graph given in Figure 8.

Using the given sample social network, the following goals will be evaluated:

> **Goal 1**: Maximize influence (flow) to node 1 from only a sub-set of two nodes from nodes 3, 4, and 5 in the formal context.

Goal 2: Maximize influence (flow) to node 1 from only a sub-set of two nodes from nodes 3, 4, and 5 in the informal context.

Goal 3: Minimize influence (flow) patterns using node 2.

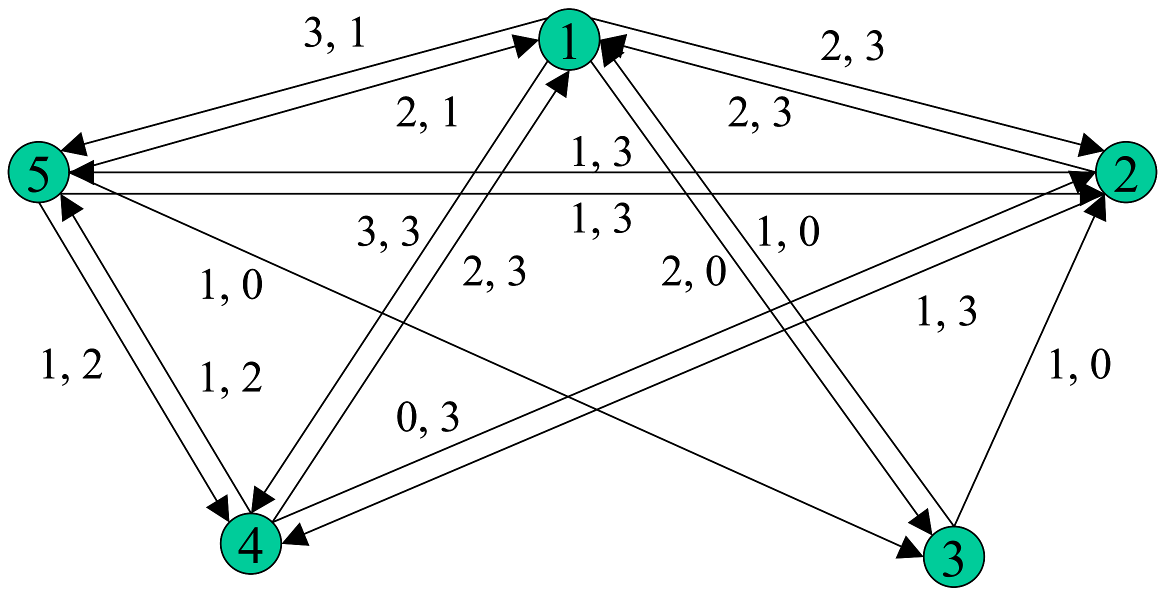

Figure 8. Multi-Criteria Flow Model Example

Goal 1 and Goal 2 imply the focus of the problem is to influence node 1. Only two people will be used due to unstated resource and time constraints. Node 2 is to be avoided in Goal 3 for possible and unstated security reasons. For this example, Goal 1 is considered twice as important as Goals 2 and 3, which are both considered equally important. This means that achieving Goal 1 will possibly override Goals 2 and 3. These weights would be determined based on the scenario under investigation and could be elicited from a decision maker as described in Chapter 6, based on doctrinal standards, or on the known priorities of the case defined by the decision maker.

To fully demonstrate the impact of Goal Programming, Goal 3 will first be ignored to determine the optimal solution to the sub-problem involving only Goal 1 and

2. This sub-problem solution may then be compared to the optimal solution when Goal 3 is considered. Goal 3 competes with the other goals because constraining how flow is allowed to occur across the network can only result in a lesser or equal flow than the optimal solution to the unconstrained problem. Goal 1 and Goal 2 do not compete. The formal and informal social networks are separate networks. The Goal 1 and Goal 2 problems, thus, form two completely independent flow problems. While we have more than one path of influence (multi-criteria in terms of the formal and informal context), this is not a true multi-commodity flow problem (*i.e.*, with shared capacity on edges).

It should be observed that the flow to node 1 is bounded above by the capacity of all directed edges terminating in node 1 (7 for both the formal context and the informal context, respectively). Note that node 3 has no associations in the informal context represented by a 0 on all edges incident on node 3. If this problem were represented in two graphs rather than the vector weighted capacity graph, node 3 would have no edges incident in the informal social network graph. Both these representations are equivalent and have no impact on the solution.

Neglecting Goal 3 for the moment, the two flow problems for the three cases (choosing two nodes from nodes 3, 4, 5 as sources) may be solved as single-commodity flow problems as defined earlier in this chapter with those two maximum flows added together to get the total maximum multi-context flow to node 1. This representation has the solutions given in Table 4:

Table 4. Goal Programming Example Optimal Solutions

Sources	Goal 1 Max Flow	Goal 2 Max Flow	Total Max Flow
Nodes 3 and 4	5	7	12
Nodes 3 and 5	6	6	12
Nodes 4 and 5	6	7	13

This solution indicates that using nodes 4 and 5 has the most potential to influence node 1. In the graphical depiction, Figure 9, of the node 4 and 5 solution, it is clear that node 2 is relied upon in both the formal and informal context.

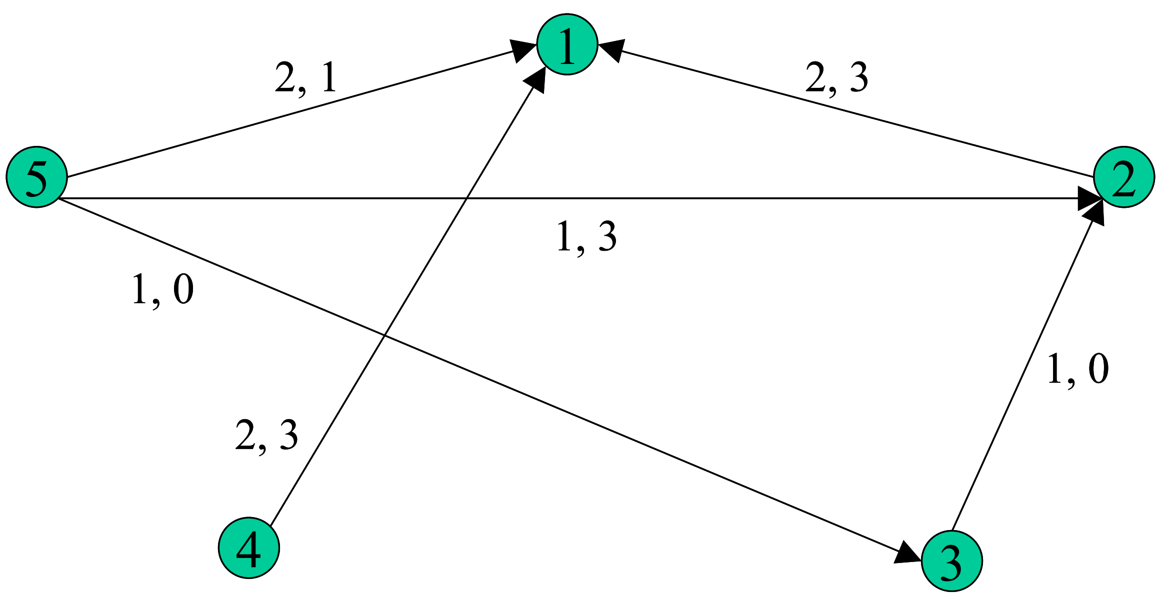

Figure 9. Goal Programming Example Graphical Solution Without Goal 3

When Goal 3 is added, a weighted deviation Goal Programming representation is required and the 2:1:1 ratio of Goal 1:Goal 2:Goal 3 impacts the solution. If Goal Programming were not used and Goal 3 was implemented simply by not allowing any flow through node 2 at all (*i.e.*, using a *hard* constraint as opposed to using deviational variables), the resulting solution would not necessarily be a truly optimal solution to the stated goals as the model would then be a misspecification of the stated goals.

Including Goal 3 in the analysis, the following mathematical program must be solved (Winston, 1994:778, Evans 1992:178):

$$\text{Minimize } w = W_1a_1^- + W_2a_2^- + W_3a_3^+ \quad \text{where } W_1=2,\ W_2=1,\ W_3=1 \qquad (34)$$

$$\begin{array}{lll} \text{Subject to:} & z_1 + a_1^- - a_1^+ = 7 & \text{Goal 1 (Formal Max Flow)} \\ & z_2 + a_2^- - a_2^+ = 7 & \text{Goal 2 (Informal Max Flow)} \\ & \sum_i \sum_k x_{i2k} - a_3^+ = 0 & \text{Goal 3 (Avoid Node 2)} \\ & \sum_j x_{sjk} - z_k = 0 \ \forall\, k & \\ & \sum_j x_{ijk} - \sum_j x_{jik} = 0 \ \forall\, i, k & \\ & z_k - \sum_i x_{itk} = 0 \ \forall\, k & \\ & x_{ijk} \leq s_{ijk} \ \forall\, i, j, k & \\ & \text{All variables non-negative} & \end{array}$$

Note that in this formulation the decision variables (deviational variables) a_1^-, a_2^-, a_1^+, a_2^+, and a_3^+ are included to account for how much the goals are over or under achieved. W_1, W_2, and W_3 are the relative weights of goals 1, 2, and 3, respectively. The objective function is minimized implying that the overall objective is to maximize goals 1 and 2 and minimize goal 3. The first three constraints are what would have been the objective functions for the three goals, if they were solved as separate mathematical programs, with the appropriate goal programming decisions variables included. The right hand sides of the first three constraints are their bounds (*i.e.*, maximum flow in either the formal or informal context may not exceed 7 and the flow transshipped through node 2 may not be less than 0). Observe that a_3^- is not included in this formulation. When $a_3^- > 0$, if it were included, a negative flow exists. The remaining constraints are the same classic flow model constraints (conservation of flow, capacity, and so on) seen in the single-commodity flow model with the subscript k added to denote, in this case, the two separate flow models for the formal and informal context. Table 5 gives the optimal solutions for the three cases:

Table 5. Goal Programming Maximum Flow Optimal Solution

Sources	Goal 1 Max Flow	Goal 2 Max Flow	Total Max Flow
Nodes 3 and 4	5	4	9
Nodes 3 and 5	6	3	9
Nodes 4 and 5	6	4	10

From these results it is clear that using nodes 4 and 5 has the greatest total flow to node 1. In addition, when the results are compared to Table 4 it can be seen that Goal 3 has no impact on the Goal 1 maximum flow, but did impact the Goal 2 maximum flow. The solution with the maximum total flow is depicted in Figure 10, showing the path that this flow travels. Note that while the selection of node 4 and 5 remains optimal, the path changes significantly in the informal context to avoid node 2 and minimizes the use of node 2 in the formal context.

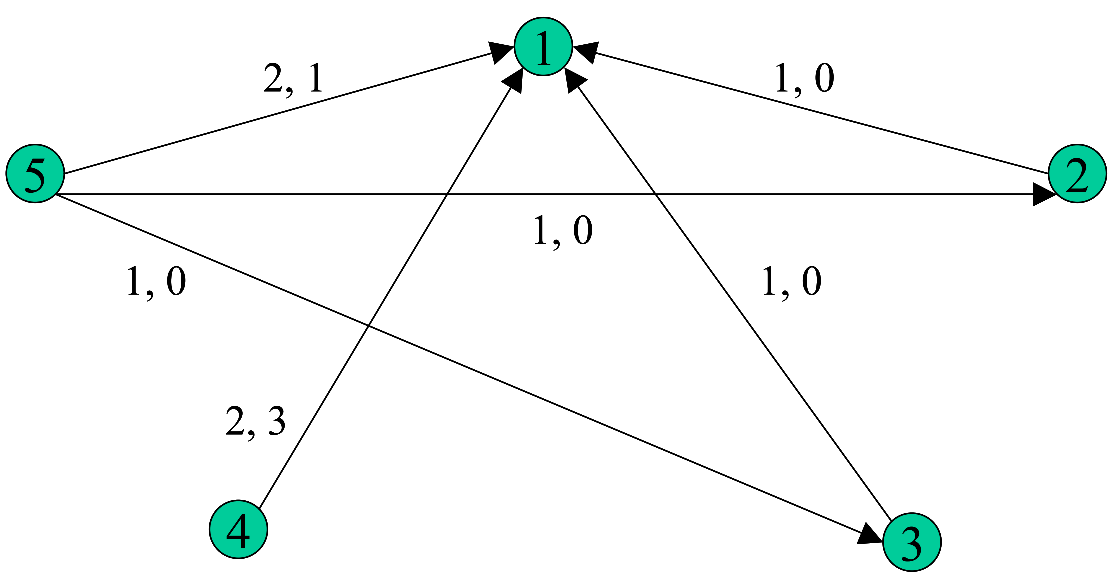

Figure 10. Goal Programming Maximum Flow Depicted Graphically With Goal 3

The selection of the flow path causing Goal 3 to impact Goal 2 more than Goal 1 is a direct result of the ratio assigned to the goals relative importance.

For cases where this ratio may not be easily defined, it may be prioritized ($P_1 >>> P_2 >>> P_3$, for example). The case where goals are prioritized in this manner is known as "preemptive" Goal Programming (Romero, 1991:3-4). In preemptive cases, the most important goals will be satisfied first, before any lower priority goals are considered. The prioritization of goals in this case establishes preemption classes. Goals with the same priority are in the same class. With preemptive Goal Programming, sub-problems are solved sequentially starting with the greatest preemption class, until a solution is found that completely satisfies all of the subproblems or a subproblem cannot be optimized without lowering the attainment of a higher priority goal. In cases where the specific ratio or even the prioritization scheme is uncertain, the ratio may be varied to determine sensitive ranges (*i.e.*, where the solution changes).

Weighting of goals may be obtained from the decisions-maker(s) when they are known with certainty or by policy. In Chapter 6, the use of elicitation as an aspect of Decision Analysis is discussed and is applicable for determining weights based on the values of the decision-maker(s). The use of Decision Analysis methods is highly recommended when the decision-maker(s) are accessible and results in a quantitative approach using a replicable methodology.

Using weighted Goal Programming when data is available or may be collected on the weighting scheme or preemptive goal programming when only priorities are known, is advantageous to the analyst over a single weighted objective function representation primarily due to the use of deviational variables in Goal Programming. These deviational variables, allow the goal program to find a solution that attempts to achieve the stated goals and serve as measures of how much the optimal solution over (under) achieves the stated goal. Preference is expressed in relation to goal achievement, rather than the optimization of a specific criteria. A single weighted objective function would clearly not provide data on these deviations. Goal Programming offers a different method of representing and analyzing the social network model, adding to the SNA tool kit.

Violations of underlying assumption and sensitivity analysis are the subjects of the next two sections of this chapter. A complete analysis of a problem should include sensitivity analysis of any uncertain values or measures. Certainty is one of the assumptions of deterministic mathematical programming. Uncertainty is addressed via sensitivity analysis. Violating the other assumptions may severally limit the type of analysis that may be conducted using mathematical programming. Recall, however, that mathematical programming requires fewer assumptions than techniques currently in use by Social Scientists for social network analysis. Violating the assumptions of mathematical programming indicates that these other methods are also inapplicable. Those methods requiring metric measures have very strict assumptions.

Violation of Assumptions

As described in the literature review, it is common that many existing measures of social closeness (or social distance) violate one or more of the assumptions of linear programming: linear, proportional, additive, divisible, and certain. Each of these assumptions and consequences of violating them is described below.

Linear. Non-linearities may enter a social network analysis in several ways. The most likely case is that one of the goals of the analysis may form a non-linear objective function or constraint. It is also possible that in the flow representation that a non-classic representation, particularly one lacking conservation of flow and/or including feedback, may result in non-linear constraints in the flow model representation.

Non-linearity is not a particular problem for use of the Flow Model representation or Goal Programming representation, as non-linear flow network models exist (Evans, 1992: 18). This is another advantage of these methods over other social network analysis methods. A non-linear problem may be formulated as a Non-Linear Program (NLP). This formulation would be similar to the Linear Programming (LP) representation given except that the objective function and/or constraints would now have a non-linear functional form.

The resulting NLP may be solved using a number of methods (Rao, 1996:428). however, the non-linearity has the potential to cause convergence problems. For these cases, heuristic methods may be considered. These cases and applicable methods are not detailed here as each specific case may require different methods. Non-linear methods may be found in readily available textbooks (Rao, 1996:15; Winston, 1994:639; Hillier, 1990:499). Non-linear network methods also exist (Castro, 1996:37, Dembo, 1989:353, Mulvey, 87:1). Lagrangian Duality, as an NLP method, is discussed in the section of this chapter dealing with Goal Programming for a special case denoted Partial Lagrangian Duality.

Proportionality and Additivity. Violations of the assumption of proportionality and additivity would occur when measures are non-ratio (*i.e.*, they are ordinal or nominal). Non-ratio measures are not additive or proportional. If measures are ordinal, for example, an influence of 2 is not necessarily twice an influence of 1. In the case of ordinal measures, 2 is only interpreted to be greater than 1. For nominal measures, measures are only categorical and a state defined as category 2, for example, may not even represent more influence than a state defined as category 1. This is the most serious potential violation of the modeling assumptions. Its violation would make all of the proposed techniques inapplicable. Note that these violations also make any other methods requiring metric or non-metric ratio measures, such as Multi-Dimensional Scaling inapplicable. That said, there are still approaches to correctly use such data in both the Flow Model and Goal Programming representation. The consequence is a loss of information.

For non-ratio measures of closeness, similarities, distances, or differences, it is always possible to extract undirected, unweighted, affinity connections between people and groups in a social network by using only the data from an adjacency matrix. Based on the proofs earlier in this chapter, it is possible to model the affinity network. If the resulting social network is *Perfect Triangular*, then affinity as a measure is metric and all mathematical programming representations are appropriate. If the social network is not *Perfect Triangular*, then affinity as a measure is non-metric. If affinity is non-metric, affinity remains in the class of measures defined by social closeness where all edges are assumed to have equal weight (or equal capacity, in the case of a flow model representation).

Divisibility. The most likely case of violating the assumption of divisibility is the situation where one or more of the measures or other decision variables takes on only integer (including binary) values. If none of the other assumptions are violated, this situation may be modeled using Integer Programming (IP) for all integer valued measures and decision variables, Binary Integer Programming (BIP) for the binary case, and Mixed Integer Programming (MIP) for cases where some measures and/or other decision variables are integer (Rao, 1996:667-668; Hillier, 1990:457). For cases where the constraints retain the form (unimodularity) of the classic network model given, flow network methods given remain an appropriate and efficient solution technique. Cases where some of the constraints do not conform to a unimodular structure may be solved using Partial Lagrangian Duality to exploit this advantageous structure or other techniques. As noted earlier, the Partial Lagrangian Duality approach is discussed later in this chapter.

There exist several methods available to solve IP, BIP, and MIP problems including cutting plane methods and branch-and-bound methods for linear problems and generalized penalty function methods and sequential linear IP methods for non-linear problems (Rao, 1996:668; Aarts, 1997:19-22). IP, BIP, and MIP methods are well defined in the existing literature.

Certainty. Certainty is the assumption most likely to be violated. Uncertainty may exist with respect to the existence of connections (edges in the social network graph), the weight or strength of connections (capacities in a flow model representation), weighting or prioritization in a goal program, and other aspects of the problem. Clearly, the first option is to collect more factual data such that these aspects of the problem are known with certainty, if such data exists and can be collected.

For cases where further data collection is either not timely or not possible, there are other ways to handle uncertainty within the models discussed in this chapter. For cases with very high uncertainty, an analyst may desire to consider Stochastic

Programming (Rao, 1996:32) or simulation (Kelton, 1991:1). Stochastic Programming and simulation should only be used when the nature of the uncertainty is understood or can be estimated. In addition, one could extract and analyze only affinity relationships as previously described. It is not expected, however, that the knowledge of uncertainties in most problems will support the use of these methods.

When data is collected from decision-makers or groups of decision-makers about their own values, Decision Analysis (DA) methods may be applied. Properly using Decision Analysis elicitation methods will help mitigate uncertainty with respect to otherwise subjective data. Decision Analysis methods are applicable to both elicitation of the problem statement and associated data. As noted in Chapter 2, Bayesian Network approaches, such as that implemented in SIAM, also serve as possible approaches similar to elicitation and easily implemented for groups of decision-makers.

Uncertainty for most problems may be handled via sensitivity analysis. In general, it is not necessary to test the sensitivity of all aspects of a problem simply to deal with the issue of uncertainty. One may, however, desire to conduct sensitivity analysis on certain aspects of a problem to better understand the nature of the problem and its solution or as a form of *What if?* analysis. For these reasons, sensitivity analysis should be conducted as part of any significant analysis effort (Rao, 1996:228; Winston, 1994:196). Sensitivity analysis is the subject of the next section.

Sensitivity Analysis

This section discusses and demonstrates sensitivity analysis relevant to the Linear Programming models for Flow Modeling and Goal Programming. The reader should be aware that sensitivity analysis methods can be conducted the other modeling methods discussed previously (*i.e.*, NLP, IP, BIP, MIP, DA, and others) with varying degrees of effort. Sensitivity analysis is "the study of the effect of discrete parameter changes on the optimal solution" (Rao, 1996:229). There are five basic types of sensitivity analysis (Rao, 1996:229):

1. Changes in the right-hand-sides of constraints
2. Changes in the weighting of decision variables
3. Changes in the coefficients of the constraints
4. Addition of new variables
5. Addition of new constraints

The Operations Research literature is rich with applications of post-optimality analysis. Such analysis allows the analyst to test the robustness of the model, its assumptions, and its parameters. The analysis can be tailored to the key aspects of a scenario, or applied to all factors. While the complete array of options can now be applied to the social network flow model, only two types of sensitivity analysis of broad interest to the methods demonstrated in this chapter for social network analysis will be demonstrated. These are: (1) changes to the right-hand-sides of the capacity constraints and (2) changes to the weights of decision variables related to goals in the Goal Programming representation.

The examples used to demonstrate sensitivity are larger scale than those used in pervious examples. This is done for several reasons. First, the methods described in this chapter are applicable to analysis of any size network. Second, even in larger scale examples sensitive data may still have significant impact on the resulting solution. Third, in Chapter 5 aggregation and disaggregation methods are discussed to demonstrate means to reduce larger scale data down to the resolution required for a given analysis effort.

Large scale is determined by the number of nodes and edges where edges define the density of the graph when the number of nodes is fixed (West, 1996:362). While density is what makes a graph larger scale, density, in terms of edges, is bounded by the number nodes in a digraph such that density may not exceed $n(n-1)$ where n is the number of nodes in the network. Sensitivity analysis itself may reveal sub-graphs which do not require high resolution to solve the problem under investigation (*i.e.*, insensitive aspects of the network). These insensitive subgraphs should be considered as possible targets for the aggregation methods described in the next chapter.

Sensitivity of Capacity Constraints. It is likely that for many cases, capacity, representing the strength of relationships in the social network, may not be known with certainty. This would be the case for any non-cooperative situation, for example in an analysis of a political or business adversary. This case is also applicable when capacity data may be known for the contexts observed, but not known for other potential contexts that may exist.

To demonstrate sensitivity analysis of capacity constraints, the following sample network was generated by specifying a 50 node directed social network of individuals each with an out-degree of 5 (*i.e.*, each person in the network has a direct relationship with exactly 5 other people). Thus, this graph has 250 total edges. These directed edges were then randomly assigned to terminate at other nodes in the graph and randomly weighted with a capacity of 1 to 10 assumed to be a social closeness measure. An out-degree of 5 randomly assigned to terminal nodes results in no special network or social structure (*i.e.*, the sample problem has no loss of generality). The data matrix for the social closeness measures may be found in Appendix B. The sample case social network is shown in Figure 11.

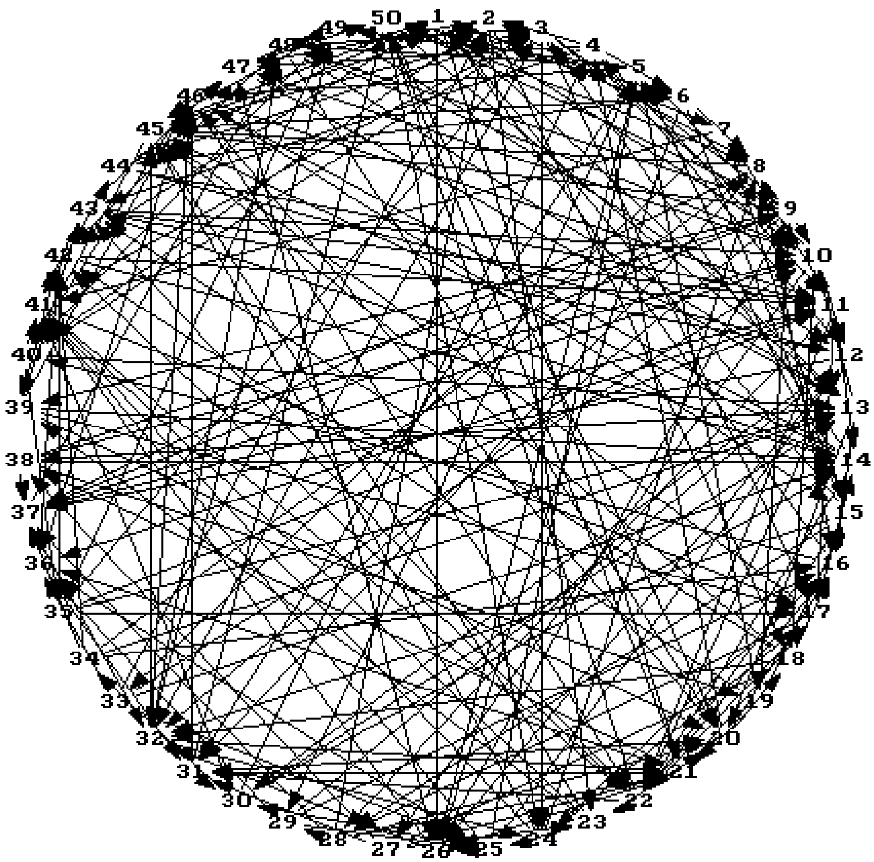

Figure 11. Randomly Generated Social Network Example

The scenario considered for this illustrative analysis consists of: individuals 1 to 5 are actors in the network that have been co-opted by an external decision-maker. Individuals 1 to 5 will be used by the decision-maker to influence the target individuals. The target individuals are represented by nodes 40 to 50. It is assumed that the decision-maker cannot directly influence any other individuals in the network than nodes 1 to 5. The goal is to generate the most influence on the individuals represented by nodes 40 to 50.

The example problem is modeled as a single-commodity flow problem exactly as discussed earlier in this chapter with no gains or losses. The solution to this problem, solved as a maximum flow network problem, indicates that nodes 1 to 5 have a potential to influence (maximum flow) nodes 40 to 50 with 115 units of influence.

However, it is uncertain whether or not others in the network know (in part or in whole) whether nodes 1 to 5 have been co-opted by the decision-maker. It is understood that if anyone knows or suspects the subversion of nodes 1 to 5, their relative influence on those who suspect will be significantly reduced. Therefore, the social closeness values for node 1 to 5 are somewhat uncertain and should be analyzed for sensitivity.

It is clear that when the social closeness values for nodes 1 to 5 are all zero, indicating that they are now considered entirely untrustworthy, the resulting influence, expressed as maximum flow, originating from them to nodes 40 to 50 (or anyone else) must also be zero. It also clear that reducing their social closeness values may only reduce the maximum flow to nodes 40 to 50. In other words, the initial problem solution is an upper bound on the potential influence, in this example.

It is thought by the decision-maker in this example that it is likely that if nodes 1 to 5 are suspected by others, then there is a reduction by 5 units of influence, but not less than 1 unit (*i.e.*, they still have will have at least an ability to communicate a message, this message may or may not have much potential to influence). This reduction in influence represents a loss in potential of at least 50% in all cases. The worst case occurs when all of nodes 1 to 5 are suspected by all others with whom they have an affinity. This worst case, thus, establishes a lower bound on the potential influence. Both classic sensitivity analysis and parametric programming can be applied. There are many potential combinations of some or all of nodes 1 to 5 being suspected by combinations of the others with whom they have an affinity. Without further insight into who may suspect whom, it is clear that potential influence decreases from the upper bound (*i.e.*, the initial solution) to the lower bound (*i.e.*, worst case).

In the worst case, nodes 1 to 5 have a potential to influence nodes 40 to 50 by 40 units of influence (a reduction by 65.22% compared to the initial solution). If the decision-maker knows a specified level of influence desired, then it can be easily determined whether or not the worst case exceeds the target threshold. If it does exceed the threshold, then clearly the plan should be executed (assuming there is no other relevant decision criteria to be used). If the potential influence in the worst case does not exceed the threshold level, then further analysis or other alternatives must be considered to insure the potential influence is sufficient (for example, collect data to determine who is suspected by whom, co-opt other members of the network, and so on).

The example presented here demonstrates one case where sensitivity analysis of social closeness values is important. There are many similar scenarios one can envision for other cases of social network analysis. When the analysis includes multiple goals (or objectives) then the weighting of these goals must also be considered in terms of sensitivity analysis. Sensitivity of goal programming weights is the subject of the next section.

Goal Programming Example. Weighting of goals in a goal program are likely in many cases to be uncertain. As already indicated, weighting of goals may come from doctrine, a statement of priorities for a given scenario (which may be pre-emptive or not), or via elicitation as part of Decision Analysis (discussed in Chapter 2 and further in

Chapter 6). In many cases, especially those that are more subjective, such a weighting may be uncertain. Further, for non-cooperative cases, the uncertainty is likely to be even greater, as the actual decision-maker's values may only be estimated.

To demonstrate the use of post-optimality analysis on Goal Programming weights, a business sector example is used. The book *Social Network Analysis: Methods and Applications* provides data used in several real-world applications of social network analysis applied primarily to private sector problems (Faust, 1994:59-66, 738-755). This data is also available electronically from the Institute of Social Network Analysis website (http://www.heinz.cmu.edu/project/INSNA/). For the example used in this section, data denoted "Krackhardt's High-Tech Mangers" from 1987 is used (Faust, 1994:60).

The "Krackhardt's High-Tech Managers" dataset consists of three relations (or commodities in the flow problem representation) for "advice", "friendship", and "reports to" in a "small manufacturing organization on the west coast of the United States" (Faust, 60, 738). The data contains directed, asymmetric, binary values (1 representing a relationship and 0 representing none) from a self-reporting survey of 21 managers (Faust, 1994:60). Thus, there are three contextual networks of the same 21 individuals with a maximum of 420 edges per graph (*i.e.*, $n(n-1) = 420$ when $n = 21$) for a total of up to 1260 edges. This is the first example using real case study data and using binary valued social closeness measures. As noted earlier, binary affinity relationships will always meet the definition of social closeness. In addition, note that this data is not *perfectly triangular* and, hence, is non-metric (*i.e.*, indicating that MDS and other metric methods are not appropriate for this analysis). The data for this example is presented graphically in Figures 12, 13, and 14 and may be found in Appendix B in matrix form.

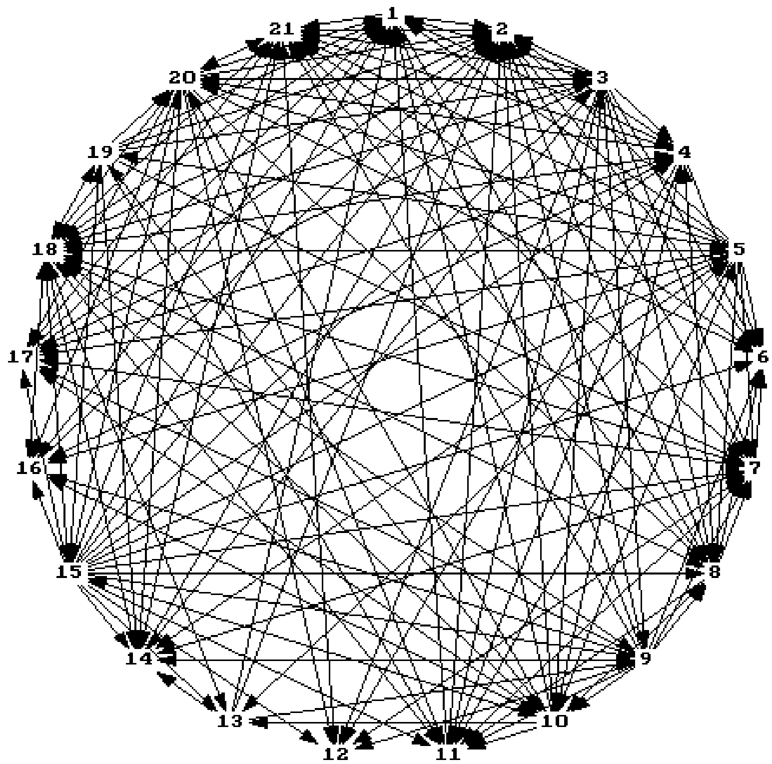

Figure 12. “Advice” Relationship

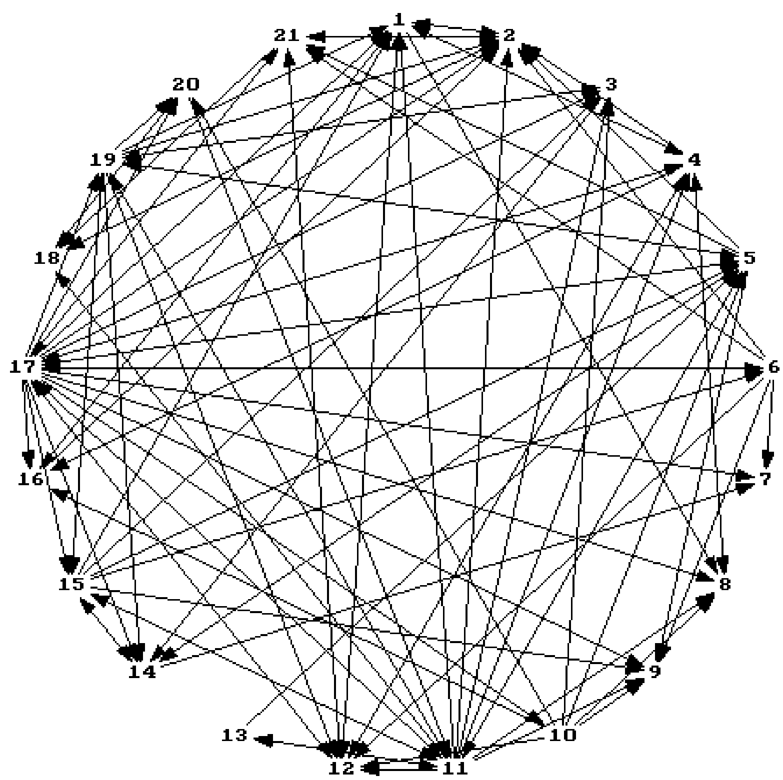

Figure 13. “Friendship” Relationship

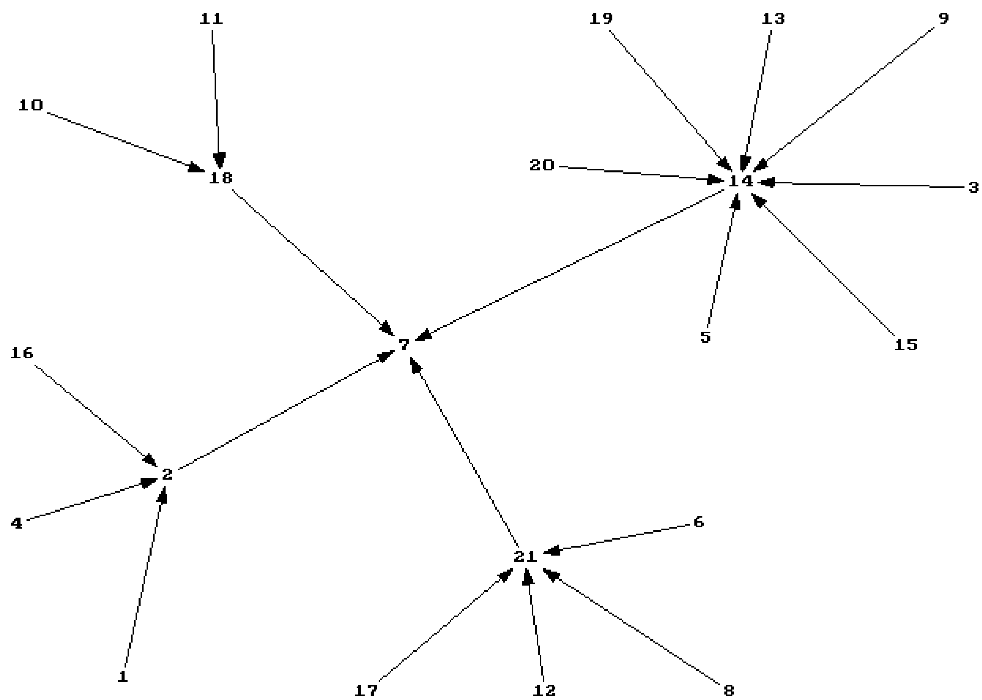

Figure 14. "Reports to" Relationship

Three goals are established for this sample analysis: (1) maximize influence from level 2 managers (nodes 2, 14, 18, and 21) to the level 1 manager (node 7) in terms of the "advice" relationship, (2) maximize influence to level 1 and level 2 managers in the "friendship" relationship, (3) minimize influence outside of official channels to the level 1 manager (node 7) found in the "reports to" relationship (*i.e.*, do not jump the chain of command). Note that Goal 3 is equivalent to maximizing the use the chain of command. It is assumed that these goals have a ratio of weights (W_1, W_2, W_3, respectively) elicited from a hypothetical decision-maker of 10:5:1 . For this example, influencing node 7 in the advice relationship is twice as important as influencing this same node in the friendship relationship and ten times more important than maintaining the chain of command. In addition, influence in the friendship relation is five times more important than maintaining the chain of command. The next section describes the approach to solving this type of problem, including the use of deviational variables in the Goal Programming representation.

Formulation of the Goal Program for the example problem is very similar to the formulation to the previous Goal Programming example:

$$\text{Minimize} \quad w = W_1 a_1^- + W_2 a_2^- + W_3 a_3^- \qquad (35)$$

$$\text{where } W_1 = 10,\ W_2 = 5,\ \text{and } W_3 = 1$$

$$\begin{array}{lll}
\text{Subject to:} & z_1 + a_1^- - a_1^+ = M & \text{Goal 1} \\
 & z_2 + a_2^- - a_2^+ = M & \text{Goal 2} \\
 & \sum_p x_{pqk} + \sum_q x_{q7k} + a_3^- - a_3^+ = M & \text{Goal 3} \\
 & \sum_j x_{sjk} - z_k = 0 \ \forall k & \\
 & \sum_j x_{ijk} - \sum_j x_{jik} = 0 \ \forall i, k & \\
 & z_k - \sum_i x_{itk} = 0 \ \forall k & \\
 & x_{ijk} \leq s_{ijk} \ \forall i, j, k & \\
 & \text{All variables non-negative} &
\end{array}$$

In this formulation, the Goal 1 constraint indicates that flow from the sources (nodes 2, 14, 18, and 21) to the sink (node 7) must be maximized where these nodes are connected to the artificial source (s) and sink (t). In Goal 2, the sinks are all level 2 managers and the level 1 manager. For Goal 2, the sources are all other nodes. The right-hand-sides for these two constraints is M where M is any number large enough not to bound the problem artificially. M must be equal to or larger than the upper bound, $M = 421$ (*i.e.*, $n(n\text{-}1) + 1$, where n=21) for example, in this case is an appropriate specification as there may be no more than 420 edges in any given network and each edge may have no more than a capacity of 1 unit of influence (note that this is not the least upper bound necessarily, but will apply to every case). The constraint for Goal 3 indicates that the flow from level 2 managers (denoted q, where $q = \{2, 14, 18, 21\}$) to node 7 should be maximized and flow from all others to their level 2 managers (denoted p, where $p = n - q - \{7\}$) should be maximized in all k contexts. W_1, W_2, and W_3 equal 10, 5, and 1, respectively as per the problem specification. The deviational variables (a^+ or a^-), indicate the amount by which a goal is over or under achieved, respectively.

Algorithmic Solution to Goal Programming Example. To this point the formulation of the Flow Model and Goal Programming model mathematical programs has been discussed; however, explicitly how to solve these mathematical programs has not. It is possible to solve these mathematical programs using classic Linear Programming methods, such as the Simplex Method, or even the Non-Linear Programming methods, if appropriate, already discussed. Software designed to implement specialized network Goal Programming approaches is also available (Glover, 1992:65). For problems with a strict network structure, however, these gradient approaches are not the most efficient methods (Evans, 1992:4). Several algorithms have been found to be far more efficient for this class of model (Evans, 1992:4).

For the single-commodity maximum flow problem, Flow-Augmenting Paths, Pre-Flow Push, and other algorithms are more efficient than the Simplex method. These algorithms are not detailed here, as they can be commonly found in many texts devoted to the subject of network optimization (Evans, 1992:123-177; Ahuja, 1993:168-243). These algorithms, in general, yield polynomial time solutions (Ahuja, 1993:207). Such algorithms also exist for minimum cost flow and multi-commodity flow problem classes.

McGinnis and Rao note, however, that in Goal Programming of network problems, the additional Goal Programming constraint(s) "obliterates the problem's natural network structure" (McGinnis, 1977:243). They suggest that one way to recapture the network structure is by formulating the Partial Lagrangian Dual problem where the goal constraints then become part of the objective function and the remaining constraints retain the network structure of the underlying flow model. This formulation has the form of a classic flow model with a somewhat different objective function. Network algorithms may then be used to solve the goal program more efficiently than classic methods such as the Simplex Method (McGinnis, 1977:243).

Lagrangian Duality is a method most commonly associated with solving Non-Linear Programs (Rao, 1996:91). Linear Programs may also be solved using this method. In this case, Partial Lagrangian Duality is used to reformulate the problem in such a way that its resulting subproblems may be solved using existing flow algorithms (McGinnis, 1977:245). This is only possible because the resulting mathematical program retains the flow model structure. If this were not the case, Subgradient Optimization or another method would be required and the stated efficiency would not be gained (Rao, 1996:243).

The approach suggested by McGinnis and Rao for Minimum Cost Flow problems is extended in the to the Maximum Flow problem for the example problem under investigation. To implement this approach for the problem classes discussed here, it is first necessary to define how to transform the multi-context (*i.e.*, multiple independent flow models) into a single-commodity flow problem. For any case, this may be done by the inclusion of an artificial super source and sink connected to the artificial sources and sinks already described in terms of a single-commodity flow problem. The capacity on the edges in these connections, like the other artificial edges from the artificial sinks and sources, must be large enough so as not to bound the solution.

Figure 15 shows the general structure of such a representation for three networks (denoted Net 1, Net 2, and Net 3) where *ss* is the super source and *tt* is the super sink.

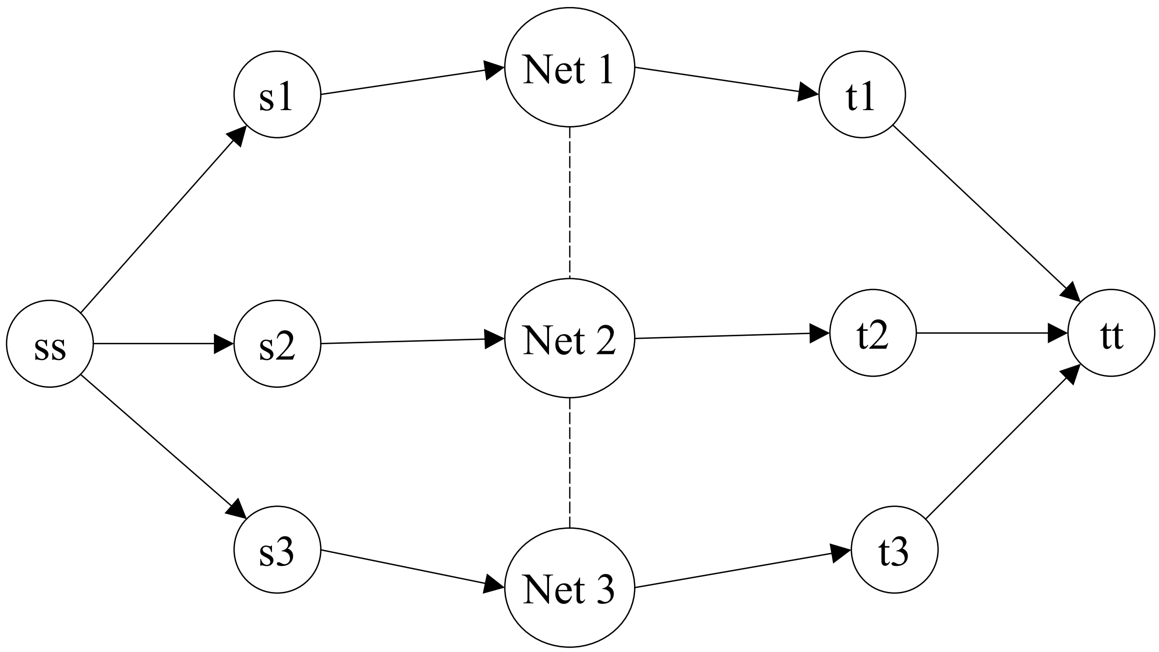

Figure 15. Three Interlocking Contextual Network Model

Note that the edges from the independent artificial sources, *s(i)*, and sinks, *t(i)*, must still be connected only to those initiating and terminating (*i.e.*, the target individuals or groups) the flow, respectively. The dashed edges between the networks indicate that it is possible, for some instantiation, that these networks may be connected. If the networks are connected, the edges connecting them must be multi-commodity, as they would, by definition, carry influence for more than one context.

When desirable for the efficiency of analysis, the independent artificial sources and sinks may be aggregated, as described in the next chapter, into the super source and sink. Implicitly this aggregation makes the super source and sink multi-commodity, however, the artificiality of these edges does not require multi-commodity flow modeling as the fundamental problem is unchanged. The proof that aggregation, performed properly, does not change the solution of the network problem is provided in the next chapter.

The McGinnis and Rao approach with the extensions described above is demonstrated in for example under investigation. The example problem as stated involves three otherwise independent single-commodity networks. The representation of these commodities based on context is retained. The data does not indicate that multi-commodity flow occurs (*i.e.*, no flow between the networks is described).

Reformulating this representation into the Partial Lagrangian Dual has the form:

$$\text{Maximize}_u\ Q(u) = \text{Maximize}_u \{\text{Minimize}_a\ L(a,u)\} \tag{36}$$

$$\begin{aligned}\text{where } L(a,u) = {} & W_1 a_1^- + W_2 a_2^- + W_3 a_3^- + u_1(z_1 + a_1^- - a_1^+ - M) + \\ & u_2(z_2 + a_2^- - a_2^+ - M) + u_3(\textstyle\sum_p s_{pqk} + \sum_q s_{q7k} + a_3^- - a_3^+ - M)\end{aligned}$$

$$\begin{aligned}\text{Subject to:}\quad & \textstyle\sum_j x_{sjk} - z_k = 0\ \ \forall\, k \\ & \textstyle\sum_j x_{ijk} - \sum_j x_{jik} = 0\ \ \forall\, i, k \\ & z_k - \textstyle\sum_i x_{itk} = 0\ \ \forall\, k \\ & x_{ijk} \le s_{ijk}\ \ \forall\, i, j, k \\ & \text{All variables non-negative}\end{aligned}$$

Note that the Partial Lagrangian Dual formulation has only the network flow structure in terms of the constraints. This property indicates that it may be solved by exploiting this structure using efficient algorithmic methods. Goal 1, Goal 2, Goal 3 are now associated with the Lagrange variables u_1, u_2, and u_3, respectively. In addition, note that this mathematical program is simply a reformulation, it has the same solution as the previous formulation.

The results of this analysis using weighted Goal Programming combined with the flow model representation for the three commodities (influence in each of three relationships) is 38 in terms of potential influence represented by maximum flow. The total maximum flow (*i.e.*, maximum potential influence) is the sum of maximum flow in

Goal 1, Goals 2, and Goal 3. This aggregate flow results from a flow of 13 in the "advice" relationship, 21 in the "friendship" relationship, and 4 in the "reports to" relationship. Goals 1 and 2 do not compete (*i.e.*, they deal with flow in independent networks). Goal 3, flow in the "reports to" relationship, does not constrain Goals 1 and 2 in this problem as its weight is much less than the weight of Goals 1 and 2.

From these results alone it is clear that Goals 1 and 2 may be achieved resulting in the maximum influence (flow) indicated. If the decision-maker stated a threshold level of influence, it would be easy to determine if that threshold had been achieved. If the data were available, it would be possible to determine whether the target node would be influenced sufficiently. Short of this type of data, this approach could be compared to other alternatives in terms of influence or implemented where the results could be observed and future action taken if necessary.

Observe that if Goal 3 preempted all other goals, the maximum flow is simply the sum of the maximum flows in Goal 1, 2, and 3 that occurs on paths found in the "reports to" network. The resulting maximum flow to node 7 is 9 in this case. Recall, however, that Goal 2 also involves influencing level 2 managers, making the solution hard to determine by only observation. Sensitivity analysis, however, allows the true impact of Goal 3 to be better understood.

Assuming the elicitation process was conducted appropriately in the initial assessment of weighting goals, the resulting weights should fully capture the decision-maker's values. The decision-maker, however, knows that, as noted in Chapter 2, informal relationships represented by the "friendship" relationship may be as powerful (or even more powerful) than formal relationships. If the decision-maker wants to more strictly enforce (or encourage enforcement) the chain of command defined by the "reports to" relationship, it is possible to observe how the solution changes as the weights on these goals change.

Post-optimality analysis is performed on this example to determine the impact of changing the weights on goals 2 and 3. Specifically, results are presented below starting with a ratio of 10:1:10 (goal 3 equal in importance Goal 1 and ten times Goal 2) and terminating with a ratio of 10:10:1 (Goal 2 equal in importance to Goal 1 and ten times Goal 3). Intermediate cases may be tested continuously or discretely. For this case, the following intermediate cases were considered discretely: 10:5:10, 10:10:10, and 10:10:5 . This results in a total of 5 cases tested. To perform this analysis it is necessary to reevaluate the sub-problems, using the Partial Lagrangian Duality approach makes this reevaluation more efficient than resolving the problem with other methods. Cases with a weight of zero were not tested, as these cases represent the exclusion of a stated goal, which is inconsistent with the sample problem statement that these goals do in fact exist. The results of this sensitivity analysis are given in Table 6.

Table 6. Goal Programming Example Sensitivity Analysis

Weights (W_1:W_2:W_3)	**Maximum Flow**
10:1:10	28
10:5:10	28
10:10:10	38
10:10:5	38
10:10:1	38

Based on the results of this post-optimality analysis it is observed that Goal 3 only constrains the solution when its weight exceeds that of Goal 2. In this sample problem the change occurs whenever W_3 exceeds W_2 . This means that the initial solution is insensitive to changes in the weight of Goal 3 (W_3) when $0 \leq W_3 < 5$. When W_3 exceeds W_2 , the flow in the "friendship" network is restricted to only those paths found in the "reports to" network. The "friendship" network only has one edge from a level 2 manager, node 14, to node 7, the level 1 manager. Note that post-optimality is applicable to pre-emptive Goal Programming as well.

Again if the decision maker were aware of a desired threshold level of influence, it would be possible to determine if Goal 3 still allows this threshold level of influence to be achieved when it is considered more important than Goal 2. The results of the sensitivity analysis without knowledge of such a threshold, reveals a 26.32% reduction in potential influence when the Goal 3 weight exceeds that of Goal 2. Clearly, a reduction in the level of influence makes it less likely to accomplish the overall objective of influencing the level 1 manager in this example problem.

This section has demonstrated several applicable uses of sensitivity analysis for social network analysis based on Flow Modeling and Goal Programming methodologies. It is clear from this analysis that there may exist insensitive subgraphs. Further, there are likely subgraphs of individuals that do not play a significant role in the scenario under consideration in any given analysis effort. Rather than carrying high resolution data on these insensitive subgraphs through an entire analysis effort, aggregation of these individuals is a far more efficient approach (*i.e.*, reduces the number of decision variables and constraints in the mathematical programming representation). Aggregation is the subject of the next chapter.

This chapter has demonstrated that a flow model representation of a social network allows for more detailed analysis than existing methods. Data required has fewer necessary mathematical assumptions than existing Social Science methods. Further, the flow model representation in combination with goal programming offers tremendous flexibility in terms of applicable problem classes. Side constraints may be used in the flow model representation to explicitly represent structural and behavioral properties of the social network, such as thresholds on the level of influence or other similar properties. Sensitivity analysis allows the analyst to perform *What if?* analysis of changes in the problem statement and to better understand both uncertain and certain aspects of the model implemented. The use of Operations Research network models has opened up a wide array of modeling and post-optimality analysis methods applicable to social networks.

Efficient solution methods exist for even the most complex problem classes dealing with multiple competing objectives in multi-context, multi-criteria, overlapping networks. Chapter 5 adds further capability to the analysis of large scale problems by proving an appropriate aggregation methodology. Chapter 6 extends this entire research effort to include psychological profile based measures and adds the analysis capabilities of Decision Analysis methods extended to accommodate the specific behavior and structural properties of social networks.

Chapter 5. Aggregation in a Social Network

This chapter investigates the benefits of aggregation in a social network. Aggregation/disaggregation is critical to increasing the efficiency of any analysis effort where the resolution of the available data exceeds that required for the given problem. It is quite possible that in any social network not all of the individuals in a given network are of interest to every scenario being analyzed. Aggregation can be used to reduce the number of nodes and edges in a social network. Reducing the number of nodes and edges reduces the number of decision variables and constraints in the mathematical programming representation. Aggregation alone may make previously intractable problems feasible using existing technology.

As noted in Chapter 2, Social Science methods do not currently accommodate the analysis of networks where nodes are a mix of individuals and groups or organizations. The aggregation method developed in this chapter provides a repeatable, logically consistent, and mathematically founded means of creating a social network of mixed individuals and groups applicable to the models developed in the previous chapter.

The methodology described here starts with a social network graph of individuals with an associated social closeness measure. Aggregation of nodes in this graph then collapses sets of related nodes into single nodes representing groups of individuals, much as statistical cluster analysis creates similar clusters. When this aggregation is done in a contextually logical manner, these groups of people represent their associated organizations.

The aggregation method developed here is based on the graph theoretic contraction procedure described in Chapter 2. If e is an edge between vertices u and v in G, then

> [the] *contraction* of e is the operation of replacing u and v by a single vertex whose incident edges are the edges other than e that were incident to u or v. The resulting graph, denoted $G \bullet e$, has one less edge than G (West, 1996:65).

This graph theoretic procedure defines a method of contracting unweighted (*i.e.*, uncapacitated edges in the flow model formulation) in a simple graph.

The weighting of contracted edges must be both *logical* and *repeatable*. A logical contraction is one that retains all of the mathematical properties of the flow model representation. In other words, the solution found in the aggregated representation should be the same as the solution found in the disaggregated network. A repeatable contraction should yield the same aggregated graph every time the same edges are contracted in the same graph. For multiple edge contractions, the order in which edges are contracted should not change the resulting aggregated network.

Based on the above assumptions and requirements, the following aggregation procedure is defined by extending the simple graph contraction procedure to accommodate the properties of a social network digraph.

> **Definition.** *Social Network Aggregation* is the edge contraction in a social network graph G performed by contracting edges e, edges between vertices u and v in G, then replacing u and v by a single vertex denote u' whose incident edges are the edges other than e that were incident to u or v and weighted (capacitated) by the sum of the weights (capacities) of those edges. Edges e must not be a bottleneck, thus $s_{uv} \geq \Sigma_i s_{iu}$ and $s_{vu} \geq \Sigma_j s_{jv}$ for all nodes i and j incident to u and v, respectively. In a simple graph e is at most one edge and in a digraph e is at most two edges. The resulting graph is denoted $G \bullet e$ and has at least one less edge and at most two less edges than G. $G \bullet e$ has one less node than G. Further aggregation may be performed by the iteration of this procedure.

Theorem. The social network resulting from *Social Network Aggregation* has the same flow model solution as the original social network.

Proof. The flow in terms of social closeness, representing potential influence, from (to) nodes *u* and *v* to (from) all incident nodes is the social closeness between *u* and *v* and these other nodes, respectively. Therefore, the total maximum flow between *u* and *v* and their respective incident nodes is the sum of the social closeness from (to) *u* to (from) its incident nodes and *v* to (from) its incident nodes. The node *u*' is incident to all of the nodes incident to both *u* and *v*. Three cases exist for the incidence of nodes *u* and *v* to these nodes: (1) only node *u* was incident, (2) only node *v* was incident, or (3) both nodes *u* and *v* were incident. In case (1), node *u*' remains incident to these nodes with a weight (capacity) equal to that of node *u*. In case (2), node *u*' remains incident to these nodes with a weight (capacity) equal to that of node *v*. In case (3), node u' is incident to these nodes with a weight equal to the sum of the weights to (from) node *u* and *v*. Therefore, no weight (capacity) has been lost between node *u*' and those incident to *u* and *v*. The maximum flow between *u*' and these nodes remains the sum of the social closeness from (to) *u* to (from) its incident nodes and *v* to (from) its incident nodes.

∴ Therefore, the social network resulting from *Social Network Aggregation* has the same flow model solution as the original social network.

Theorem. Iteration of the *Social Network Aggregation* procedure produces the same resulting social network graph independent of the order of contractions.

Proof. The first contraction in an iterative application of the *Social Network Aggregation* procedure results in the contraction of node *u* and *v* into node *u*'. Let *u*' be *u* for all subsequent contractions of incident nodes *v*. The resulting graph then represents the contraction of all incident nodes into *u*'. Every pairwise iteration insures that maximum flow has not changed based on the proof above. If starting nodes *u* and *v* are changed to nodes *x* and *y* where *x* and *y* are nodes contracted into *u*' previously, the resulting social network graph following the iterative contraction of the same nodes contracted into *u*' then represents the contraction of all incident nodes into *x*'. Observe that *u*' and *x*' represent the contraction of the exact same nodes and every pairwise iteration again insures that the maximum flow has not changed. Thus, $u' = x'$. Without loss of generality, *x*' may be relabeled *u*' $\forall$ *u*, *v*, *x*, and *y* in the social network graph.

∴ Therefore, iteration of the *Social Network Aggregation* procedure produces the same resulting social network graph independent of the order of contractions.

It follows naturally from the definition and proofs given that aggregation in a network of groups or organizations has the same properties when the *Social Network*

Aggregation procedure is applied. This is exemplified by the fact that when the *Social Network Aggregation* procedure is iterated, every iteration after the first represents the aggregation of individuals into a group.

That this aggregation procedure does not apply to bottlenecks has several implications. Observe that a bottleneck is a weak tie using Watts' definition already discussed in Chapter 2. A contextually logical aggregation would combine those in close friendship groups (*i.e.*, those with strong ties). Using the *Social Network Aggregation* procedure to aggregate across weak ties preserves the aggregate capacity (represented as a weight on edges in the graph) in and out of that group; however, no longer properly represents the maximum flow (*i.e.*, the weak tie forming a bottleneck is lost in its contraction).

Data with respect to the existence and weight (capacity) of relationships between those nodes and edges contracted is lost in the contraction procedure. This data must be stored in order to disaggregate the network for subsequent or future analysis. It is likely that one might use an aggregated network for screening purposes (*i.e.*, determining which groups are significant in a particular problem). Significant groups (*i.e.*, those found important to the solution) might then be disaggregated to further analyze the problem. As noted, subsequent analysis of the disaggregated network will not change the maximum flow solution; however, will give more detailed path information with respect to the previously contracted subgraph(s).

Failing to save the aggregated data or starting with a case where this data is unknown yields significant problems for disaggregation. All that can be determined without the aggregated data is that at a minimum the aggregated nodes exist in a connected subgraph (*i.e.*, at least a tree) and at a maximum a fully connected subgraph. There is no way to derive the edge weights for these subgraphs, as capacity in a subgraph is not bounded by capacity in any other subgraph. The actual flow to or from the formerly aggregated subgraph is bounded above by the capacity of incident edges to the aggregated node(s).

For any digraph, it is possible to determine the maximum number of edges contracted by any possible contraction. The maximum number of edges in a digraph is $e = n(n\text{-}1)$ where e is the cardinality of the total possible edges in the graph and n is the cardinality of the set of nodes in the graph. The change in the maximum number of edges in the graph subsequent to a contraction of r nodes where $r > 0$ (*i.e.*, any non-trivial case), is the difference between e and e' where e' is the cardinality of the total possible edges in the contracted graph. This difference is denoted Δe where $\Delta e = e - e'$. Δe is calculated as follows:

$$\begin{aligned} \Delta e &= e - e' \\ &= n(n\text{-}1) - ((n\text{-}r)(n\text{-}r\text{-}1)) \\ &= (n^2\text{-}n) - (n^2\text{-}rn\text{-}n\text{-}(rn\text{-}r^2\text{-}r)) \\ &= (n^2\text{-}n) - (n^2\text{-}rn\text{-}n\text{-}rn+r^2+r) \\ &= 2rn\text{-}r^2\text{-}r \\ &= r(2n\text{-}r\text{-}1) \end{aligned} \tag{37}$$

Thus, for a social network digraph where r nodes have been contracted, the number of contracted edges is $\Delta e = r(2n\text{-}r\text{-}1)$. As noted in the previous section, increasing density defined in terms of the number edges is what makes a problem larger in scale. The *Social Network Aggregation* procedure has a second order reduction in edges with only a reduction of r nodes. For a simple graph, the results follow naturally by observing that the maximum number of edges in a simple graph is $e = (n(n\text{-}1))/2$. The advantages of the *Social Network Aggregation* procedure are illustrated by the following example.

Sample Case: Iranian Government

Social Network Aggregation is demonstrated in the following example. Note that when individuals, represented by nodes, are aggregated they form groups of people. When this aggregation is done for groups of people who share an organizational affiliation in the context of the network under analysis, their aggregation represents the flow to and from this organization from or to the remainder of the social network. This methodology allows for the aggregation of a network of individuals without changing the solution to the maximum flow found in the disaggregated network, as demonstrated in the example below.

The example used in this section is a geo-political scenario based on Iran. Sample case data comes from Foundation for Democracy in Iran (FDI) (http://www.iran.org). FDI provides data for Iran in 1997 with regard to President Khatami's Cabinet, the Council of Expediency and Discernment, the Council of Guardians, the Judiciary Branch, the Majlis, and the Supreme National Security Council. The data for these key Iranian government organizations is provided in Appendix C. There are 384 individuals in these bodies.

In the graphical representation to follow, the membership in organizations other than senior leaders has been aggregated into their organizations. The number of people aggregated into an organizational node is denoted in parentheses below its name. Membership in an organization need not be mutually exclusive (for example, the Executive Branch has 31 members, this includes the 22 Cabinet members, the 8 Vice

Presidents, and President Khatami). The weighting of connections is depicted by the width of the edges in the graph. Weighting is provided for example purposes based on the following social closeness measure:

> 1. Social closeness between members of a group they are primarily a member of are three times that of only administrative connections. Secondary group membership is twice as important as administrative connections. Therefore, there is a ratio of 1:2:3 for administrative:secondary:primary connections.
>
> 2. Edges are directed based on the rules that: (1) people influence other people and groups down their chain-of-command and (2) groups influence other groups.

This notional weighting is done for example purposes only. The data, while representative of the 1997 Iranian government, should not be taken as authoritative as FDI is as an Iranian opposition group which advocates the overthrow of the existing regime (*i.e.*, the data was not provided by the Iranian government or approved for use by any domestic of foreign government agency). The Iranian government social network is depicted in Figure 16. The complete disaggregated data for the entire network is available in Appendix C.

Consider, for example, the problem of identifying who among Iran's senior leaders depicted (*i.e.*, sources) in the network (Khatami, Rafsanjani, Nouri, Mohammad, Jannati, and Firouzabadi) has the greatest ability, in terms of maximum flow, to influence the key Iranian government bodies (*i.e.*, sinks) depicted in the network (Executive Branch, Council of Expediency and Discernment, Majlis, Supreme National Security Council, Judiciary, and Council of Guardians). This problem is a single-commodity maximum flow problem as discussed in Chapter 4.

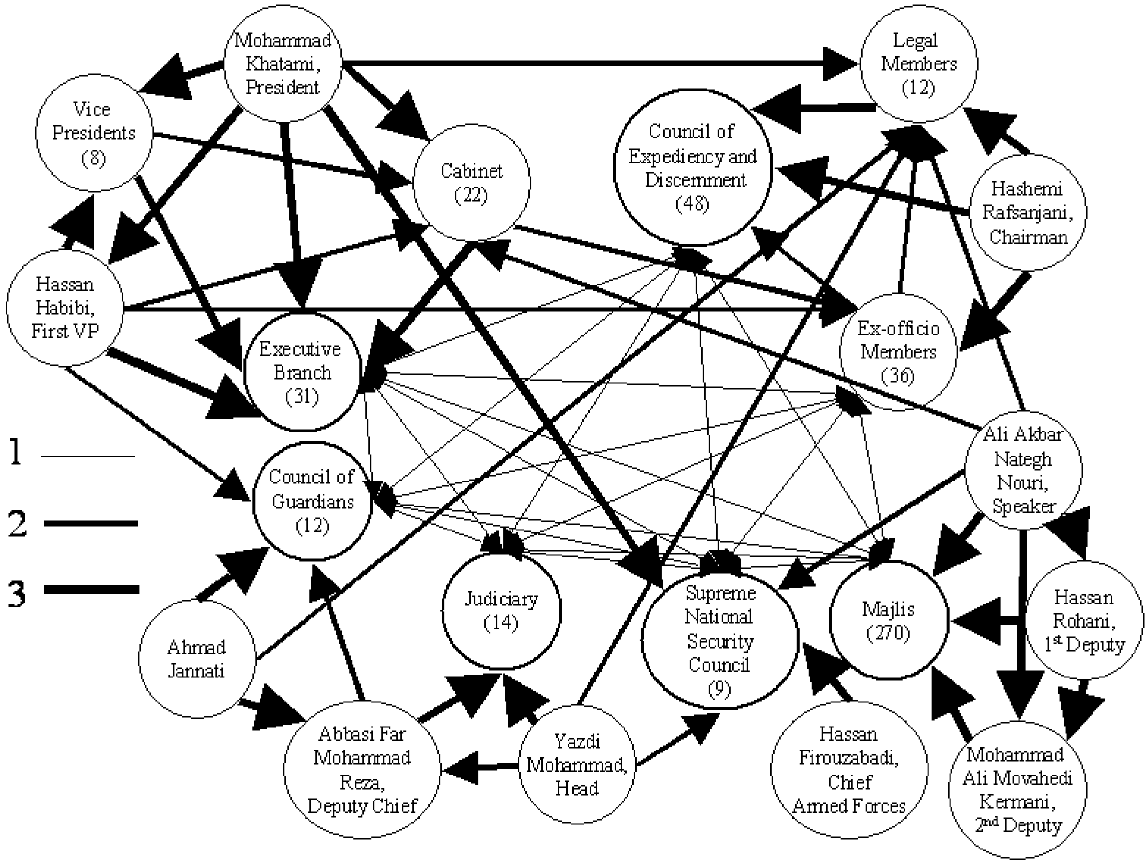

Figure 16. Iranian Government Social Network

The results of this analysis indicate that Khatami has the maximum flow, indicating maximum influence, of 17 in terms of the social closeness measure defined based on primary, secondary, and administrative organizational membership. The influence of Rafsanjani was 9, Nouri was 15, Mohammad was 9, Jannati was 8, and Firouzabadi was 3. The maximum flow solution is depicted graphically in Figure 17.

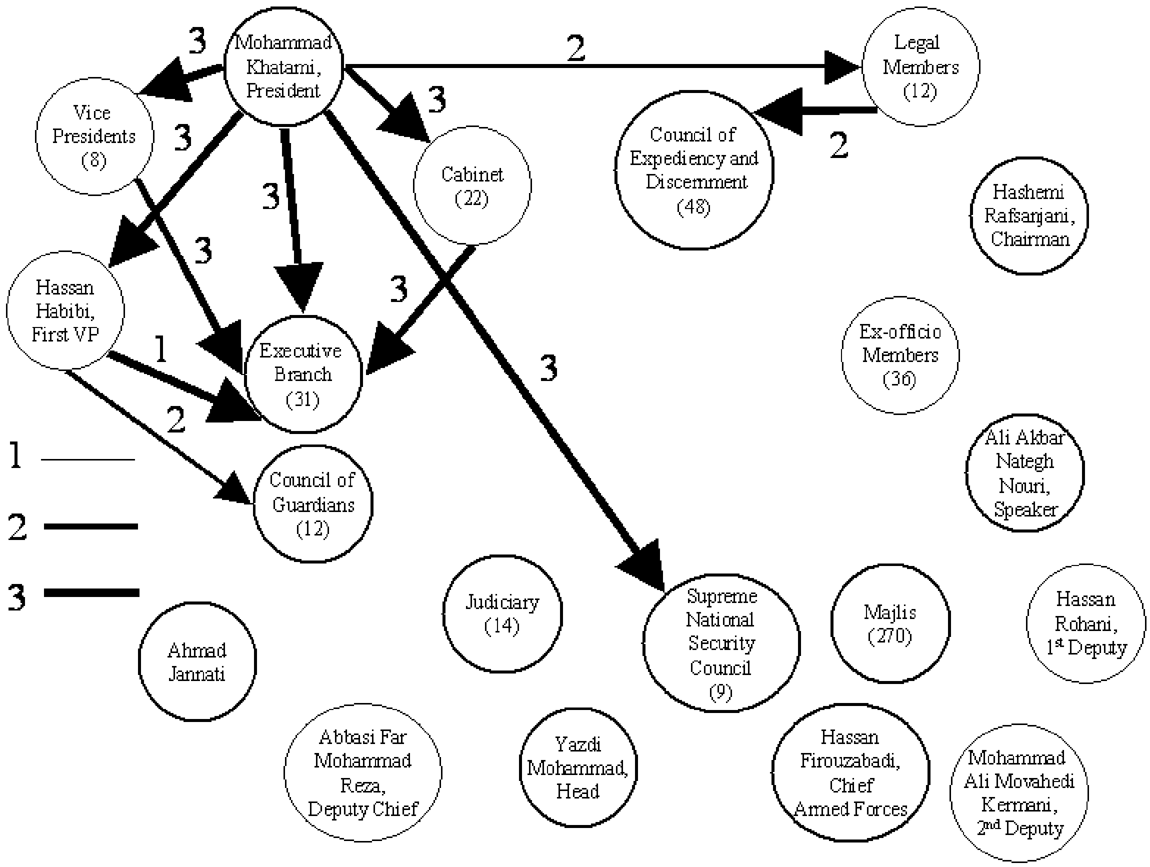

Figure 17. Iranian Government Maximum Flow Solution

The results of this sample problem are not unexpected. The social closeness measure applied essentially represents strength in terms of the given organizational hierarchy. Therefore, the result that President Khatami would exercise the greatest influence in the formal hierarchy of the government of Iran is expected. Based on these results an analyst might then desire to focus on the influence of the Executive Branch as a whole. For the purpose of demonstrating the aggregation procedure, only the induced subgraph for the Executive Branch is considered. This graph is depicted in Figure 18.

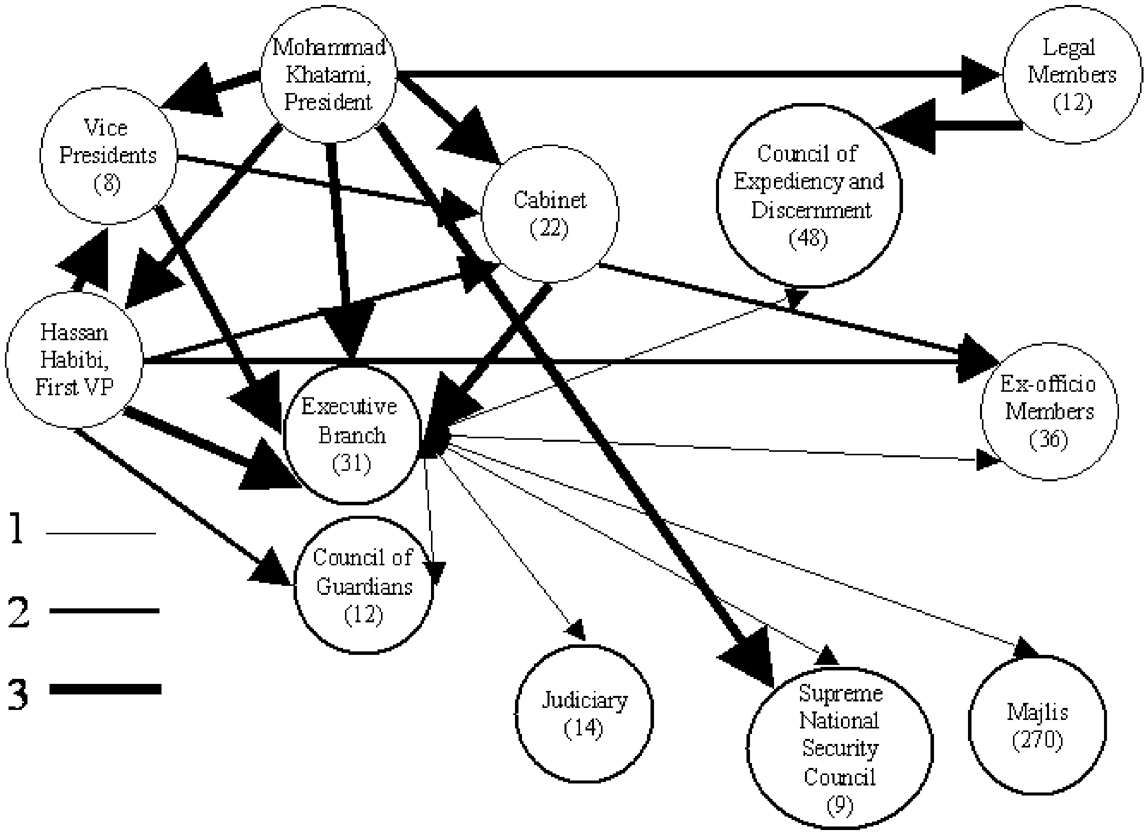

Figure 18. Induced Subgraph for the Iranian Executive Branch

It can be seen in Figure 18, that all of the individuals in the Executive Branch and the Cabinet may be aggregated into a single Executive Branch node. The resulting aggregated graph is given in Figure 19, depicting only those edges originating from the Executive Branch. Such an aggregation may, for example, be the first step in an analysis of the influence of the Executive Branch as a whole on the other government organizations represented.

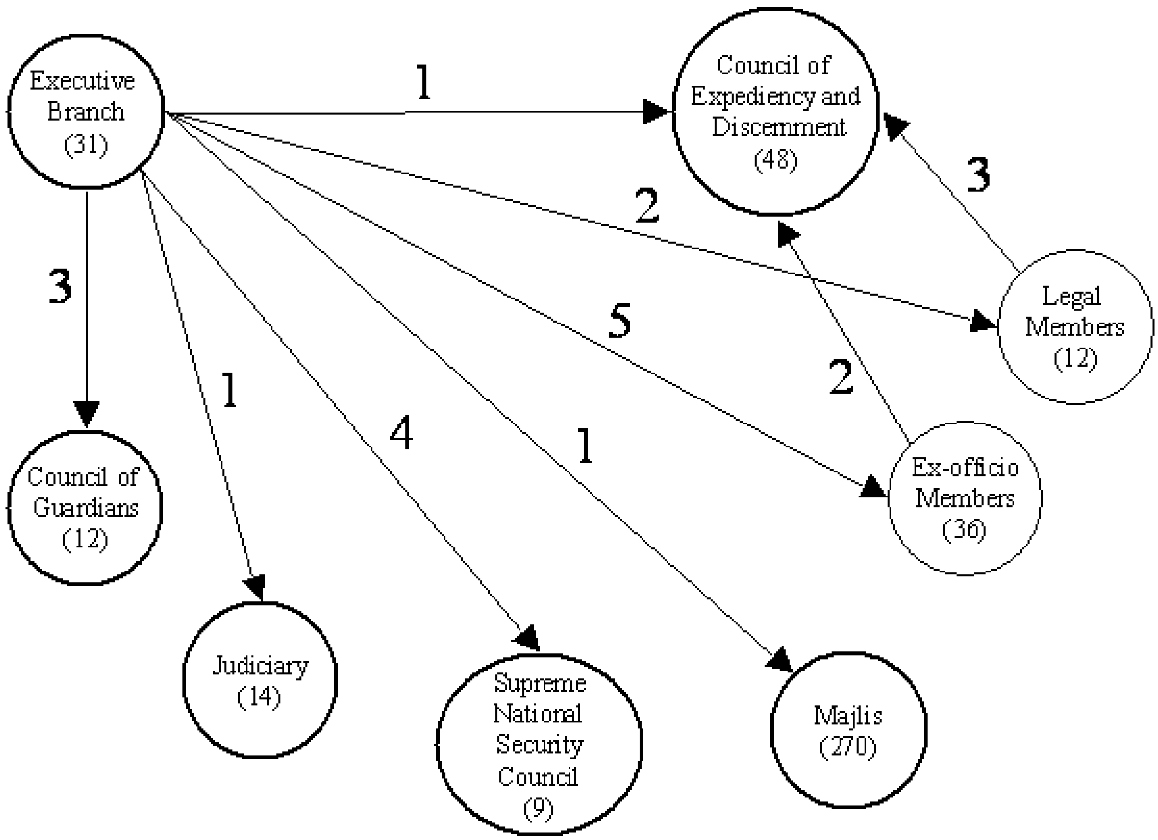

Figure 19. Aggregated Iranian Government Social Network

In the graph aggregated for the Executive Branch (Figure 18) the aggregation now represents what would have been a graph of 384 nodes and associated edges. This graph has only 8 nodes, a reduction of 97.92%. Using the formula already given, the reduction in the maximum number of edges is $\Delta e = r(2n\text{-}r\text{-}1) = 147016$ where $n = 384$ and $r = 384\text{-}8 = 376$ from 147072 (*i.e.*, $n(n\text{-}1)$) or 99.96%. If this level of resolution is adequate for a given analysis effort, this aggregation is significantly more tractable than dealing with the disaggregated network.

To further understand the aggregation procedure, consider only the aggregation of the resultant edge from the Executive Branch to the Ex-officio Members of the Council of Expediency and Discernment. The resulting edge has a weight (or capacity) of 5. This weight is calculated as the sum of the weights in the previous disaggregation of the weights from the Executive Branch to the Ex-officio Members (1), the weight from Hassan Habibi, First Vice President to the Ex-officio Members (2), and the weight from the Cabinet to the Ex-officio Members (2). Note that this sum is 5 no matter in what order Hassan Habibi and the Cabinet are aggregated pairwise into the Executive Branch node.

This chapter has defined, proven, and demonstrated a mathematically founded means of aggregating a directed, weighted (capacitated), social network. When appropriate for a given analysis effort, aggregation represents a useful tool for increasing the tractability of analysis without changing the properties of the disaggregated network in terms of flow. While the capacities of the aggregated relationships where depicted as the sum of the capacities aggregated, other standards might be used ***if justified*** for a given scenario. These might be the influence of a *Lickert lynchpin* in an aggregated node representing an organization, where the influence of the most (least) influential individual in the organization, or other justifiable criteria. While not directly discussed here, parallel and series contractions also exist.

The reduction in the number of nodes and maximum edges may be transparently calculated using the formulas provided. Understanding and predicting the decisions in a given social network relies directly on the aggregation of influence terminating in the target (*i.e.*, decision-making) node (individual or group). Overall, aggregation in a social network is another valuable tool for social network analysis.

Chapter 6. Decision Analysis and Social Networks

This chapter describes how Decision Analysis may be used to improve on existing Social Network Analysis methods. In the previous chapters, Flow Modeling and Goal Programming have been described, demonstrating applications to Social Network Analysis. This chapter adds additional capability to these methods. Specifically, Value Focused Thinking (VFT) is used to elicit, in a formal manner, the values that are often subjective and uncertain. The results of a Value Focused Thinking analysis are then used to derive social closeness values for the underlying network. The resulting network may then be used to understand, analyze, and predict decision making behavior within the social network structure.

It is first necessary to establish a generalized Value Hierarchy framework that holds for all people, where the measures are the same for all people in the network, but particular value scores and weighting may vary between individuals. Value scores will differ between individuals due to varying factors influencing their current psychological state. Weighting will vary based on the relative importance of these factors. Social closeness is then determined by calculating the delta sender-receiver values in terms of influence. The delta sender-receiver calculation is explained in detail later in this chapter; however, the essential concept is taking the value scores of an individual initiating influence (the sender) and subtracting the value scores of the receiver of the influence to determine a social closeness value based on culturally specific rules of behavior.

The delta sender-receiver technique generates properly defined social closeness values based on psychological and environmental factors while utilizing sociological and anthropological properties. These social closeness measures are then used to weight (capacitate) a social network. The social network may then be aggregated into a single node. The resulting aggregated value scores may then be used in the value hierarchy to represent the decision process of the entire social network. This aggregated value hierarchy is used to evaluate alternatives for the individual node now representing the entire network.

This chapter proposes a method for such analysis based on Trait Theory. Other models using different trait theoretic or Psychodynamic Theory may be used, if preferred for a particular analysis. Diverse theories, such as those discussed in Chapter 2, provide a robust understanding of individual psychology and for the purpose of modeling and analysis their use in combination is complementary (Beckerian, 1997:44-45; Dasen, 2000:429). When properly implemented, this technique adds capabilities to Social Network Analysis that are beyond any existing techniques by using data collected only through psychological profile data for the individuals involved.

The technique discussed in this chapter is especially useful for analysis of high cardinality, non-cooperative cases (terrorist networks, for example). The psychological profile data may be obtained through existing tests or surveys; however, this is an unlikely source for most cases and in other cases the number of people in the social network (cardinality) may make such data collection methods impractical. Alternatively, psychological profiles may be assessed by domain experts based on available speeches, writing, observations of behavior, background, and known experiences of the individuals in a given social network under analysis where appropriate cultural conventions and understandings are included in the assessment.

Building a Common Individual Value Hierarchy

Trait Theory is the foundation for the analytical model for the reasons reviewed in Chapter 2. Specifically, Trait Theory is quantifiable, additive, linear, and measurable making it a natural fit to Decision Analysis methods. Having already identified some of the desired properties of a decision model, the type of analytical model for use and its requirements will now be defined. Following an examination of the type of analytical model selected, the specific theories incorporated in the model and a discussion of these theories follows.

The type of analytical model selected for this study is a *value hierarchy*, which will be shown to have a natural fit to trait theory. A value hierarchy is a "value structure with a hierarchical or 'treelike' structure" (Kirkwood, 1997:12). A value structure is:

> the entire set of evaluation considerations [traits], objectives [preferred direction of movement], and evaluation measures [measures of traits] for a particular decision analysis (Kirkwood, 12).

In this study, the decision analysis is conducted with respect to considering alternative environments and their value (change in psychological state) relative to the *Current* state for a given target individual's personality. An alternative environment may increase susceptibility overall or for a specific pressure point of interest, given particular changes to environmental conditions.

A value hierarchy has several desirable characteristics. These characteristics guide to some degree the selection of specific theories or specific aspects of theories to include in the model. Desirable characteristics are the properties of completeness, nonredundancy, independence, operability, and small size (Kirkwood, 1997:17-18).

Completeness requires that the value hierarchy include all relevant factors involved in the given decision analysis. Nonredundant indicates that a value is represented only once in the hierarchy. Independent, a broader concept than nonredundant, states that no values should be directly correlated to each other. Operable is defined as a representation that is helpful to the user. Small size implies that a smaller model is preferred to a larger model, if the results are similar.

In the value model, values in the hierarchy are traits. Associated with the lowest tier of the value hierarchy are measures and single dimension value functions (examples are given Appendix D). The next sections of this chapter presents a model of *Individual Psychological State*. The values at every tier of the hierarchy are discussed in detail including the lowest tier representing measures. Measures are scored based on an individual's personality and the environment for each alternative. These scores, representing the strength of a given trait, are converted to values via a *value function*. Values in this model represent the amount of susceptibility associated with the strength of the trait being scored. The only requirements for value functions are that they are monotonic, representative, and measurable.

Associated with every tier of the hierarchy are weights. Each value is weighted relative to the other values in its tier that share the same parent in the hierarchy. Within a tier (*i.e.*, locally) the weights sum to 1 where a 0 weight implies that that the value and all of its children in lower tiers have no impact on the overall solution. Cumulatively (*i.e.* , globally), the impact of a weight on a particular value to the overall solution (*i.e.*, *Individual Psychology State* value) is the product of its weight and the weights on all of its parent nodes. Values are propagated up the hierarchy often in a linear, additive weighted manner. Multiplicative methods also exist (Kirkwood, 1997:253); however, it is known that Trait Theory has linear additive relationships, making such methods unnecessary for this study. It is possible to observe the value of each alternative at any tier in the hierarchy. Useful points of evaluation are described.

Value Hierarchy

Figure 20 shows the value hierarchy developed in this study. The next sections take the reader through each stage of its construction. A description of the values, measures, value functions, weights, and output is also given. A detailed definition of each value in the hierarchy is given in the Appendix D. Hypothetical value functions for each of these values are also provided in Appendix D. The values and their associated value functions were constructed based on the underlying psychological and social science theories discussed in Chapter 2, however, are defined here for example purposes only. An actual value model and, particularly, its associated functions used in any case study should result from elicitation of the decision maker(s) involved based on the problem under investigation.

The shaded boxes in the value hierarchy are measures. The value hierarchy for Individual Psychological State has three main pillars: *Common to All People*, *Cultural Effects*, and *Individual Traits*, as discussed earlier in this work.

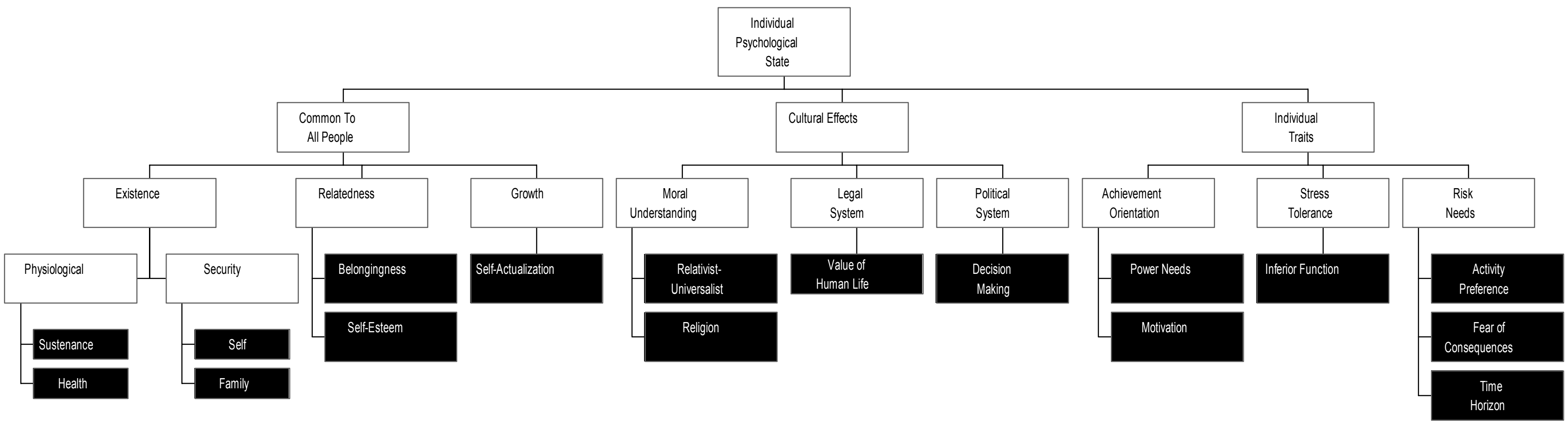

Figure 20. Individual Psychological State Value Hierarchy

The values (traits) comprising each of the three fundamental pillars, *Common to All People*, *Cultural Effects*, and *Individual Traits*, of the *Individual Psychological State* Value Hierarchy are discussed in the next sections of this chapter. Note that the measures for these traits, represented by the lowest level of the hierarchy, are proposed for discussion and to clarify the use of this methodology and are not appropriate for all problem cases or decision makers. The correct specification of these measures, like the hypothetical value functions, must be elicited from decision makers involved in a given analysis effort.

Common to All People

The theoretical foundation of the values in the *Common to All People* pillar is based on Maslow's Hierarchy of Needs (Maslow, 1954:80-92) as extended by Alderfer's Existence, Relatedness, and Growth (ERG) Theory (Alderfer, 1972:25). Maslow's Hierarchy of Needs asserts that human motivations are in response to satisfying needs in the following order: *Physiological*, *Security*, *Belongingness*, *Self-Esteem*, and *Self-Actualization* (Maslow, 1954:80-92). Formal definitions for all terms may be found in Appendix A; however, as Mischel points out, the colloquial understanding of these terms is sufficiently close to their formal definition for most uses (Mischel, 1968:65). Relying only on Maslow's theory would mean that these needs form successive tiers of a hierarchy; however, Alderfer's ERG Theory suggests that this may not necessarily be the case.

Alderfer groups Maslow's *Physiological* and *Security* needs into a category of needs he called *Existence* (Alderfer, 1972:25). He groups *Belongingness* and *Self-Esteem* into the *Relatedness* category and *Self-Actualization* in to the *Growth* category (Alderfer, 1972:25). Alderfer originally split aspects of esteem into *Relatedness* ("interpersonal" esteem) and *Growth* ("self-confirmed" esteem) (Alderfer, 1972:25); however, later work included esteem entirely under *Relatedness* (Curphy, 1993:263). Here the broad concept of esteem is described in terms of *Self-Esteem* using the definition that *Self-Esteem* "refers to the overall positiveness or negativeness of a person's feelings about … experiences and roles [self-concept]." (Curphy, 1993:175). This definition includes what Alderfer called interpersonal esteem and self-confirmed esteem and is consistent with Maslow's original definition (Maslow, 1954:92).

ERG theory also adds two other important concepts in determining the structure of this pillar. First, ERG theory identifies that people often satisfy more than one of these needs at the same time (Curphy, 1993:263). This means that needs are not strictly hierarchical in the way that Maslow had originally postulated. Alderfer goes further in a similar concept called "Frustration Regression" (Alderfer, 1972:16-17). This concept basically holds that frustration (or inability) with satisfying a higher-level need can lead to efforts to satisfy a lower-level need (Alderfer, 1972:17).

Frustration Regression is not represented as a value in the hierarchy, it is incorporated into the weighting of the hierarchy. For example, if satisfaction in *Growth* needs are low and *Existence* and *Relatedness* needs are more satisfied, greater weight will be placed on *Existence* or *Relatedness* away from *Growth*, if Frustration Regression is occurring. This is developed in more detail later for the specific case under consideration.

Although not necessarily a unique representation, Maslow's and Alderfer's theories form a comprehensive representation of the needs common to all people. As described previously, the analytical model uses measures of an individual's satisfaction of these needs. The value hierarchy indicates that *Belongingness*, *Self-Esteem*, and *Self-Actualization* are measured directly, as they are in the bottom tier of the hierarchy. *Physiological* needs are broken down into the measures *Sustenance* and *Health*. *Security* is broken down into *Self* and *Family* to describe the relative physical security of the target individual and his family, respectively. For the purpose of this model, *family* is anyone with whom the target individual has a familial-like devotion. Associated with each of these measures is a value function.

Value functions have the requirement to be monotonic, although, they may be continuous or discrete in nature (Kirkwood, 1997:60-61). In Appendix D, hypothetical discrete value functions for all the measures in the value hierarchy are given. These value functions map a category of observable behavior (score) to a value from 0 to 10, where 0 is the most susceptible psychological state and 10 is least susceptible state. These functions form a strawman developed for use primarily in considering alternative actions that affect the target's environment. Further development of these functions with interdisciplinary experts (*e.g.*, psychologists, sociologists, etc.) is required before they should be used for a particular case study. Figure 21 shows the value function associated with the measure *Health*, as an example.

Recall from the discussion of value hierarchies that independence is one of the desirable characteristics. In reviewing the literature for an appropriate value function for *Self-Actualization*, it was found that *Self-Actualization* is best determined in relation to *Physiological*, *Security*, *Belongingness*, and *Self-Esteem* needs. As Maslow indicates, "the clear emergence of these needs [self-actualization] usually rests upon prior satisfaction of the physiological, safety [security], love [belongingness], and esteem [self

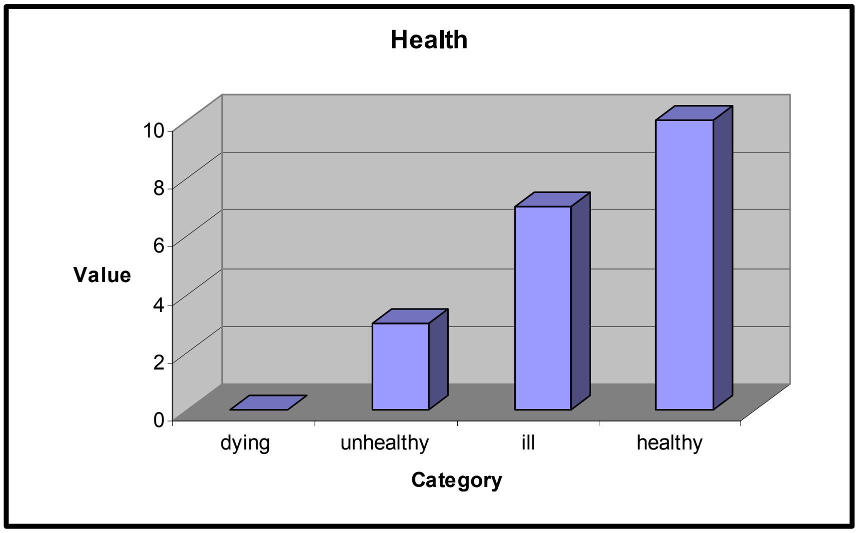

Figure 21. Value Function for the Health Measure

esteem] needs" (Maslow, 1954:92). Rather than remove *Growth* and *Self-Actualization*, which would take away from completeness, *Self-Actualization* is scored by the average score of *Physiological*, *Security*, *Belongingness*, and *Self-Esteem*. This dependency in the model then has a strict mathematical form. Note that *Self-Actualization* is not evaluated explicitly by the user, which would cause theoretical contradictions in the model. A proof follows that certain cases of dependency, such as this, still meet the underlying assumptions of Value Focused Thinking when evaluated as described.

The proof demonstrates that dependency between attributes in a value hierarchy may be modeled such that the resulting functional form maintains an additive weighted form identical to a model lacking such dependency and consistent with the assumptions of Value Focused Thinking. In other words, there exists a mapping to a correctly specified value hierarchy (which may have a different structural form). Since both representations yield the same solution, either is appropriate for VFT analysis. Any combination, such as the linear combination described, is simply a representation of independent attributes as proven:

> **Theorem**. A linear combination of attributes maintains the additive weighted model of independent values assumed in Value Focused Thinking.
>
> **Proof.** Let x_i be attributes $i = 1, \ldots, n$ in the same tier of a Value Hierarchy. Let these attributes x_i share the same parent attribute, denoted x_0 . Let w_i be the weights associated with attributes x_i , respectively. Then, by definition,
>
> $$x_0 = \Sigma_i\, w_i x_i \tag{37}$$
>
> Suppose $x_j = \Sigma_{\{m\}}\, x_{\{m\}}/k$ where k is the cardinality of $\{m\}$ and $\{m\} \in (\{1, 2, 3, \ldots, n\} - \{j\})$. Let $\{q\} = (\{1,2,3, \ldots, n\} - \{j\})$, thus $\{m\} \in \{q\}$. Then,
>
> $$\{1, 2, 3, \ldots, n\} = \{q\} + \{j\} = \{q\} + \{m\} - \{m \cap q\} + \{j\} \tag{38}$$
>
> $$\begin{aligned} x_0 &= \Sigma_{\{q\}}\, w_{\{q\}}x_{\{q\}} + w_j\, \Sigma_{\{m\}}\, x_{\{m\}}/k \\ &= \Sigma_{\{q\}}\, w_{\{q\}}x_{\{q\}} + w_j/k\, \Sigma_{\{m\}}\, x_{\{m\}} \end{aligned} \tag{39}$$
>
> Let $w'_{\{m\}} = w_{\{m\}} + w_j/k$, $w'_{\{q - m\}} = w_{\{q\}}$ and
> let $\{n'\} = \{q\} + \{m\} - \{m \cap q\} - \{j\}$, then
>
> $$x_0 = \Sigma_{\{n'\}}\, w'_{\{n'\}}x_{\{n'\}} \tag{40}$$
>
> Thus, x_0 is an additivity weighted function of attributes $1, \ldots, n'$ consistent.
>
> ∴ Therefore, a linear combination of attributes maintains the additive weighted model of independent values assumed in Value Focused Thinking..

This concept can be better understood by examining the case of *Self-Actualization*. *Physiological* (x_1), *Security* (x_2), *Belongingness* (x_3), and *Self-Esteem* (x_4) needs are the values used to form the proxy measure for *Self-Actualization* (x_5). The proxy measure for *Self-Actualization* has the form: $x_5 = (x_1+x_2+x_3+x_4)/4$. All x_i for $i = 1, \ldots, 4$ values are used to calculate the value at the next tier of value hierarchy comprised of *Existence* (y_1), *Relatedness* (y_2), and *Growth* (y_3) . This relationship has the form: $y_j = \Sigma_i\, w_i x_i$ for all x_i children of value y_j , where w_i is the elicited weight on x_i (for example $y_1 = w_1x_1 + w_2x_2$). Likewise, *Common to All People* (z_1) has the form: $z_1 =$

$w_e y_1 + w_r y_2 + w_g y_3$ where w_e , w_r , and w_g are the weights on *Existence*, *Relatedness*, and *Growth*, respectively. By substitution, $z_1 = w_e(w_1x_1+w_2x_2) + w_r(w_3x_3+w_4x_4) + w_g(w_5x_5) = w_e(w_1x_1+w_2x_2) + w_r(w_3x_3+w_4x_4) + w_g(w_5((x_1+x_2+x_3+x_4)/4))$. Combining terms, $z_1 = (w_ew_1 + (w_gw_5)/4)x_1 + (w_ew_2 + (w_gw_5)/4)x_2 + (w_rw_3 + (w_gw_5)/4)x_3 + (w_rw_4 + (w_gw_5)/4)x_4$. Letting w_i' equal the resulting coefficients for i = 1, 2, 3, and 4 (*i.e.*, for example, $w_1' = (w_ew_1 + (w_gw_5)/4)$) , $z_1 = w_1'x_1 + w_2'x_2 + w_3'x_3 + w_4'x_4$. By observation, z_1 is a weighted sum of only independent measures. Therefore, z_1 is defined consistently with the linear additive weighted model specification of Value Focused Thinking. It is thus possible to weight *Self-Actualization* (w_5) independently, even though x_5 is a dependent proxy measure, without violating the assumptions of Value Focused Thinking. Extending this methodology to more complex dependencies follows naturally, as all tiers of a value hierarchy have the same addivitive weighted functional relationships.

Another important theory incorporated into the value functions for *Sustenance*, *Health*, *Self*, and *Family* is Herzberg's Two-Factor Theory. Two-Factor Theory divides traits into two categories: motivators and hygiene factors (Curphy, 1993:271). Motivators are those traits that lead to increased satisfaction. Hygiene Factors have limited impact on overall satisfaction, but lead to dissatisfaction when not achieved to some level (Herzberg, 1959:113). *Sustenance*, *Health*, *Self*, and *Family* are modeled as Hygiene Factors where failing to meet a specified threshold value results in a zero score for the entire pillar *Common to All People* (see also Appendix D).

There are aspects of human psychology and behavior that are influenced more specifically by factors other than those common to all people. These influences make up the other two pillars of the value hierarchy: *Cultural Effects* and *Individual Traits*.

Cultural Effects is discussed in the next section, followed by a discussion of *Individual Traits*.

Cultural Effects. Any understanding of culture carries with it the idea that across a common grouping (or culture) there are certain shared traits (Soukhanov, 1984:335). By inference, this means that there are traits that have not been addressed in the pillar *Common to All People*. Further, it can also be inferred that traits not common to all people or to a particular culture, must be those unique to the individual. This section discusses the modeling of *Cultural Effects* as part of the value hierarchy.

A necessary question to ask is: *To what culture does a person belong?* For example, Usama Bin Ladin is an Arab, was born a Saudi, is a Muslim, and is an extremist of the type sometimes referred to as an *Afghani Arab* (referring to Muslims, particularly Arab, who fought in Afghanistan and now share a particular world view). The answer to this question of culture is not simple. At this point the most definitive answer is to consider the culture that is most relevant to the psychology of the individual under consideration. This problem is moderated by the fact that some traits may be common across all the cultures to which the individual belongs. These common traits are those that are likely most assimilated by the individual under consideration, hence membership in that culture. Clearly religion is a key factor in Usama Bin Ladin's culture; all *Afghani Arabs* are Muslim, most Saudi's are Muslim, and many Arabs are Muslim.

Classification is not that simple, however. The violent behavior demonstrated by *Afghani Arabs* is not common across all Muslims nor encouraged by the greater religious body or its beliefs. For this reason, it is necessary to break *Cultural Effects* into specific values and measures. The primary underlying theory used in developing the *Cultural Effects* pillar of the value hierarchy is "Value Programming" (Curphy, 1993:169).

Value Programming is founded on the idea that in addition to genetic factors, "forces outside the individual shape and mold personal values" (Curphy, 1993:169). This theory speaks broadly of religion, technology, media, education, parents, peers, and other societal factors (Curphy, 1993:163). For example, the training of *Afghani Arabs* includes religious indoctrination, limited access to the free press, and formal combat training. Three focus areas are represented in the proposed model: *Moral Understanding*, the *Legal System*, and the *Political System*. These areas are modeled as independent and, when examined in the context of the entire model, considered complete.

Moral Understanding has two measures: *Relativist-Universalist* and *Religion*. The measure *Relativist-Universalist* identifies for a given culture the nature of its moral reasoning. Moral reasoning may be situational or "majority opinion rather than universal principles of justice" (Curphy, 1993:171). *Relativist* moral reasoning describes this situational or majority opinion view whereas *Universalist* moral reasoning asserts that there are universal principles of justice that must be followed.

The measure *Religion* is not intended to identify a specific belief system (such as Christian, Muslim, etc.) and, for the purpose of this model, includes any belief system that serves as a religion for the target individual. The measure *Religion* identifies the nature of how an individual practices and interprets religious teachings, ranging from an extremist view all the way to an atheist view. Conceptually, the stronger an individual practices and internalizes religion indicates how strong of a psychological factor religion is for an individual's culture. *Afghani Arabs*, for example, clearly fit the *Extremist* definition; whereas, clergy (for example, The Pope) would fit the *Orthodox* definition (see also Appendix D).

The value *Legal System* is measured by the degree to which a culture values human life. The measure *Value of Human Life* is defined across a culture by looking at the existence and to what level the culture's legal system allows and uses corporal and capital punishment. Possible measures of the *Value of Human Life* for decision analysis are expected lifetime earnings, current earnings, or remaining years of life (Kirkwood, 1997:41). For the hypothetical value functions used in this study, legal systems which are more likely to lessen the number of years of life by corporal or capital punishment are understood to represent a lesser value for human life than those which do not have corporal or capital punishment. For example, both Saudi Arabia and the United States have capital punishment; however, Saudi Arabia actually uses capital punishment far more often and for far more crimes than the United States. Further, Saudi Arabia has corporal punishment and the United States does not. It is also possible to differentiate between these two perspectives on the *Value of Human of Life* (and perhaps its trade-off with order and security), especially when compared to the many European countries that have neither corporal nor capital punishment.

The value *Political System* is measured by the *Decision Making* processes within a culture based on the degree of public and governmental involvement and authority in making decisions. The reason this is important with respect to the psychology of the individual is that if the target is the only person involved in the decision process, then influence only needs to be applied to the target. If the target uses some form of consultation or advisors, then these advisors must be influenced as well. However, if the target relies on a consensus process, all of the relevant constituents must be influenced in order to realize a change in the psychological state of the target. This latter case makes influencing the target much more difficult.

The traits common to all people and those traits specific to a given culture have been presented, but there are still many relevant psychological factors that must be considered. These factors are those that are specific to an individual. The third and final pillar, *Individual Traits*, is described next.

Individual Traits. There are many trait-based assessment tools available for the identification of individual personality. The Myers-Briggs Type Indicator (MBTI) is a well-known example of such a comprehensive assessment tool (Myers, 1998:1). MBTI and other recognized psychological assessment theories, were used to form the *Individual Traits* pillar of the model. Given the desire to maintain completeness, nonredundancy, and independence within the value hierarchy; only aspects of these theories and methods which are not already subsumed under the pillars *Common to All People* and *Cultural Effects* are used in the *Individual Traits* pillar.

Particular areas viewed as necessary to complete a formulation of the model are *Achievement Orientation*, *Stress Tolerance*, and *Risk Needs*. These values and their measures are very specific to individuals and do not rely directly on culture or the human condition.

Achievement Orientation is the "tendency to exert effort toward task accomplishment" (Curphy, 1993:264). Alderfer adds that:

> the achievement-oriented personality is generally attracted to activities which require the successful exercise of skill … Whatever the level of challenge to achieve, he will strive more persistently than others when confronted with an

> opportunity to quit and undertake some different kind of activity instead (Alderfer, 1972:368).

To measure *Achievement Orientation*, it is further broken down in to *Power Needs* and *Motivation*. *Power Needs* focuses on the nature of this orientation, either personalized or socialized. Personalized power is "selfish, impulsive, uninhibited, and lacking self-control. These individuals exercise power for their own self-centered needs, not for the good of the group or the organization" (Curphy, 1993:122). Socialized power "implies a more emotionally mature expression of the motive. Socialized power is exercised in the service of higher goals to others or organizations and often involves self-sacrifice toward those ends" (Curphy, 1993:122). Clearly, an individual whose *Achievement Orientation* leans towards high personalized *Power Needs* is more susceptible psychologically than someone who leans toward socialized *Power Needs*.

Motivation "is anything that provides direction, intensity, and persistence to behavior … a sort of shorthand to describe choosing an activity or task to engage in, establishing the level of effort to put forth on it, and determining the degree of persistence in it over time" (Curphy, 1993:257). *Motivation* may be internal or external (Maslow, 1954:176; Atkinson, 1966:118-119). Internal motivation is "behavior seemingly motivated for its own sake, for the personal satisfaction and increased feelings of competence or control one gets from it" (Curphy, 1993:264). External motivation is the exact opposite, behavior motivated only due to factors outside the individual (Curphy, 1993:274).

Internal motivation fosters a less susceptible *Individual Psychological State* than does external motivation, as factors such as rewards and punishments have a far greater impact on externally motivated individuals. In understanding *Achievement Orientation*, *Power Needs* indicate why a person wants to achieve (or gain power) and *Motivation* indicates how they are influenced. The weight of *Achievement Orientation* indicates how important this trait is in the *Individual Psychological State*.

Stress Tolerance is the amount of negative psychological and environmental factors one can handle prior to entering a dysfunctional psychological state (or inferior functioning). To measure *Stress Tolerance*, the concept of the *Inferior Function* from MBTI theory is applied. An individual's *Inferior Function* is defined by the individual's MBTI type. Entering inferior functioning (termed "The Grip"), is the weakest psychological functioning possible for a given personality (Quenk, 1996:4). "The smallest share of conscious psychic energy goes to the inferior function, so it is essentially unconscious" (Quenk, 1996:4).

> The inferior function appears in a specific and predictable form. The form is similar to the qualities that would describe a person who has that dominant function, but compared to the dominant form of the function the inferior will be: exaggerated or extreme – like a caricature of that type; inexperienced or immature – the person will come across childish, touchy, easily angered; undifferentiated or categorical – perceptions and judgments will be black and white, all or none (Quenk, 1996:6-7).

Common triggers include: fatigue, illness, stress, and alcohol or mind-altering drugs. Each MBTI has it own specific triggers and propensity for entering The Grip (Quenk, 1996:7).

Risk Needs is included to support both the accommodation of criminal personalities in the model as well as to address the *Activity Preference* aspects of motivation neglected under the measures of *Achievement Orientation*, to prevent redundancy. According to Atkinson, a problem "of behavior which any theory of motivation must come to grip with … is to account for an individual's selection of one path of action among a set of possible alternatives" (Atkinson, 1966:11). The constant cause of these differences is related to risk-taking behavior defined as the "the relationship of strength of motive, as inferred from thematic apprehension, to overt goal-directed performance" (Atkinson, 1966:11).

To measure *Risk Needs*, *Activity Preference*, *Fear of Consequences*, and *Time Horizon* were identified as measures. *Activity Preference* is defined as the amount of risk the target individual prefers in activity choices, where risk could be of life, money, freedom, or other valuable resources. *Fear of Consequences* acts as a deterrent, in varying degrees, to participating in certain activities even if the person has a high preference for that activity (Samenow, 1998:5). *Time Horizon* is the amount of time in the future that the target individual considers relevant when making plans or decisions.

A basic review of the value hierarchy, the values and measures related to the three pillar structure, and discussion of how measures are scored and weighted has been presented and is explored in detail in the example to follow. The model output based on these inputs and how to interpret those results must also be discussed.

Output

The model developed in this study reports the *Individual Psychological State* and which alternatives achieved the minimum and maximum value, but there are also several other important outputs of interest to report relevant to the psychology of the target individual and his or her reaction to changing environmental stimuli. For this reason, the model also reports the weakest and strongest pillar in the target's *Current* psychological state, each alternative's value in every pillar, the alternatives that achieved the minimum and maximum in each pillar, and a *Criminality* value. The following sections describe each of these outputs of interest and their general interpretation.

Individual Psychological State. *Individual Psychological State* values for each alternative and the *Current* state are an aggregate measure across all of the values represented in the model. The *Individual Psychological State* is the weighted sum of the values for each measured trait, as already described. A useful way to interpret these values is in terms of distance and direction from the *Current* state value. Recall, from the discussion of value functions earlier in this chapter, scores range from 0 to 10. The *Current* state value falls somewhere in this range, as do the values for the alternatives.

Alternatives that have greater values than the *Current* state represent moving the *Individual Psychological State* to a less susceptible state. This state can be understood as harder to influence, or more rigid. Alternatives that have lesser values than the *Current* state represent moving the *Individual Psychological State* to a more susceptible position.

The alternatives (including *Current*) that have the associated maximum or minimum *Individual Psychological State* values are the options, which when considered in aggregate, have the greatest influence on the target individual. The maximum value alternative strengthens and brings the greatest satisfaction to the target individual for the scenarios under consideration. The minimum value does exactly the opposite; it causes the most dissatisfaction in the target individual for the scenarios under consideration.

Individual Psychological State values provide an overall understanding of an alternative's effect on the target individual. Other results reported focus on identifying specific weaknesses and pressure points.

Weakest and Strongest Pillar in the Current. The weakest and strongest pillars in the *Current* psychological state can now be identified quantitatively. This output does not consider the alternatives, but indicates what the possible pressure points are for the current psychological state. The weakest pillar is the one that is most susceptible (*i.e.*, can be most influenced by *increasing* or *strengthening* psychological satisfaction). The strongest pillar is the least susceptible (*i.e.*, can only be influenced by first *decreasing* or *weakening* psychological satisfaction). This gives a clear indication of pressure points and may lead to inference with respect to influence tactics and even specific means. Note that this assessment of susceptibility is not based on the cost of resources or time required to induce a particular change in psychological state.

Pillar Values. The value for each alternative and the *Current* state is reported for each of the three pillars, *Common to All People*, *Cultural Effects*, and *Individual Traits*. The maximum and minimum in each pillar is also reported. This indicates which aspect of the target's *Individual Psychological State* is affected by each alternative. The maximum and minimum values indicate which alternative would have the greatest effect for the various aspects of the *Individual Psychological State*. For example, it is possible that an alternative that seemed promising in its conception performs poorly overall (both in the value model and in implementation) because it has a contradictory effect, increasing one or more pillars while decreasing another. Depending on the relative weight of the pillars in such a case, a small and unintended effect could have an equal or larger impact in the opposite direction on the resulting *Individual Psychological State* than the intended effect.

Criminality. The *Criminality* value is the degree to which an individual's personality is inclined toward criminality given specific environmental factors, which may allow or prevent the expression of criminality. This value is on a scale from 0 to 10, where 0 represents no criminality and 10 is the strongest indication of criminality. Based on the theoretical concepts primarily taken from the work of Samenow described in Chapter 2, a measure of *Criminality* was constructed for demonstration purposes by computing 10 minus the average of the values for *Value of Human Life, Decision Making, Power Needs, Inferior Function, Activity Preference, Fear of Consequences, Time Horizon,* and (-1)**Motivation*. Donating these values, respectively, as x_i where i = 1, …, 8 , *Criminality* $= 10 - ((\Sigma_{i=1,\ldots,7}\, x_i) - x_8)/8$. Since all x_i scores range from 0 to 10, their average is also on the same 0 to 10 scale. The resulting average is subtracted from 10 to add clarity in that *Criminality* then has an increasing monotonic nature such that 0 is the weakest indication of criminality and 10 is the strongest indication.

The theoretical foundation based on psychological and social theory, the nature and construction of the analytical model, and the general functionality of the representative value hierarchy for *Individual Psychological State* has been presented. In the next section, this model is applied to a sample case for Usama Bin Ladin.

Sample Case: Usama Bin Ladin

It is necessary to point out that this example is provided to ***demonstrate*** the capability of the value hierarchy model. Although an attempt was made to keep the psychological state consistent with that of Usama Bin Ladin developed from open-source reporting, it should **in no way** be interpreted as a definitive analysis. The analysis of Usama Bin Ladin is based on the sources cited and the judgment of the author and does not represent a validated psychological profile. For this analysis to have the validated conclusions necessary for executing a specific course of action, interdisciplinary expertise **must** be sought to validate the model conceptually, determine representative value functions, and to score and weight the model with broad consensus.

Profile-Based Assessment. The information used to score the value hierarchy for Usama Bin Ladin is based primarily on two open-source profiles. The first source is a United States Information Service document titled, "Fact Sheet: Usama Bin Ladin," dated August 22, 1998. Effort has been made to consider cultural bias by using a profile of Usama Bin Ladin found in the periodical *The Muslim Magazine* titled, "Usama Bin Ladin: The Complete File," dated October 1998 as a source (Kabbani, 1998:20-67). It is clear, however, that a rigorous effort is required when making a culturally unbiased assessment. Any appropriate use of this model requires detailed cultural and individual knowledge.

To properly construct a profile-based assessment both subject matter experts such as psychologists, sociologists, anthropologists, and so forth are needed as well as those with a native understanding of the relevant culture. For this study, experts in analytical modeling (such as Operations Research analysts, statisticians, mathematicians, etc.) and their use, design, assumptions, and interpretation are also necessary. When possible, elicitation of the actual subject and his associates should be included in the assessment process.

This initial effort represents a demonstration of the prototype model's capabilities and is not intended to suggest that validation is unnecessary prior to an actual implementation. As with all prototypes, the need for revisions is assumed. In the next section is a description of the *Current* psychological state and environment for Usama Bin Ladin used in later sections to determine possible alternative environments and scoring. The next section is not a complete psychological profile, but gives some key elements used in this process.

Current State. Usama Bin Ladin is a Saudi Arabian national born to Muhammad Awad Bin Ladin, a Saudi Arabian of Yemeni origin. Muhammad Awad Bin Ladin founded one of the largest construction companies in the Middle East, Bin Ladin Construction based in Jeddah, Saudi Arabia (Kabbani, 1998:21). Usama Bin Ladin is currently believed to have ordered the recent bombings of the U.S. embassies in Nairobi and Dar Es Salaam (Kabbani, 1998:20) and his network of terrorists may also be linked to the Khobar Towers bombing in 1996 in Riyadh (Kabbani, 1998:64). Most recently, Bin Ladin has been linked to the September 11, 2001 terrorist attacks on the World Trade Center and Pentagon.

The source of Usama Bin Ladin's extreme behavior is linked to a radical understanding of Islam that led him to, and was strengthened by, travel to Afghanistan to fight the Soviet occupation of that country in 1979 (Kabbani, 1998:20). Usama Bin Ladin returned to Saudi Arabia in 1989, but was expelled shortly thereafter for supporting terrorists (Fact Sheet, 1998:2). He next setup his operations in Sudan. He was expelled from Sudan and fled to Afghanistan in 1996 under pressure from United States (Fact Sheet, 1998:3). At that time he was linked to the attempted assassination of President Mubarak of Egypt (Fact Sheet, 1998:3).

Usama Bin Ladin uses his financial resources, gained from his family's wealth, to directly and indirectly support several terrorist organizations (Kabbani, 1998:21). His radical religious understanding tells him not only that he must "purify Muslim land of non-believers," but that "existing moderate Islamic governments are outside Islam and must be toppled by force" (Kabbani, 1998:21). This belief has helped Usama Bin Ladin earn his place not only on the United States Federal Bureau of Investigations (FBI) Most Wanted List, but has also placed him as a target of law enforcement in many other countries, including Saudi Arabia. Since August 1998, the United States has also undertaken an effort to block his financial assets (Fact Sheet, 1998:3).

Usama Bin Ladin's current location is unknown, however, he is believed to be in Afghanistan where he maintains several terrorist training camps which includes both religious indoctrination and military training (Kabbani, 1998:23). The most elite of these camps trains suicide bombers (Kabbani, 1998:62-63). Usama Bin Ladin has tried his hand at military training and action, however, has found his true talents lie in serving as a "venture capitalist" for terrorist groups around the world who share his ideology (Kabbani, 1998:63). As such, he maintains a position of power and influence over many groups, taking advice from only a handful close associates (Kabbani, 1998:22-23).

On August 20, 1998, Usama Bin Ladin felt the consequences of his actions when the United States struck a number of his facilities in Afghanistan (Fact Sheet, 1998:1). The United States attributes attacks both realized and planned against U.S. citizens on Usama Bin Ladin's network of terrorists in Yemen, Somalia, Egypt, Pakistan, and Saudi Arabia (Fact Sheet, 1998:2) and most recently in the United States leading to further military action. According to the U.S. Information Service, his network supports terrorists in Afghanistan, Bosnia, Chechnya, Tajikistan, Somalia, Yemen, Kosovo, Philippines, Algeria, and Eritrea all bent on carrying out his mission to "unite all Muslims and establish a government which follows the rule of the Caliphs" (Fact Sheet, 1998:2).

Alternative Environment. The previous discussion gives some insight into Usama Bin Ladin's personality and describes the *Current* state from which he is operating at the time of this analysis, prior to September 11, 2001. For demonstration purposes, an alternative environment is considered. Its effect on Usama Bin Ladin's *Individual Psychological State* is measured. This alternative is described conceptually in this section. In the following section, the resultant scores of the *Current* situation described above and the alternative state are given.

The alternative environment is an attempt to strengthen Usama Bin Ladin's psychological state by having a religious leader, trusted by Usama Bin Ladin, attempt to move him from his radical understanding of Islam to a more mainstream understanding. This alternative is denoted *Religion* in the model. This approach would include recognizing his positive contributions to the Arab and Islamic communities, but at the same time helping Usama Bin Ladin better understand the immorality and negative impact of his violent strategies.

The next section illustrates the formal scoring for the *Current* state and the alternative across all of the measures in the model. After the *Current* state and alternative are scored, the value hierarchy must still be weighted. The weighting process used in this example is described in detail below as well and is followed by the results of this sample case.

Scoring. Usama Bin Ladin was scored across the 16 measures already described for the *Current* state and the alternative. These scores are based solely on the author's judgment for example purposes and are not meant to be definitive. This scoring can be seen in Tables 7 and 8 for each measure and the category scored. Further explanation of these measures and categories can be found in Appendix D.

Table 7. Current State Scoring

Measure	**Category**	**Measure**	**Category**
Sustenance	Satiated	Value of Human Life	Low
Health	Healthy	Decision Making	Consultative
Self	Paranoid	Power	Socialized
Family	Safe	Motivation	Internal
Belongingness	Limited	Inferior Function	Common Triggers
Self-Esteem	High	Activity Preference	Adventurous
Relativist-Universalist	Relativist	Fear of Consequences	Rational
Religion	Extremist	Time Horizon	Forecaster

Table 8. Religion Scoring

Measure	**Category**	**Measure**	**Category**
Sustenance	Satiated	Value of Human Life	Capital
Health	Healthy	Decision Making	Consultative
Self	Safe	Power	Socialized
Family	Safe	Motivation	Internal
Belongingness	Belong	Inferior Function	No Triggers
Self-Esteem	High	Activity Preference	Rational
Relativist-Universalist	Mixed	Fear of Consequences	Rational
Religion	Orthodox	Time Horizon	Planner

Weights. As the purpose of this notional sample case is to demonstrate the potential of the approach, weights were set equal across most sub-groupings. Exceptions were *Self* and *Family* where *Self* is weighted 0.75 and *Family* weighted 0.25. This decision was based on the family relationship and separation described in Usama Bin Ladin's background above.

To demonstrate Frustration Regression, ERG weights were initially set equal then *Growth* regressing to *Relatedness* was assigned 0.10, *Relatedness* regressing to *Existence* was assigned 0.05, and *Growth* regressing to *Existence* was assigned 0.05. Regression was represented by subtracting the designated amount of weight from the frustrated trait and adding that weight to the trait to which that frustration regressed. For example, *Growth* started with a weight of 0.34 (*Existence* and *Relatedness* both started with 0.33), 0.10 of the weight for *Growth* went to *Relatedness* and 0.05 went to *Existence*. Therefore, the final weight for Growth was (0.34)-(0.10)-(0.05)= 0.19 . The Frustration Regression in this example resulted in an actual weight of 0.43 for *Existence*, 0.38 for *Relatedness*, and 0.19 for *Growth*, as shown in Figure 22. In actual practice, the weighting, a critical factor, would be based on expert opinion and reflect the decision maker(s) best estimate of their relative importance.

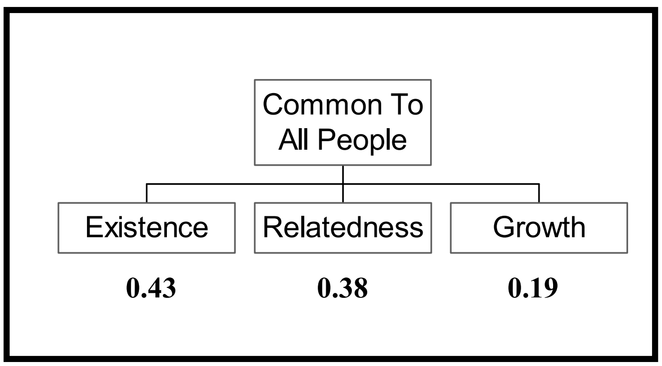

Figure 22. Sample Weighting

Results. Table 9 reports the results for the sample case. In the next section is a brief interpretation of these results and their implications beginning with a sensitivity analysis. Recall that values range from 0 to 10, where 0 is the most susceptible psychological state and 10 is the least. For the *Criminality* value, 10 is the strongest indication of criminality and 0 is the weakest.

Table 9. Sample Case Results

Measure of Interest	Alternatives	
	Current	Religion
Individual Psychological State	5.41	7.60
Common to All People	7.83	10.00
Cultural Effects	1.02	6.07
Individual Traits	7.31	9.10
Criminality*	6.88	5.00

*Criminality, as previously defined, is based on the traits Value of Human Life, Decision Making, Power Needs, Motivation, Inferior Function, Activity Preference, Fear of Consequences, and Time Horizon

Sensitivity Analysis. VFT Sensitivity analysis allows one to evaluate the impact of changes in scores and weights on results. This would normally be done for scores or weights where significant uncertainty existed in their evaluation. The graph below depicts how *Individual Psychological State* values change for each alternative as the weight on *Cultural Effects* ranges from 0 to 1. It is assumed that the weights for *Common to All People* and *Individual Traits* remains in the same proportion as initially assigned, equal in this case, and that all three weights sum to 1. For example, when the weight on *Cultural Effects* is 0.75 then *Common to All People* and *Individual Traits* both have weights of (1-0.75)/2 = 0.125 .

Figure 23 shows the *Individual Psychological State* values for each alternative as the weight on *Cultural Effects* goes from 0 to 1. More importantly the graph shows that *Religion* always achieves a greater *Individual Psychological State* value than, *Current*.

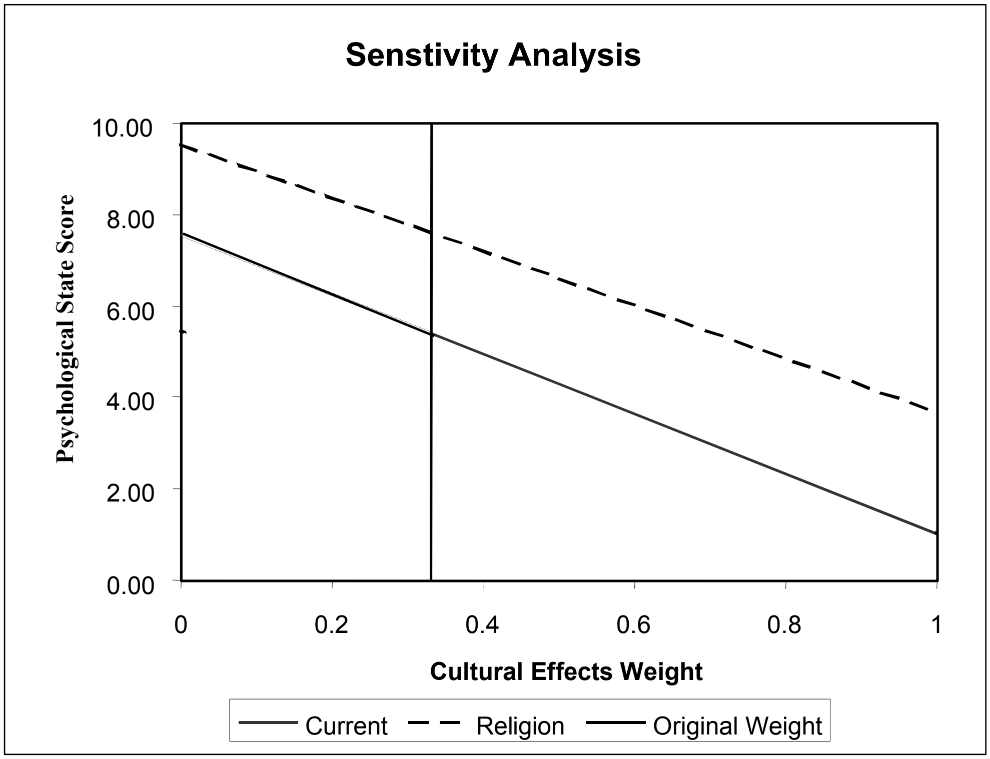

Figure 23. Sensitivity Analysis of Cultural Effects

Implications. For the current environment and psychological profile, Usama Bin Ladin's most exploitable pillar is *Cultural Effects* and his least exploitable is *Common to All People*. *Religion* moves him to a less susceptible psychological state by raising values for all traits. Even though Religion makes Usama Bin Ladin *less* susceptible overall, it reduces the potential for *Criminality*. Both states have positive and negative consequences. Choosing an alternative must support an overall plan to induce some specific overt behavior. *Religion* might support rehabilitation by reducing potential for criminal behavior and increasing psychological satisfaction, for example.

Based on these results, the alternative had the intended effect, *Religion* strengthened the *Individual Psychological State*. We can see that *Religion* exploited *Cultural Effects*, the weakest pillar in the *Current* psychological state. The usefulness of these results is predicated on the user's ability to infer from the change in *Individual Psychological State* a related change in overt and specific behavior. This is a much more precarious task and requires further research.

The prototype model described, and the sample case analysis, indicates that this methodology is appropriate in general for the application proposed in the objectives of this research; however, much work and research remains before a validated operational model can be constructed. Recommendations and areas for future study are described in Chapter 7. The next section of this chapter describes how the *Individual Psychological State* model may be used to generate social closeness measures.

Determining Social Closeness

To illustrate how the Value Focused Thinking model may be used to determine social closeness, a hypothetical example is used for demonstration purposes. The sample case used for this example uses values only from the tier of the hierarchy containing the values *Common to All People*, *Cultural Effects*, and *Individuals Traits*. The method described is applicable to the values at any level of the value hierarchy. Selecting the level of the hierarchy to use should be based on the level of resolution required for a given analysis.

VFT Analysis of Sample Case

Individual Psychological State is a weighted sum of three attributes *Common to All People*, *Cultural Effects*, and *Individual Traits*. Using this data, form a vector (**x**) of the value taken on by attributes *Common to All People*, *Cultural Effects*, and *Individual*

Traits in that order where if **w** is the vector of ordered weights for these attributes, then *Individual Psychological State* equals **w*****x** (**w** is 1xn and **x** is nx1 so **w*****x** is (1xn)*(nx1) = 1x1). Values for each attribute are on a continuous scale from 0 to 10 where 0 represents the absence of that attribute and 10 represents the greatest strength of that attribute.

Vector $\mathbf{x}^{(i)}$ is used to determine social closeness between four different individuals $i = \{1, 2, 3, 4\}$, representing the ordered set {Jack, George, Sally, Paula}, where $\mathbf{x}^{(i)}$ is the vector **x**, defined above, for person *i*. All of these people participate in an informal meeting, denoted Informal Meeting 1. To determine social closeness within this set, it is necessary to make some assumptions about the implications of the strength of these attributes. These assumptions must be based on the relevant behavioral, anthropological, and culturally specific (*i.e.*, micro-climate or subculture) conventions determined for the scenario under analysis. The following hypothetical assumptions were used to demonstrate this method:

- The value taken on by the attribute *Common to all People* (x_1) indicates the amount that an individual's needs are being met where a lower value implies a greater need for survival (subsistence and security) and a higher value indicates a greater desire for higher level needs (belongingness, self-esteem, self-actualization).

- The greater the need for survival (*i.e.*, obtaining food, earning income), the less likely people are to make relationships with other people socially, whereas, to achieve high level needs people must be in contact with others (for example, belongingness requires the existence of a group to belong to).

- People would like to have all their needs meet.

- The value taken on by the attribute *Cultural Effects* (x_2) indicates the degree to which a person participates in their culture. So, a greater value for x_2 indicates a greater tendency to have relationships with those in a shared culture.

- All of the individuals in the example problem share a common culture.

- People in a culture who are not fully participating in a culture would like to fully participate, if they could.

- The value taken on by the attribute *Individual Traits* (x_3) indicates the degree of uniqueness a person has. People with a greater x_3 value are assumed to get more attention and are more likely to be influencers or leaders in the relationships they make, whereas people with a lower x_3 value tend to be followers not challenging the status quo.

Using these assumptions, it is can be seen that the vector $\mathbf{x} = (x_1, x_2, x_3)'$. In a shared culture (as assumed for the example problem), people with a high x_1, high x_2, and high x_3 would tend to have the greatest influence as these people have all their basic survival needs met and need contact with others to fulfill their higher level needs, participate most fully in the culture, and have a natural inclination toward leading others or trend setting by defining the cultural norms (*i.e.*, insiders). People in a shared culture who have a lower x_1, x_2, and x_3 tend to be outsiders who are just trying to survive, do not participate in their culture, and tend to go with the status quo. These outsiders, who desire to participate fully in the culture by assumption, would include those inclined to take orders given to them by the insiders without question in their quest to be a part of the culture.

The delta sender-receiver social closeness measure, s_{ij}, may now be defined from individual i to j in a population (people 1, 2, 3, and 4, in this example) as follows:

$$s_{ij} = (\mathbf{I}^*(\mathbf{x}^{(i)} - \mathbf{x}^{(j)}))/3 \text{ where } \mathbf{I} = (1,1,1) \tag{47}$$

Between any pair of individuals i and j, s_{ij} and s_{ji} will equal y and $-y$, respectively, or $s_{ij}=s_{ji}=0$. The arc with a positive social closeness indicates the direction of greatest influence, as the person with a positive social closeness has more (*i.e.*, supply) of what the person with a negative social closeness wants (*i.e.*, demand). Thus in understanding influence, it is only necessary to consider the directed arc with a positive social closeness (where the negative arc is implicit). In other words, influence as a commodity flows along the positive arc; whereas, the negative arc implies a need (*i.e.*, demand for the commodity). Since, in this formulation, the needs of individuals are always equal to the capacity of others to influence them as a result of the delta sender-receiver based measure, the negative arc does not add information to the analysis. In general, the people with $s_{ij} = s_{ji}$ exert no relative influence on each other and, for this example, will have no arc between them.

Developing Social Closeness from VFT. Table 10 lists the hypothetical value scores for *Common to All People* (x_1), *Cultural Effects* (x_2), and *Individual Traits* (x_3) calculated for people 1 to 4, Jack, George, Sally, and Paula, respectively.

Table 10. Individual Pillar Scores for Informal Meeting 1

	Jack	George	Sally	Paula
x1	4	5	7	10
x2	7	10	4	10
x3	10	10	4	3

As shown in the Table 11, social closeness (s_{ij}) is determined between every pair of individuals participating in this culture.

Table 11. Social Closeness of Individuals in Informal Meeting 1

Sij	**To**			
From	Jack	George	Sally	Paula
Jack		-1.33	2.00	-0.67
George	1.33		3.33	0.67
Sally	-2.00	-3.33		-2.67
Paula	0.67	-0.67	2.67	

Figure 24 depicts the amount of directed influence in Informal Meeting 1 based on this measure of social closeness:

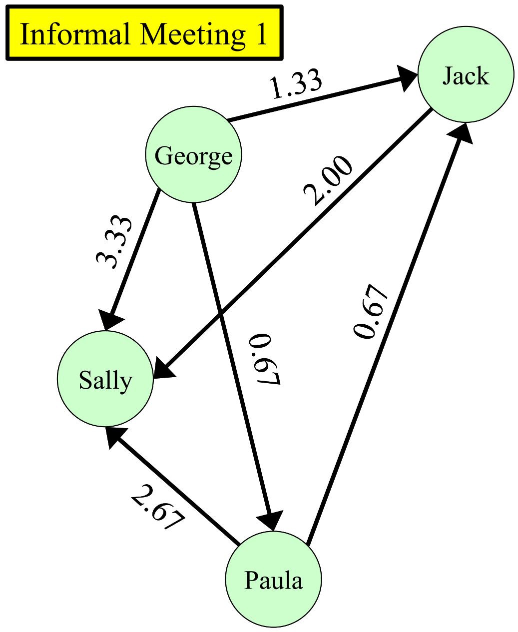

Figure 24. Influence of Issue A Voters in Informal Meeting 1

From this graph observe that George is not influenced by anyone else in this meeting and that Sally does not influence anyone in this meeting.

Using this social network, it is now possible to aggregate the *Individual Psychological State* value scores to form a group psychological state using the methodology described in the next section of this chapter.

Social Network Aggregation and Decision Analysis

When the social network is developed with a value hierarchy for each node (*i.e.*, individual) and the edges weighted using the delta sender-receiver social closeness measure defined above, it is then possible to aggregate value scores for the entire social network to determine the aggregated value scores for the entire social network using the social closeness values as a weight. Since Trait Theory was used to develop the individual value hierarchies, social closeness as defined in Chapter 2, and the underlying Value Focused Thinking model are all additive, an additive approach is appropriate and mathematically consistent. Specifically, hierarchies may be aggregated using the following algorithm:

1. Normalize s_{ij} to a [0, 1] scale. This transformation insures that the resulting aggregated **x** vector for psychological state remains defined on the [0, 10] scale. Since s_{ij} is a social closeness measure it is by definition a ratio value and this transformation, therefore, is admissible.

2. Let a and b be two nodes in the social network such that the directed edge between, denoted ab , a and b is from a to b (*i.e.*, s_{ab} exists). Let **a** represent the set of all edges terminating in b .

3. Define **x** as the cumulative psychological state and initialize $\mathbf{x} = \mathbf{0}$.

4. For every edge ab in **a** calculate $\mathbf{x}^{(b')} = \Sigma_a\, s_{ab}\mathbf{x}^{(a)} + (1\text{-}s_{ab})\mathbf{x}^{(b)}$. $\mathbf{x}^{(b')}$ is then a weighted average based on the influence defined by s_{ab} . Add $\mathbf{x}^{(b)}$ to **x**.

5. Repeat steps 2 and 4 for all nodes b in the network.

6. Define the total number of edges in the network as e .

7. The aggregate psychological state, **xx**, is $\mathbf{xx} = (1/e)\mathbf{x}$. **xx** is the vector of the weighted average of cumulative psychological state based on the delta sender-receiver social closeness measure, s_{ij} .

Applying this methodology to the sample problem, the resulting aggregate value scores are: *Common to All People*, $xx_1 = 6.37$, *Cultural Effects*, $xx_2 = 8.40$, *Individual Traits*, $xx_3 = 7.30$ (*i.e.*, $\mathbf{xx} = (6.37, 8.40, 7.30)'$).

This methodology aggregates the entire social network into a single node with a value hierarchy identical in form to that of an individual. The value hierarchy is now scored based on the influence defined by social closeness on the behavior of the social network. The analysis of this hierarchy and its alternatives is identical to that already described and demonstrated for individuals, however, now defines the aggregate behavior of the entire network. For example, the *Individual Psychological State* for the *Current* environment of the individual node now representing the entire network is $w_1 xx_1 + w_2 xx_2 + w_3 xx_3$.

This chapter has described the applicability of Decision Analysis and Value Focused Thinking, specifically, to social network analysis. As demonstrated, these methods may be used to develop social closeness measures between individuals in a social network based on very limited data. Aggregation allows one to predict behavior of the social network given a specific environment and changes to that environment.

Alone these methods extend existing methods to allow the development of social closeness without surveys or other direct contact methods when those methods are impractical or impossible. In the cases where other social closeness measures are available, such as polling data and other measures described in Chapter 4, the delta sender-receiver social closeness measure may be used in a vector of measures for multi-criteria analysis.

Using the methods described in Chapter 4, 5, and 6, it is possible for an analyst to determine an influencing strategy that most effectively moves the social network's decision making process in a desired direction. The next and final chapter of this dissertation presents the overall conclusions of this research on modeling social networks and recommended areas for future research.

Chapter 7. Conclusions and Recommendations

This dissertation has introduced the concept of social network analysis, discussed the current capabilities of the Social Sciences for modeling social networks, and described areas where Operations Research may contribute to furthering the ability to describe and predict social network behavior. Social network analysis is of broad interest to both private sector and government analysis. The methods developed in this research add to the existing capability of social network analysis.   In this chapter the broad conclusions of the research are discussed. Attention is then given to recommendations for future research.

Conclusions

This research began with, and is founded upon, the complementary lineage of Psychological, Sociological, Anthropological, and other theories that form a starting point for understanding social networks. The methodological focus of this research concentrated on relevant areas of Operations Research, including Graph Theory, Optimization, Network Models, and Decision Analysis that where shown to add insight to the analysis of social networks. The discussion of Operations Research methods included the current capabilities and limitations of these methods as well as areas open to theoretical expansion.

The techniques developed in this research, extend existing Operations Research methods to social network analysis applications. This mapping of concepts opens a wide array of potential analysis tools for the Operations Research analyst and Social Scientists when properly applied. Key elements are demonstrated in this dissertation, but a wide selection of Operations Research techniques exist that were not directly discussed. The methodology formally defines a class of non-metric measures termed social closeness. These measures were then mapped to a flow model representation of a social network. The flow model analysis was demonstrated for single-commodity (single-criteria), multi-criteria, and multi-commodity cases. The multi-criteria and multi-commodity representation accommodates a vector of multiple social closeness measures flowing across multiple networks (contexts) that may be overlapping.

Gains and losses in the flow model representation were used to model predispositions and the communication environment. Thresholds were discussed as a means to model minimum levels of influence required for individuals to act on the influence. The flow model representation led directly to a discussion of Goal Programming.

Goal Programming was applied to social network analysis to consider the multiple, possibly competing, goals that decision makers may consider in order to better understand or to induce influence in a given network. Efficient means of solving goal programs to exploit the underlying network structure were discussed. These efficient methods allow for the analysis of large scale problems. Further discussion of large scale problems was expanded to consider aggregation and disaggregation.

Aggregation in a social network has many desirable benefits. First, aggregation is a means of reducing the size of a network problem to the resolution required for a given analysis, without losing the fundamental properties necessary to insure the consistency and accuracy of the solution. Disaggregation then allows the analyst to increase resolution for detailed analysis, as needed. This benefit alone makes previously intractable problems tractable. Second, through aggregation, there is a consistent and mathematically correct means of combining individuals in a graph into a graph of individuals and groups. Forming these groups in a contextually logical manner allows organizations to be considered within the same graph as individuals.

Beyond the added insight and modeling capabilities provided by the flow model representation and Goal Programming, Decision Analysis methods add the value of predicting behavior of individuals in the social network. Value Focused Thinking was first used to develop a model of *Individual Psychological State*. This model, by itself, allows the analyst to measure the change in psychological state of a target individual based only on the target's psychological profile and environment. Changes in the environment form the alternatives in this model, and provide a measure of the change in psychological state across a hierarchy of psychological traits.

When the *Individual Psychological State* of all of the individuals in a social network is known or assessed by experts, a psychological profile-based measure of social closeness may be calculated. The resulting delta sender-receiver social closeness measure may then be used to construct the social network. Aggregation of this network weighted by the social closeness measure may then be performed. The resulting aggregated psychological state values may then be used in the *Individual Psychological State* value hierarchy with one node representing the entire network. The reaction of this node is then analyzed exactly as in the case of an individual's reaction to environmental stimuli.

Violations to the many assumptions required for the techniques developed in this research are discussed with corrective actions suggested. Post-optimality analysis in mathematical programming and sensitivity analysis in Decision Analysis are demonstrated to both counter uncertainty in the data and to perform analysis of excursions from the base model.

These techniques as a whole, combined with sensitivity analysis, provide a robust analysis capability with fewer underlying assumptions than existing Social Science methods. The results of these techniques provide more detailed solutions and, especially in the case of Goal Programming, accommodates the analysis of many more problem classes than existing Social Science methods. All of the techniques are well-founded, proven, and demonstrated for their mathematical correctness and consistency as they relate to the underlying Social Science theories.

Theoretical Contributions

This research clarifies, develops, and defines the limitations of what can be accommodated by the proposed methodology. This includes contributions to math programming, Graph Theory, and Decision Analysis. Specifically certain Social Science measures are expected to violate the assumptions of additivity and certainty. The fact that some Social Science measures violate these assumptions has already been established. The question of the sensitivity of these optimization models, given these violations, is a subject of this research.

In addition, this research requires and seeks to define an effective means of applying Graph Theory with multi-dimensional weights. Representing vector weights on arcs is known to be acceptable and is seen in such techniques are multi-commodity flow models, goal programming, and others (Rao, 1996:779-783). The theoretical problem here is to define the mapping of social network models to problem domains for which these methods are applicable (flow, for example).

Using VFT for profile-based social network analysis requires expansion of existing VFT methods to handle dependencies as well as profile-based assessment rather than direct elicitation based assessment of value functions. The problem of dependent measures in a value hierarchy is a direct violation of the underlying assumptions of VFT and the proposed methodology provides a formal proof of appropriateness of the methods required in this research.

This research extends current single-criteria social network analysis methods by the use of Graph Theory and Operations Research techniques. Assumptions and weaknesses of these methods are identified. The robust approach explored in this research is further extended to multi-criteria analysis identifying methods, assumptions and weaknesses. The formal proof and sample cases with random excursions approach to validation establishes an initial proven foundation for further research.

Practical Contributions: A Look at Applications

The practical contribution of this research is very significant to an array of problem domains. Clearly, the Social Science domains underlying the development of the analytical findings of this research will directly benefit. Sociology and Anthropology have long been without such analytical tools.

There are many business applications of this research as well. This research adds to understanding and describing organizational behavior. In addition, a predictive ability complements traditional descriptive tools for organizational development as well as decision analysis. In terms of business applications, marketing and advertising will benefit from both descriptive and predictive models of social networks. Even for cases where a predictive model may contain too great of a potential for error, a descriptive model alone is a valuable tool for analysis and understanding the problem under consideration.

Government and military analysis stands to gain significantly from this research. The government and military are faced with many of the same financial and business type decisions as those found in the private sector. The government sector also has an array of other problems such as granting security clearances, modeling and predicting foreign government and military behavior, modeling foreign acquisition strategies, and analyzing terrorist networks. All of these problems revolve around understanding and predicting social networks and often under great uncertainty with limited or no direct access to those making the decisions.

Recommendations

While the techniques developed in this dissertation contribute significantly to existing analysis capability, there are still a number of areas for continued research. First. future research efforts should consider a better understanding of the nature and modeling requirements of measures that do not meet the strict definition of social closeness defined in this dissertation. The use of the many existing nominal and ordinal measures should be investigated. The use of all existing measures adds to the overall capability of the Operations Research methods applied. Second, the search for metric measures should be considered. The advantages of metric measures have been detailed in Chapters 2 and 4.

Beyond issues dealing with properties of measures, other Operations Research techniques should be considered for use in social network analysis. Other optimization problem class mappings (Transportation Problems, Location Theory, and Stochastic Programming, for example), other single and multi-criteria decision analysis approaches (Random Utility Theory, for example), simulation, and Chaos Theory are all possible frameworks. The foundation for such modeling has been set, however, by this work.

In terms of the Value Focused Thinking model developed, several aspects remain open to additional research. The first issue to address is the creation of a validated and widely acceptable model of *Individual Psychology State* for all people, in all cultures, at all times. Alternatively, one might find a set of culturally specific models appropriate. The relationship of psychological state to overt behavior is also an important aspect requiring additional research. The ability to correctly infer specific overt behavior from psychological state would mean that alternative courses of action could be analyzed that would result in reliably known and predictable specific behavior. Psychodynamic (State Theory) models should be consider as they are complementary to the Trait Theory approach used in this research.

Overall this research has advanced the science of analytical, quantitative social network analysis. This directly results in improved analysis capability and better analysis tools for both existing and new problem classes. This research has advanced the theory of the Operations Research methods used in many ways necessary to accommodate social network modeling. These advances, including defining a broad space of measures applicable to optimization methods, specific Graph Theoretical aggregation methods, and dealing with dependencies in VFT, have benefits beyond their use in the context of this research. The efficient methods of analyzing large scale network problems are applicable to classic network problems with high cardinality.

Based on this research, it is now possible to measure, understand, and predict the behavior of individuals in a multi-criteria, multi-context, multi-objective, cross-cultural social network. Applications to private sector and government problems have been discussed and demonstrated as sample problems. The extensions of these methods to other real-world problems is easily understood and recommended.

Appendix A: Glossary of Terms

Achievement Orientation	"Tendency to exert effort toward task accomplishment… strength of … motive to achieve success" (Curphy, 1993:264). "The achievement-oriented personality is generally attracted to activities which require the successful exercise of skill … Whatever the level of challenge to achieve, he will strive more persistently than others when confronted with an opportunity to quit and undertake some different kind of activity instead." (Alderfer, 368). Achievement-Oriented Personality is the opposite of the Failure-Threatened Personality (Alderfer, 1972:369).
Belongingness	"Hunger for affectionate relations with people in general, namely, for a place in his group … In the society the thwarting of these needs is the most commonly found core in cases of maladjustment and more severe psychopathology." (Maslow, 1954:89)
Existence	"Existence needs are the most concrete and least ambiguous of human desires. Lack of some satisfaction of these needs can threaten the material survival of an organism. For these reasons, they may be termed the most basic of human needs. Some represent the various physiological needs of man and may have somatic sources in the human body. All are potentially scarce and therefore can generate situations where one person's gain becomes another person's loss." This includes "protection from physical danger." (Alderfer, 1972:102).
Growth	Growth needs "account for the frequently observed facts which indicate that persons seems to interact with their environments so they can use their abilities learn. Most persons live in more than one ecological environment. Each of us faces several physical settings in which a stable set of people carry out some regular pattern of activities. Specific growth needs are defined in terms of different environments such as homes, jobs, and hobbies" (Alderfer, 1972:132).
Individual Personality	Personality is "the underlying, unseen structures and processes 'inside' a person that explain why the person behaves in a characteristic manner" (Curphy, 1993:146).

Inferior Function	Defined by the target individuals Myers-Briggs Type Indicator (MBTI). Entering inferior functioning (termed "The Grip") is the weakest psychological functioning possible for a given personality (Quenk, 4). "The smallest share of conscious psychic energy goes to the inferior function, so it is essentially unconscious" (Quenk, 4). "The inferior function appears in a specific and predictable form. The form is similar to the qualities that would describe a person who has that dominant function, but compared to the dominant form of the function the inferior will be: exaggerated or extreme – like a caricature of that type; inexperienced or immature – the person will come across childish, touchy, easily angered; undifferentiated or categorical – perceptions and judgments will be black and white, all or none" (Quenk, 1996:6-7). Common triggers include fatigue, illness, stress, and alcohol or mind-altering drugs; however, each MBTI has it own specific triggers and propensity for entering The Grip (Quenk, 1996:7).
Motivation	"Motivation is anything that provides direction, intensity, and persistence to behavior … a sort of shorthand to describe choosing an activity or task to engage in, establishing the level of effort to put forth on it, and determining the degree of persistence in it over time" (Curphy, 1993:257). Motivation may be internal or external (Maslow, 1954:176; Atkinson, 1966:118-119). Internal motivation is "behavior seemingly motivated for its own sake, for the personal satisfaction and increased feelings of competence or control one gets from it" (Curphy, 1993:264). External motivation is the exact opposite, behavior motivated only due operant factor outside the individual (Curphy, 1993:274).
Physiological Needs	"Physiological needs are the most prepotent of all needs. What this means specifically is that in the human being who is missing everything in life in an extreme fashion, it most likely that the major motivation would be the physiological needs rather than any others. A person who is lacking food, safety, love, and esteem would most probably hunger for food more strongly than anything else." (Maslow, 1954:82)
Power Needs	Power is "the capacity to produce effects on others or the potential to influence" (Curphy, 1993:109). Where influence is defined "as the change in a target agent's attitudes, values, beliefs, or behaviors as the result of influence tactics. Influence tactics refer to one person's actual behaviors designed to change another person's attitudes, beliefs, values, or behaviors" (Curphy, 1993:109).

Relatedness	"People require relationships with others in order to be fully human" (Alderfer, 1972:113). "Satisfying human relationships are achieved by persons who are psychologically significant to each other and who are able to share their relevant feelings and thoughts mutually. This means both parties give and receive. The assumption … is that the satisfaction of the parties in a relationship is positively correlated. … Significant others refers both to individuals of importance and to key human groupings. … Respect … is a word that may be used to characterize the state of satisfying interpersonal relationships. A person who is respected by another is seen as he is in all of his unique individuality" (Alderfer, 1972:114).
Risk Needs	A problem "of behavior which any theory of motivation must come to grip with … is to account for an individual's selection of one path of action among a set of possible alternatives" (Atkinson, 1972:11). The constant cause of these differences is related to risk-taking behavior defined as the "the relationship of strength of motive, as inferred from thematic apprehension, to overt goal-directed performance" (Atkinson, 1972:11).
Self-Actualization	"The individual is doing what he is fitted for. A musician must make music, an artist must paint, a poet must write, if he is to be ultimately at peace with him himself. What can be, he must be. … A man's desire for self-fulfillment, namely, to the tendency for him to become actualized in what he is potentially. This tendency might be phrased as the desire to become more and more what one is, to become everything that one is capable of becoming. The specific form that these needs will take will of course vary greatly from person to person. In one individual it may take the form of desire to be an ideal mother, in another it may be expressed athletically, and in still another it may be expressed in painting pictures or in inventions. The clear emergence of these needs usually rests upon prior satisfaction of the physiological, safety, love, and esteem needs" (Maslow, 1954:92).
Self-Esteem (Esteem)	"All people … have a need or desire for a stable, firmly based, usually high evaluation of themselves, for self-respect, or self-esteem, and for the esteem of others. These needs may therefore be classified into two subsidiary sets. These are, first, the desire for strength, for achievement, for adequacy, for mastery and competence, for freedom. Second, we have what we may call the desire for reputation or prestige… status, dominance, recognition, attention, importance, or appreciation." (Maslow, 1954:90).

Appendix B: Sample Case Data

Krackhardt's High-tech Managers
(Faust, 1994:60)

Advice Relationship:

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	1
2	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
3	1	1	0	1	0	1	1	1	1	1	1	1	0	1	0	0	1	1	0	1	1
4	1	1	0	0	0	1	0	1	0	1	1	1	0	0	0	1	1	1	0	1	1
5	1	1	0	0	0	1	1	1	0	1	1	0	1	1	0	1	1	1	1	1	1
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
7	0	1	0	0	0	1	0	0	0	0	1	1	0	1	0	0	1	1	0	0	1
8	0	1	0	1	0	1	1	0	0	1	1	0	0	0	0	0	0	1	0	0	1
9	1	1	0	0	0	1	1	1	0	1	1	1	0	1	0	1	1	1	0	0	1
10	1	1	1	1	1	0	0	1	0	0	1	0	1	0	1	1	1	1	1	1	0
11	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
13	1	1	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0
14	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
16	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0
17	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
18	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	0	0	1	1	1
19	1	1	1	0	1	0	1	0	0	1	1	0	0	1	1	0	0	1	0	1	0
20	1	1	0	0	0	1	0	1	0	0	1	1	0	1	1	1	1	1	0	0	1
21	0	1	1	1	0	1	1	1	0	0	0	1	0	1	0	0	1	1	0	1	0

Friendship Relationship:

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	0	1	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0
2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0
4	1	1	0	0	0	0	0	1	0	0	0	1	0	0	0	1	1	0	0	0	0
5	0	1	0	0	0	0	0	0	1	0	1	0	0	1	0	0	1	0	1	0	1
6	0	1	0	0	0	0	1	0	1	0	0	1	0	0	0	0	1	0	0	0	1
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	1	0	1	0	0	1	1	0	0	1	0	0	0	1	0	0	0	1	0
11	1	1	1	1	1	0	0	1	1	0	0	1	1	0	1	0	1	1	1	0	0
12	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
13	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
15	1	0	1	0	1	1	0	0	1	0	1	0	0	1	0	0	0	0	1	0	0
16	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	1
18	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	1	1	1	0	1	0	0	0	0	0	1	1	0	1	1	0	0	0	0	1	0
20	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0
21	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0

“Reports to” Relationship:

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
4	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
9	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
13	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
14	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
16	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
18	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
21	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Randomly Generated Social Network Data

	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	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
1	0	0	0	0	0	0	9	0	0	0	0	0	9	0	0	0	0	0	0	0	4	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	5	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	5	0	7	0	0	0
3	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	6	0	0	0	0	0	0	2	0	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
4	0	6	0	0	0	6	0	0	0	0	8	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	0	3	0	0	0	4	0	0	0
5	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	4	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	4	9	0
6	0	0	0	0	0	0	0	3	0	0	0	0	0	0	2	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	0	0	0	4	0	0	0	0	0	9
7	4	0	0	0	0	0	0	0	0	0	9	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
8	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	4	0	0	0	0	0	0	0	4	0	0	0	0	0
9	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	0	0	0	0	0	4	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	8	0	6
10	5	0	0	0	1	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0
11	0	0	0	0	0	0	9	0	0	0	0	0	0	6	0	0	0	0	0	0	0	9	0	0	0	0	0	4	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	2	0	0	0	2	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	9	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	7
14	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	9	3	0	0	0	0
15	5	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	7	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	9	0	0	9	0	0	0	0	0	0	0	7	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	3	0	3	0	0	0	0	0
19	0	0	0	0	2	0	0	0	3	0	0	0	0	0	5	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
20	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	6	0	8	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	9	0	5	0	0	0	0	0	0	0	0	0	0	0	6
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	9	1	0	0	0	0	0	0	2
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	3	0	0	0	5	0	0	0	0	0
24	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	4	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	6	0	0	0	0	0
25	0	0	0	0	9	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	6	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0
26	0	0	0	0	3	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	9	0	0	0	0	0	7	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	5	0	5	0	0	0	0	0	0	0	6	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0
28	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	7	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	1	0	0	0	0	0	0	8	0	0	0	5	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	3	0	0	0	0	0	0	0	0	8	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	3	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	6
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	9	9	0
33	0	2	0	0	0	0	0	0	0	8	0	0	0	7	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	9	0	0	0	0	1	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	2	0	0	0	0	0	0	0	0
35	0	0	1	0	0	0	0	0	0	0	9	0	9	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	5	0	0	0	2	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0
37	0	0	0	0	0	0	0	0	4	9	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0
38	0	0	0	0	0	0	0	0	9	3	0	0	0	5	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	7	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	4	0	0	3	0	0	0	0
40	0	4	9	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0
41	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	6	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	5	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	8	0	0	5	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	1	9	7	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	5	0	0	0	0	0	9	0	0	0
44	7	0	6	0	0	0	0	0	0	0	4	4	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	6	0	0	0	0	0	0	0	0	0
45	7	0	5	0	0	5	0	0	6	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
46	0	0	0	0	0	0	0	0	0	0	4	0	0	0	2	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	6	9
48	0	0	5	0	0	0	0	0	0	5	0	0	2	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	1	0	0	0	0	8	0	0	9	0	0
50	0	0	0	0	0	3	0	8	0	0	0	0	8	0	0	0	0	0	0	4	0	0	0	4	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

Appendix C: Iranian Government Data

President Mohammad Khatami's Cabinet (1997)

President: Hojjat-ol eslam Mohammad Khatami

Vice Presidents:

- Hasan Habibi, First VP (carry-over)
- Mohammad Hashemi, Executive Affairs (carry over)
- Ms. Masoumeh Ebtekar, VP in charge of the Environmental Protection Organization
- Gholam-Reza Aqazadeh, VP in charge of Atomic Energy
- Mohammad Baqerian, VP in charge of the Organization for Administrative Affairs, Civil Service, and Employment
- Mohammad Ali Najafi, who served as minister of education in the outgoing government, was put in charge of the Planning and Budget Organization
- Seyed Abdul-Vahed Mousavi-Lari, VP for legal and parliamentary affairs.
- Mostafa Hashemi-Taba, VP for Physical Training Organization (carry over)

Cabinet Ministers:

- Defense & Military Logistics: Rear Admiral Ali Shamkhani
- Foreign Affairs: Kamal Kharrazi
- Intelligence and Security: Qorban-Ali Dori-Najafabadi
- Interior: Abdollah Nuri
- Islamic Guidance & Culture: Ataollah Mohajerani
- Oil Bijan Namdar-Zanganeh
- Economy and Finance: Hossein Namazi
- Justice: Mohammad Esmail Shustari
- Construction Jihad: Mohammad Saidi-Kia
- Industries: Gholam Reza Shafei
- Post, Telephone & Telegraph: Mohammad Reza Aref
- Education & Training: Hossein Mozaffar
- Roads & Transport: Mahmoud Hojati
- Housing & Urban Development: Ali Abdolalizadeh
- Mines & Minerals: Eshaq Jahangiri
- Cooperatives: Morteza Haji
- Agriculture: Issa Kalantari
- Higher Education: Mostafa Moin
- Energy: Habibollah Bitaraf
- Health & Medical Education: Mohammad Farhadi
- Labor and Social Affairs: Hossein Kamali
- Commerce: Mohammad Shariatmadari.

Council of Expediency and Discernment (*Farhang va Andisheh*)

Legal members:

1. Hashemi Rafsanjani, Akbar, Hojjatoleslam (Chairman)
2. Rezaei, Mohsen (Secretary)
3. Khatami, Mohammad, Hojjatoleslam (President)
4. Nateq, Nouri, Ali Akbar, Hojjatoleslam (Majlis Speaker)
5. Yazdi, Mohammad, Ayatollah (Judiciary Chief)
6. Jannati, Ahmad, Ayatollah (Member of Guardians Council)
7. Emami Kashani, Mohammad, Ayatollah
8. Rezvani, Gholamreza, Ayatollah
9. Mo'men, Mohammad, Ayatollah
10. Hashemi, Seyed Mahmoud, Ayatollah
11. Khazali, Abolqasem, Ayatollah
12. The minister concerned depending on the subject under discussion

Ex-officio members:

13. Mahdavi Kani, Mohammad Reza, Ayatollah
14. Amini Najafabadi, Ibrahim, Ayatollah
15. Vaez Tabasi, Abbas, Hojjatoleslam
16. Jannati, Amad, Ayatollah
17. Emami Kashani, Mohammad, Ayatollah
18. Mousavi, Mir Hussein
19. Velayati, Ali Akbar
20. Mohammadi Reyshahri, Mohammad, Hojjatoleslam
21. Sane'i, Hassan, Hojjatoleslam
22. Fereidoun Rowhani, Hassan, Hojjatoleslam
23. Mousavi Khoeiniha, Mohammad, Hojjaoleslam
24. Asgar Owladi, Habibollah
25. Dorri Najafabadi, Qorbanali, Hojjatoleslam
26. Larijani, Ali
27. Mirsalim, Mostafa
28. Tavassoli Mahallati, Mohammadreza, Ayatollah
29. Nouri, Abdullah, Hojjatoleslam
30. Nabavi, Morteza
31. Firouzabadi, Hassan, Lt. General
32. Aqazadeh, Gholamreza
33. Namdar Zanganeh, Bijan
34. Hashemi, Mohammad
35. Nourbakhsh, Mohsen
36. Habibi, Hassan Ibrahim

Members of the Council of Guardians

- Alizadeh, Ahmad
- Alizadeh, Mohammad Reza
- Abbasifard, Mohammad Reza
- Bizhani, Khosro
- Djannati, Ahmad, Ayatollah
- Emami Kashani, Mohammad, Ayatollah
- Habibi, Hassan
- Hashemi, Seyyed Mahmood, Ayatollah
- Khazali, Abolghasem, Ayatollah
- Mohammadi Gilani, Mohammad, Ayatollah
- Rezvani, Gholamreza, Ayatollah
- Zavarehei, Seyyed Reza

Judiciary Branch

Head of Judiciary: Yazdi Mohammad, Ayatollah

Prosecutor General: Moqtadaii Mortaza, Ayatollah

- Chief Justice of the Supreme Court: Mohammadi Gilani Mohammad, Ayatollah
- President of the Administrative Court of Justice: Ferdosi Puor Esmail, Hojjatoleslam
- Head of the Judicial organization of the Armed Forces : Yuonesi Ali, Hojjatoleslam
- Deputy Chief of the Judiciary for Executive Affaris: Abbasi Far Mohammad Reza, Hojjatoleslam
- President of the Islamic Revolution's Court Rahbar Pour Gholam-Hossein, Hojjatoleslam
- Head of the Iuspectorate General: Raisi Ebrahim, Hojjatoleslam
- President of the Clerics Court: Mohammadi Reyshahri Mohammad, Hojjatoleslam
- President of the Supreme Disciplinary Court for Judges: Marvi Hadi, Hojjatoleslam
- President of the Coroners Office: Tuofiqii Hassan, Dr.
- Director General of the State Organization for Registeration of Documents and Properties: Zavareii Reza
- Director General of the State Organization in Charge of Prisons and Security and Educational Measures: Lajevardi Asadollah
- Director General of the Public Relations of Judiciary: Elmi Hosseini Hossein, Hojjatoleslam

Members of the Presiding Board of the Islamic Consultative Assembly (Majlis)

Speaker: Executive Nategh Nouri, Ali Akbar

First Deputy: Rohani, Hassan

Second Deputy: Movahedi Kermani Mohammad, Ali

- Abbaspour Tehranifard, Ali
- Akrami, Mohammad Reza
- Angaji, Seyyed Javad
- Bahonar, Mohammad Reza
- Shahrzad, Mohammad Karim
- Sobhaninia, Hassan
- Taghavi, Seyyed Reza
- Yahyavi, Seyyed Mohsen
- Agha alikhani, Gholam abbas
- Astane, Mahmood
- Alkazhem, Ali (Hojjatoleslam)
- Abuotorabifard, Seyyed Ali Akbar (Hojjatoleslam)
- Ahmadi Zadsaray, Valiollah
- Ardeshire Larijani, Mohammad Javad
- Abtahi, Seyyed Mahmod
- Ahmadi, Aliasghar
- Ahmadi, Ali
- Akrami, Seyyed Reza (Hojjatoleslam)
- Ahmadiye, Mostafa
- Akhoavan, Bahman
- Adab, Bahoddin
- Ashrafi, Gholamreza
- Afghahi, Alireza
- Akbari, Saleh
- Akbari Talarposhti, Ezatollah
- Allahgholizade, Gholi
- Almasi, Hasan
- Ansari, Majid (Hojiatoleslam)
- Ansari, Fariborz
- Ansarirad, Hosein (Hojjatoleslam)
- Anvari, Hossein
- Amaniangeneh, Shahrbano
- Abdolvand, Gholamreza
- Azizi, Ebrahahim
- Azimi Targhadri, Mohammad
- Alae, Eynollah

- Abbasi, Abbas (Hojjatoleslam)
- Alavi, Seyyed Mahmood (Hojjatoleslam)
- Abedinzadeh, Kamel
- Ali Hosseiniabbasi, Mohammad reza
- Asgari, Hossein
- Abdollahi, Reza
- Baghuomiyan, Artavas
- Bahonar, Mohammad Reza
- Bagheri (Banayi), Abdolhamid (Hojatoleslam)
- Barfgartakmedash, Taheragha
- Bohlolighashghaei, Sohrab
- Behniya, Manochehr
- Bayank, Amin
- Beygmoradi, Hemat
- Daneshyar, Kamal
- Daneshjaefari, Davod
- Darvishzadeh, Mahdireza
- Dabestani, Majid
- Dosti, Esmaeil
- Dorri Najafabadi, Qorban Ali (Hojjatoleslam)
- Doaie, Seyyed Mahmood (Hojjatoleslam)
- Dolatibakhshah, Abdolaziz
- Dahgan, Hasan
- Dana, Seyyed Mohammad Hossein
- Esmailzade, Habiboolah
- Eliasi, Manochehr
- Ebrahimian Salami, Gholam Heidar
- Ebadi, Seyyed Ali Reza (Hojjatoleslam)
- Eydigdtapeei, Ghazanfar
- Faker, Mohammadreza (Hojjatoleslam)
- Fotoohi, Mohammad Sharif
- Fazlali, Morteza
- Fooladi, korosh
- Fayyazbakhsh, Nafiseh
- Ghanbari Maman, Jamshid
- Golbai, Ja'afar
- Ghasempoor, Samad
- Ghasemzadeh, Hosseinali
- Ghasemi, Khodanazar
- Ghasemipoor, Abdollah
- Ghobadi, Khodada
- Ghorbani, Moosa
- Ghrmezi, Shahriyar
- Ghazaei, Ahad

- Gholizadeh, Rahmangholizade
- Ghanbarj, Ali
- Ghandehari, Ghorbanali (Hojjatoleslam)
- Ghahremani, Mohammad Mahdi
- Ghanizadeh, Alireza
- Ghaforifard, Hassan
- Golshani, Faramarz
- Ghaderi, Mohammad Raoof
- Hajiyani, Abdollah (Hojjatoleslam)
- Hosseini, Seyyed Mohammad
- Hojibabayi, Hamidreza
- Habibzadey Bokani, Anvar
- Hadidchi (Dabagh), Marzeye
- Harizavi, Abdozahra
- Hosseininezhad, Seyyed Akbar
- Hosseini, Seyyed Abdollah
- Hosseini Vaez, Seyyed Mahmod
- Heshmatiyah, Ghodratali
- Heydari Darani, Gholamreza
- Hazrati, Elias
- Holakou, Moama
- Hashemizadeh, Faramand
- Hashemi Tagharvoljerdi, Seyyed Taha (Hojjatoeslam)
- Hashemi, Seyyed Mohammad
- Hashemi Bahramani, Faezeh
- Hashemirise, Seyyed Mostafa
- Hadizadeh, Ali Asghar
- Holakoo, Moa'ama
- Hashemi, Seyyed Hossein
- Hashemzadeh, Hashem (Hojjatoleslam)
- Irani, Hossein (Hojjatoleslam)
- Jamali, Mahmood
- Jabbarzadeh, Ismaiel
- Jamshidi, Ardeshir (Hojjatoleslam)
- Jafari, Seyyed Mohamadreza
- Jelodarzadeh, Soheila
- Jamshid nezhad, Iraj
- Jandaghi, Abas
- Jaderi, Jasem
- Khatami, Hadi (Hojjatoleslam)
- Khabbaz, Mohammad Reza
- Khazaei, Mohammad Mahdi
- Khajeh Pour, Mohammad
- Khadem arabbaghi, Mohssen

- Khodadadi, Salman
- Kheirkhah, Kamel
- Karamatloo, Abassali (Hojjataeslam)
- Kordetamandani, Khodabakhsh
- Karimi, Hamid
- Karimimonjarmoei, Ebrahim (Hojjatolesalm)
- Karimiyan, Mohammad
- Ka'abi, Abdollah
- Kazemi, Seyyed Motahhar (Hojjatoleslam)
- Karimian, Mohammad
- Majidi, Mohammad Reza
- Mofatteh, Mohammad Mahdi
- Mousavi Hosseini, Seyyed Ali Akbar (Hojjatoleslam)
- Mahdizadeh, Mahdi
- Mirhosseini, Abbas
- Mirkhalili, Seyyed Ali Beman (Hojjatoleslam)
- Mavalizadeh, Seyyed Mohammad Reza
- Movahhed, Seyyed Haji Mohammad (Hojjatoleslam)
- Movahhedi Savoji, Ali
- Movahedi Kermani, Mohammad Ali (Hojjatoleslam)
- Mousavi, Seyyed Mohammad Ali (Hojjatoleslam)
- Motamedinia, Gholam Reza (Hojjatoleslam)
- Moghadamizad, Isa
- Maghsoud Pour, Shamshoun
- Marvi, Ali
- Mojtahed Shabestari, Mohsen (Hojjatoleslam)
- Majd Ara, Mohammad
- Mohassel Hamedani, Seyyed Mohammad Taghi
- Talesh, Gilan
- Aligodarz, Lorestan
- Kerman, Kerman
- Khoramshahr, Khoozestan
- Ghaemshahr, Mazandarn
- Mousavi, Seyyed Abbas
- Mousaviojagh, Seyed Hojtaba
- Mousavi Jahandabad, Sayyed Bagher
- Mousavi Kozekanani, Seyyed Ali
- Mousavinasab, Seyyed Ali
- Mousavinanekaran, Mirfakhredin (Hojjatolesalm)
- Mahdavi, Ahmad
- Milani Hosseini, Seyyed Mohamadreza
- Mohjob, Alireza
- Mohammadi, Abass
- Naserygohar, Ahmad

- Najafi, Ghodratollah (Hojjatoeslam)
- Naiari, Chodratollah (Hojjatoleslam)
- Nea'amatzadeh, Ali
- Noura, Abassali
- Nouri, Abdollah (Hojjatoleslam)
- Nouri, Ezatollah
- Mortazavi, Seyyed Fattah (Hojjatoleslam)
- Nourizadeh, Seyyed Mahmood (Hojjatoleslam)
- Nategh Nouri, Ali Akbar (Hojjatoleslam)
- Nategh Nouri, Ahmad
- Nabavi, Seyyed Morteza
- Nejabat, Ahmad
- Nokhbatolfoghahaie, Mohammad Hossein
- Nobakht, Monireh
- Nobakht Haghighi, Mohammad Bagher
- Nozari, Gholamhossein
- Nourbakhsh, Abdolrahim
- Norooz Zadeh, Seyyed Reza
- Paknezhad, Seyyed Abas
- Pishbin, Ahmad
- Pirnemati, Ebrahim
- Qomi, Mohammad
- Raheb, Jaefargholi
- Rahchamani, Mohammad Reza
- Razmian Moghadam, Hassan
- Rastad, Abdolmohammad (Hojjatoleslam)
- Rezaeri Mirghaed, Omidvar
- Ramezanpor Nargesi, Ahmad
- Rahmani, Rajab
- Ramezanzadeh, Fatemeh
- Rasouli Nezhad, Seyyed Ahmad
- Rashidi Kouchi, Jalil
- Rezaie, Seyyed Abolghasem
- Reisi, Khodabakhsh
- Razavi, Asadollah
- Reisidehordi, Asghar
- Razavi Ardakani, Seyyed Abolfazl (Hojjatoleslam)
- Ramazan Pour Nargesi, Ghasem
- Rohani, Hassan (Hojjatoleslam)
- Ravani, Parviz
- Rahbari, Mohammad Mahdi
- Sobhani, Hassan
- Sepahvand, Abdolreza
- Sarhadizade, Abolghasem

- Saghaei, Mohammad
- Samarghandi, Balal
- Sohrabi, Ali
- Seyedzadeh, Seyed Hossein
- Shahroki, Seyyed Mohammad Mahdi (Hojjatoleslam)
- Shahrokhi Arablou, Mohammad (Hojjateleslam)
- Saiedi, Seyyed Jasem
- Shakibi, Seyyed Mashaallah
- Sheikh, Mohammad Ali
- Shirazian, Seyyed Gholamreza
- Salehi Khansari, Seyyed Mortaza (Hojjatoleslam)
- Sedighi, Marziye
- Safati Dezfoli, Iraj
- Safaei, Zabihollah
- Seyyed Hashemi, Seyyed Mostafa
- Seyyedi Alavi, Ghodsieh
- Shakhesi, Hassan
- Shoja'a, Abdolghaffar
- Shojaie Fard, Mohammad Mahdi
- Sharifi, Seyyed Hossein
- Sheibani, Abbas
- Sadr, Seyyed Shahaboddin
- Samadi, Seyyed Ma'rouf
- Taghavi, Seyyed Reza (Hojjatoleslam)
- Tavassoli Zadeh, Mohammad Naser
- Torabizade, Heshmatollah
- Taraghi, Hamidreza
- Torang, Enayatollah
- Tavakoli, Seyed Valiyollah
- Tahernezhad, Yadollah
- Taheri, Seyed Taher
- Vartanian, Vartan
- Vahid Dastjerdi, Marziyeh
- Yousefnezhad, Aliasghar
- Yahyavi, Seyyed Mohsen
- Yaghoubi, Ali
- Zakeri, Mohamad Bagher (Hojatoleslam)
- Zajkaniha, Hossein
- Zareei, Mostafa
- Zargar, Mosa
- Zaringol, Morteza
- Zadsar, Ali (Hojjatoleslam)
- Zare'eie Ghanavati, Lotfollah

Supreme National Security Council

President(Chairman): Khatami, Seyed Mohammad

- Nouri, Abdullah (Interior Minister Secretary)
- Nateq Nouri, Ali Akbar (Majlis Speaker)
- Yazdi, Mohammad (Judiciary Chief)
- Firouzabadi, Hassan (Chief of the Supreme Command Council of the Gen. Armed Forces)
- Kharrazi, Kamal (Foreign Minister)
- Najafi, Mohammad Ali (Planing & Budget Organization)
- Dorri Najafabadi, Qorbanali (Intelligence Minister)
- Rowhani, Hassan (Representative of the Leader)

Appendix D: Representative Value Functions

Measure	Value	Category
Sustenance	0 3 10	**1.** Starvation (threshold): unable to meet basic survival needs. **2.** Survival: minimal food and water to sustain life. **3.** Satiated: maximum utility for food and water.
Health	0 3 7 10	**1.** Dying (threshold): unable to perform basic functions. **2.** Unhealthy: requiring immediate medical attention. **3.** Ill: distracts from normal duties, but does not require immediate medical attention. **4.** Healthy: no adverse medical factors.
Self	0 3 5 10	**1.** Danger (threshold): clear, present, known, and immediate threat to life. **2.** Threatened: clear and present threat to life. **3.** Paranoia: ambiguous, but perceived threat to life. **4.** Safe: no perceived threat to life.
Family	0 3 5 10	**1.** Danger (threshold): clear, present, known, and immediate threat to life. **2.** Threatened: clear and present threat to life. **3.** Paranoia: ambiguous, but perceived threat to life. **4.** Safe: no perceived threat to life.
Belongingness	0 5 10	**1.** Isolated: separated from any social structures. **2.** Limited: separated from desired social structures. **3.** Belong: currently in all desired social structures.
Self-Esteem	0 3 5 7 10	**1.** Low: sees oneself in a negative light; depressed, possibly suicidal. Unable to perform duties. **2.** Negative: Lacks desire to perform. May interfere with performance of duties. **3.** Nominal: Neither negative nor positive. May see every day as the same. **4.** Positive: Attitude supports performance. May consider himself a key member of the group. **5.** High: sees oneself in a positive light; visions of self-grandeur and invincibility.
Relativist-Universalist	0 3 5 10	**1.** Relativist: sees all morals as situational. **2.** Mixed: willing to make exceptions on occasion when provided reasons he accepts. **3.** Principled: rarely makes exceptions; however, rationalizes and accepts deviations. **4.** Universalist: see all morals as law.

Religion	0 3 5 7 10	**1.** Extremist: claims to be orthodox, while using religion for personal gain. Includes violent activists and those who incite violence and disharmony. **2.** Orthodox: internalizes and practices beliefs in daily life; regularly practices his stated religion. Includes clergy, missionaries, non-violent activists. **3.** Practical: regularly practices religion. Includes those who belong to a congregation and regularly attend church service for example. **4.** Member: claims affiliation with a church, but rarely if ever attends religious functions. **5.** Atheist: has no use for or fails to believe in any god.
Value of Human Life	0 5 7 10	**1.** Low: regularly enforces capital punishment. **2.** Capital: allows, but rarely enforces capital punishment. **3.** Corporal: allows corporal, but not capital punishment. **4.** High: has no capital or corporal punishment.
Decision Making	0 3 5 7 10	**1.** Autocratic: one decision-maker with no other formal structures. **2.** Consultative: one decision-maker, structured process of opinion gathering. **3.** Oligarchy: government by a small group. **4.** Democratic: representative government, majority rule. **5.** Consensus: everyone has an equal vote, all decisions require unanimous vote.
Power Needs	0 3 5 10	**1.** Personalized: self-serving, not for the good of the whole. **2.** More Personalized: realizes the good of the whole as a side effect of self-serving decisions. **3.** More Socialized: keenly aware of the personal gain from serving the greater good. **4.** Socialized: serves the greater good, often involving self-sacrifice.

Motivation	0 5 10	**1.** External: derived from satisfying others; performance is based on some positive or negative consequence. **2.** Operant: motivated both internally and externally. Likely internal applies to positive motivation and external applies to negative motivation (*i.e.*, punishment). **3.** Internal: derived from personal satisfaction; increased feeling of competence and control.
Inferior Function (determined by MBTI)	0 5 7 10	**1.** Many Triggers: for a given type, the person has many inferior function triggering (both unique and common) events occurring. **2.** Unique Triggers: some or all of the triggers known to be particularly stress inducing for a given personality. **3.** Common Triggers: this would include one or all of fatigue, illness, physical stress, or drugs and alcohol. **4.** No Triggers: for a given type, the person has no inferior function triggering events occurring.
Activity Preference	0 5 7 10	**1.** High Risk: always prefers activities that involve risk of life, money, freedom, or other valuable resources. **2.** Adventurous: enjoys risk only in certain areas. **3.** Rational: accepts only certain risks and sets limits on the amount of potential losses. **4.** Conservative: always prefers an activity with known outcomes and very low probability for loss.
Fear of Consequences	0 3 5 10	**1.** Anarchist: always breaks rules no matter the consequences; does not believe in rules. **2.** Personal: believes in rules, however, breaks rules for personal gain with out concern for consequences. **3.** Rational: believes in rules, but may break a rule if the potential gain outweighs the consequences. **4.** Obedient: never violates a rule no matter how much potential for personal gain.
Time Horizon	0 5 10	**1.** Impulsive: makes decisions with little information and immediately as decision opportunities arise. **2.** Forecaster: makes an effort to predict unknown information prior to making a decision. **3.** Planner: requires almost complete information prior to making a decision.

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Vita

Captain Rob Renfro, USAF, graduated from the United States Air Force Academy with a BS in Operations Research and a minor in Arabic in 1994. As an undergraduate, he was able to study Arabic, Arab Anthropology, and Islamic History at the University of Aleppo, Syria in 1993. He graduated with an MS in Operational Analysis from the Air Force Institute of Technology in 1996. In addition, he graduated from the Post-Graduate Intelligence Program of the Joint Military in Intelligence College in 1998. Captain Renfro served as a Combat Effectiveness Analyst and Air Combat Simulation Analyst at the National Air Intelligence Center. Additionally, he served as Chief of the no notice deployable Scientific and Technical Intelligence Liaison Officer Team providing direct strategic intelligence support to deployed forces.

Captain Renfro has been honored as a Malone Fellow of the National Council on U.S.-Arab Relations. He has studied and traveled to Saudi Arabia, Oman, and Tunisia. Captain Renfro has also taught the course *Middle East Intelligence Issues and Concepts* for the Joint Military Intelligence College as an Adjunct Instructor. In 1998, Captain Renfro was assigned as a doctoral student studying Operations Research at the Air Force Institute of Technology. While a student, he volunteered as the Executive Director of the Ohio Valley Committee on U.S.-Arab Relations representing Ohio, Pennsylvania, and West Virginia. His research interests are information operations, intelligence, social network modeling, communications, human factors, cultural bias, and Arab area studies. Following his graduation from the Air Force Institute of Technology, Captain Renfro will be assigned to the Air Force Studies and Analysis Agency at the Pentagon.

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14. ABSTRACT
This dissertation develops new methods for the modeling and analysis of social networks. Social networks depict the complex relationships of individuals and groups in multiple overlapping contexts. Influence in a social network impacts behavior and decision making in every setting in which individuals participate. This study defines a methodology for modeling and analyzing this complex behavior using a Flow Model representation. Multiple objectives in an influencing effort targeted at a social network are modeled using Goal Programming. Value Focused Thinking is applied to model influence and predict decisions based on the reaction of the psychological state of individuals to environmental stimuli.

This research advances the science of Operations Research and its application to broad classes of problems dealing with social networks. Application areas span academic, private sector, and government analysis. Sample cases are used in this research from the private sector and government. Specifically, influencing foreign government decision making is demonstrated for the case of Iran. Counter-terrorism applications are demonstrated for a sample case using Usama Bin Ladin. The contributions of this research serve private and public sector users.

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