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Modeling and Analysis of Clandestine Networks

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CLANDESTINE NETWORKS

THESIS

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Abstract

Since Sept. 11, 2001, there has been great interest in the military and intelligence communities in using Social Network Analysis (SNA) to support the disruption and destruction of global terrorist networks. SNA results, however, tend to be descriptive and are limited due to the lack of advantageous properties of the relationship measures applied to the arcs in a social network. Further, SNA techniques generally focus on a single network context while real relationships are based in multiple contexts. This thesis develops a new proxy measure of pair-wise potential influence between members of a network, a Holistic Interpersonal Influence Measure (HIIM). The HIIM considers the topology of the multiple formal and informal networks to which group members belong as well as non-network characteristics such as age and education level that may indicate potential influence. The HIIM, once constructed results in a network of pair-wise potential influence between group members. Further, the numeric properties of the HIIM are appropriate for use in Operations Research Network Flow models, which will enable analysts to provide prescriptive analysis focused on specific actions and their outcomes. In addition to an overall measure of influence, the HIIM methodology provides important intermediate results such as the development of operational group profiles.

The methodology is applied to open source data on both Al Qaeda and the Jemaah Islamiah (JI) terrorist networks. Key leaders are identified, and leadership profiles are developed. Further, a parametric analysis is performed to compare influence based on individual characteristics, network topology characteristics, and mixtures of network and non-network characteristics.

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Clinton R. Clark

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MODELING AND ANALYSIS OF CLANDESTINE NETWORKS

1. Introduction

1.1. Background

1.1.1. Operational Problem

After a half century of focusing on a Major Theater War with a near-peer competitor, the nation awoke on Sept. 11, 2001 to find out that a new principal threat to the U.S. is terrorism. Terrorism has been defined by the Office of the President of the United States (OPOTUS) as "premeditated, politically motivated violence perpetuated against noncombatant targets by sub-national groups or clandestine agents." The history of the U.S. has been punctuated by terrorist activity, and it appears that for the foreseeable future the nation will be engaged in a battle against terrorism (OPOTUS, 2003: 1-5). To be successful, the military (and other organizations) must continue the effort to uncover the individuals and groups engaged in terrorist activities (OPOTUS, 2003: 1-5).

At the conclusion of the Cold War, military planners in the U.S. made the assumption that a military organized, trained, and equipped to fight a near-peer competitor would be able to handle any type of conflict, which would, after all, be considered a subset to a Major Theater War (Barnett, Mar 2004). The pattern that has emerged since the end of the Cold War, however, is not one of conflict with powerful industrialized nations; rather the U.S. has been engaged in locations that were considered to be no immediate threat to national survival, the Third World. It is the Third World that has spawned the "gravest threat we face", the threat from trans-national terrorism (Barnett, Mar 2004). U.S. military operations since the end of the Cold War also suggest, by their mixed results, that the U.S. military is not fully prepared to handle the threats from trans-national, clandestine terror organizations. This fact was most emphatically highlighted on Sept. 11, 2001 (Barnett, Mar 2004).

Combating terrorism and protecting the Homeland have now become the top priorities of U.S. national security, the focus of which is now the "identification and diffusion of [terrorist] threats before they arise" (OPOTUS, 2003: 1-2, 15). Global operations against terror organizations in Afghanistan, Indonesia, Iraq and elsewhere have had significant impact on terrorist capabilities, forcing them to adapt to the new security environment. The terrorists have responded by organizing into loose flexible networks with smaller, informal groups, increasing the difficulties in combating them (OPOTUS, 2003: 1-2, 15). A thorough understanding of these networks is required to mount an effective counter-terror campaign (Sageman, 2004: vii).

The understanding of terror networks is critical in planning precision, effects based operations. The ability to uncover individuals and subgroups critical to the operations of the network are instrumental in "influencing" terrorist operations. In order to focus operations on terror networks, the U.S. defense establishment requires tools to assist in analyzing the structure of terror networks; these tools should be able to highlight strengths and weaknesses of the network (robustness) as well as uncover individuals and subgroups that are critical to network operations.

1.1.2. Understanding the System

"A new type of terrorism threatens the world, driven by networks of fanatics determined to inflict maximum civilian and economic damage on distant targets in pursuit of their extremist goals."—Marc Sageman

Our operational focus on the near-peer competitor for the past half century has led to the development of large scale mathematical models and simulations with the primary goal of helping us to organize, train, and equip to win a Major Theater War. With our focus now shifting to a war against trans-national clandestine organizations, the operations research community is faced with the challenge of developing tools appropriate for supporting a war on terrorism.

A defining characteristic in the global war on terrorism is that global jihad is “an emergent quality of the social networks formed by alienated young men who become transformed into fanatics yearning for martyrdom, and eager to kill” (Sageman, 2004: vii). Further, it is the “shape and dynamics of these networks that affects their survivability, flexibility, and success” (Sageman, 2004: vii). For example, the social and organizational networks of terrorist can be evaluated on many levels or layers, and the combinations, or interactions, of these relationship layers is critical to the understanding of terror networks.

The threat posed by terrorists today grows out of the flexible, trans-national networks enabled by modern global telecommunications. Different terror organizations also appear to be mutually supporting each other through a loose interconnectivity both within and between groups (OPOTUS, 2003: 8). Because of these interconnected, mutually supportive, dynamic networks, terror groups are becoming much more resilient, and, over time, terror groups have begun working together in “funding, sharing intelligence, training, logistics, planning and executing attacks” (OPOTUS, 2003: 8).

The membership size, organizational structure, and availability of resources may determine a terrorist organization’s capabilities and reach, but it is the ability to bring the members and resources together at the right place and the right time, along with the practice of good operational security (OPSEC) that ultimately determines the success of a terrorist organization. Conventional wisdom tells us that leadership is a key to bringing personnel, resources, and operations together, and that the loss of a leader can cause many organizations to collapse. Experience in the war on terrorism has shown, however, that many terror organizations can withstand the loss of a leader and still operate efficiently (OPOTUS, 2003: 6-7). Unlike a rigid, centralized, hierarchical structure that is highly susceptible to an attack on the leadership, terrorist networks, with their dense interconnectivity, are robust enough to withstand significant losses with limited impact on network integrity (Sageman, 2004: 140). There is also the possibility that a lost leader who becomes a martyr, will actually strengthen a terrorist organization. Despite these difficulties, knowing who the leaders are, and understanding how their influence flows through the network is still vital in understanding and defeating terror operations.

Clandestine networks must constantly balance the desire for organizational effectiveness with the need for OPSEC. By definition clandestine networks are organizations that must operate in secrecy. Simmel (Simmel, 1906: 470), in his seminal work on secret societies, states that when a group chooses "secrecy as part of its existence", it has then determined the nature of relationships that must exist between persons who possess the secret. Erickson (Erickson, 1981: 188) further states that "risk enforces recruitment along lines of trust," which forces clandestine networks to use pre-existing networks of relationships. The use of pre-existing social networks sets limits on the social structure of the clandestine network (Erickson, 1981: 188). The trust premium paid by clandestine organizations is their reliance on pre-existing networks. This enables analysts tasked to understand and influence clandestine network operations to bound the problem space by focusing on the trusted relationships of a particular group.

The primary concerns of any clandestine network are organizational effectiveness and OPSEC. In order to disrupt or eliminate the organizational effectiveness of a clandestine network, one must understand how leadership influence flows through the network to manage operations. Groups practicing good OPSEC make it difficult for analysts to uncover the influence relationships within their network. However, the reliance of clandestine networks on trusted, preexisting relationships to maintain OPSEC places limits on their size and structure. By focusing analysis on group leadership influence and trusted pre-existing social networks, analysts may help to uncover critical "hubs" across the networks. Operations focused on identified centers of gravity may be able to induce systemic failures across the system thereby reducing or removing the threat posed by a clandestine network or networks.

The Global War on Terrorism, the War on Drugs, the fight against street gangs, organized crimes and other ongoing operations against clandestine networks highlights our need for improved analysis tools. These tools need to enable analysts to identify positions of power and "attribute them to specific individual traits or structural roles that these individuals fulfill" (Klerks, 2001: 53).

1.1.3. Current Strategies

Researchers (ex. Simmel, 1906; Gross, 1980; Geis and Stotland, 1980; Erickson, 1981; Baker and Faulkner, 1993; Klerks, 2001) have conducted psychological and sociological analyses of clandestine networks for the past century, however since Sept. 11, 2001 there has been a dramatic increase in the number of publications (ex. Krebs, 2001; Carley *et al*, 2003, Sageman, 2004) on clandestine networks, specifically terror networks. These recent researchers have chosen Social Network Analysis (SNA) to help them "map," (Krebs, 2001) "uncloak," (Krebs, 2002) "identify key players," (Borgatti, 2002) "destabilize," (Carley *et al*., 2003) and "understand" (Sageman, 2004) terror networks.

SNA is based on the assumption that the relationships between and amongst individuals is important. The focus of SNA on formal and informal networks of relationships makes it an appropriate tool for the analysis of terror organizations. In addition to relationships, Wasserman and Faust (Wasserman and Faust, 1994: 4) outline the following major concepts important to SNA:

- Actors and their actions are viewed as interdependent rather than independent, autonomous
- Relational ties (linkages) between actors are channels for transfer or "flow" of resources (material or non-material)
- Network models focusing on individuals view the network structural environment as providing opportunities for or constraints on individual action
- Network models conceptualize structure (social, economic, political, and so forth) as lasting patterns of relations among actors

What is clear from early analysis of terrorist groups is that the major SNA concepts are appropriate assumptions. Individuals become members of terrorist groups based primarily on the strength of prior relationships. Their actions and capabilities are supported by the interdependent relationships between members. Communication and resources are able to move through the network through relational ties, and the location of the member in the organization does have the effect of empowering or inhibiting (Krebs, 2001; Krebs, 2002; Borgatti, 2002; Carley *et al*., 2003; Sageman, 2004).

The focus of SNA on relationships requires that the theoretic concepts be relational, that relevant data be relational, and statistical testing use distributions based on relational properties (Wasserman and Faust, 1994: 6). In SNA individuals are tied to other individuals who are tied to still other individuals. The analysis of the network of individuals focuses on depicting the structure of the group, the key members of the group, the impact of the structure on the operations of the group, as well as the influence of the structure on individuals (Wasserman and Faust, 1994: 9). SNA provides the analyst tools to evaluate the importance of individuals and groups to the network and the means to analyze the structure of the network that can enable effects based operations focused on reducing or removing the threat posed by a group.

1.1.3.1. Operations Research Support to SNA

SNA results, however, are limited due to the "lack of advantageous properties" of the relationship measures applied to the arcs in a social network (Renfro, 2001; Renfro and Deckro, 2004). SNA studies typically produce descriptive results such as which actor is the most "central", which actors belong to which "cliques", and which actors are "structurally equivalent". Renfro and Deckro (Renfro, 2001; Renfro and Deckro, 2004) state that Operations Research (OR) techniques can extend and refine SNA with results that are "measurable, quantifiable, and organized in a manner that allows for specific courses of action to be evaluated."

The key to extending SNA to classic OR flow problems is having the relationship measures applied to the arcs represent "potential influence" between individuals (Renfro and Deckro, 2004). By mapping social networks to network flow models, analysts are able to provide prescriptive results such as a "minimum cut set" required to isolate particular actors. Renfro (Renfro, 2001: 47) outlines the required property assumptions of measures for use in network flow models (proportionality, additivity, divisibility, certainty) as well as a discussion of the impacts of violating these assumptions. What is left to researchers is to develop methods to produce valid measures of potential influence that satisfy these assumptions.

1.1.3.2. Descriptive vs. Prescriptive Analysis

Descriptive measures focus on providing results that will enable analysts to describe their problem context. SNA measures of individual importance and cohesive subgroups help analysts to describe the network on the basis of its topology. Analysts can determine who is the most central, who belongs to certain subgroups, and which members are structurally similar, to name a few. What SNA measures do not do is provide results that suggest specific actions to be taken against the network and their potential outcomes.

Prescriptive measures focus on specific actions and their outcomes. OR network flow models, in contrast to SNA, provide specific, quantifiable results that are actionable. The results are tied to specific outcomes, and can be tested for robustness through post optimality analysis. Using network flows, analysts can determine the maximum flow of influence through a network, recommend cut sets to separate specific network members, or determine the optimal locations to deploy intelligence assets. Further, network flow models will highlight alternate optimal solutions if they exist, thereby providing alternate courses of action of equal value.

SNA measures were designed to help *describe* the network and its topology, not on highlighting opportunities to influence the networks. For the social scientist descriptive network measures are fine, but for the military, intelligence, and law enforcement analyst, results that can *prescribe* courses of action to influence a group are desirable. While SNA measures fall short on prescriptive results, many Operations Research techniques were designed with actionable results in mind. Many of these techniques can be extended to support analysis of social networks, and are discussed further in Chapter 5.

1.1.4. Measuring Influence

"Being perceived as a leader allows one to exert greater influence."—Robert G. Lord

In order to map social networks into network flow models the arc measures must represent pair-wise interpersonal influence between members. Researchers have been studying leadership, power, and influence since the beginnings of civilization (Bass, 1990: 3). The terms leadership, power, and influence have occasionally been used interchangeably in the literature. Cartwright (Cartwright, 1965: 13) equated leadership with the "domain of influence," and the concept of influence was used by researchers as an attempt to generalize the definition of leadership (Bass, 1990: 13). Bass (Bass, 1990: 227) further stated that "power is the potential to influence."   The vast amount of research on leadership, power, and influence provide an excellent starting point for the development of measures of potential influence in social networks. For the purposes of this paper, leadership and power are used interchangeably and are defined as ones potential to influence others.

There have been two primary threads of research on leadership, power and influence. One thread, the psychological perspective, focuses on the personal characteristics of the individual, and ultimately tries to determine "how much individual differences account for the emergence of leadership and its effectiveness, and if the effects transcend situational circumstances" (Bass, 1990: 87). Trait theories fell out of favor with leadership researchers because of the literature reviews by Stogdill (Stogdill, 1948) and Mann (Mann, 1959) that reported "no traits consistently differentiated leaders from non-leaders across a variety of situations" (Lord, De Vader and Alliger, 1986: 402). Lord *et al*. (Lord, De Vader and Alliger, 1986: 402) noted, however, that the conclusions of the Mann and Stogdill reviews have been misinterpreted because there *were* many "consistently significant" relationships between individual characteristics and leadership in both reviews. It is clear from a review of the literature that individual characteristics are important in determining potential influence; however, analysts must also consider the situational context.

The other primary thread of research on leadership, power, and influence, the sociological perspective, focuses on structural characteristics of the organization, and tries to determine "the relative net influence of each group member on others based on the structure of the network" (Friedkin, 2003: 90). Hanneman states that "all sociologists" would argue that influence is fundamental property of social structure (Hanneman, 2001: 60).

Power in a social network arises from occupying an advantageous position. SNA researchers have developed a number of specific definitions and measures of different notions of influence based on positions in social structures (Hanneman, 2001: 61). The limitation of these definitions is that they are only concerned with influence based on the network structure. It is very likely that individuals will have power that is not dependent on connections, but rather based on personal characteristics.

The history of study in leadership, power, and influence provide a starting point for developing measures of potential influence in social networks that meet the required assumptions for use in OR flow models. Further, "as we discover methods which help us to understand the relationships which exist among the members of any group, we shall also gain better insight into the factors important to the leadership role of that group" (Browne and Cohn, 1958: 213). The potential limitation in extending the psychological and sociological research is the assumption that theories and concepts developed in the U.S. have universal application (Marshall and Gitosudarmo, 1995: 6). One must be careful to consider the culture of the group, their situational context, and their OPSEC practices when developing measures of potential influence.

1.1.5. Nature of Intelligence

To collect the necessary data required to measure potential influence in a clandestine network, it must recognized that one is facing an enemy focused on practicing good OPSEC. Social network analysts "approach empirical situations armed with questionnaires for participants to fill out, unfortunately criminals in their natural habitat seldom fill in researchers' questionnaires" (Klerks, 2001; 58). The difficulty in collecting data places limits on the results from SNA. Measuring and counting presuppose that there is something to measure and groups practicing good OPSEC are not readily exposing themselves to intelligence collectors, much less sociologists (Klerks, 2001: 58). The difficulty collecting data, the means of collecting data, and the nature of the data itself are going to play a role in making the data imprecise.

The measurement of relationships in a terror network requires a flexible methodology able to distinguish the influence between father and son, the influence amongst a group of friends, and the influence of an Imam. Unfortunately, almost all of our current mathematical tools are based on data from rigid constructs. For modeling purposes, Zimmerman (Zimmerman, 1991:1-7) highlights two main problems for rigid constructs:

- Real situations are very often not crisp (rigid) and deterministic and they cannot be described precisely
- The complete description of a real system often would require by far more detailed data than a human being could ever recognize simultaneously, process and understand

Often when one thinks of uncertainty in a mathematical system, one thinks of the stochastic nature of unknown future states of a system and this stochastic uncertainty has long been studied and understood by statisticians and operations researchers (Zimmerman, 1991: 1-7). Stochastic states however, are still based in a rigid "set theory" universe. Zimmerman contrasts stochastic uncertainty with the "vagueness concerning the description of the semantic meaning of the events, phenomena, or statements themselves," which he termed fuzziness (Zimmerman 1991: 107). When faced with the task of modeling terms such as relationship, influence, trust, and belief there is a clear need for a more flexible construct. Fuzzy set theory was developed to provide the necessary flexibility required to measure these relational concepts.

1.1.6. Social Influence Network Theory

"Social influence network theory is a mathematical formalization of the process of interpersonal influence that occurs in groups."—Noah Friedkin

Social influence network (SIN) theory attempts to describe how a network of interpersonal influences enters into the process of affecting attitudes and opinions within a group, and it enables an analysis of the impact of the structure of the influence network on individual and group level outcomes (Friedkin, 2003: 90). SIN theory focuses entirely on the topology of the social networks underlying a group to explain the interpersonal influences. For Friedkin (Friedkin, 2003) the social structure consists of

- members initial opinions
- susceptibilities to influence
- interpersonal influences; which is represented by a matrix (**W**)

While Friedkin and Johnson (Friedkin and Johnson, 1997; Friedkin, 2001; Friedkin, 2003) are focused on describing attitude and opinion formation, Leenders (Leenders, 2002: 21) states that many social phenomena are embedded within networks of interpersonal influence. In addition, the representation of interpersonal influence assumed to be present in a network can be "operationalized" in many ways (Leenders, 2002: 22). The results and conclusions based on the analysis of a SIN are completely dependent on the specification of **W,** the matrix of interpersonal influence. Friedkin (Friedkin, 2003) and Leenders (Leenders, 2002) are both concerned with the lack of "attention and justification paid" to the development of meaningful measures of interpersonal influence input into the **W** matrix.

1.1.7. Operational Definition of Influence

Influence is defined as the power to sway or affect based on prestige or position. Understanding influence within an organization can be simplified by considering two extreme cases, "E. F. Hutton" and "Ma Bell" as shown in Figure 1-1.

E. F. Hutton has influence over everyone in his network because of his prestige. Prestige can be based on personal traits such as intelligence, judgment, knowledge, piety, accomplishments, aggressiveness, age, wealth, and popularity (Bass, 1990: 76). The consequence of his prestige is that "when E. F. Hutton speaks, people listen." From an influence operations perspective, knowledge of E. F. Hutton and who has access to him presents an array of potential opportunities including discrediting him or disrupting his messages.

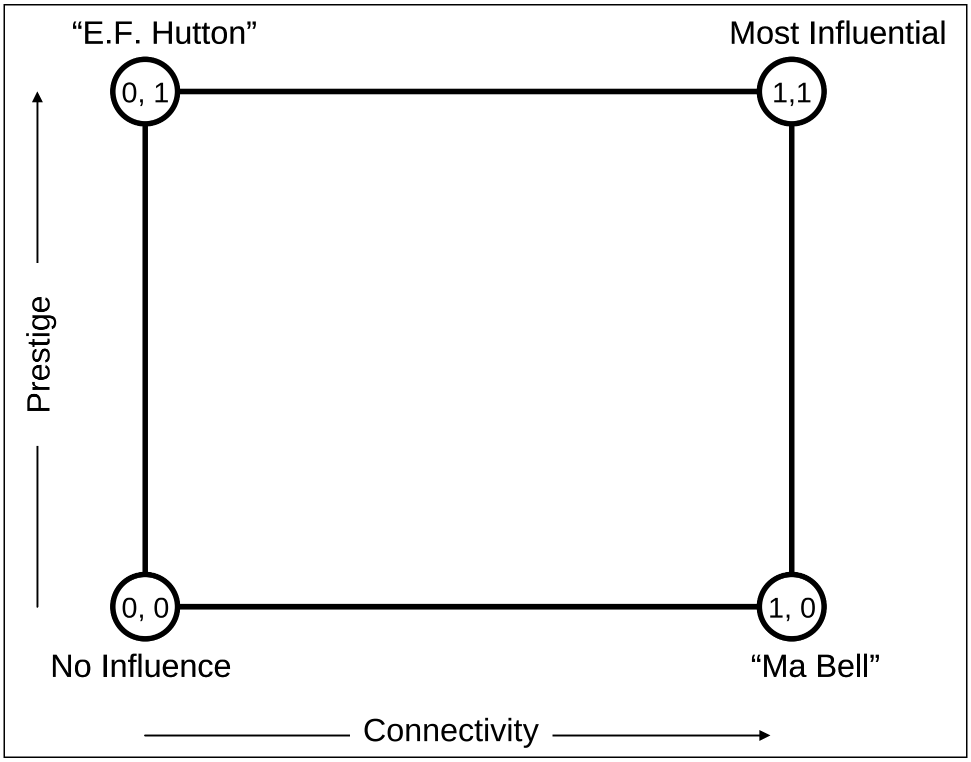

Figure 1-1: Operational Definition of Influence

Ma Bell, on the other hand, has influence not because of her personal traits, but solely because of her network connections. The ability to "reach out and touch" every other network member personally, makes Ma Bell a high value target for influence operations. Ma Bell also presents an array of opportunities, including serving as an informant or delivering *our* messages.

Measures of interpersonal influence should be able to uncover, quantify, and explain the nature of influence possessed by E. F. Hutton and the mail clerk, as well as all other network members.

1.2. Problem Statement

To provide measurable, quantifiable, and actionable results based on the analysis of clandestine networks the relationship arcs between actors must meet the required assumptions for OR flow models. In order to map SNA models into OR flow models the relationship arcs must represent potential influence (Renfro and Deckro, 2004, pp). Potential interpersonal influence within a group is a function of both individual characteristics and the social structure. OPSEC practices by clandestine networks make data collection difficult and can lead to imprecise individual characteristic and social structure data. This thesis advances the modeling and analysis of clandestine networks by developing a methodology to create a valid measure of interpersonal potential influence based on individual characteristics and social structure that captures the uncertainty of imprecise data. The new measure of interpersonal potential influence is appropriate for SNA studies, OR flow models, and Fuzzy Linear Programming models.

1.3. Problem Approach

A tenet of this thesis is that interpersonal influence is a combination of one's personal characteristics and one's position in his/her networks of relationships. Given this assertion, a measure of interpersonal influence, then, must capture the functional relationship between influence, and the non-network and network characteristics of individuals in its development.

Current SIN theory literature accounts for a measure of non-network influence, but offers no method to develop such a measure. Stogdill's (Stogdill, 1948) review of leadership studies from the early 20th century highlights multivariate data analysis as the primary tool for determining individual characteristics that were associated with influence. Therefore, Discriminant Analysis was used to develop a measure of non-network influence. In addition to a proxy influence measure, Discriminant Analysis was used to profile, differentiate, and classify clandestine network members on the basis of an observed set of characteristic data. Discriminant Analysis was chosen because it is easy to implement and interpret; however it is based on assumptions of multivariate normal predictor variables with constant variance across multiple subgroups. If these assumptions are violated, one could apply Logistic Regression, which has no distributional assumptions, with no impact to the overall methodology.

Influence in social networks is attained by possessing advantaged positions. There are three primary techniques for calculating pair-wise measures of interpersonal influence based on the topology of a social network. Each technique has its advantages and disadvantages. Based on the elements of the measure and its intended use in modeling clandestine networks, Information Centrality was used to calculate pair-wise measures of interpersonal influence for groups in this study. Information Centrality produces a measure of interpersonal influence that is based completely on network topology for *each* informal social network to which clandestine network members belong.

Clandestine networks are based on the pre-existing, trusted, informal social networks to which they belong. Measures of pair-wise interpersonal influence can be calculated and analyzed for *each* informal social network for which there is data, but to develop a more accurate understanding, the information from *each* of these networks must be considered simultaneously. To capture the influences from multiple network contexts, this study used a linear combination of the interpersonal influences from each informal network.

Combining the individual influence results from Discriminant Analysis with the combined topology based influence results from Information Centrality enables the creation of a new measure of interpersonal influence within clandestine networks. This new measure was termed the Holistic Interpersonal Influence Measure (HIIM), because it attempts to measure the functional relationships and interdependence between the parts (individual characteristics and social network characteristics) and the whole (interpersonal influence) of social influence.

1.4. Research Scope

The general focus of this paper is on terrorist networks. It is realized that many clandestine networks share common traits with terror networks, yet there are fundamental differences in some areas that may not be captured within the current model.

The ongoing war on terrorism has focused the intelligence community's research efforts on certain organizations. The focus of this research is to support the analysis of the most important groups to U.S. forces.

Due to classification levels of some of the data concerning clandestine networks this analysis will rely on open source demographic and social network data.

1.5. Assumptions

The methodology utilized in this thesis assumes the following:

- There exists a means to collect individual demographic and social network data
- The data collected is complete and correct
- Social network connections are undirected

- Individual characteristic data is distributed multivariate normal with equal variance across various subgroups

Each of these assumptions and their potential impacts are discussed in detail in subsequent chapters.

1.6. Overview and Format

The structure of this thesis begins with a review of social influence modeling literature in Chapter 2. In particular, Chapter 2 reviews Social Network Analysis (SNA) theory, Social Influence Network (SIN) theory, Discriminant Analysis, and methods for developing pair-wise interpersonal influence measures. Chapter 3 develops a methodology to create the HIIM, a new measure of interpersonal influence that considers non-network and network characteristics. Chapter 4 provides a demonstration of the Discriminant Analysis methodology developed in Chapter 3, Section 3 based on open source Al Qaeda data. Chapter 5 provides a demonstration of the complete HIIM methodology developed in Chapter 3 based on open source Jemaah Islamiah data. Chapter 6 presents conclusions from this analysis, highlighting key results, and presents recommendations for future research.

2. Social Influence Modeling Literature Review

2.1. Introduction

This chapter reviews the pertinent literature relating to Social Influence Network (SIN) Modeling, specifically focusing on techniques for developing meaningful pair-wise measures of influence between individuals in a clandestine network. Social Influence Network Theory is an extension of Social Network Analysis (SNA), therefore a brief introduction to SNA is provided. The chapter then sets out the underlying assumptions and rational for Social Influence Network (SIN) theory, followed by an overview of Discriminant Analysis, which has the potential to aid development of non-network influence measures. The chapter concludes with a review of the development of pair-wise measures of social influence.

2.2. Introduction to Social Network Analysis (SNA) Measures

SNA focuses on depicting the structure of a group, the critical members of the group, the impact of the structure on the operations of the group, as well as the influence of the structure on individuals (Wasserman and Faust, 1994: 9). SNA measures tend to focus on identifying the key members of the network and uncovering any cohesive sub-groups.

Uncovering critical individuals is important when analyzing terror networks; however, groups practicing good operational security (OPSEC) make it very difficult to locate critical individuals through SNA techniques. Many of the assumptions made by social scientist about individual importance to a network are based on the members' connections; more connections imply greater importance. Leaders of clandestine networks practicing good OPSEC, however, by design will likely have very few connections, and *may* not be uncovered through classic SNA techniques. Because of the potential difficulty in finding key individuals, it is important to also search for key subgroups within organizations. Knowledge of these subgroups, highlighted by tight bonds, can also be critical in influencing a terror organization. The remainder of this section details the classic SNA measures of individual importance and measures for detecting cohesive subgroups.

2.2.1. SNA Measures of Individual Importance

SNA Measures of individual importance tend to focus on the location of the individual within the network topology, and attempt to quantify the importance of the individual (Wasserman and Faust 1994: 169). SNA measures of individual importance within the network are basic extensions of Graph Theoretic measures that have, in practice, revealed actors of high importance to the network. In open organizations such as a business these measures can reveal individuals of high importance. However, when faced with an organization practicing good OPSEC individuals in leadership positions may, through the use of cutouts and other planned efforts, have extremely low values on standard SNA measures.

A formal discussion of SNA measures of individual importance is provided in *Social Network Analysis: Methods and Applications* (Wasserman and Faust, 1994). Table 2-1 provides an overview of each of the standard SNA measures used in this thesis. Table 2-1 highlights what each measure calculates, what it attempts to measure, and appropriate references:

Table 2-1: Comparison of SNA Individual Centrality Measures

SNA Measures of Individual Importance	Calculates	Measures	References
Degree Centrality	Number of direct connections to other nodes	Connection to others; network activity; power	Freeman, 1979; Wasserman and Faust; 1994 Hanneman, 2001
Closeness Centrality	Inverse of the sum of the shortest paths to all other nodes in the network	Members "key" to network communication; reach; reachability	Freeman, 1979; Wasserman and Faust; 1994 Hanneman, 2001
Betweenness Centrality	Proportion of times a node is on the shortest path between other pairs of nodes	Information control; role as an intermediary; brokers; "gatekeepers"	Freeman, 1980; Wasserman and Faust; 1994 Hanneman, 2001
Information Centrality	Proportion of times a node is on any path between other pairs of nodes	Information control; role as an intermediary; brokers	Sthepenson and Zelen, 1989; Wasserman and Faust; 1994 Hanneman, 2001
Eigenvector Centrality	Nodes assigned loading on first principal component, calculations identical to Principal Components Analysis	Overall importance to the network; how close am I to actors who are close to others	Bonacich, 1972; Bonacich, 2001

The social network perspective suggests that an individual's influence is not an individual attribute, but rather that it arises from their relations with others (Hanneman, 2001: 75). Each of the aforementioned measures is limited because the calculations are based on the assumption that influence within a network is based solely on the occupation of privileged positions within the topology of the network. Currently there is no method to validate the results obtained using these measures. To improve the usefulness of SNA measures of individual importance there must be a means to validate their results.

2.2.2. SNA Measures for Sub-Group Detection

Measures for subgroup determination were developed to help explain the intuitive idea of social groups using SNA properties (Wasserman and Faust 1994: 249). Social groups have been described structurally by Freeman and Webster (Freeman and Webster, 1994: 225) as "collections of individuals who are linked by frequent interaction and often by sentimental ties." The idea of the social group used by social and behavioral scientists is quite general, with numerous network properties that suggest group cohesiveness. There are, therefore, many different possible definitions of cohesive subgroup. Having multiple definitions can, in general, be undesirable, however, when using SNA to model terror organizations, having multiple options for uncovering cohesive subgroups may have advantages.

A formal discussion of SNA measures for subgroup detection is provided in *Social Network Analysis: Methods and Applications* (Wasserman and Faust, 1994). Table 2-2 provides an overview of the primary measures from SNA literature; the types of groups found, the implications of these groups, and appropriate references:

Table 2-2: Comparison of SNA Measures for Subgroup Detection

SNA Measures for Subgroup Detection	Finds	Implication	References
Clique	Groups in which each member is directly connected to every other member in the group	Completely connected groups; Impossible to distinguish between group members	Luce and Perry, 1949; Wasserman and Faust, 1994; Hanneman, 2001;
n-clique	Largest group such that each member is within n connections of any other group member	Larger more prevelant groups; long stringy groupings;	Luce, 1950; Wasserman and Faust, 1994; Hanneman, 2001;
n-clan n-club	Restriction to n-clique, all connections must remain within the group	Larger more prevelant groups; tighter groupings than n-clique	Mokken, 1979; Wasserman and Faust, 1994; Hanneman, 2001;
k-plex	In a group size g, each member must be connected to at least g-k other members	Large number of small groupings; focus on overlaps and co-membership	Seidman and Foster, 1978; Wasserman and Faust, 1994; Hanneman, 2001;
k-core	Subgroup in which each node is adjacent to at least k other nodes	relationships based on connection; id's areas where interesting subgroups may exist	Seidman, 1983 Wasserman and Faust, 1994; Hanneman, 2001;

The potential difficulties in uncovering critical individuals presented by clandestine networks make techniques for uncovering cohesive subgroups important. Cohesive subgroups within clandestine networks, often based on friendship, kinship, and worship ties (Sageman, 2004: pp 107-114), identified by these SNA measures, *may* indicate leadership counsels, logistics cells, or operational cells. Identification of these subgroups may provide additional insight into the influence process of a clandestine network.

2.3. Fuzzy Cliques

As discussed in the previous section, one of the major concerns of SNA is the identification and analysis of cohesive subgroups (Wasserman and Faust, 1994: 249). The graph theoretic subgroup detection and analysis techniques discussed previously, however, are *all* limited to binary undirected networks. Yan provides a taxonomy of the limitations of traditional subgroup detection and analysis techniques (Yan, 1987: 364). Yan classifies five limitations of traditional clique detection and analysis techniques: Redundant Connection Limitation, Membership Limitation, Structure Limitation, Network Limitation, and Computation Limitation (Yan, 1987: 361-363).

To form a clique requires $n(n-1)$ connections, where n is the cardinality of the clique. This requires each member be directly connected to every other clique member, and the absence of a single connection will preclude someone from clique membership. Further, for a node and any given clique there exist only two possibilities, the node is either a member of the clique or not (Yan, 1987: 360). Further, because each member must have the same number of connections, members within a clique cannot be distinguished. In addition, analysis of relationship strength or the amount of social interactions is precluded by a limitation to 0-1 connections (Yan, 1987: 361). Finally, and perhaps most importantly, the detection of cliques as defined by Luce and Perry (1949) is an NP-complete problem.

To overcome the identified limitations of traditional subgroup detection and analysis techniques, Yan defines a fuzzy clique as "a maximum strongly connected node subgroup in which each node is connected to all others directly or indirectly, regardless of the number of intermediate nodes" (Yan, 1987: 378). Based on this definition and an *assumed* relationship measure, Yan defines three subgroup analysis techniques. Table 2-3 provides an overview of Yan's fuzzy clique analysis measures; the purpose of the measure, the implications of the results, and appropriate references:

Table 2-3: Fuzzy Clique Analysis Measures

Fuzzy Clique Analysis Measures			
	Finds	**Implication**	**Reference**
Node Membership Value	Measure of how important a member is within his own subgroup	Core of subgroup; Percent of members over which one has above average influence	Yan, 1987; Sterling, 2004
Node-Clique Coefficient	Measure of ones relationship to a subgroup of which he is not a member	Identifies key deputies; members who have the most access to a subgroup of interest	Yan, 1987; Sterling, 2004
Clique-Clique Coefficient	Measure of the relationship between two separate subgroups	How do different subgroups relate; Informal leadership structure	Yan, 1987; Sterling, 2004

By enabling an analysis of subgroups based on valued relationship measures, Yan's technique *may* enable analysts to identify critical relationship structures within clandestine networks. The Node Membership Value *may* highlight a groups core leaders. Further, the Node-Clique coefficient has the *potential* to identify key deputies and cut-outs with privileged access to the leadership group. Finally, the Clique-Clique coefficient *may* help to uncover the informal leadership structure within a given network.

Highlighting key individuals and uncovering key subgroups are two of the primary objectives for any SNA study. In addition to these objectives, there has been a movement within SNA, starting with French (French, 1956), to measure interpersonal influence based on social structures. Over time this movement has evolved into what is referred to as Social Influence Network (SIN) theory. The next section briefly discusses the development of SIN theory.

2.4. Introduction to Social Influence Network Theory

Social Influence Network (SIN) Theory is a mathematical formulation of the process of interpersonal influence that occurs in groups (Friedkin, 2003: 89). SIN theory attempts to link the structures of social networks to the attitudes and behaviors of the individuals in those networks (Marsden and Friedkin, 1994: 3). While SIN theory is primarily concerned with modeling information diffusion and opinion formation, Leenders (Leenders, 2002: 21) states that many social phenomena are embedded within networks of interpersonal influence. This section focuses on the most current literature concerning SIN theory, which is dominated by Friedkin. The methods proposed by Katz and Hubbell are, however, highlighted in the last section of the chapter.

SIN theory is rooted in the work of Katz (1953), French (1956), Harary (1959), Hubbell (1965), and Friedkin (1997, 1998, 2001, 2003), and can be summarized by its two fundamental equations. The first equation is concerned with the initial opinions of the actors on a particular issue, and the second is concerned with the subsequent transformation of actor opinions (Friedkin, 1998: 2-3):

$$Y^{(I)} = XB$$

$$Y^{(t)} = AWY^{(t-1)} + (I - A)Y^{(1)}$$

$$\left\{ \begin{array}{l} 0 \le w_{ij} \le 1 \\ \sum_{j}^{n} w_{ij} = 1 \\ w_{ii} = 1 - a_{ii} \end{array} \right\}$$

In the first equation, $\mathbf{Y^{(I)}}$ is an $(n \times 1)$ vector of initial opinions, **X** is an $(n \times k)$ matrix of exogenous (non-network) variables that affect actor opinion, and **B** is a $(k \times 1)$ vector of coefficients for the exogenous variables. In the second equation, $\mathbf{Y^{(t)}}$ is an $(n \times m)$ matrix of opinions at time *t*, **A** is a diagonal matrix of weights of the endogenous characteristics, and **W** is an $(n \times n)$ matrix of the endogenous interpersonal influences in the network.

Despite the inclusion of the exogenous influence equation, $\mathbf{Y^{(I)} = XB}$, which is designed to capture non-network measures of influence, Friedkin offers no information about how to develop or use the equation (Strang, 2000: 162). Further, Strang comments that there is no discussion of "actual opinions, no indirect measures of opinion similarity, and no measures of influence" in Friedkin's (1998) book (Strang, 2000: 162). When Friedkin offers example problems, he uses **W** to develop **X**, thereby using endogenous (network structure) relationships to develop his exogenous measure of initial opinion. Without the proper application of the exogenous equation, Friedkin's method becomes a purely structural based measure of influence. Friedkin (Friedkin, 2003: 90) later concedes that his work is a built from a "distinctly sociological perspective."

To improve upon the current state of the art in SIN theory there must be a focus on the development of exogenous (non-network) measures of individual influence. If one assumes that within a network there exists a group of individuals with more influence than ordinary network members that can be identified, Discriminant Analysis may be able to identify the characteristics of this influential group. Further, if there are identifiable differences between influential network members and non-influential network members on some measurable set of characteristics, then Discriminant Analysis may enable researchers to develop meaningful exogenous measures of influence. The next section details the development and application of Discriminant Analysis.

2.5. Discriminant Analysis

Discriminant Analysis is a statistical technique used to classify individuals into mutually exclusive and collectively exhaustive groups on the basis of a set of independent variables (Dillon and Goldstein, 1984: 360; Lattin *et al*., 2003: 426-7). It does this by developing a weighted average of each individual's scores on the independent variables and transforming them into *a posteriori* probabilities used to determine the likelihood of an individual belonging to each of the groups (Dillon and Goldstein, 1984: 361).

Dillon and Goldstein assert that Discriminant Analysis, as a methodology, is principally concerned with two things, explanation and prediction (Dillon and Goldstein, 1984: 364). A principle measure of the quality of a Discriminant Analysis function is its ability to classify individuals into the correct groups. If one develops a "good" Discriminant function, meaning it classifies well, the function will help to explain the dimensions on which groups differ and also serve as an assignment rule for predicting to which group new individuals belong.

Lattin *et al.* (Lattin *et al*., 2003: 427-8) ascribe three primary objectives to Discriminant Analysis; profiling, differentiation, and classification.

> "When the purposes of a study are primarily exploratory in nature, the first objective of Discriminant Analysis is usually descriptive: How do groups differ with respect to the underlying variables? Once the groups have been profiled, it may be important to ask whether the apparent differences across groups are, in fact, significant; Discriminant Analysis allows us to test for differences in means between and across groups. In addition to profiling and differentiation, one might also be interested in predicting

group membership—that is using the Discriminant function to categorize observations when the value of the dependent variable is unobserved."

2.5.1. Discriminant Analysis Overview—Two Group Problem

Assume that one has a population **G** consisting of 2 subgroups, $\mathbf{G_1}$ and $\mathbf{G_2}$ and a set of measurements on *p* characteristics. Let **X** = [x_{ij}] be the ($n \times p$) matrix of measurement characteristics. Let **Y** = [y_i] be the ($n \times 1$) vector of *a priori* classifications of **G** into $\mathbf{G_1}$ and $\mathbf{G_2}$. The purpose of Discriminant Analysis, then, is to create an assignment rule for **X** that will classify individuals into groups such that the misclassification rate is minimized.

Given the pooled sample variance-covariance matrix **S**, and group means $\overline{x_1}$ and $\overline{x_2}$, the assignment rule is created by calculating **b** = [b_i], the ($1\times p$) vector of discriminant weights associated with each independent individual characteristic where:

$$b = S^{-1}(\overline{x_1} - \overline{x_2})$$

A Discriminant Function is defined by the following equation:

$$Y = b'X$$

Each element of **Y**, then, is a linear combination of the discriminant weights and each individual's personal characteristics:

$$y_i = b_1 x_{i1} + b_2 x_{i2} + \ldots + b_p x_{ip}$$

Figure 2-1 provides a graphical depiction of the two-group Discriminant Analysis problem.

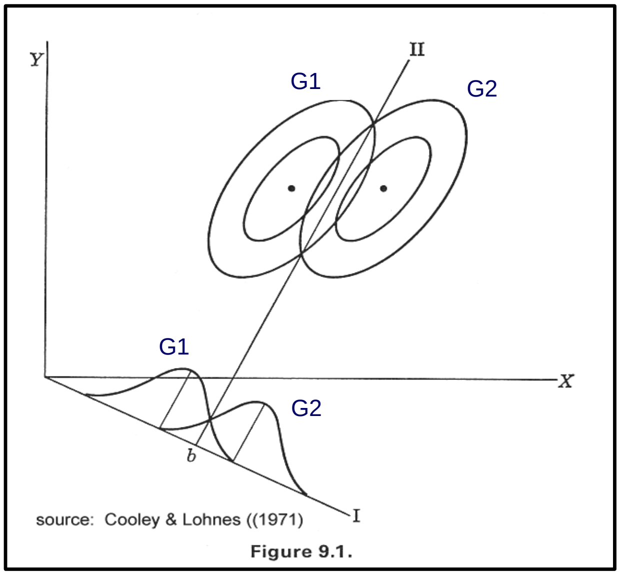

Figure 2-1: Graphical illustration of two-group Discriminant Analysis

A detailed discussion of the calculations and assumptions for Discriminant Analysis is provided in *Multivariate Analysis* (Dillon and Goldstein, 1984) and *Analyzing Multivariate Data* (Lattin, *et al.*, 2003). The next section discusses the limitations of Discriminant Analysis

2.5.2. Limitations of Discriminant Analysis

The optimality of the classifier created using Discriminant Analysis is conditional on the following assumptions outlined in Dillon and Goldstein (1984):

- The independent predictor variables are from a multivariate normal distribution
- The variance-covariance matrix of independent variables is the same across the two (multiple) subgroups

Discriminant Analysis is known to be robust to violations of normality due to skewness (Pohar, *et al*., 2004: 157), however violations of these assumptions, in general, have an adverse impact on statistical tests of significance and classification accuracy (Dillon and Goldstein, 1984: 380-381). When the Discriminant Analysis assumptions are violated, Logistic Regression provides an alternative approach to group discrimination that does not rely on any distributional assumptions. Further, application of Logistic Regression in place of Discriminant Analysis will not impact the methodology presented in Chapter 3.

Pohar *et al*. (2004), provide a comparison of appropriate situations for applying Discriminant Analysis and Logistic Regression. For a complete discussion of Logistic Regression, the reader is referred to *Analyzing Multivariate Data* (Lattin *et al*., 2003). The next section discusses the potential of Discriminant Analysis to support the modeling and analysis of clandestine networks.

2.5.3. Differentiation, Profiling, and Classification

Recall that the three primary objectives of Discriminant Analysis are to differentiate between groups, profile the characteristics that distinguish the groups, and classify group members into appropriate groups (Lattin *et al.*, 2003: 427-8). Differentiation, profiling, and classification of clandestine network members have many potential operational impacts such as identifying leaders or potential recruits. Whether one's mission is to profile network members and non-members, or to distinguish group leaders from the rank and file, Discriminant Analysis techniques can support the analysis.

Discriminant Analysis results enable analysts to determine *if* subgroups differ significantly based on the *observed* set of individual characteristics. If a significant difference between groups exists, Discriminant Analysis is able to highlight which variables were important in differentiating between the groups. The relative contributions of each characteristic in discriminating between groups can then be used to develop a profile for each subgroup. Finally, the Discriminant Function developed can be used to assign members to the appropriate subgroup. A "good," accurate, classifier can then be used to predict group membership for newly identified members.

In addition to providing methods to differentiate, profile, and classify, Discriminant Analysis has a series of statistical tests to determine the significance of each of these results. A formal discussion of the statistical testing associated with Discriminant Analysis is provided in *Multivariate Analysis* (Dillon and Goldstein, 1984).

2.5.4. Individual Influence Measure

A Discriminant Function produces a score for each group member based on the set of characteristics they possess. Given subgroups $\mathbf{G_1}$ and $\mathbf{G_2}$, assume $\mathbf{G_1}$ is the leadership group of an organization and $\mathbf{G_2}$ is the rank and file. The Discriminant Function created to distinguish between $\mathbf{G_1}$ and $\mathbf{G_2}$ can be used to develop a proxy measure of influence within a group. To the extent that leadership is associated with influence (Browne and Cohn, 1958; Cartwright, 1965; Lord, De Vader and Alliger, 1986; Bass, 1990), an individual possessing leadership characteristics can be assumed to have influence within the group.

Discriminant Analysis can be used as a stand alone approach to differentiating, profiling, and classifying social groups. In this study Discriminant Analysis will also serve as an input to a new measure of interpersonal influence. A technique to develop a proxy measure of influence based on individual characteristics using Discriminant Analysis is developed in Chapter 3.

2.5.5. Section Summary

This section has provided a brief overview of Discriminant Analysis and its applications for modeling and analysis of clandestine networks. Discriminant Analysis enables analysts to distinguish between subgroups, profile groups, and classify group members on the basis of an observed set of characteristics. The ability to profile and classify group members has many operational implications. In addition, Discriminant Analysis can also be used to develop a measure of individual influence within a group.

Using Discriminant Analysis to develop a measure of influence based on individual characteristics is a psychology based approach. Hanneman, however, states that “all sociologists” would argue that influence is a fundamental property of social structure (Hanneman, 2001: 60). The next section reviews the development of pair-wise measures of social influence based on network topology.

2.6. Modeling Pair-Wise Influence

SNA has many proxy measures to identify key individuals based on their positions in the overall topology of the network. Much of SNA theory ascribes power or influence to these key individuals. While these measures *may*, under certain conditions, offer a rank ordering of the importance of individuals, they do not give insight into the interrelations between the individuals. Katz (Katz, 1953: 39) recognized this limitation, lamenting, that researchers were “forced to accept the popularity index as valid, at least a first approximation, or to make a near-anthropological study of a social group in order to pick out the *real* leaders.” Including Katz’s initial development of a pair-wise measure of social influence, there are very few measures of pair-wise influence.

Critical to the development of each measure of interpersonal influence is the consideration of “paths” between network members (Katz, 1953; Hubbell, 1965; Freeman, 1980; Stephenson and Zelen, 1989; Leenders 2002). The term path used by these authors is equivalent to the Graph Theoretic term *chain*. A chain is a sequence of undirected arcs $e_1, e_2, e_3, ..., e_n$, such that the endpoints of e_i are nodes x_i and x_{i+1} (Minieka, 1978: 5). Node x_1 is called the initial node of a chain, and x_{n+1} is called the terminal node of the chain (Minieka, 1978: 5). A chain is said to extend from its initial node to its terminal node, and the length of a chain is the number of arcs in the chain (Minieka, 1978: 5).

The term path is used throughout this study to maintain consistency with traditional SNA research; however, the term path as used in SNA research is considered equivalent to Minieka's definition of a chain. Network members are represented as nodes, and identified relationships or connections are represented as arcs. Network members are said to be adjacent if they are connected by a chain of length one; adjacent nodes are said to have a direct connection. Network members connected, through intermediaries, by chains of length *n* are said to be connected by an *n*-step path; nodes connected through intermediaries are said to have indirect connections. If no chain exists between two members, they are not connected. The remainder of this section discusses the development of each of the pair-wise measures of interpersonal influence as well as their capabilities and limitations.

2.6.1. Katz Influence

Katz's development of a measure for evaluating importance in a network was motivated by the failings of "popularity contest" measures such as degree centrality (Katz, 1953: 39). When modeling a friendship network, if person *x* lists person *y* as a friend on a questionnaire, then person *y* has been "chosen" by person *x*. Katz's measure is based not only on how many persons "choose" an individual, but also *who* chooses them (Katz, 1953: 39). In other words, Katz's measure is based on the direct and indirect connections within a network.

Katz formulation begins with a binary (0-1) node-node adjacency matrix, **A** = $[a_{ij}]$. For the purposes of his development, Katz assumed that a_{ij} represented person *i* "choosing" person *j*. The powers of A ($A^2 = [a_{ij}^{(2)}]$; $A^3 = [a_{ij}^{(3)}]$; etc.), then, represent the number of paths of corresponding lengths from one individual to another (Katz, 1953: 40). The Katz measure is a combination of all the one-step, two-step, three-step, and so forth paths (chains) appropriately weighted and added together (Katz, 1953: 40).

To build appropriate weights, Katz, introduced the concept of "attenuation" in a link of a chain. While attenuation is generally defined as the loss of signal strength during transmission, for Katz, it represents the loss of influence as path lengths between individuals increase (Katz, 1953: 30-41). Attenuation requires the assumption that the researcher has complete and correct data. Links between members identified in the data represent the potential for influence flow, and where there is no path between members in the data, there is no potential for influence to flow between them (Katz, 1953: 40). Further, Katz assumes that the links (arcs) in the network are *independent* and have the same probability of being effective. Note, however, that paths are *not* necessarily independent, and Katz's formulation does not account for path dependencies. Katz realizes that these assumptions may not be valid; however, he asserts that they are reasonable for developing a first order approximation of the true situation (Katz, 1953: 40).

Define attenuation, α, as the probability of the effectiveness of a single link. A k-step chain, then, has probability α^k of being effective. At the extremes, $\alpha = 0$ implies complete attenuation; α = 1 implies no attenuation. Assuming complete attenuation in a network implies that only adjacent nodes have influence over each other. For example, the Sergeant can only influence the men in his platoon. Assuming no attenuation in a network implies that indirect connections have the same amount of influence as direct connections. For example, the Force Commander can influence every soldier under his command.

To calculate Katz's measure one needs to create the following matrix **T** which is a linear combination of all weighted paths in the network:

$$T = \alpha A + \alpha^2 A^2 + ... + \alpha^k A^k + ... = (I - \alpha A)^{-1} - I$$

Katz was concerned with calculating the column sums of the **T** matrix, which would serve as an alternative measure of influence to the classic SNA measures of centrality. Katz's formulation is based on the sum of an infinite geometric series. The calculations will not work, however, if $1/\alpha$ is not larger than the largest eigenvalue of **A,** because (I- α A) will not be full rank and its inverse will not exist (Katz, 1959: 42). Katz, based on his experiments (Katz, 1959: 42), suggests values of $1/\alpha$ between the largest eigenvalue and twice the largest eigenvalue. Katz standardizes his measure by dividing by the following term, $m = (n-1)!\alpha^{n-1}e^{1/\alpha}$.

The adjacency matrix, **A**, in Table 2-4 was used by Katz to highlight the new capability his measure provides:

Table 2-4: Katz (1953) Example Node-Node Adjacency Matrix

	A	B	C	D	E	F
A	0	0	0	0	0	1
B	0	0	1	0	0	1
C	0	1	0	1	0	1
D	1	0	0	0	1	0
E	0	0	0	1	0	1
F	1	0	0	1	0	0

Based on Katz's definition of "choosing", for the group of six persons in this example, A chooses F; B chooses C and F; C chooses B, D, and F; D chooses A and E; E chooses D and F; and F chooses A and D. Figure 2-2 shows the graph of this network:

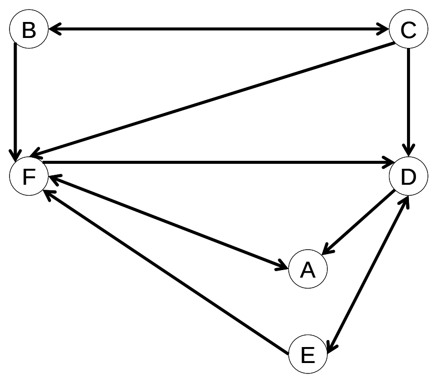

Figure 2-2: Network Representation of Katz (1959) Example

The context of this network makes in-degree centrality an appropriate measure of individual importance (Katz, 1959: 41). Katz sets α = 0.5 before calculating his results which are compared to in-degree centrality in Table 2-5.

Table 2-5: Comparison of In-Degree Centrality and Katz Centrality Results

	In-Degree Centrality	**Katz Centrality**
A	0.4	0.4692
B	0.2	0.0361
C	0.2	0.0361
D	0.6	0.4114
E	0.2	0.2238
F	0.8	0.4547

Analysis of the in-degree centrality scores suggests that F is the most influential network member followed by D and then A. It also suggests that B, C, and E have an equal amount of influence. Inspection of the graph, however, reveals that A is chosen by both F and D, the "most influential" members in the group, suggesting that A's status should be higher. In addition, B, C, and E have equal in-degree centrality scores, but are structurally much different. B and C each choose each other, but are not chosen by any other members of the group, while E on the other hand has contact with the rest of the group through D. Comparison of Katz's measure to degree centrality "indicates that every change is in the appropriate direction to overcome the short-comings" of in-degree centrality and that the Katz measure ranks the individuals in a better relative position (Katz, 1959: 43).

Later authors (Hubbell, 1965; Taylor 1969) recognized that there was value in the **T** matrix itself because it represented influence between network members based on their positions within the topology of the network. The **T** matrix in Table 2-6 highlights the pair-wise influence between members of this group:

Table 2-6: Katz T-matrix, Measures Pairwise Influence

	A	B	C	D	E	F
A	1	0	0	0.8	0.4	1.2
B	2.6667	0.3333	0.6667	2.4	1.2	2.9333
C	3.3333	0.6667	0.3333	3.2	1.6	3.4667
D	2	0	0	1.4	1.2	1.6
E	2	0	0	2	1	2
F	2	0	0	1.6	0.8	1.4

Cell T_{ij} represents the influence of *j* over *i*, based purely on the topology of the network, and the given attenuation factor, α. There are, however, two limitations of Katz's formulation for developing pair-wise measures of structural influence, however:

- Selection of arbitrary attenuation factor
- No discussion of the meaning of the diagonal values of **T**

The attenuation factor, α, chosen for different networks, represents the value of indirect connections in the network. The choice of α should be made based on the context of the network; that is, based on the importance of indirect connections. Intelligence analysts could provide a subjective value of α based on repeated observation of group operations and interactions. A centralized command structure would suggest small values for α, while a distributed command structure might suggest larger values of α. Figure 2-4 provides a comparison of influence attenuation for various values of α. The selection of α, however is governed not by the context of the network, but rather by its structure. If the largest eigenvalue is greater than the context-based attenuation factor, the calculations call for taking the inverse of a singular matrix, which does not exist. In the absence of better information, choosing α according to Katz's recommendations provides a reasonable starting point. As ones understanding of group influence increases however, researchers are forced to choose values of α, based on purely structural reasons that may in fact be contrary to the context of the network.

In addition, the diagonal values of **T** do not have a clear meaning. Interpreting the values as influence over oneself is counter to the SNA convention of no self loops. Further, the implication that structural characteristics give one more or less influence over oneself does not appear to be backed by current SNA literature. The values of T_{ii} do appear to be perfectly correlated with Katz's measure of influence; however he offers no discussion of this fact or its implications.

2.6.2. Hubbell Influence

Hubbell (Hubbell, 1965: 377) states that interpersonal links in social network structures could be interpreted as input-output channels for the transmission of influence. Hubbell's intention, when developing his influence measure, was the determination of cohesive subgroups (Hubbell, 1965: 377-378). His goal was to move away from the rigid definition of a clique based on mutual connections in a social network defined by a binary adjacency matrix. Hubbell's clique definition enables the consideration of indirect links, is able to handle valued connections (positive or negative), and determines cliques based on a predefined influence threshold.

Hubbell's model of influence begins with **A**, an adjacency matrix representing a social network, and it is specifically concerned with the following sum:

$$
\begin{aligned}
Y &= A^0 + A^1 + A^2 + A^3 + \ldots \\
&= I + A + A^2 + A^3 + \ldots \\
&= (I - A)^{-1}
\end{aligned}
$$

The convergence of the geometric series requires that all a_{ij} values be fractional (Hubbell, 1965: 378). Node-node adjacency matrices, however have only binary (0-1) values, requiring Hubbell to adopt Katz's attenuation factor α. Thus, $\mathbf{Y} = (\mathbf{I} - \alpha\mathbf{A})^{-1}$. Once calculated, Hubbell (Hubbell, 1965: 379) states that Y_{ij} is j's total influence on i based on all direct and indirect ties.

Hubbell then develops his input-output model of influence. Let v_{ij} represent j's contribution to i's status, and let v_{i0} represent i's exogenous (non-network) influence. In a group of n persons, define s_i as the status score of member i, such that:

$$s_i = v_{i0} + (v_{i1} + v_{i2} + \ldots + v_{in})$$

Simply stated, ones status is the sum of their exogenous influence and the contributions of other network members to ones influence based on the topology of the network. Hubbell (Hubbell, 1965: 381) terms this the influence input for *i*.

To make the status relationship between network and non-network influence clearer, Hubbell defines the vector, **E** = [e_i], as one's exogenous contribution to influence and sets $v_{i0} = e_i$. He further assumes $v_{ij} = (\alpha a_{ij}) s_j$, that is, the value v_{ij} of *j*'s contribution to *i* is proportional to *j*'s own status. Substituting these terms into the input-output model yields the following linear equation:

$$s_i = e_i + \alpha(a_{i1}s_1 + a_{i2}s_2 + ... + a_{in}s_n).$$

This model now considers both the status of the chooser as well as the strength with which he chooses (Hubbell, 1965: 382). The model can be written in vector notation as follows:

$$S = E + \alpha AS$$

Simplification of this equation yields:

$$\begin{aligned} S &= (I - \alpha A)^{-1} E \\ S &= YE \end{aligned}.$$

Once the structure of **A** is specified and the attenuation factor α is chosen, **Y** is fixed, which allows for quick analysis of the changes in the exogenous influence on the status of individuals in the network. To reap this benefit, however, there are assumptions that must be made about the structure of α **A**. To guarantee a solution to this model Hubbell assumes that:

$$\alpha\left(\left|a_{1j}\right| + \left|a_{2j}\right| + ... + \left|a_{nj}\right|\right) \leq 1,$$

which he believes is reasonable because "a person in society is faced with the fact of limited resources," and "must decide on the proportion in which he will distribute his influence" (Hubbell, 1965: 384). The above equation sets the column sums to one; however, in situations where weights are determined by the receiver of the influence, analogous row restrictions are more appropriate (Hubbell, 1965: 385). Hubbell's input-output model is the basis for Friedkin's social influence network model discussed in Section 2.3.

The limitations of Hubbell's model stem from his lack of discussion in the development of **E**. Hubbell's discussion of exogenous variables suggests that his model is able to incorporate non-network influences, however he does not suggest how to develop these exogenous influences and for his example he uses arbitrarily chosen values (Hubbell, 1965: 386). Given that $v_{i0} = e_i$, by arbitrarily choosing e_i, researchers are arbitrarily assigning value to the αA matrix. Hubbell, distributed the remaining (1-e_i) evenly across the remaining $(\alpha \mathrm{a}_{\mathrm{ij}})$ that represented a connection. For these reasons, it is common to set E = [1]. Solving the geometric series for this problem yields:

$$S = YE$$
$$S = (I - \alpha A)^{-1}[1]$$
$$S = (I - \alpha A)^{-1}$$

The off-diagonal cells of this matrix are identical to Katz's **T** matrix, and the diagonals are larger by 1 (one).

2.6.3. The Gatekeeper (Betweenness Centrality Revisited)

Freeman (Freeman, 1980) developed a measure of pair-dependency specifically to measure the gatekeeper phenomenon in social networks. The measure is based on the assumption that if one is located between others in a network, then he or she has the potential to control the flow of information and is somehow central to the network (Freeman, 1980: 585). Freeman defined a gatekeeper as an "individual located in a communication structure so as to control messages flowing through a communication channel" (Freeman, 1980: 586). The definition of gatekeeper is analogous to a cut out.

Freeman bases his measure on the shortest paths (geodesics) between each pair of points in the network. To calculate pair-dependency, first define g_{ik} as the number of geodesics between i and k. Then let $g_{ik}(p_j)$ be the number of geodesics between i and k that contain j as an intermediary point. The proportion of geodesics between i and k containing j can be expressed as:

$$b_{ik}(p_j) = \frac{g_{ik}(p_j)}{g_{ik}}.$$

Simply stated, Betweenness Centrality is the ratio of the number of geodesics between nodes i and k containing node j to the total number of geodesics between nodes i and k.

Freeman then defines the pair-dependency as the degree to which an individual must depend on another to relay messages along geodesic paths to other individuals in the network. For a network with n members the pair-dependency of i on j is:

$$d_{ij} = \sum_{\substack{k=1 \\ (i \neq j \neq k)}}^{n} b_{ik}(p_j)$$

where d_{ij} measures the dependence of node i on node j to reach all other nodes k in the network. The results of this calculation can be expressed in a matrix, **D**, in which each cell represents the dependence of i on j (Freeman, 1980: 588).

Freeman's model has limited applicability to the calculation of pair-wise influence. First, Freeman implicitly assumes that geodesics are critical for the flow of information through a network. While this may be true in general, for groups practicing good OPSEC communication paths may be intentionally routed through longer paths. The shortest path assumption, however, may be appropriate for the informal networks upon which clandestine networks are built. Second, while pair-dependence may imply a certain amount of influence, Freeman's measure is focused on control of information on a local level and does not account for the broader context of indirect connections.

2.6.4. Stephenson and Zelen Centrality (Information Centrality Revisited)

Stephenson and Zelen were motivated by the limitations of both closeness and betweenness centrality based on their reliance on geodesic paths (Stephenson and Zelen, 1989: 1). They were concerned with the very real possibility that communications may be intentionally channeled through many intermediaries to hide information (Stephenson and Zelen, 1989: 1). Stephenson and Zelen, like Katz and Hubbell, consider weighted combinations of all possible paths between nodes to develop a measure of influence. Unlike Katz and Hubbell who calculate the sum of a geometric series that requires an arbitrary weighting, Stephenson and Zelen's technique is motivated by statistical designs of experiment.

Stephenson and Zelen (Stephenson and Zelen, 1989: 28-31) develop their measure structuring social networks as incomplete statistical block designs with two treatments per block. The foundation for their proof lay in the assertion that any social network can be represented as an incomplete block design by constructing a node-arc incidence matrix **X**. The proof of their formulation is given in the appendix of their paper

(Stephenson and Zelen, 1989: 28-34). Their solution is an augmentation of the inverse of the information matrix, $\frac{(X'X)}{\sigma^2}$. By assuming $\sigma^2 = 1$, the inverse of the information matrix is $(X'X)^{-1}$, the large sample covariance matrix for maximum likelihood estimates.

Empirical testing performed for this thesis has shown that $(X^T X)^{-1}$ does not exist for various network structures. Stephenson and Zelen, therefore augment $(X^T X)$ so that it is always invertible. The measure concludes that the amount of influence in a path is the inverse of the variance in a path. Stephenson and Zelen define the variance in a path equal to the length of the path (Stephenson and Zelen, 1989: 29). Pair-wise information flow then is the sum of the information in all paths between *i* and *j*. The construction of pair-wise Information Centrality begins with an adjacency matrix, **A**, representing a social network.

To calculate pair-wise Information Centrality first define a matrix B = [b_{ij}], where b_{ij} = 0 if points i and j are adjacent, and 1 otherwise; and where b_{ii} = 1 + degree of point *i*. The next step is to calculate the matrix **C**, $C = B^{-1}$. The matrix of pair-wise Information Centrality **I**, can then be populated through the following equation:

$$I_{ij} = (c_{ii} + c_{jj} - 2c_{ij})^{-1}.$$

Information Centrality can only be calculated for undirected networks. Table 2-7 contains the undirected social network, **A**, which are used to compare the results of Katz's influence measure and Information Centrality:

Table 2-7: Example Undirected Node-Node Adjacency Matrix

	A	B	C	D	E
A	0	1	0	1	1
B	1	0	1	0	1
C	0	1	0	1	0
D	1	0	1	0	0
E	1	1	0	0	0

Matrix **A**, shown in Table 2-7 can be represented by the graph in Figure 2-2 below:

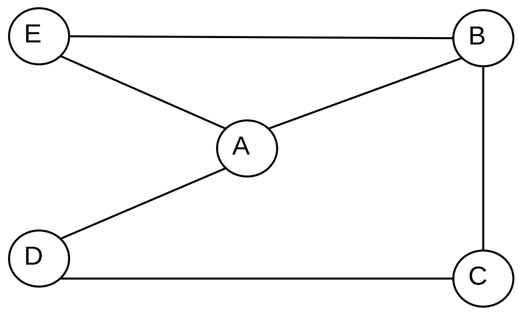

Figure 2-3: Graph Representation of Sample Undirected Network

In general, Katz and Information Centrality calculate the same relative influence for each member. Table 2-8 compares the top-level influence measures produced using Katz's method (α = ½) with Information Centrality for matrix **A**. It is clear from Table 2-8 that Katz and Information Centrality produced the same relative influence for each member in the sample network.

Table 2-8: Comparison of Katz Centrality and Information Centrality Top-Level Measures of Influence

	Katz Centrality	Information Centrality
A	0.941	1.7742
B	0.941	1.7742
C	0.6385	1.4103
D	0.6385	1.4103
E	0.7393	1.375

Table 2-9 and Table 2-10 show the pair-wise measures of influence for Katz Centrality and Information Centrality respectively.

Table 2-9: Pairwise Influence (Katz Centrality)

	A	B	C	D	E
A	1.2	1.4	0.8	1	1.2
B	1.4	1.2	1	0.8	1.2
C	0.8	1	0.6	0.8	0.6
D	1	0.8	0.8	0.6	0.6
E	1.2	1.2	0.6	0.6	0.8

Table 2-10: Pairwise Influence (Information Centrality)

	A	B	C	D	E
A	0	1.8333	1.1	1.375	1.5714
B	1.8333	0	1.375	1.1	1.5714
C	1.1	1.375	0	1.375	0.8462
D	1.375	1.1	1.375	0	0.8462
E	1.5714	1.5714	0.8462	0.8462	0

The pair-wise matrices again show that Katz and Information Centrality assign the same relative influence weightings. Information Centrality produces very similar results to the Katz method for this small matrix; however because Information Centrality attenuates influence much slower than Katz's method; it is better able to model influence due to longer paths. Figure 2-4 compares Information Centrality influence attenuation with Katz influence attenuation for various values of α :

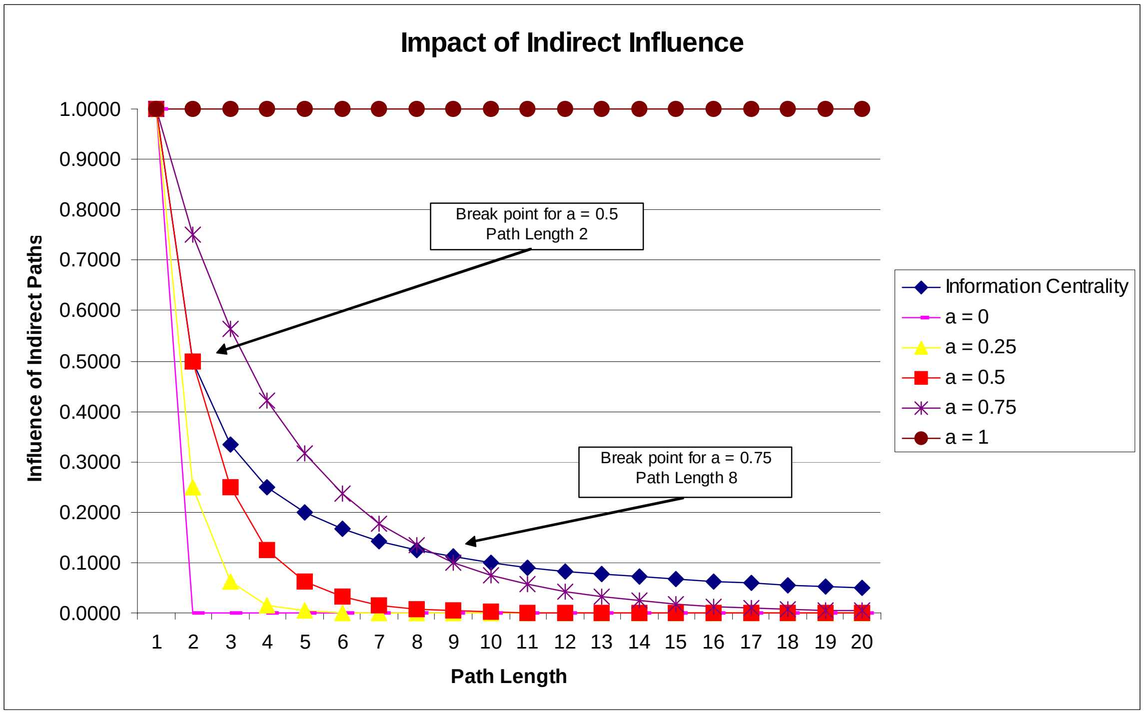

Figure 2-4: Comparison of Information Centrality Influence Attenuation with Katz Influence Attenuation for multiple values of alpha

The development of **B** suggested by Stephenson and Zelen is only appropriate for undirected networks. To highlight this limitation, consider the following directed network in Figure 2-5:

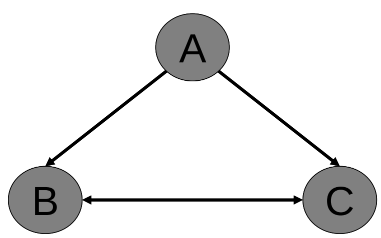

Figure 2-5: Sample Directed Network

This directed social network can be represented by the following node-node adjacency matrix:

$$A = \begin{bmatrix} 0 & 1 & 1 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

Table 2-11 shows the Information Centrality scores produced for this network. The results indicate that nodes *B* and *C* both have influence over node *A*, however there is no directed path from either *B* or *C* to node *A*. According to Stephenson and Zelen's development, however, if no path exists between two nodes there should be no influence flow between them.

Table 2-11: Information Centrality Scores for Sample Directed Network

	A	B	C
A	0	1.2	1.2
B	0.8571	0	1
C	0.8571	1	0

2.6.5. Section Summary

The Katz and Hubbell methods consider all possible paths, and use the sum of an infinite geometric series to produce their influence measures. Both of their techniques, however, require the analyst to choose an arbitrary attenuation factor to ensure that the geometric series converges. Hubbell's formulation is the only one to consider non-network and network characteristics in an influence model, although it is not clear where **E** comes from. Betweenness Centrality only considers shortest paths in its development, and is better suited to measuring pair-wise dependence. Information Centrality produces results comparable to Katz and Hubbell for undirected networks without requiring the analyst to choose an arbitrary attenuation value. In addition, Information Centrality is able to capture the impact of longer paths than the Katz or Hubbell methods. Information Centrality, however, is only appropriate for undirected networks. This section has described the development of the current methods to develop pair-wise measures of interpersonal influence. An improved model of social influence should incorporate the best of each of these models, avoiding arbitrary value assignments, and enabling the use of non-network characteristics in the calculation of social influence.

2.7. Chapter Summary

The review of literature provided in this chapter provides a foundation for understanding the relevant techniques for modeling pair-wise interpersonal influence within clandestine networks. Social Influence Network (SIN) theory provides a mathematical formulation of the process of interpersonal influence that occurs in groups. To accurately model social influence one must consider both network and non-network measures of influence. The techniques discussed in Chapter 2 provide a starting point from which an improved measure of pair-wise interpersonal influence can be developed.

The next chapter defines a methodology for creating an improved measure of pair-wise interpersonal influence based on non-network characteristics as well as the topology of the multiple formal and informal networks to which clandestine network members belong. Chapters 4 and 5 provide demonstrations of the methodology developed in Chapter 3, highlighting the key results.

3. Methodology for Developing an Improved Measure of Interpersonal Influence

3.1. Introduction

A tenet of this thesis is that interpersonal influence is a combination of one's personal characteristics and one's position in his/her networks of relationships. Given this assertion, a measure of interpersonal influence, then, must capture the functional relationship between influence, and non-network and network characteristics of individuals in its development. A review of Social Network Analysis (SNA) and Social Influence Network (SIN) theory (Katz, 1953; French, 1956; Harary, 1959; Hubbell, 1965; Taylor, 1969; Granovetter, 1973; Freeman, 1980; Stephenson and Zelen, 1989; Friedkin, 1997, 1998, 2001, 2003; and Leenders, 2002) has revealed three primary shortcomings that this thesis overcomes:

- Inadequate development of non-network measure of influence
- No consideration of multiple networks and network contexts in measures
- Focus on Descriptive analysis not Prescriptive analysis

Modeling and analysis of interpersonal influence in clandestine networks must consider personal characteristics as well as the trusted pre-existing social networks from which members and leaders are drawn. Further, the measures of interpersonal influence developed must enable analysts to provide specific, quantifiable results that are actionable. Chapter 3 outlines the development of a new, proxy measure of interpersonal influence that is based on the personal characteristics and social structural characteristics of a group. This new measure are referred to as the Holistic Interpersonal Influence Measure (HIIM), because it attempts to measure the functional relationships and interdependence between the parts (individual characteristics and social network characteristics) and the whole (interpersonal influence) of social influence. Section 3.2

details the data requirements for the development of the HIIM. The development of non-network influence measures is outlined in Section 3.3. Section 3.4 outlines the development of a measure of interpersonal influence based on network topology. Section 3.5 details methods to combine the outputs of multiple social network layers into a single influence network. Section 3.6 then explains how to combine the information gained in sections 3.3, 3.4, and 3.5 into an improved measure of social influence, the HIIM. The chapter concludes with a summary of the development of the HIIM.

An overview of the HIIM development process is shown in **Figure 3-1**. Analysts begin with individual demographic data and social network data from multiple informal networks to which clandestine network members belong. Individual characteristics and SNA centrality measures are used as inputs to develop a Discriminant Function that will serve as a proxy measure of *individual influence*. Connection data from each informal social network are used to develop pair-wise measures of *interpersonal influence* based solely on network topology. The contributions of each informal network to overall influence are considered simultaneously by creating a linear combination of their effects. The relative importance of each informal network, to the clandestine network, will serve as network weights in the linear combination. Finally, the *individual influence* measures and combined *interpersonal influence* measures are combined to produce a new proxy measure of interpersonal influence that considers both non-network and network contributions to influence in its development, the HIIM.

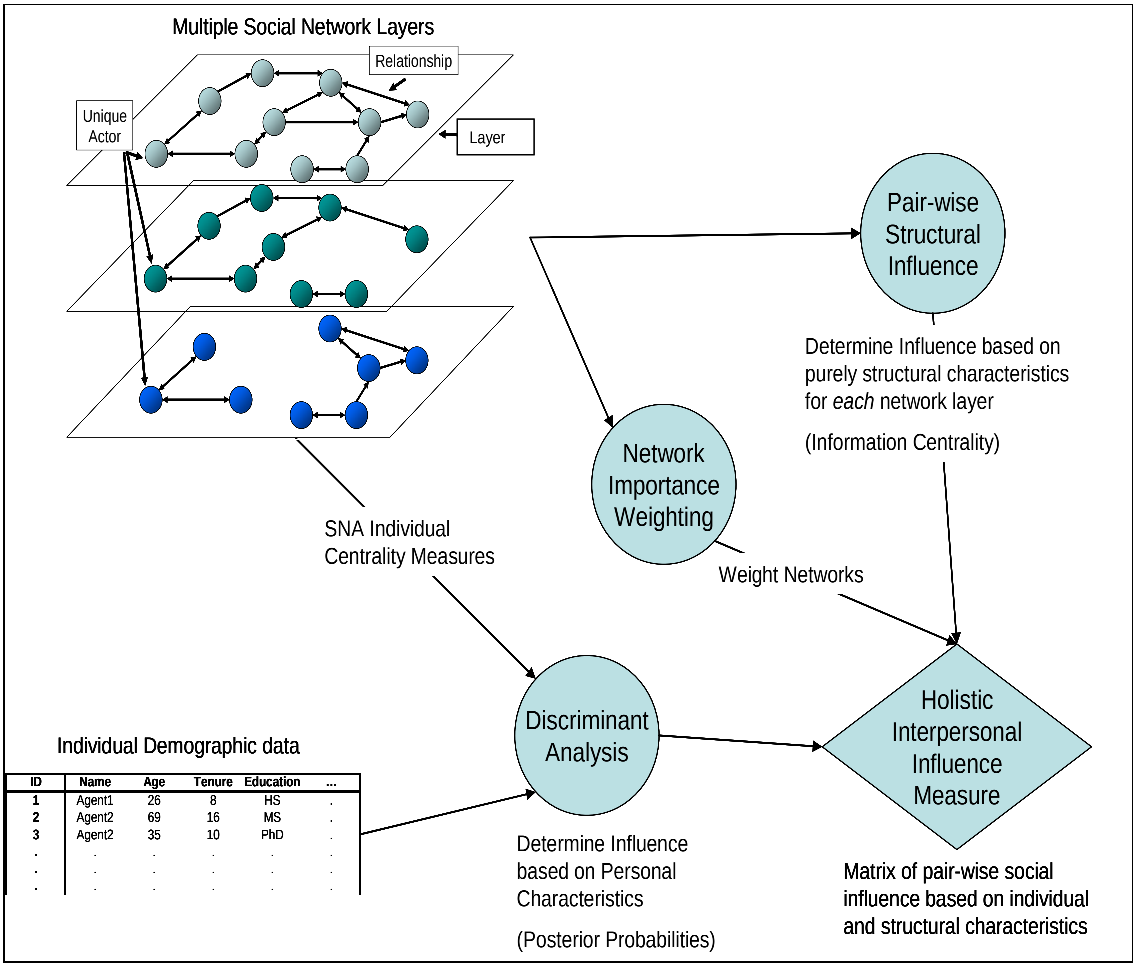

Figure 3-1: Holistic Interpersonal Influence Measure Methodology Framework

3.2. Data Requirements

To calculate the HIIM, two types of data are required, individual characteristic data and social network data. Critical to the development of individual measures of influence are demographic type characteristic data. The history of psychology based leadership research (Cartwright, 1965; Lord *et al*. 1986; Bass 1990) has shown that demographic characteristics, such as age, wealth, education level, and so forth, can be predictive of influence in many different types of groups. In addition to personal characteristics, sociologists have long investigated the impact of social network topology on influence. Sociologists agree that influence is a fundamental property of social structures (Henneman, 2001: 60).

Analysts calculating measures of interpersonal influence based on personal and social structural characteristics often must make certain assumptions about their data. The literature in both psychology and sociology generally assume that the data sets are complete and correct. Having complete psychological data implies that one has information on all group members under investigation for all of the personal characteristics being incorporated in the evaluation. Complete social network data implies that one knows all group members and has identified all possible interactions between the members of the group. Correct data implies that each characteristic or social connection has been accurately observed and quantified. These assumptions, difficult to meet in a clinical experiment, are highly unlikely to be satisfied for an analysis of any real world group, let alone an uncooperative real world group. Further, analysis of clandestine networks practicing good OPSEC makes satisfying these assumptions even more difficult. A good measure of interpersonal influence, however, should enable post optimality analysis to highlight the potential impacts of incomplete or incorrect data. In this chapter, it is assumed one has access to complete and correct individual characteristic and group social network data from multiple formal or informal network contexts. This assumption is relaxed later in this thesis. The next section begins the development of a new measure of interpersonal influence, focusing specifically on individual influence based on personal characteristics.

3.3. Individual Influence Measurement

Social Influence Network (SIN) theory literature (Friedkin, 1997, 1998, 2001, 2003; and Leenders, 2002) accounts for exogenous (non-network) influence in its development. Friedkin (Friedkin, 1998: 24) suggests that an individuals' non-network influence can be modeled as a weighted combination of an actor's non-network characteristics. Friedkin (Friedkin, 1998: 24-25) further states that the exogenous influence values must be normalized to be between zero and one. Friedkin's model can be written as:

$$\mathrm{E} = XB$$

where **E** is an $(n \times 1)$ vector of exogenous influence measures; **X** is an $(n \times p)$ matrix of p characteristics for n group members; and **B** is a $(p \times 1)$ vector of coefficient weights for the characteristics.

Construction of an appropriate measure of exogenous influence, however, is not discussed. In addition, in the examples of the works cited above, exogenous influence is assumed to be equal (e_i = 1) across all members. For most networks, including clandestine networks, this is an inappropriate assumption. This section describes the development of an individual influence measure using Discriminant Analysis.

3.3.1. Techniques to Develop a Measure of Exogenous Influence

The equation, $\mathbf{E} = \mathbf{XB}$, is in the form of a multiple linear regression equation (Dillon and Goldstein, 1984: 215; Bartholomew, et al., 2002: 149; Lattin et al., 2003: 44). Regression is primarily used for assessing the relationships between a dependent *response* variable, **E**, and a set of independent *predictor* variables, **X** (Dillon and Goldstein, 1984: 209). The key to building a regression model is the estimation of the coefficient weights, **B**. To estimate the coefficients, however, requires observed values of **E**, the individual influence measure that one wishes to calculate. In the absence of an ability to fully observe and accurately measure **E**, one must choose an alternative to regression.

Discriminant Analysis involves a qualitative, dependent *response* variable, and a set of independent *predictor* variables. The categorical variable serves to group the individuals into mutually exclusive, collectively exhaustive *a priori* groups (Dillon and Goldstein, 1984: 360). Based on the *a priori* groupings, Discriminant Analysis produces **B** coefficients such that the linear combination of the independent variables, **X**, provides "maximally different" discriminant scores across groups (Lattin *et al.,* 2003: 429). Using Discriminant Analysis to develop a measure of influence based on leadership, then, requires that one assigns individuals to an influential (leadership) group and a less-influential (non-leadership) group (Any groupings of interest can be investigated). Discriminant Analysis can then be used to calculate the coefficient weights, **B**, that are needed to create a measure of individual influence.

3.3.2. Data Requirements

To perform a Discriminant Analysis one must have, individual characteristic data and an *a priori* classification of individuals into mutually exclusive and collectively exhaustive groups. Individual characteristic data typically implies demographic data such as age and education level, but this thesis also considers an individuals score on classic SNA measures, such as a degree centrality, as appropriate. In addition, the classification of individuals into groups implies that one has enough understanding of the group to make an initial classification of its members. For the remainder of this chapter, it is assumed that there exists a data set with N members on P characteristics, and the data has been divided into two groups, G_1 and G_2 of sizes n_1 and n_2 respectively.

3.3.3. Discriminant Analysis Overview

Discriminant Analysis is a statistical technique used to classify individuals into mutually exclusive and collectively exhaustive groups on the basis of a set of independent variables (Dillon and Goldstein, 1984: 360; Lattin *et al*., 2003: 426-7). It does this by developing a weighted average of each individual's scores on the independent variables and transforming them into *a posteriori* probabilities used to determine the likelihood of an individual belonging to each of the groups (Dillon and Goldstein, 1984: 361). Discriminant Analysis has many practical applications for use in modeling clandestine networks. This study focuses on group leadership in an effort to develop a measure of individual influence. The methodology, however, could be used to analyze a variety of subgroups within a clandestine network.

A thorough Discriminant Analysis can be completed by performing the following steps (Dillon and Goldstein, 1984: 360-380):

1. Divide the data into Test and Validation Sets
2. Test for underlying assumptions of Discriminant Analysis
3. Perform Discriminant Analysis Calculations
4. Test Hypothesis—Are the group means different?
5. Interpretation of Betas and Discriminant Loadings
6. Validation

Once performed, the Discriminant Analysis provides the analyst with a great deal of information in addition to a measure of individual influence. Discriminant Analysis will help the analyst to answer the questions (Lattin, *et al*., 2003: 427-428):

- Are the leaders (influential persons) different than the followers on the observed set of characteristics?

- If so, on which characteristics do they differ?
- Can we predict leadership based on these differing characteristics?

The answers to these questions not only help an analyst to determine the "quality" of the measure of individual influence, but can also be used to build an operational profile of group leaders.

Hypothesis testing determines if there is sufficient statistical evidence to support the contention that the two groups differ on the set of observed characteristics. If the groups are not statistically different, there are two possible conclusions. It could mean there is no difference between the influential and non-influential group on the basis of individual characteristics and thus assigning them equal influence scores such as Friedkin and Leenders suggest is appropriate. On the other hand, it may only suggest that the groups are not statistically different on the basis of the observed characteristics. This could suggest that one or more key characteristics were missed or that there is insufficient data available.

If the groups are statistically different however, the Discriminant Analysis results can support a variety of analysis. First, assigning equal influence scores to all members is no longer appropriate. The ability to distinguish between the influential and non-influential members of a group enables the calculation of meaningful influence scores. In addition, the discriminant loadings can be used to identify the most important discriminating characteristics. The discriminating characteristics can then be used to build a profile of group leaders (Dillon and Goldstein, 1984: 372-373). This profile can be used by operators in the field to identify potentially influential group members.

Finally, Discriminant Analysis produces a function which can be used to predict into which group newly identified individuals should be classified. The predictive quality of the Discriminant Function is tested during the validation step. A Discriminant Function that classifies well gives further credibility to the hypothesis testing and to the group profile (Dillon and Goldstein, 1984: 363-364). Once completed, the Discriminant Analysis results can be used to develop a proxy measure of individual exogenous influence. The next section details the final calculation of this measure.

3.3.4. Determination of Individual Influence Measure

Assuming the data set has satisfied the Discriminant Analysis assumptions, and a Discriminant Function that is a "good" classifier has been created, the new proxy measure of individual influence can be calculated. While the discriminant scores could be used as this new measure, the *a posteriori* probability of belonging to the leadership group is a more appropriate choice. Posterior group membership probabilities are a function of the discriminant scores (Lattin *et al.*, 2003: 453-454), which have two primary advantages over the discriminant scores.

First, discriminant scores for an individual are difficult to interpret without reference to discriminant scores of other individuals. Posterior probabilities, however, have very clear interpretations. They represent the likelihood of membership in the leadership group (Lattin, et al., 2003: 453-454). A known leader with a high posterior probability of membership or a known non-leader with a low posterior probability helps to confirm the Discriminant Analysis results. Posterior probabilities that agree with the *a priori* classification give confidence that the Discriminant Analysis was successful. Misclassifications, however, if there are few enough to analyze, can offer very interesting interpretations. An individual *a priori* classified as non-influential who has a high posterior probability suggests several possibilities; for example this may suggest a potentially disgruntled member who has been passed over for promotion, or an up and coming leader who has yet to be discovered. In addition, a known leader with a low posterior probability of membership may indicate that the analysis has not yet identified all of the key leadership characteristics, or simply, that Discriminant Analysis may be inappropriate for the given data set. If Discrimimant Analysis assumptions are violated, Logistic regression offers a suitable alternative that will not change the overall methodology.

The other advantage of posterior probabilities over raw discriminant scores is due to the compatibility with SIN theory. SIN theory requires that exogenous influence measures be between zero and one. Producing discriminant score values between zero and one would require scaling or normalization. Posterior probabilities are again attractive because they are the discriminant scores scaled based on *a priori* probabilities of group membership. The remainder of the section details the calculation of the posterior probability of membership in the influential group.

Given a population G with N members, divided into two groups, the influential members in group 1 (G_1), and the less-influential members in group 2 (G_2), with group sizes n_1 and n_2 respectively. The discriminant scores using Mahalanobis' method can be calculated as follows (Lattin, *et al*., 2003: 453):

$$dQ_i = -\frac{1}{2}\ln(\det(C_i)) - \frac{1}{2}(x_o - \overline{X})' C_i^{-1}(x_o - \overline{X}) + \ln(P_i)$$

where dQ_i, is the group i discriminant score for a particular individual, P_i, $\left(P_i = \frac{n_i}{n_i + n_j} \right)$,

is the *a priori* probability of membership in group *i*, , x_o are the characteristic values of a particular individual, and C_i is the variance—covariance matrix of group *i*. If it is appropriate to pool the covariance of the two groups, the pooled estimator is used. If it is not appropriate to pool the covariance, the appropriate variance—covariance matrix from each group is used. Once the discriminant scores are calculated for each individual for each group, posterior probabilities can be calculated as:

$$P(Leader \mid x_o) = \frac{e^{dQ_1}}{e^{dQ_1} + e^{dQ_2}}$$

where *e* is the base of the natural logarithm, sometimes called Euler's *e*. The posterior probability of belonging to the influential group, then, may serve as a proxy measure of individual influence that satisfies the requirements of SIN theory. There are several current statistical software packages such as JMP, SAS, SPSS, and S-PLUS that perform a complete Discriminant Analysis, providing the posterior probabilities as a standard output. The next section supports the addition of traditional SNA measures of individual importance as independent predictor variables used during Discriminant Analysis.

3.3.5. Inclusion of SNA Measures in Discriminant Analysis

SNA measures of individual importance, such as degree centrality, attempt to measure influence based on an individuals' position within the overall topology of a social network. All such measures attempt to *describe* and measure properties of actors' locations within a network (Wasserman and Faust, 1994: 169). Further, each of these measures attempts to assess the importance or prominence of an individual based on their position. The question of the validity of the measures remains however; that is, “do they really capture what we substantively mean by ‘importance’ or ‘prominence’?” (Wasserman and Faust, 1994: 172).

In general, sociologists suggest that individuals with high centrality scores in relation to the other members of their network are important. It has consistently been shown, however, that individual centrality measures are fallible when analyzing real organizations (Taylor, 1969; Bonacich, 1972; Freeman, 1980; Mizruchi, 1981; Stephenson and Zelen, 1989; Renfro, 2001; Ashworth, 2003). In the analysis of clandestine networks practicing good OPSEC, it is likely that these measures may perform even worse.

Using individual centrality measures as inputs into a Discriminant Analysis can help to overcome the potentially invalid assumptions of importance made by these measures, and it may also help to improve the Discriminant Function by uncovering structural characteristics common to group leadership. An example using Krackhardt’s High Tech Manager (Krackhardt, 1987) data has been used to highlight the potential benefits of using SNA centrality scores as independent predictor variables. Krackhardt’s High Tech Manager data is available in Appendix B of *Social Network Analysis: Methods and Applications* (Wasserman and Faust, 1994: 740-743).

Krackhardt’s data consists of three social network structures, an “Advice” relation, a “Friendship” relation, and a “Reports to” relation, as well as individual characteristic data. For the purposes of this example, a Discriminant Analysis using Age and Tenure (number of years employed by the company) alone is compared with a Discriminant Analysis using Age and Tenure as well as member in-degree, out-degree and eigenvector centrality measures from the "Advice" and "Friendship" networks as independent variables. The "Reports to" network and the "Level" characteristic were used to develop the classification into influential and less-influential groups. For the purposes of this demonstration, Level 1 and 2 managers were assumed to be leaders; Level 3 managers were assumed to be non-leaders.

In both cases, the null hypothesis that the group means were equal was rejected at the $\alpha = 0.05$ level. Table 3-1 shows the confusion matrix created by the classifier using Age and Tenure alone has a classification accuracy of approximately 63%.

Table 3-1: Demographic Characteristic Confusion Matrix

		Predicted Membership	
		Group 1	Group 2
Actual Membership	Group 1	2	3
	Group 2	3	13

Table 3-2 shows the confusion matrix created by the classifier using Age, Tenure and SNA centrality measures, displayed 100% classification accuracy.

Table 3-2: Demographic and Social Network Data Confusion Matrix

		Predicted Membership	
		Group 1	Group 2
Actual Membership	Group 1	5	0
	Group 2	0	16

The improved classification accuracy in this example suggests that the inclusion of SNA centrality measures *may* reduce both Type I (false positive) and Type II (false negative) classification errors. A reduction in misclassifications will enable better use of limited resources tasked to observe, disrupt, or destroy a given clandestine network.

In addition to the confusion matrices, the discriminant loadings can also be compared. Table 3-3 compares the discriminant loadings of the two classifiers:

Table 3-3: Discriminant Loadings for Krackhardt's High Tech Managers Data

	Classifier 1	Classifier 2
Age	0.3809	0.0828
Tenure	0.9704	0.2109
Advice-In-Degree		-0.0296
Advice-Out-Degree		0.6621
Advice-Eigen		0.1439
Friendship-In-Degree		-0.2883
Friendship-Out-Degree		0.0843
Friendship-Eigen		-0.231

The discriminant loading of Classifier 1, using only Age and Tenure, identifies Tenure as the key discriminating characteristic. Classifier 2, however, shows that Out-Degree in the Advice Network and In-Degree in the Friendship Network are the best discriminators, with Tenure shown to be fourth best. In addition, Classifier 2 has positive and negative Discriminant Loadings which can be used to contrast the two groups. The positive Discriminant Loadings are associated with characteristics for which the leadership group had higher values; similarly, the negative Discriminant Loadings are associated with higher values for the non-leadership group.

The results of this Discriminant Analysis imply leaders score high on Out-Degree centrality for the Advice network, but leaders score low on In-Degree centrality for the Friendship network. This suggests that high centrality in an informal network is not always indicative of influence or power as suggested by traditional SNA theory. Further, this analysis has provided a measure of validation for each of these measures. For this network high Out-Degree centrality scores for the Advice network identifies leaders in the organization, while high In-Degree centrality scores for the Friendship network suggests non-leaders. The high centrality scores for the Friendship network indicating non-leaders is counter to traditional SNA assumptions about high network centrality implying influence.

This simple example highlights the potential benefits of using individual centrality measures as independent predictor variables in a Discriminant Analysis. The results also demonstrate the potential ability to improve the classification accuracy of the discriminant function. In addition, the results can identify the specific individual centrality measures for which social networks are important for identifying group leaders. The use of a Discriminant Function to check the validity of the assertions of individual centrality measures is a new capability for SNA analysts.

3.3.6. Section Summary

Current SIN theory literature accounts for a measure of exogenous influence, but offers no method to develop such a measure. Discriminant Analysis can be used to develop a measure of exogenous influence. In addition to a proxy influence measure, Discriminant Analysis provides analysts with the ability to profile, differentiate, and classify group members. These results alone improve one's understanding of the group under study. The addition of SNA centrality measures to the set of characteristics can improve Discriminant Analysis results. If the underlying assumptions of Discriminant Analysis are violated, Logistic Regression is an appropriate alternative.

Using SNA measures as predictor variables also provides the analyst validation of which networks and network measures are important to identifying group leaders. In addition to exogenous influence, SIN theory is concerned with interpersonal influence based purely on the topology of social networks. The next section discusses the development of a pair-wise measure of potential influence based on network topology.

3.4. Pair-Wise Influence Measurement

Development of an appropriate measure of interpersonal influence is critical to Social Influence Network (SIN) theory. One of the primary assumptions of SIN theory is that the relative net influence of each group member on others depends on the topology of the network (Friedkin, 2003). Friedkin (Friedkin, 1998: 25) describes **W**, the "influence network," as the pattern and magnitude of direct interpersonal influence within a network. The specification of **W** for a network is of "vital importance" to the resulting analysis (Leenders, 2002: 27).

SIN theory has been under development since the 1950's, beginning with French and Harary (French, 1956; Harary, 1959). In that time, however, there have only been a few techniques developed to calculate measures of interpersonal influence based on the topology of a network. Each of the techniques develops **W**, which is often called the weight matrix, where cell w_{ij} represents the extent to which actor i influences actor j (Leenders, 2002: 33). The next section discusses the different approaches for developing **W**, the pair-wise influence measures for a single network context, highlighting the strengths and weaknesses of each approach. The reader is reminded that relationships exist on multiple levels and in multiple contexts. To develop the HIIM, the methodology outlined in this section must be applied to all formal and informal social networks for which there is adequate data.

3.4.1. Techniques to Develop a Measure of Pair-Wise Interpersonal Influence

The matrix, **W**, is intended to represent potential pair-wise interpersonal influence in a social network based purely on network topology (Friedkin, 2003: 496). Most studies of social influence assume communication to be the underlying process

(Leenders, 2002: 27). In addition, it is assumed that influence flows along the paths of a network (Katz, 1953; Hubbell, 1965; Taylor, 1969; Friedkin, 1997, 1998; Leenders, 2002). Techniques for calculating **W**, then, have focused on the connectivity of network members through the paths in the network.

There are two primary philosophies for developing the weight matrix. Katz, Hubbell, Friedkin and Leenders (Katz, 1953; Hubbell, 1965; Friedkin, 1988; Leenders, 2002) consider a weighted average of the paths between group members. Their formulations of **W** are based on enumeration of paths, which are weighted based on path length. Stephenson and Zelen (Stephenson and Zelen, 1989) consider the information in all possible paths; however, their method is based on the structural similarities between social networks and Designs of Experiments. They weight each path based on its "potential variation." The remainder of this section discusses the development and limitations of each of these techniques.

Katz, Hubbell and Friedkin (Katz, 1953; Hubbell, 1965; Friedkin, 1998) consider all possible paths in their development. As discussed in Chapter 2, these authors rely on the solution to the geometric series:

$$I + \alpha A + \alpha^2 A^2 + \alpha^3 A^3 + \ldots = (I - \alpha A)^{-1}$$

where **A** is the node-node adjacency matrix representing network structure, and α is an attenuation factor. The benefit of this approach is that it considers all possible paths, without the need for complete enumeration. The limitation of this approach is in the selection of α. Ideally, α would represent an observed measure of influence loss as the structural distance between two members increases; however, α is governed mathematically by the structure of **A.** $(I - \alpha A)^{-1}$ does not exist if $(1/\alpha) < \lambda_{(1)}$, where $\lambda_{(1)}$ is the largest eigenvalue of **A**. In addition, the impact of indirect connections decreases exponentially with path length. If the group under consideration has potentially long paths of influence, this formulation may not capture their impact. For example, the Air Force Chief of Staff's influence over a Captain studying at the Air Force Institute of Technology may be inappropriately minimized by these measures.

Leenders (2002) considers only a limited number of paths between individuals in a group, typically only paths of three or less connections (Leenders, 2002: 35-36). In addition, Leenders considers the impact of direct and indirect paths separately in his formulations. The benefit of Leenders' approach is the flexibility of weighting path lengths individually based on an observed decrease in influence over greater structural distances. This approach, however, is limited because it calls for complete enumeration of paths. As the size of networks increase or the lengths of paths under consideration become longer, Leenders' method requires a great deal of computation. In addition, the ability to apply weights based on observed network characteristics implies that one can actually observe and measure accurately the influence loss as path lengths increase; a situation that may not be clear when analyzing clandestine networks.

Stephenson and Zelen (1989), like Katz, Hubbell, and Friedkin consider all possible paths in their measure development. Stephenson and Zelen, however use the similarities between network structures and experimental design methodology to develop their measure, called Information Centrality. A key to the proof of their construction is the transformation of a node-node adjacency matrix, **A**, into a node-arc incidence matrix **X** (Stephenson and Zelen, 1989: 28). To calculate information flow through a path, defined as the inverse of the variance in a path (Stephenson and Zelen, 1989: 12, 29), Stephenson and Zelen must determine the variance-covariance structure of the network, $(X'X)^{-1}$. By construction, however, $(X'X)^{-1}$ does not exist. To enable calculation of the variance-covariance matrix, Stephenson and Zelen suggest adding to $(X'X)$, the diagonal matrix, $diag(2(d_i))$ with diagonal values equal to twice the degree of each node, and an $(n \times n)$ matrix of ones. This produces an invertible matrix from which they can compute Information Centrality. The benefit of using Information Centrality is its ease of calculation. The measure is limited however, because it is not appropriate for undirected networks. As shown in Chapter 2, Information Centrality produces comparable results to Katz, and Hubbell for directed networks, but it fails on even the simplest undirected network.

Each of these techniques can be used to calculate pair-wise measures of interpersonal influence. They each have their benefits and limitations and are appropriate in different situations. The next section briefly discusses the appropriate situations for each technique.

3.4.2. Appropriate Use of Pair-Wise Influence Measures

When developing a measure of pair-wise interpersonal influence, it is important to choose the technique appropriate for the context of the analysis being performed. The methods discussed above can be compared for appropriateness based on three criteria:

- Network Symmetry
- Influence of Indirect Connections
- Computational Complexity

Table 3-4 compares each method on these three factors:

Table 3-4: Comparison of Techniques to Develop Pair-Wise Influence Measures

	Network Symmetry	**Indirect Connections (attenuation factor)**	**Computation Complexity**
Katz, Hubbell, Friedkin	Appropriate for symmetric and non-symetric networks	Attenuation factor limited by size of largest eigenvalue λ of **A**	Calculation of inverse, will exist by construction
Leenders	Appropriate for symmetric and non-symetric networks	Attenuation factor can be specified for each path length	Complete enumeration of paths
Stephenson and Zelen	Appropriate for symmetric networks only	Uniform attenuation, inverse of path length	Calculation of inverse, will exist by construction

The Katz-Hubbell-Friedkin and Stephenson-Zelen methods are attractive because of their ease of computation, while the Leenders method is attractive because of its flexibility in choosing attenuation factors.

The Katz-Hubbell-Friedkin method is appropriate for directed and undirected networks. Further, because of its simple calculations, it is appropriate to use for large networks. This technique is limited by its choice of attenuation factor. In addition, by construction the influence of indirect connections decreases exponentially as path lengths increase. Networks with distributed leadership, operating through long lines of communication may not be appropriate for this technique.

The Leenders method is also appropriate for directed and undirected networks. Leenders' method is very flexible because it enables analysts to specify a weight for each path length. Assignment of appropriate weights, however, requires greater knowledge of the network. In addition, this technique requires the complete enumeration of paths.

This typically limited Leenders to consider paths of no more than length 3. The combinatorial cost of complete path enumeration limits Leenders' approach to networks with short lines of communication. Improved path finding algorithms or exploitation of k-shortest path algorithms, however, could make Leenders' method practical.

The Stephenson-Zelen method is only appropriate for undirected networks. Its ease of calculation and results are comparable to the Katz-Hubbell-Friedkin method. Information Centrality, however, considers the impact of indirect connections to be the inverse of path length and in general, this technique attenuates much slower. Slower attenuation enables greater consideration to indirect connections in overall influence. When one has limited information on the impact of indirect connections the inverse of path length is a reasonable assumption. Information Centrality is most appropriate when analyzing symmetric networks in which one has limited information about how influence diminishes through indirect connections. The implications of modeling influence in clandestine networks is next discussed, along with the selection of the appropriate technique for developing pair-wise interpersonal influence measures for clandestine networks.

3.4.3. Appropriate Techniques for Clandestine Networks

Clandestine networks, because of their need to practice good OPSEC, are built on a foundation of pre-existing, trusted social networks. The use of pre-existing social networks sets limits on the social structure of the clandestine network (Erickson, 1981: 188). The trust premium paid by clandestine organizations is their reliance on pre-existing networks. This enables analysts tasked to understand and influence clandestine network operations to bound the problem space by focusing on the trusted relationships of a particular group.

These pre-existing networks, such as family, friends, and schoolmates, by their very nature are two-way relationships. In addition, current literature offers little discussion on the impact of indirect connections in such networks for clandestine groups. Given these conditions, Information Centrality is appropriate for the development of interpersonal influence measures for clandestine networks.

3.4.4. Determination of Pair-Wise Influence Measure

The informal networks upon which clandestine networks are built are most often undirected networks. Information Centrality, then, can be calculated for these informal networks. Information Centrality calculations however require that the network be connected, that is, every member can reach every other member. Within a single network context, this is likely an unreasonable assumption for two reasons. Relationships may exist in several network layers; however, members may not be connected in every layer. By focusing on a single network layer such as friendship, there is a possibility that different groups of friends are not connected to each other. In addition, all of the network data is based on observation; connections may exist that have not yet been observed. It is therefore necessary to account for the possibility of independent subgroups within these networks in the calculation of Information Centrality.

Let the matrix, **A**, represent an undirected informal network to which members of the clandestine network of interest belong. To calculate a pair-wise measure of interpersonal influence based on Information Centrality, the following steps must be followed. First define an $(n \times n)$ matrix **B,** such that

$$B_{ii} = 1 + \sum_{j=1}^{n} A_{ij}$$
$$B_{ij} = 1 - A_{ij}$$

Define the matrix **C** = **B**$^{-1}$. The matrix, **I**, representing pair-wise measures of Information Centrality can be calculated as:

$$I_{ij} = (c_{ii} + c_{jj} - 2c_{ij})^{-1}$$

Each cell, I_{ij}, represents the combined flow of "information" from node *i* to node *j* through all possible paths joining *i* and *j*.

If the matrix **A** is not connected, however, **B** will not be full rank and therefore cannot be inverted. If **B** cannot be inverted, I_{ij} cannot be calculated. When this occurs the additional step of observing the network as separate components must be taken. The first step is to remove isolates; known clandestine network members with no connections in a particular informal network. The second step is to divide the network into its separate independent components. Information Centrality calculations can be performed on the independent components. Once Information Centrality has been computed for each component, the network must be rebuilt by rejoining the components and adding in the isolates. Members of independent components are assumed to have no known influence over members of another independent component in a given network context. Isolates are assumed to have no influence over, and are not influenced by, other network members. Figure 3-2 graphically displays this process:

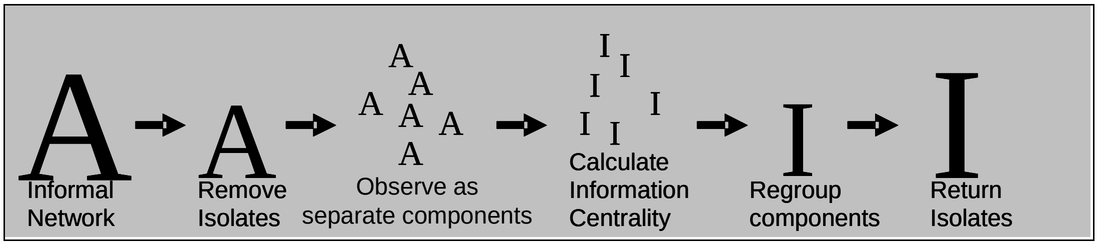

Figure 3-2: Steps to Calculate Information Centrality

Another practical advantage provide by Information Centrality is the ability to quickly assess the number of independent subgroups within a clandestine network. Again, if the matrix **A** is not connected, that is, there are independent subgroups, **B** as previously discussed, will not be full rank, and $\mathbf{B}^{-1}$ will not exist. Although not proven, empirical testing has shown that the rank of **B** is determined by the number of independent subgroups. If there are *k* independent subgroups in **A**, the rank of **B** are *n*-*k*. This observation has very practical purposes in the analysis of clandestine networks, because it provides the capability to uncover subgroups within the informal networks that may be of importance in the clandestine network. For example, if the informal network being analyzed represented friendship, independent groups of friends could be identified and potentially exploited.

3.4.5. Section Summary

There are three primary techniques for calculating pair-wise measures of interpersonal influence. Each technique has its advantages and disadvantages. Based on the elements of the measure and its intended use, Information Centrality appears to be the most appropriate technique to calculate pair-wise measures of interpersonal influence in clandestine networks. Information Centrality produces a measure of interpersonal influence that is based completely on network topology.

This section has detailed the steps necessary to develop influence measures for a single informal network. Social networks however exist in more than one context and on multiple levels. There are many informal networks that clandestine networks are based on, and pair-wise interpersonal influence measures can be developed for each informal network. The next logical step is to combine the information from each of these informal networks to develop an overall measure of pair-wise interpersonal influence. The next section discusses techniques to combine multiple network layers.

3.5. Multiple Network Layers

Most social network analysis studies focus on a single network; however, most relationships exist in several contexts. Social network techniques, in general, do not explore these situations (Bonacich *et al.*, 2004: 189). Effective analysis of clandestine networks must consider the impact of multiple social contexts. Pair-wise interpersonal influence measures can be calculated for every formal or informal network for which one has connection data. While the determination of interpersonal influence for each of these networks has its own intrinsic value, the ability to analyze these networks simultaneously develops a more complete picture of the clandestine network. A multiple-layered network of interpersonal influences can be developed through a linear combination of the interpersonal influences from each informal network to which clandestine network members belong. This multi-layered influence measure can be represented by:

$$W = w_1 I_1 + w_2 I_2 + ... + w_n I_n$$

$$\sum_{i=1}^{n} w_i = 1$$

where $\mathbf{I_i}$ is the matrix of pair-wise interpersonal influences from network *i* as defined in the previous section, and w_i is the perceived importance of network context *i* in determining influence within the group.

Because the true form of the function is unknown, a linear model was chosen based on the Sparsity of Effects Principle, which states that when there are several variables, a system or process is likely to be driven primarily by the main effects and low-order interactions (Myers and Montgomery, 2002: 155). Interaction terms are generally products of main effect terms, however matrix multiplication is not an appropriate transformation for Information Centrality values which are ratio. Interactions, despite their likely importance, are not considered in this study because the underlying theory remains to be developed. This section discusses techniques to combine the information from multiple network layers.

3.5.1. Hyper-edges and Multidimensional Centrality

Node-arc incidence matrices can be used to represent hypergraphs, defined as graphs with hyperedges. Node-arc incidence matrices for graphs have exactly two non-zero elements per row; the non-zero elements indicate which nodes are adjacent. The rows in a hypergraph can have more than two non-zero elements, two for the adjacent nodes, and the other non-zero elements representing the network context.

Bonacich *et al*. (Bonacich *et al.*, 2004), use the concept of hyperedges in a graph to develop a measure called multidimensional centrality (MDC). A hyperedge can be used to describe a situation in which "more than dyadic" situations exist, such as actors in multiple social networks (Bonacich et al., 2004: 194). Bonacich *et al.* are particularly interested in modeling events that involve two or more persons such as a "buyer, seller, and broker," or that involve important aspects of the setting such as "timing or location" (Bonacich et al., 2004: 189). While not explicitly developed to examine multiple social networks, MDC does provide the capability to do so.

An example situation in which MDC can provide added insight is given in Figure 3-3. Consider three individuals A, B, and C, in three separate network contexts; work (1), members on same sports teams (2), and members of same professional society (3).

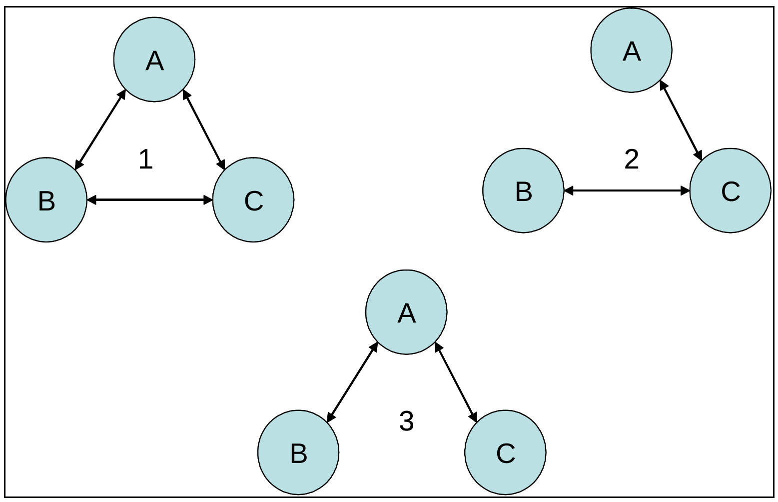

Figure 3-3: Multiple Network Contexts--Example Situation

This situation can be represented by a hypergraph using a node-arc incidence matrix. Create the matrix, **E**, where the rows represent arcs and the columns represent the nodes and the network contexts. There are six columns in this matrix, 3 for nodes *A*, *B*, and *C*, and 3 for the three network contexts, as shown in Table 3-5.

Table 3-5: Node-Arc Incidence Matrix with Hyperedges

	Node			Network		
	A	**B**	**C**	**1**	**2**	**3**
arc a-b	1	1	0	1	0	1
arc a-c	1	0	1	1	1	1
arc b-c	0	1	1	1	1	0

This yields the following node-arc incidence matrix:

$$E = \begin{bmatrix} 1 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 & 0 \end{bmatrix}$$

Once a hypergraph has been represented in a node-arc incidence matrix, MDC can be calculated. MDC is an extension of eigenvector centrality applied to hypergraphs. To calculate, let $M = E^T E$, then solve the eigenvector-eigenvalue problem for M. Node and network multidimensional centrality scores are given by the eigenvector associated with the largest eigenvalue of **M**.

For the sample situation in Figure 3-3,

$$M = E^T E = \begin{bmatrix} 2 & 1 & 1 & 2 & 1 & 2 \\ 1 & 2 & 1 & 2 & 1 & 1 \\ 1 & 1 & 2 & 2 & 2 & 1 \\ 2 & 2 & 2 & 3 & 2 & 2 \\ 1 & 1 & 2 & 2 & 2 & 1 \\ 2 & 1 & 1 & 2 & 1 & 2 \end{bmatrix}$$

Table 3-1 gives the MDC scores for the three network contexts:

Table 3-6: Multidimensional Centrality Scores

Network	MDC
1	0.5506
2	0.3816
3	0.3816

As expected, with this simple network, the scores are very similar. The MDC scores for the networks do highlight the difference between network 1 and networks 2 and 3. Network 1 has a higher MDC score because each network member was connected, while networks 2 and 3 scores were lower because at least one connection had been removed.

It still remains to clarify what these MDC scores mean. Bonacich *et al.,* suggest a network can be important for two reasons, either it connects many individuals, or the individuals it connects are well connected in other network contexts (Bonacich *et al.*, 2004: 202). MDC scores can also be calculated for each network member, providing a proxy measure of their overall connectivity across multiple networks. MDC for individuals is discussed in Appendix B.

The MDC scores can be used as weights to create a linear combination of interpersonal influence among network layers. Lootsma (Lootsma, 1999: 36) recommends a uniform scaling of weights, suggesting that uniform weighting enables a clearer interpretation of the relative importance of the criteria being weighted; in this case multiple informal social networks. In this thesis, the weights are normalized such that they sum to one. This is done by dividing each networks' multidimensional centrality score by the sum of all MDC scores. Table 3-7 shows the normalized weights for the sample network:

Table 3-7: Normalized Multidimensional Centrality Scores

Network	MDC	Normalized Weight
1	0.5506	0.42
2	0.3816	0.29
3	0.3816	0.29

MDC with hyperedges enables the creation of normalized network weights that can be used to create a linear combination of interpersonal influences based on the informal social networks to which clandestine networks belong. MDC, however, can be misleading. When analyzing clandestine networks it is likely that data for different types of informal networks are of varying quality and quantity. Networks with more connections identified will likely score highly on multidimensional centrality. This "easy" to monitor network, however, may be of little importance to the question under consideration for the clandestine network. In addition, MDC is only shown to work for undirected networks. Therefore, results of multidimensional centrality must be carefully considered with regards to the situation before developing weights for the separate layers.

There are a variety of techniques available to develop weights for the multiple informal networks under study. The next section briefly discusses other weighting techniques and their implications for analysts.

3.5.2. Other Weighting Techniques

There are a variety of techniques for soliciting weights from decision makers and subject matter experts. Weighting methods can be separated into two classes, *Numerical Estimation Methods* and *Indifference Methods* (von Winterfeldt and Edwards, 1986: 274). In general, Numerical Estimation Methods are easiest to implement, producing interval weights. Indifference Methods, while more difficult to implement, produce ratio weights. The trade-off between ease of implementation and the measurement theory properties of the weights produced must be taken into consideration prior to eliciting weights from decision makers and subject matter experts. For a complete discussion of weighting techniques, the reader is referred to *Decision Analysis and Behavioral Research* (von Winterfeldt and Edwards, 1986).

The purpose of each technique would be to develop a weighted linear combination of the pair-wise interpersonal influence measures developed for a clandestine network that would enhance one's understanding of the group. Given sufficient time, money, and information, subject matter experts should be educated in a particular method and have weights solicited by a trained facilitator.

Mathematically, one would endeavor to produce weights that can be used for statistical testing. Information available for the analysis of clandestine networks, however, may be limited, making a number of weighting techniques inappropriate. Operational realities, however may suggest that some network contexts are more important to group operations and influence than others and should be weighted. In these instances, exploratory analysis performed by selecting reasonable weights and performing sensitivity on the weights can also provide great insight into network activities.

3.5.3. Section Summary

Clandestine networks are based on the pre-existing, trusted, informal social networks to which they belong. To accurately model clandestine networks, these multiple, informal networks should be considered simultaneously. Measures of pair-wise interpersonal influence can be calculated and analyzed for *each* informal social network for which there is data, but to develop a more accurate understanding, the information from *each* of these networks must be combined. The analysis of multiple network layers simultaneously is a new capability for SNA analysts.

A linear combination of the interpersonal influences from each network is recommended. In the absence of weights, the linear combination would simply produce an average level of interpersonal influence across the multiple networks. Averaging could provide a reasonable approximation of the combined influence from the multiple networks.

Multidimensional centrality can be used to develop network weights based purely on the topology of the informal networks. MDC assesses network weights based on eigenvector centrality. A network may be identified as important for two reasons; either the number of members connected in a network context are high, or the members connected in this context are important members. MDC, because it is based on network topology, is limited by the analyst's knowledge of the connections within the multiple networks. Using this method, networks with many connections are identified as important, however, when modeling clandestine networks it may be safe to assume that networks for which a great deal of information exists may be less important to the group.

There are a variety of elicitation techniques for developing weights based on decision maker opinion or subject matter expertise. von Winterfeldt and Edwards (1986) provides an overview of techniques used to construct weights. Each of these techniques requires time and money to train decision makers and subject matter experts on the weighting technique, as well as a trained facilitator to elicit the weights.

The goal of any weighting technique is to improve one's understanding of the network. Each technique should be used with caution paid to the potential biases in results that it may produce. Proper weighting of these networks is critical; however an analysis of appropriate weighting techniques is beyond the scope of this research. Analysts are cautioned to carefully consider the impact and appropriateness of network weights and weighting techniques for their decision problem. Once the weighting is completed and the combined weight matrix **W** is calculated, one has all the necessary components to develop a new measure of interpersonal influence.

3.6. Improved Social Influence Network Model

Interpersonal influence within a clandestine network is a function of each member's personal characteristics, as well as their positions within the structural topology of their trusted pre-existing informal networks of relationships. This chapter has detailed how to develop a new measure of individual influence based on personal characteristics, and pair-wise measures of interpersonal influence based on multiple network topologies. This section develops how to combine this information into a final weight matrix, and discusses the properties of the pair-wise interpersonal influence measures and their appropriateness for use.

3.6.1. The Holistic Interpersonal Influence Model (HIIM)

Thus far, it has been shown that Discriminant Analysis can be used to develop a proxy measure of individual influence within a group. Further, it has been shown that Information Centrality can be used to develop a pair-wise interpersonal influence measure for *each* informal network from which clandestine network members are drawn. Techniques for developing weights to account for the importance of each informal networks contribution to overall influence have also been discussed. What remains is to combine the information learned into a single network that is appropriate for Operations Research (OR) Network Flow models that will enable analysts to perform prescriptive rather than descriptive analysis. The final calculations are a modification of Hubbell's (Hubbell, 1965: 381) input-output model of social status.

Hubbell was concerned with determining ones status based on how many persons "chose a member" as well as the status of the choosers (Hubbell, 1965: 381). His model can be summarized by the following equation:

$$s_{ij} = y_{ij} e_j$$

Where s_{ij} represents *j*'s contribution to *i*'s status, y_{ij} is the ijth cell of the weight matrix, and e_j is *j*'s exogenous (non-network) status.

A model of pair-wise influence can be created with a slight modification to Hubbell's equation. Let the matrix, **W** = [w_{ij}], represent the combined pair-wise interpersonal influence measures developed from *each* of the informal social networks of a clandestine network:

$$W = \lambda_1 I_1 + \lambda_2 I_2 + ... + \lambda_n I_n$$

$$\sum_{i=1}^{n} \lambda_i = 1$$

where w_{ij} represents the influence of member *i* over member *j* based purely on network topology. Let the vector, **E** = [e_i], represent the individual influence measures developed based on the personal characteristics of clandestine network members. The HIIM network, represented by **H** = [h_{ij}], can then be calculated as:

$$h_{ij} = w_{ij} e_i$$

Where h_{ij} represents the influence of member *i* over member *j* based on personal and network topology characteristics. In simple terms, h_{ij}, can be thought of as person *i*'s topological influence over person *j* scaled by person *i*'s level of individual influence.

3.6.2. Parametric Analysis

The HIIM provides a measure of influence based on network topology and individual non-network influences which are equally weighted. A simple transformation of h_{ij}, however, will result in an additive preference structure (Keeney and Raiffa, 1976: 91) that can be evaluated parametrically.

Let max(W) be the maximum element, w_{ij}, of the combined social network based influence measure. Then, let

$$\hat{w}_{ij} = w_{ij} / \max(W).$$

An additive preference structure can then be constructed as (Keeney and Raiffa, 1976: 91)

$$\hat{h}_{ij} = (\hat{w}_{ij})^{(1-\Theta)}(e_i)^{(\Theta)}, \text{ where } 0 \le \Theta \le 1.$$

By definition $\hat{w}_{ij}$ and e_i are between 0 and 1, therefore a scalar multiple, K, is required to ensure that no rank reversals occur when calculating $\hat{h}_{ij}$. Let

$$\tilde{\hat{h}}_{ij} = (K\hat{w}_{ij})^{(1-\Theta)}(Ke_i)^{(\Theta)}, \text{ where } 0 \le \Theta \le 1.$$

Parametric analysis of the modified HIIM network will enable the evaluation of interpersonal influence based on network characteristics, non-network characteristics, and combinations of network and non-network characteristics.

3.6.3. Measurement Theory Properties

To determine the appropriateness of the HIIM for use in other analysis techniques it is appropriate to discuss the “measurement type” of the measures being developed. By construction Information Centrality produces ratio numbers. Ratio numbers are such that the difference and ratio between the numbers reflects the differences and ratios of the measured attribute (Sarle, 1997: 4). Examples of ratio measures are distances such as feet, time in seconds, and temperature in Kelvin.

Each cell, I_{ij}, represents the total potential information flow from person i to person j. A value of two implies double the potential flow compared to a cell value of one. The difference between values of 5 and 6 is the same as the difference between cells valued at 13 and 14, that is 1 unit of information flow. Further, a cell value of zero implies no potential flow between members, and represents a fixed origin.

The only appropriate transformation for ratio numbers is a multiplicative transformation (Sarle, 1997: 6). Therefore weighting the pair-wise influence measures from multiple networks is appropriate. Because multiplying by a scalar is an admissible transformation, the resultant values will also be ratio. This implies that a linear combination of the pair-wise topology based influence measures is appropriate and will produce ratio values.

The final step in creating the HIIM is to scale the combined topology based influence measures (w_{ij}) by the individual influence measure (e_i). Again, multiplicative transformations are appropriate for ratio data, therefore multiplying by e_i is an appropriate transformation. The final HIIM model will consist of ratio numbers. Ratio numbers make this new measure of interpersonal influence appropriate for use in a variety of analysis techniques such as Network Flow models. The next section discusses the appropriateness of the HIIM for a few tools.

3.6.4. Appropriate Tools for Further Analysis

The new HIIM network is a proxy measure of average pair-wise interpersonal influences within a clandestine network. In addition to describing influence relationships in the network, because the measures are ratio, the HIIM is an appropriate input to other modeling techniques such as Operations Research (OR) network flow models. By mapping social networks to network flow models, analysts are able to move beyond *descriptive* analysis and provide *prescriptive* results such as a “minimum cut set” required to isolate particular actors. This section discusses a few of the analysis methods and tools that the HIIM is appropriate for.

3.6.4.1. Operations Research Network Flow Models

The key to extending SNA to classic OR flow problems is having the relationship measures applied to the arcs represent “potential influence” between individuals (Renfro, 2001). Renfro (Renfro, 2001: 66-69) mapped social network concepts to network flow models. The mapping was dependent on potential influence measures that were “at least ratio in nature” (Renfro, 2001: 66). The HIIM developed in this study produces a proxy measure of potential interpersonal influence that is ratio in nature, therefore it is appropriate for Renfro’s mapping.

Renfro’s mapping of SNA concepts to Operations Research (OR) models was based on the required assumptions for linear programs (LP). Winston (Winston, 1991: 56-57) offers a complete discussion of these assumptions:

- Proportionality
- Additivity
- Divisibility
- Certainty

Ratio measures satisfy the first three assumptions, however the Certainty Assumption is that “each parameter is known with certainty” (Winston, 1991: 57). In many cases, modeling clandestine networks, however, the analysts may be using incomplete or incorrect data which violates the certainty assumption. The robustness of results from network flow models in the face of the certainty assumption can be tested by performing post optimality analysis. If the results of the post optimality analysis indicate that small changes in the pair-wise influence measures produce different decisions it suggests an intelligence requirement to confirm the value of the input. Further discussion of the benefits of applying network flow models to SNA are given in Chapter 5.

3.6.4.2. Fuzzy Set Theory

Fuzzy Set Theory, in contrast to traditional mathematics, was developed with the explicit purpose of solving problems with imprecise data. The measurement of influence relationships within a clandestine network will invariably result in measures that are imprecise. When the Certainty Assumption is violated, Fuzzy Set Theory offers a variety of techniques to analyze ones data. These techniques include Fuzzy Linear Programming (FLP), Fuzzy Dynamic Programming (FDP), Fuzzy Multi-Criteria Decision Analysis (FMCDA), and many others. Each of these techniques is an extension of classic deterministic OR techniques modified for situations of uncertainty. A complete discussions of the modifications from standard OR models to Fuzzy OR models in given by Zimmerman (Zimmerman, 1992: 241-282)

Fuzzy Set Theory can also enhance traditional SNA techniques. Xiaoyan (Xiaoyan, 1988) developed a technique for uncovering cohesive subgroups in networks based on Fuzzy Set Theory. Xiaoyan highlights the deficiency of traditional cohesive subgroup detection techniques such as the clique, n-clique, and k-plex. The primary limitations of these techniques are that they are NP-complete problems with only two outcomes, one is either a member of a clique or one is not (Xiaoyan, 1998: 360-361).

Xiaoyan's method attempts to overcome these limitations through the use of valued and fuzzy relations. Xiaoyan's cohesive subgroup detection method is discussed in detail in Chapter 5.

3.6.5. Section Summary

This section discussed the final steps necessary to create a new pair-wise interpersonal influence measure based on individual and social topology characteristics. Modification of Hubbell's (Hubbell, 1965) input-output status model enables one to combine exogenous (non-network) measures with endogenous (network) measures to form a single pair-wise measure of interpersonal influence. The resultant measure is a ratio number, which is appropriate for a variety of analysis tools including traditional network flow models and fuzzy clique detection. The extension into network flow modeling enables analysts to provide prescriptive results that focus on specific actions and their outcomes which is a new capability for SNA analysts.

3.7. Chapter Summary

Influence within clandestine networks is a function of the individual characteristics of its members, as well as the social structure of the informal networks to which the members belong. This chapter has described the development of a new measure of interpersonal influence that captures both network and non-network characteristics.

Discriminant Analysis can be used to develop a proxy measure of individual influence based on individual characteristics. In addition, Discriminant Analysis also provides the potential capability to profile, differentiate, and classify network members. These intermediate results have the potential to support operations against clandestine networks on their own. It was also shown that Discriminant Analysis can be used to validate SNA measures of individual importance. The ability to validate SNA measures is a new capability for social network analysts.

There are two primary techniques for determining pair-wise measures of influence based on network topology, a geometric series approach and a variance-covariance approach. These techniques have a variety of strengths and weaknesses to consider before use. Information Centrality was determined to be the most appropriate technique for measuring influence in the informal networks of clandestine networks. Information Centrality is appropriate because most informal networks by their nature are symmetric. In addition, the ease of calculation and greater consideration to indirect influence afforded by Information Centrality make it a better measure than the geometric series approach of Hubbell and Katz.

Relationships exist on multiple levels and in multiple contexts. To accurately model social influence, each of these contexts must be considered. This study suggests that interpersonal influence is a linear combination of the pair-wise influence that exists between members in multiple contexts. There are arrays of techniques available to develop weights for the linear combination. Equal weighting produces an average of the influence from the multiple networks. Multidimensional centrality, although it was not expressly developed for this purpose, can provide a weighting of multiple networks based purely on network structure. In this case a network would be considered important if it connected a large number of members, or if it connected important members. The implications of elicitation techniques to develop weights based on subject matter expertise were also discussed. Simultaneous consideration of multiple network contexts is a new capability for social network analysts. While weighting is a critical element, the selection of a weighting system are scenario specific and is generally beyond the scope of this research.

Once the individual influence measure and combined pair-wise measures of influence are developed one can create the HIIM by scaling the topology based influence measures by the characteristic based individual influence measure. A simple modification of Hubbell's (1965) input-output model of social status enables the calculation of interpersonal influence based on individual and social characteristics. The measure created is a ratio number that is appropriate for use in many types of analysis techniques including network flow models and fuzzy linear programming. Extending traditional SNA descriptive techniques through the use of network flow models will enable analysts to provide prescriptive results focused on specific operational outcomes. The ability to provide prescriptive analysis is a new capability for social network analysts.

Chapter 4 details the use of the Discriminant Analysis methodology outlined in this chapter, highlighting the potential insights Discriminant Analysis results can produce. Chapter 5 details the development of the HIIM for a sample group, as well as highlights the HIIM's compatibility with different analysis techniques such as network flow models and fuzzy subgroup detection.

4. Methodology Demonstration and Analysis Results I

4.1. Introduction

In this chapter, the Discriminant Analysis methodology developed in Chapter 3, Section 3 is applied using the open source data on the Al Qaeda terrorist network collected by Marc Sageman (Sageman, 2004). Special thanks are due to Dr. Sageman for graciously allowing the use of his data set. The following steps are followed in this implementation:

Step 1: Description of Sageman's Al Qaeda Data
Step 2: State Analysis Objectives
Step 3: Exploratory Analysis of Data
Step 4: Implementation of Discriminant Analysis Methodology
Step 5: Discuss Analysis Results and Implications

4.2. Description of Data

In response to the terrorist attacks on September 11, 2001, Sageman began collecting data on Al Qaeda (Sageman, 2004: vii). Sageman limited his data set to terrorist who "targeted the far enemy," that is, those whose focus was on attacking the United States and not their own governments (Sageman, 2004b: vii-viii). Sageman's data set consists of demographic data, affiliation data from pre-existing informal networks, and affiliation data from networks formed after "joining the Jihad" for 366 terrorists. Sageman, however, was unable to gather complete information for every Al Qaeda member in his data set. Incomplete demographic data for Al Qaeda members are referred to as Missing Data. Table 4-1 summarizes the data categories collected by Sageman:

Table 4-1: Data Categories Collected by Sageman (2004)

Demographic Data		Social Network
Continuous	**Categorical**	**Affiliations**
Age joining the jihad	Children	Acquaintance
Date of birth	Country Joined the Jihad	Friendship
Year joined the jihad	Educational achievement	Links Post Joining
	Family Socioeconomic Status	Nuclear Family
	Marital Status	Operation involvement
	Occupation	Place joined the jihad
	Place of birth	Relatives (not Nuclear Fam)
	Religious Background	Teacher-Student Network
	Role in Organization	Religious Leader
	Social background	Ties not in sample
	Type of education	
	Youth National Status	

The purpose of Sageman's analysis was to test the conventional wisdom that terrorism comes "from poverty, broken families, ignorance, immaturity, lack of family or occupational responsibilities, weak minds susceptible to brainwashing, the religious fanatic" (Sageman, 2004b: 2). Sageman concluded that these assumptions were false. Sageman further concluded that "there's really no profile" for terrorists, "just similar trajectories to joining the Jihad" (Sageman, 2004b: 2). Sageman's data is based on open source literature, and has not been updated since late 2003; all analysis results and conclusions in this demonstration are therefore subject to the limitations of the data used. The results of this analysis are offered simply to demonstrate the potential of the methodology and are not intended to be for operational purposes.

4.3. Analysis Objective

In support of his analysis, Sageman (Sageman 2004) classified Al Qaeda members into four categories, Central Staff, Core Arab, Southeast Asian, and Maghreb Arab. The Central Staff, as the name suggests, is the central leadership of Al Qaeda that provides spiritual leadership, motivation, training, financing, and often times logistic support to the operations of the other three groups (Sageman, 2004: 70). The objective of the demonstration conducted here is to determine if members of the Central Staff possess characteristics that distinguish them from the rest of the Al Qaeda network. In addition, if there are distinguishing characteristics, the goal is to develop a statistically significant Discriminant Function for the Central Staff that can be used to profile its members and classify members into the appropriate group. For the duration of this chapter, the Core Arabs, Southeast Asians, and Maghreb Arabs are referred to as the Rest of Al Qaeda. Sageman identified 38 members as Central Staff, the other 328 members are in the grouping the Rest of Al Qaeda.

4.4. Exploratory Analysis of Data

> **"Exploratory analysis is about looking at data to see what it seems to say. It concentrates on simple arithmetic and easy-to-draw pictures. It regards whatever appearances we have recognized as partial descriptions, and tries to look beneath them for new insights. Its concern is with appearance, not with confirmation."— Tukey (1977: v)**

In an exploratory analysis, ones' objective is to examine the data in an attempt to identify relationships of interest within the data without imposing a definite model on the data. Tukey suggests that exploratory analysis should proceed "side by side" with confirmatory analysis (Tukey, 1977: vii). For a complete discussion of exploratory analysis techniques, the reader is referred to *Exploratory Data Analysis* by Tukey (Tukey, 1977). For the purposes of this demonstration, an exploratory analysis of the demographic characteristic data and social network affiliation data is used to develop hypotheses. The hypotheses regarding distinguishing characteristics was then tested using Discriminant Analysis. The exploratory analysis was conducted in three phases, first analyzing the continuous demographic characteristics, second analyzing the categorical demographic characteristics, and finally analyzing the social network affiliation data.

4.4.1. Exploratory Analysis of Continuous Demographic Data

There are three continuous variables in the Al Qaeda data set. To identify the potential of a "continuous" characteristic to distinguish between groups, simple summary statistics such as the mean can be used for comparison (Tukey, 1977: 27). Figure 4-1 provides a comparison of the average age of the Central Staff $(\mu = 30.5, \sigma = 7.1)$ with the Rest of Al Qaeda $(\mu = 25.2, \sigma = 6.7)$ at the time they "Joined the Jihad":

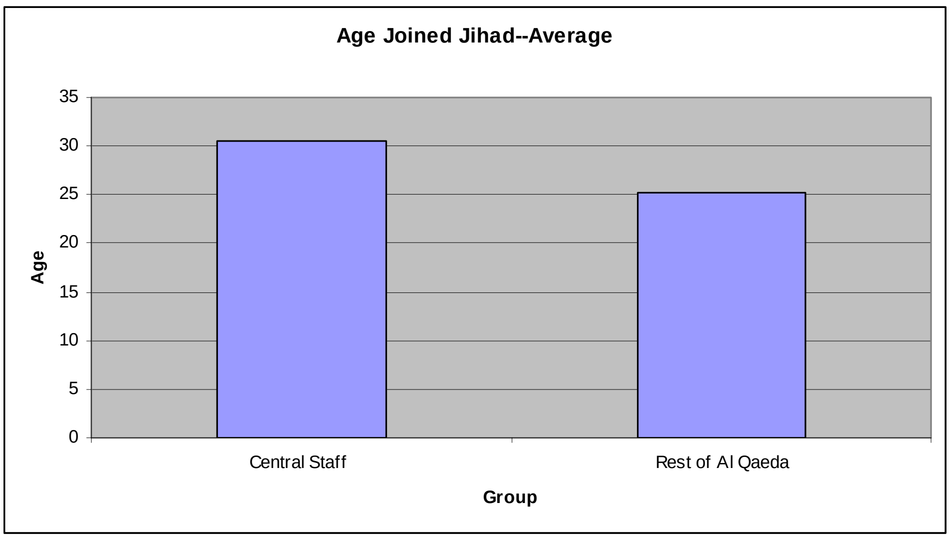

Figure 4-1: Comparison of Average Age of Al Qaeda Members When Joining

Figure 4-1 reveals that, on average, Central Staff members were six years older than the Rest of Al Qaeda when they joined. Figure 4-2 provides a comparison of the groups based on the "Year Joined Jihad":

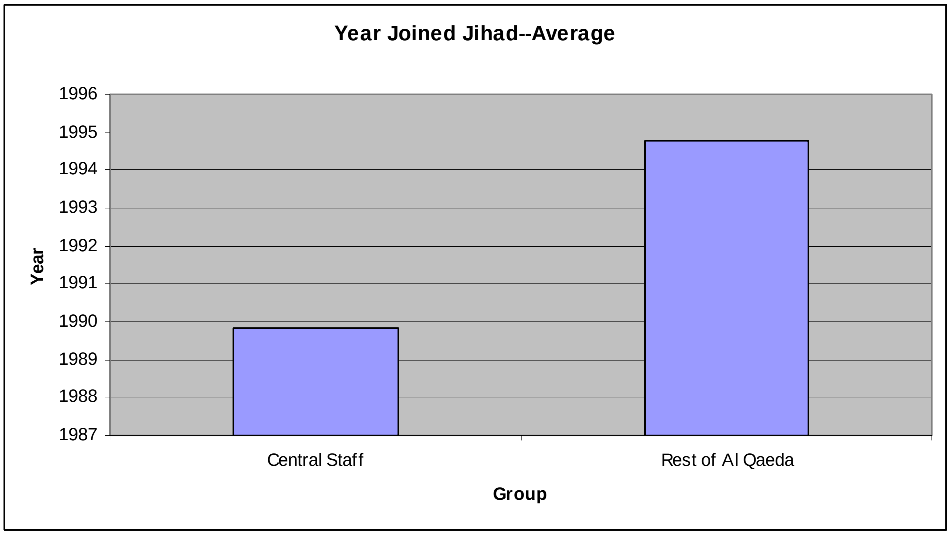

Figure 4-2: Comparison of Years when Al Qaeda Members Joined

Figure 4-2 reveals that, on average, Central Staff $(\mu = 1989.8, \sigma = 1.7)$ members joined five years earlier than the Rest of Al Qaeda $(\mu = 1994.8, \sigma = 3.8)$. Further, based on Figure 4-1 and Figure 4-2, the Central Staff is, on average, 11 years older than the Rest of Al Qaeda. Based on the results of this analysis, the hypothesis to be tested in this chapter is that "Year Joined Jihad" and "Age Joined Jihad" can be used to build a statistically significant Discriminant Function for Al Qaeda.

4.4.2. Exploratory Analysis of Categorical Demographic Data

There are 12 categorical variables in the Al Qaeda data set. To identify the potential of a categorical characteristic to distinguish between groups, simple statistics tools such as histograms can be used for comparison (Tukey, 1977: 543). Figure 4-3 compares "Education Type" received by the Central Staff to that of the Rest of Al Qaeda. It is clear from Figure 4-3 that the Central Staff have primarily Technical backgrounds, while the Rest of Al Qaeda has a less technical and more diverse educational background.

This suggests that Education Type has the potential to help discriminate between the groups.

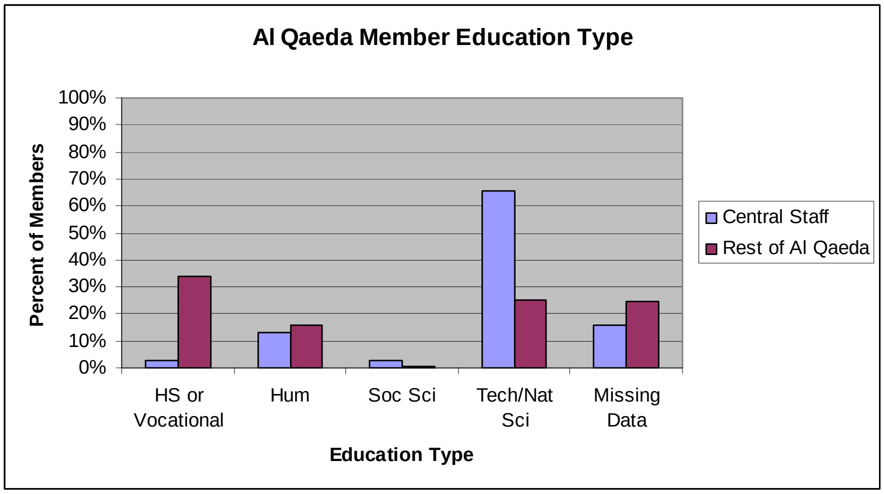

Figure 4-3: Histogram of Al Qaeda Member Education Type

Figure 4-4 compares the occupation types of the two groups. Figure 4-4 indicates that the Central Staff, in general, held jobs requiring more advanced education and training than the Rest of Al Qaeda prior to becoming members. This also suggests that Occupation Type has the potential to help discriminate between the groups.

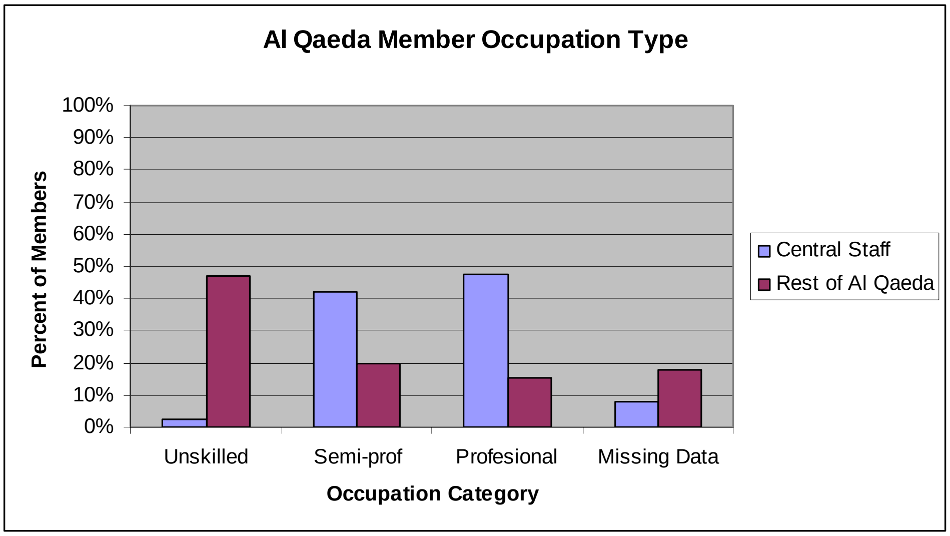

Figure 4-4: Histogram of Al Qaeda Member Occupation Type

Figure 4-5 compares the Criminal Backgrounds of the two groups.

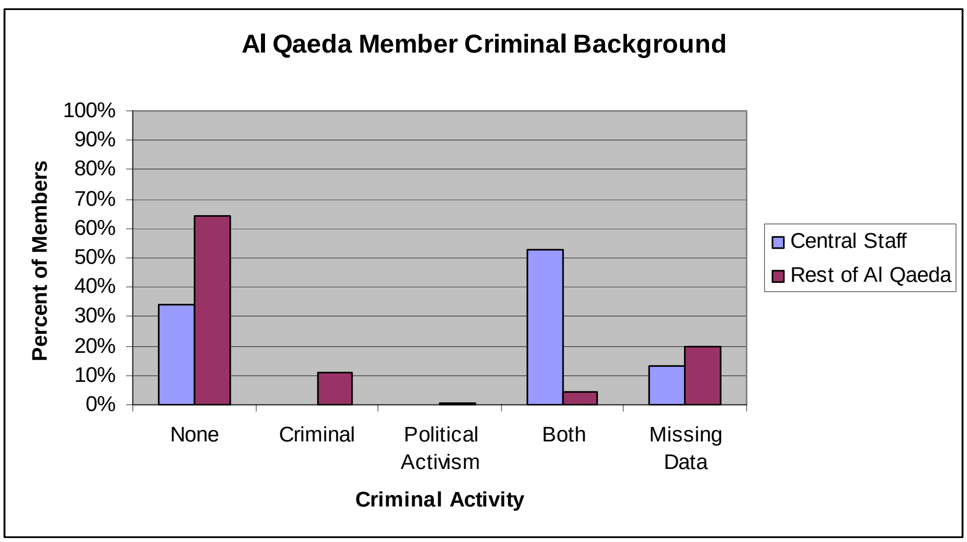

Figure 4-5: Histogram of Al Qaeda Member Criminal Background

Figure 4-5 indicates that the Central Staff participated in both criminal acts and political activism at a higher rate than the Rest of Al Qaeda prior to joining the Jihad. While the membership in general, has been involved in criminal activity as a group, Sageman's data is focused on the background of members before joining Al Qaeda. These results suggest that Criminal Background has the potential to help discriminate between the groups. Table 4-2 compares the Place of Birth of the two groups:

Table 4-2: Al Qaeda Member Countries of Birth by Percentage

Central Staff	Rest of Al Qaeda			
63% Egypt	14% Morocco	3% Malaysia	1% Canada	0.3% Mauritania
13% Saudi Arabia	13% Algeria	3% Britain	1% Philippines	0.3% Poland
8% Kuwait	13% France	3% Singapore	1% UAE	0.3% Qatar
5% Jordan	12% Saudi Arabia	3% Syria	0.3% Bahrain	0.3% Spain
3% Iraq	10% Indonesia	2% Egypt	0.3% Belgium	0.3% Tanzania
3% Lebanon	4% Turkey	2% Pakistan	0.3% Bosnia	0.3% Missing Data
3% Libya	4% Yemen	1% Jordan	0.3% Comoros Islands	
3% Sudan	3% Kuwait	1% USA	0.3% Germany	
0% Missing Data	3% Tunisia	1% Australia	0.3% Lebanon	

Table 4-2 shows that Saudi Arabia is the only country with relatively equal contributions to the makeup of the Central Staff and the Rest of Al Qaeda. It addition, it shows that Egypt has an extremely disproportionate amount of Central Staff members; suggesting that Place of Birth has the potential to help discriminate between groups. Based on the results of this analysis Place of Birth was re-categorized into two groups, Core Leadership Countries and Other Countries. The Core Leadership Countries are represented by Egypt, Saudi Arabia, Kuwait, and Jordan, Iraq, Lebanon, Libya, and Sudan.

Exploratory analysis of the categorical variables revealed four variables with the potential to aid discrimination between the two groups. Based on the results of this analysis, the hypothesis to be tested in this chapter is that “Education Type,” “Occupation Type,” “Criminal Background,” and “Place of Birth” can be used to build a statistically significant Discriminant Function for Al Qaeda leadership versus the Rest of Al Qaeda. In addition to highlighting the differences between the Central Staff and the Rest of Al

Qaeda, these four figures also highlight the amount of Missing Data in the Sageman data set. Techniques to handle missing data are presented in the Discriminant Analysis Implementation section.

4.4.3. Exploratory Analysis of Social Network Affiliations

There are nine affiliation networks in the Sageman Al Qaeda data set as shown in Table 4-1. For the purposes of this demonstration, only pre-existing social networks were considered. This limited the networks to the Acquaintance, Friendship, Nuclear Family, Relatives, Student-Teacher, and Religious Leader networks. In addition, various combinations of these networks were explored to investigate the interactions of the relationships between group members. Figure 4-6 is a network representation of Al Qaeda based on the combined Acquaintance-Nuclear Family-Relative Network.

In Figure 4-6, the Central Staff is represented by circles, the Core Arabs are represented by squares, the Southeast Asians are represented by triangles, and the Maghreb Arabs are represented by diamonds. Figure 4-6 highlights the dense connectivity of the four groups based on the Sageman data; however it also shows that the Central Staff plays an integral role connecting the network. Without the Central Staff, the other three groups would be completely independent of each other based on the Sageman data. The location of the Central Staff suggests that SNA measures such as Closeness and Betweenness may be able to help distinguish the Central Staff from the Rest of Al Qaeda. Based on an examination of the informal network connections of Al Qaeda, a hypothesis to be tested in this chapter is that SNA measures can be used to develop a statistically significant Discriminant Function.

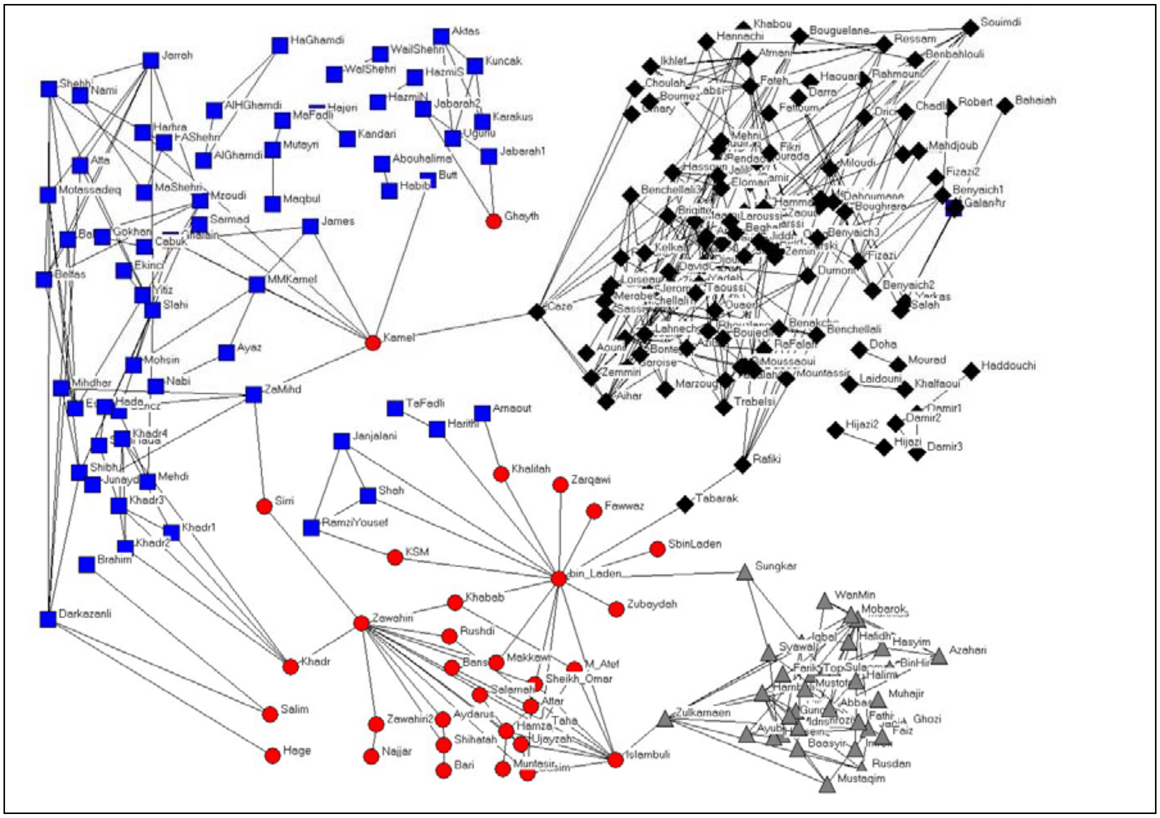

Figure 4-6: Network Representation of Al Qaeda based on Acquaintance, Nuclear Family, and Other Relative Ties created in UCINET 6

This section has provided a very brief summary of the exploratory analysis performed on the Sageman Al Qaeda data set. The purpose of the exploratory analysis was to identify the relationships that exist in the data set and to develop hypotheses to be tested in a more formal confirmatory analysis. There are a variety of additional exploratory analysis techniques available that were not discussed in this section, such as Box and Whisker Plots, counts, and trend analysis (Tukey, 1977). Based on the exploratory analysis there appear to be demographic and social network characteristics that can be used to build a statistically significant Discriminant Function for Al Qaeda. The next section discusses the implementation of Discriminant Analysis as discussed in Chapter 3.

4.5. Discriminant Analysis Implementation

The objectives of Discriminant Analysis are to determine if predefined groups differ significantly on a set of observed characteristics, to develop a profile of group members based on distinguishing characteristics, and to produce a Function that can be used to predict to which group newly discovered members *may* belong. The results of exploratory analysis suggest that the Central Staff differs from the Rest of Al Qaeda on a subset of characteristics in the Sageman data set. This section discusses the results of the confirmatory Discriminant Analysis performed to test the hypotheses developed through exploratory analysis. The Discriminant Analysis performed followed the following steps:

Step 1: Coding of Categorical Variables
Step 2: Imputation of Missing Data
Step 3: Creation of Test and Validation Sets
Step 4: Execution of Discriminant Analysis Calculations
Step 5: Hypothesis Testing—Group Discrimination
Step 6: Interpretation of Discriminant Loadings—Profiling
Step 7: Validation of Classifier—Prediction

4.5.1. Coding Categorical Variables

Exploratory analysis of the Sageman data revealed the possibility that four categorical variables could be used to discriminate between the Central Staff and the Rest of Al Qaeda. Categorical variables, however, should not be used in a Discriminant Analysis unless they are "coded." For the purposes of this demonstration a "Dummy Coding" scheme was employed (Neter et al., 1996: 455-457). Dummy coding is used when categorical variables are of interest in prediction (Neter et al., 1996: 455-457). Table 4-3 shows the coding scheme used for this analysis. A code of all zeros are referred to as the baseline for that variable.

Table 4-3: Categorical Variable Coding Scheme

Education Type	Column 1	Column 2	Column 3	Occupation Type	Column 1	Column 2
HS or Vocational	0	0	0	Unskilled	0	0
Humanities	1	0	0	Semi-Prof	1	0
Soc Sciences	0	1	0	Professional	0	1
Technical	0	0	1			
Criminal Background	**Column 1**	**Column 2**	**Column 3**	**Place of Birth**	**Column 1**	
None	0	0	0	Core Leadership Country	1	
Criminal	1	0	0	Other	0	
Political Activism	0	1	0			
Both	0	0	1			

4.5.2. Imputation of Missing Data

Missing data is a common problem in statistical analysis. This condition will only be exacerbated by attempting to model clandestine networks. Exploratory analysis revealed missing data in the continuous and categorical variables that appear capable of distinguishing between the Central Staff and the Rest of Al Qaeda. For the purposes of this demonstration, it is being assumed that the affiliation data was complete, although this almost certainly not the case in a real world analysis.

There are a number of alternatives for dealing with missing data. The alternatives can be reduced to two simple categories; deletion of the exemplar with missing data, and missing data imputation. Deletion of subjects with missing data may be practical in clinical situations, despite the induced bias, but data collected on clandestine networks is much harder to attain and potentially too valuable to discard. For this reason it was deemed more appropriate to consider a data imputation technique.

All data imputation techniques are subject to bias, and typically lower the power of ones statistical tests. The power of a statistical test is determined by the amount of Type II error (false positives) in the test. Type II error in Discriminant Analysis is the proportion of false positives; for this demonstration it would represent the number of previously identified non-Central Staff members classified as Central Staff. Advanced data imputation techniques are focused on reducing bias and Type II error. False positives, however, may be an acceptable outcome when modeling clandestine networks, and therefore a simple imputation technique was chosen for this analysis. For a complete discussion, the reader is referred to *Statistical Analysis with Missing Data, Second Edition,* by Little and Rubin. In addition, further research and testing is recommended to determine appropriate data imputation techniques for modeling clandestine networks.

Al Qaeda members with missing values on continuous variables were assigned their groups' mean value for that variable. Table 4-4 summarizes the values imputed for the continuous variables:

Table 4-4: Imputed Values for Missing Continuous Data

	Central Staff	Rest of Al Qaeda
Year Joined	1990	1995
Age Joined	31	25

Categorical variables were also imputed by coding missing values as the baseline for their category. Table 4-5 summarizes the data imputation used for the categorical variables:

Table 4-5: Imputed Values for Missing Categorical Variables

Missng Data	Coding Scheme	Level
Education Type	0 0 0	HS or Vocational
Occupation Type	0 0	Unskilled
Criminal Background	0 0 0	None
Place of Birth	0	Other

Referring to Table 4-3, coding Education Type as [0, 0, 0] is equivalent to saying all members with missing data for this variable received a high school or vocational education type. Each of the coding schemes can be interpreted similarly by comparing the imputation scheme in Table 4-5 with the coding scheme in Table 4-3.

4.5.3. Creation of Test and Validation Sets

One of the most important characteristics of a Discriminant Function is its ability classify members into the correct categories. Splitting the data into two samples, one to create the classification rule and one to validate the classification rule, enables the analyst to develop a consistent and unbiased estimate of classification error rate. For this demonstration ¾ of the data was randomly assigned to the creation set, and ¼ was randomly assigned to the validation set. Table 4-6 summarizes the separation:

Table 4-6: Number of Al Qaeda Members Assigned to Creation and Validation Sets

	Creation Set	Validation Set
Central Staff	28	10
Rest of AQ	246	82

4.5.4. Discriminant Analysis Calculations

This section identifies the variables used to perform the Discriminant Analysis. The creation data set was divided into two groups G1 (Central Staff) and G2 (Rest of Al Qaeda). Define n_1 for the creation data set as the size of G1, $n_1 = 28$. Define n_2 as the size of G2, $n_2 = 246$. Exploratory analysis highlighted 14 variables with the potential to discriminate between G1 and G2. Table 4-7 lists the characteristics considered in this section:

Table 4-7: Continuous and Categorical Variables Considered for Discriminant Analysis

Demographic Data	Social Network Measures
Place of Birth	Betweenness Friendship
Date of Birth	Betweenness Friend-Relative
Year Joined Jihad	Closeness Acq-NucFam-Rel
Age Joined Jihad	Eigenvector Acq-NucFam-Rel
Education Type	Betweeness Religious Leader
Occupation Type	Eigenvectore Religious Leader
Criminal Background	Closenss Student/Teacher

The matrix, **X1**, is a (28×19) matrix, and contains the characteristic measurements of G1 on the 14 characteristics. The categorical variable coding scheme increases the number of columns from 14 to 19. **X2** is defined as the characteristic measurements of G2 on the 14 characteristics, **X2** is a (246×19) matrix.

The Discriminant Analysis calculations, as described in *Multivariate Analysis* (Dillon and Goldstein, 1984), were performed in order to build a model that can discriminate between G1 and G2 with $(1-\alpha) = 95\%$ confidence. To maintain a simultaneous 95% confidence for all variables included in the model, Bonferroni's inequality was used. Bonferroni's inequality states that

$$Confidence \geq 1 - \sum_{j=1}^{m} \alpha_j ,$$

where *m* is the number of variables included in the model and α_j is the confidence level of characteristic *j* (Wackerly, Mendenhall, and Scheaffer, 2002: 666-667). Table 4-8 summarizes the characteristics selected for inclusion in the Discriminant Function with their associated α_j levels:

Table 4-8: Variables Included In Discriminant Function with Associated Confidence Levels

Imputation Method 1	
Characteristic	**p-value**
X1-- Place of Birth	0.0000
X2-- Educataion Type (Technical)	0.0075
X3-- Criminal Background (Both)	0.0000
X4-- Year Joined Jihad	0.0000
X5-- Age Joined Jihad	0.0037
X6-- Closeness Acq-NucFam-Rel	0.0000
X7-- Eigenvector Religious-Leader	0.0001
Simultaneous Confidence Level	**98.9%**

The Discriminant Function developed for the Sageman data is:

$$y = 7.7685X_1 + 1.1494X_2 + 6.4646X_3 - 0.5599X_4 + 0.2226X_5 + 4.5948X_6 + 0.1748X_7$$

The Discriminant Function was developed to produce a classifier that can distinguish between the Central Staff and the Rest of Al Qaeda with 95% confidence. In addition, this Function has helped to validate Closeness and Eigenvector Centrality measures for specific social networks as potentially identifying group leaders. Implicitly, however, the Discriminant Function also suggests that the SNA measures of individual importance for other networks (e.g. Friendship, Student-Teacher, etc.) do not help to distinguish the Central Staff. The next analysis step is to test the ability of the Discriminant Function to discriminate between groups through hypothesis testing.

4.5.5. Hypothesis Testing—Group Discrimination

The first objective of Discriminant Analysis is to determine if G1 and G2 differ significantly on the characteristics measured. To determine if the Discriminant Function produces a significant difference between the average discriminant scores of G1 and G2, Hotelling's T-test is performed as discussed in *Analyzing Multivariate Data* (Lattin *et al.*, 2003: 447-448). The null hypothesis for this test is that the mean of G1 is equal to the mean of G2; the alternative is that they are different:

$$H_o : \mu_1 = \mu_2$$
$$H_a : \mu_1 \neq \mu_2$$

The hypothesis test results are summarized in Figure 4-7:

$$\boxed{F_{obs} = 367.84 \gg \mathrm{F}_{.05;(7,358)} = 0.3080}$$

Figure 4-7: Hypothesis Testing F-test Results

The null hypothesis can be rejected at the 95% confidence level because the observed value of the F-statistic is larger than the expected value of the F-statistic.

The results of hypothesis testing indicate that the Discriminant Function is capable of distinguishing between the Central Staff and the Rest of Al Qaeda at the 95% confidence level. Since it has been determined that there is a significant difference between the groups it is appropriate to begin developing a group profile.

4.5.6. Interpretation of Discriminant Loadings—Profiling

The second objective of Discriminant Analysis is to create a profile for the groups under study. Profiling is done by considering the contribution of the characteristic variables to the differences between the groups. Variable contributions are determined by comparing the Discriminant Loadings; Table 4-9 summarizes the Discriminant Loadings for the Sageman data:

Table 4-9: Discriminant Loadings Highlighting Variable Contribution to Discrimination

Characteristic	Discriminant Loading
Place of Birth	0.5683
Education Type (Technical)	0.2338
Criminal Background (Both)	0.4651
Year Joined Jihad	-0.3866
Age Joined Jihad	0.2808
Closeness Acq-NucFam-Rel	0.1554
Eigenvector Religious Leader	0.0691

The magnitude of the Discriminant Loadings indicates a variables importance to the Discriminant Function. The loadings for the Sageman data set indicate that Place of Birth, Education Type, and Year Joined Jihad are the most important variables for discriminating between the Central Staff and the Rest of Al Qaeda. A very simple Central Staff profile could be developed from these three variables. The profile would suggest that Al Qaeda members born in the Core Middle East countries, with Technical Education backgrounds that joined the Jihad early (1989-1990) are likely to be Central Staff members. Obviously, if more detailed data were available for these groups, an improved profile might be developed

The Discriminant Loadings also provide insight into the social network topology of Al Qaeda. Although their respective loadings are the smallest, Closeness Centrality for the Acquaintance-Nuclear Family-Relative network and Eigenvector Centrality for the Religious Leader network suggest by their presence that network topology can be used to distinguish between group members. In addition, for this example, because the values are positive, the Discriminant Loadings suggest the Central Staff has higher values for these SNA measures. This information could also be used to support profiling of Al Qaeda members.

The Discriminant Loadings have enabled the development of a Central Staff profile. To adequately discuss the implications of the Discriminant Analysis performed thus far, however, it is critical to understand the quality of the results obtained.

4.5.7. Validation of Classifier—Prediction

One of the most important characteristics of a Discriminant Function is its ability to classify members into the appropriate groups. The quality of a Discriminant Function can be assessed by evaluating its ability as a classifier. Figure 4-8 compares the expected accuracy of a Discriminant Function , based on the *proportional chance criterion* (Lattin et al., 2003: 450), with the observed accuracy of the calculated Discriminant Function on the Validation Set:

Expected Accuracy

Actual Group \ Predicted Group	Group 1	Group 2
Group 1	1	9
Group 2	9	72

Expected Hit Rate = 73.2%

Observed Accuracy

Actual Group \ Predicted Group	Group 1	Group 2
Group 1	8	2
Group 2	1	80

Actual Hit Rate = 96.7%

Figure 4-8: Classification Accuracy of Discriminant Function on Validation Set

The observed classification accuracy of the Discriminant Function appears to perform much better than expected based on the confusion matrices and hit rates. A t-statistic for the classifier was also calculated:

$$t_{obs} = 3.9117 > t_{0.5,89} = 1.645$$

The result of the t-test confirms that the Discriminant Function classifies better than is expected based on the proportional chance criterion with 95% confidence, suggesting that the quality of the results obtained were good.

4.6. Analysis Results and Implications

The analysis to this point has shown that the Central Staff is statistically different from the Rest of Al Qaeda on a subset of characteristics measured in the Sageman data set. In addition, it has been shown that a profile of the Central Staff can be developed based on these characteristics. Throughout the demonstration a 95% level of confidence in the results was maintained through statistical testing.

4.6.1. Analysis of Misclassifications

Seven characteristics were used to build the final Discriminant Function which had 96.7% prediction accuracy. The high prediction accuracy suggests that the characteristics identified are "good" discriminators for predicting membership in the Central Staff or the Rest of Al Qaeda. While the classification accuracy of the Discriminant Function is high, it is not perfect suggesting that there is more to learn about Al Qaeda. Figure 4-9 shows the confusion matrix and prediction accuracy for all Al Qaeda members in the Sageman data set:

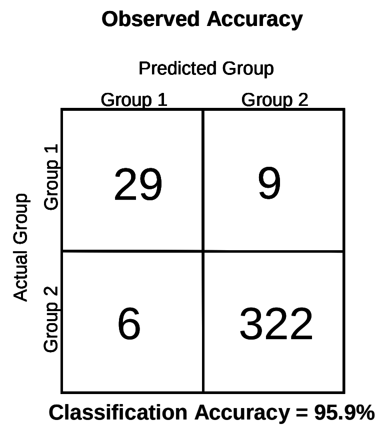

Figure 4-9: Overall Prediction Accuracy of Discriminant Function Including Creation and Validation Set

The overall confusion matrix shows 15 misclassifications, 6 false positives and 9 false negatives. False positives are non-Central Staff members classified as Central Staff; false negatives are Central Staff members classified as non-Central Staff. Table 4-10 lists the misclassified members:

Table 4-10: Al Qaeda Members Misclassified by Discriminant Function

Central Staff	Rest of Al Qaeda
Zain al-Abidin Mohammed Hussein	Ali Abd el-Suud Mohamed Mustafa
Mustafa Ahmed al-Hawsawi	Abdul Basit Mahmoud Abdul Karim
Omar ibn Mahmoud abu Omar Othman	Mohammad Hamdi al-Ahdal
Hamid al-Fakhiri	Mohammad Jaman Saluk al-Mutayri
Jamal Ahmed Mohamed al-Fadl	Mohamed Zinedine
Osama Siddiq Ali Ayyub Muntasir	Abdelilah Ziyad
Sulayman Abu Ghayth	
Sabri Ibrahim al-Attar	
Saad bin Laden	

The members misclassified by the Discriminant Function offer a great deal of potential for further analysis; however it should be clear that this Discriminant Function misclassified Central Staff members (9 of 38) at a much higher rate than the Rest of Al Qaeda (6 of 328). Further analysis revealed that the disproportionate misclassifications are affected by the data imputation method chosen for missing categorical variables. Missing data was given the baseline coding for each categorical variable. The Discriminant Analysis results, however, revealed that members of the Central Staff possessed characteristics that were statistically different than the baseline for Place of Birth, Education Type, and Criminal Background. For comparison purposes missing categorical variables were recoded as shown in Table 4-11:

Table 4-11: New Values Imputed for Missing Categorical Data

Missng Data	Coding Scheme	Level
Education Type	0 0 1	Technical
Occupation Type	0 1	Professional
Criminal Background	0 0 1	Both
Place of Birth	1	Core Leadership Country

The implication of this coding scheme is that missing data will now be given the coding associated with the majority of the Central Staff. Referring to Table 4-3, coding Education Type coded as [0, 0, 1] is equivalent to saying all members with missing data for this variable received a Technical or Natural Sciences education. The Discriminant Function produced using this coding scheme improved overall classification accuracy by reducing both false positives and false negatives, however there is no statistically significant difference in the quality of the classifiers. Figure 4-10 summarizes the results of the new classifier:

Observed Accuracy

		Predicted Group: Group 1	Predicted Group: Group 2
Actual Group	Group 1	34	4
Actual Group	Group 2	6	322

Actual Hit Rate = 97.2%

Figure 4-10: Classification Accuracy of Modified Missing Data Imputation Method

The improved classifier still misclassified 10 members, but did have less actual Central Staff members misclassified than the previous coding scheme. Table 4-12 lists the misclassified members:

Table 4-12: Al Qaeda Members Misclassified by New Discriminant Function

Central Staff	Rest of Al Qaeda
**Omar ibn Mahmoud abu Omar Othman	**Ali Abd el-Suud Mohamed Mustafa
**Jamal Ahmed Mohamed al-Fadl	**Abdul Basit Mahmoud Abdul Karim
**Sulayman Abu Ghayth	Abdal Rahim al-Nashiri
**Saad bin Laden	**Mohammad Hamdi al-Ahdal
	Omar al-Faruq
	Abdel Qader Mahmud Es Sayed
** indicates misclassifed by both discriminanat functions	

Seven of the Al Qaeda members were misclassified by both classifiers, and warrant a much closer look. For demonstration purposes, Abdul Basit Mahmoud Abdul Karim (alias—Ramzi Yousef) are examined in greater detail.

Ramzi Yousef was classified by Sageman as a member of the Core Arab group; however he possesses many characteristics in common with the Central Staff. Ramzi Yousef was born in Kuwait, a Core Middle East country, has a Technical Education, no

Criminal Background, and Joined the Jihad in 1989. In addition to his similar demographic characteristics, Ramzi Yousef is more closely associated with members of the Central Staff (circles) than with the Core Arab (squares) group on the basis of his informal social networks. Figure 4-11 highlights Ramzi Yousef in the network of affiliations:

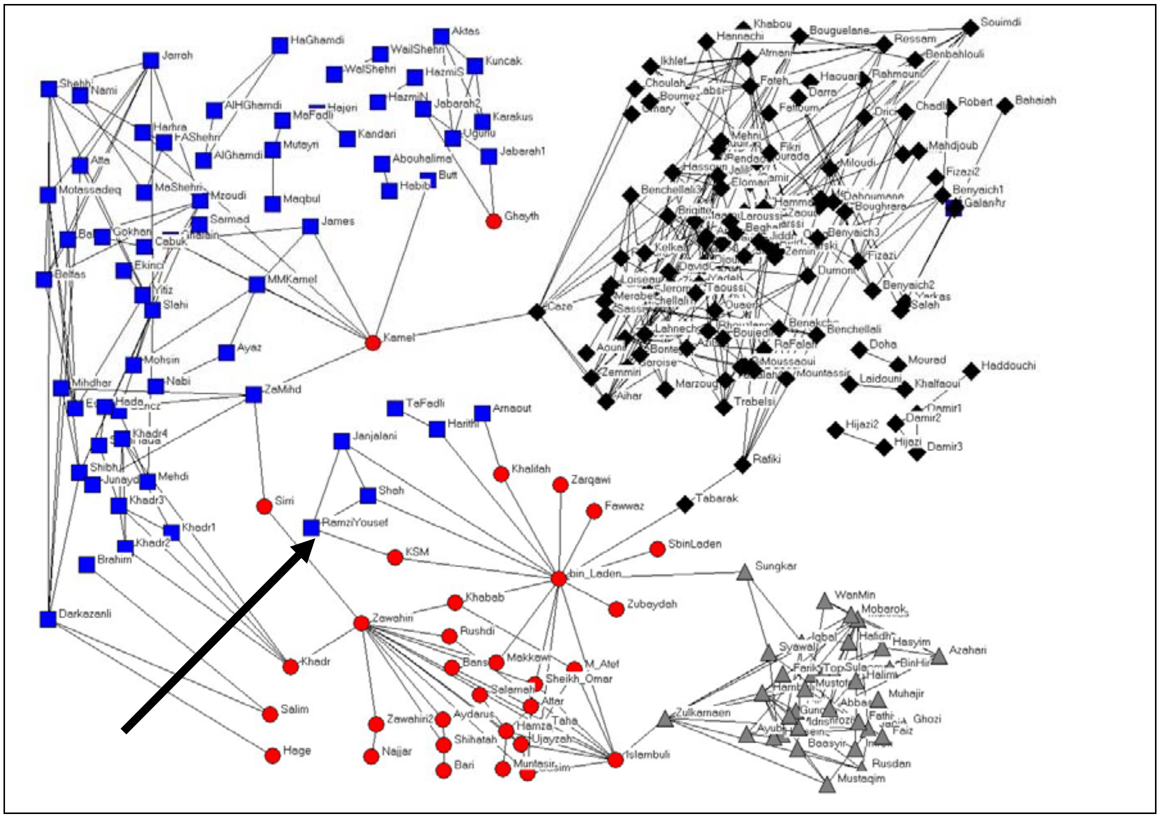

Figure 4-11: Network Representation of Al Qaeda based on Acquaintance, Nuclear Family, and Other Relative Ties Highlighting Ramzi Yousef; created in Ucinet 6

The focused analysis of Ramzi Yousef supports the classification produced by the Discriminant Function, that is, Yousef was likely misclassified by Sageman. Based on open source data, Ramzi Yousef appears to be a top-level planner for Al Qaeda. Ramzi Yousef was convicted on September 11, 1996 of masterminding the 1993 World Trade Center bombing (Mylroie, 1995; CNN, 1996; MSNBC, 2004). Ramzi has also been linked to assassination plots against the Pope and former President William J. Clinton (Mairesse, 2005; CNN, 1996; MSNBC, 2004). In addition, Yousef's "Project Bojinka" plan laid the groundwork for the September 11, 2001 attacks (CNN, 1996; Mairesse, 2005). If it is assumed that the Central Staff represents the leadership of Al Qaeda, the results of this analysis could have many implications. Yousef appears to have all the characteristics of the Central Staff; however he was not identified with them, suggesting that Discriminant Functions *may* be able to identify up and coming leaders, yet to be identified leaders, or passed over non-leaders. Each of these possibilities suggests a potential for exploitation.

4.6.2. Potential Pitfalls of Discriminant Analysis

Discriminant Analysis results are based on the assumption that one's data is continuous, and specifically multivariate normal. This demonstration, however, produced a Discriminant Function using both continuous and categorical predictor variables. Though a linear Discriminant Function can be developed from categorical variables, as in this demonstration, there is no guarantee of its optimality or even that good results are obtained (Dillon and Goldstein, 1984: 381).

The following example adapted from Dillon and Goldstein (1984: 382) highlights a situation in which a linear Discriminant Function performs poorly. Consider a group **G**, divided into two groups $\mathbf{G_1}$ and $\mathbf{G_2}$, and two categorical predictor variables **X1** and **X2** with three levels each. Let the observed values for the members of $\mathbf{G_1}$ and $\mathbf{G_2}$ on the predictor variables be as shown in Figure 4-12:

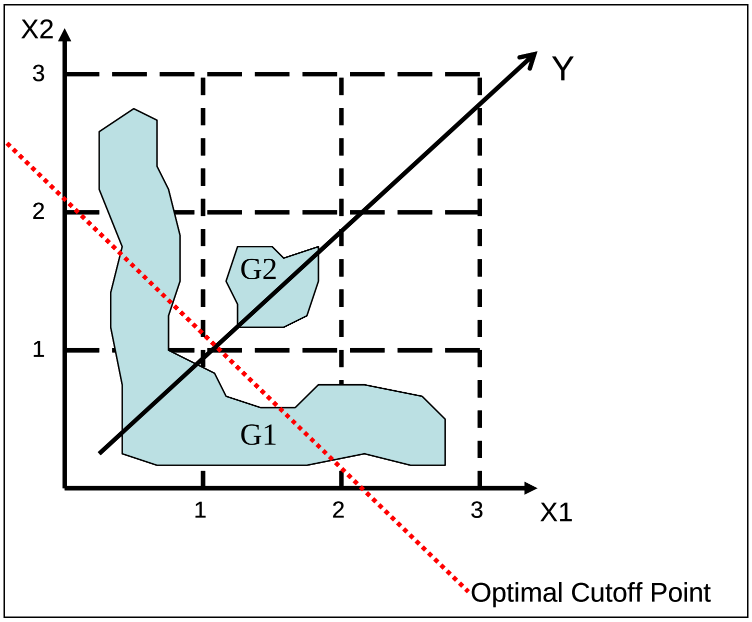

Figure 4-12: A situation in which the linear Discriminant Function performs poorly (Dillon and Goldstein, 1984: 382)

Discriminant Analysis was used to build the linear Discriminant Function, denoted as **Y** in Figure 4-12, to discriminate between $\mathbf{G_1}$ and $\mathbf{G_2}$. The optimal cutoff line however will not do a good job of assigning members to either group (Dillon and Goldstein, 1984: 382).

If, however, one views the space defined by **X1** and **X2** in terms of the nine independent regions formed by the combination of the categorical variables, "the separation and assignment of observations are much improved" (Dillon and Goldstein, 1984: 383). The dummy coding scheme used in this study views that categorical variables in terms of regions and *may* be able to capture the distinguishing characteristics. For this example, {**X1** = 2, **X2** = 2} could be represented by a dummy coding scheme, and would completely describe the observed values of $\mathbf{G_2}$ (Dillon and Goldstein, 1984: 384).

The reader is also cautioned about model building for small data sets. A general rule of thumb is that one candidate characteristic can be investigated for every 10 network members. In this demonstration seven characteristics were used in the final model of the 38 member Central Staff. The 10:1 rule is simply a rule of thumb, and it is possible to build appropriate models when one does not meet this condition (ITCSR, 2005). Each analysis is unique, however, and the reader is cautioned to check the validity of underlying assumptions *before drawing conclusions* based on Discriminant Analysis results.

4.6.3. Section Summary

The results of this analysis indicate that the Central Staff was different from the Rest of Al Qaeda on a subset of characteristics collected by Sageman. In addition, a statistically significant Discriminant Function for the Sageman data was produced that was able to provide a profile for the Central Staff as well as accurately predict group membership. It was also shown that misclassifications, if there are few, can be very important to an analysis. Further analysis of Ramzi Yousef, a Core Arab classified as Central Staff by the Discriminant Function, revealed a potential error in Yousef's initial classification. Yousef possesses many of the traits associated with the Central Staff, and he is also more closely connected to the Central Staff in the network of affiliations than he is to the Core Arabs. The in depth analysis of Ramzi Yousef highlighted the potential of a Discriminant Function to possibly uncover previously unidentified leaders in the Al Qaeda network. The final section summarizes the demonstration provided in Chapter 4.

4.7. Summary

This chapter has demonstrated the potential of Discriminant Analysis to support the modeling and analysis of clandestine networks. It was shown that Discriminant Analysis could be used to determine the underlying differences between two groups. In addition, a Discriminant Function was developed that could be used to both profile and classify group members. The ability of a Discriminant Function to validate SNA measures of individual importance was also shown. Further it was shown that these measures could be used to distinguish between group members. The identification of distinguishing demographic and social network characteristics that enable profiling and classification could prove to be a vulnerability for clandestine networks that can be exploited by operators. The analysis of misclassified members highlights the ability of a Discriminant Analysis to uncover previously unknown group members. The result of detailed analysis of misclassified members also provides an opportunity for exploitation. Given sufficient data, this methodology could be applied to various groups of interest to support operations against clandestine networks, aiding an analysts search for key pressure points and vulnerabilities.

5. Methodology Demonstration and Analysis Results II

5.1. Introduction

The Holistic Interpersonal Influence Measure (HIIM) developed in this thesis provides a unique capability for analysts to evaluate interpersonal influence within a clandestine network based on individual characteristics and multiple social network relations. Further, the measurement theory properties of the HIIM are appropriate for use with techniques such as Operations Research (OR) Network Flow models. Through these tools, analysts are able to provide prescriptive results that focus on specific actions and their outcomes which is a new capability for SNA analysts.

In this chapter, the methodology developed in Chapter 3 is applied using the open source data on the Al Qaeda terrorist network collected by Marc Sageman (Sageman, 2004). A subset of 48 Al Qaeda members were identified as members of the Jemaah Islamiah terrorist network by appropriate subject matter experts (SMEs). Special thanks are due to Dr. Sageman for graciously allowing the use of his data set. The following steps are followed in this implementation:

Step 1: Description of Sageman's Jemaah Islamiah Data
Step 2: Statement of Analysis Objectives
Step 3: Create Individual Influence Measures with Discriminant Analysis
Step 4: Create Pair-wise Interpersonal Influence Measures for Each Network
Step 5: Develop Network Weights to Enable Simultaneous Network Analysis
Step 6: Create the Holistic Interpersonal Influence Measure (HIIM) Network
Step 7: Demonstrate Network Flow Application of HIIM Network
Step 8: Demonstrate Fuzzy Clique Analysis Application of HIIM Network

5.2. Jemaah Islamiah

Jemaah Islamiah (JI) is a terrorist group based in Southeast Asia. The attack by JI on a nightclub in Bali in 2002 brought the group to the world's attention and forced increased concern with Southeast Asian governments. Their primary goal is to establish an Islamic government throughout Indonesia, Malaysia, Singapore and parts of the Philippines and Thailand. The two most important reasons to focus time and resources on the elimination of the threat from JI are 1) their links to Al Qaeda and the role they play in global terrorism; and 2) the threat they pose to the governments and economies of Southeast Asia.

JI is primarily important to the U.S. military because there exist multiple links between JI and Al Qaeda dating back to the war between Afghanistan and the former Soviet Union. The relationships between JI leadership and Al Qaeda leadership have given JI a more global focus, and as such they have supported many Al Qaeda operations including the Sept 11, 2001 bombing of the World Trade Center in the United States. In addition, JI is an extension of Al Qaeda's global reach, providing training, safe haven, and recruits to a global terror network. Finally, they are a major threat in the Pacific Region, an major area of responsibility for the DOD.

JI is also important to the United States military, in the long term, because they endeavor to violently replace democracy in Southeast Asia with an Islamic extremist government and disenfranchise over 400 million people. Indonesia, Malaysia, Singapore, the Philippines, and Thailand are emerging economic powers in Southeast Asia that interact heavily with the economies of the United States and Japan. Conversely, U.S. and Japanese economies rely on these nations for inexpensive imported goods. The threat that JI poses to the economies of these Southeast Asian nations can have a direct impact on the economies of the U.S. and Japan.

JI is clearly a dangerous terrorist organization with the capability of inflicting significant damage to the governments, economies, and populous of Southeast Asia. The increased focus on JI over the last three years by local governments, the United States, and Australia, has led to the arrest of over 200 JI members including its two most high profile leaders; Abu Bakar Baasyir—JI's spiritual leader, and Riduan Isamuddin a.k.a. Hambali—JI's operational mastermind and reportedly its strongest link to Al Qaeda. To this point authorities are not certain of the effect of these arrests on JI; however, JI targets have been limited to soft targets since the arrest of Hambali.

Because of the uncertainty surrounding the current operational capabilities of JI, it is important for the U.S. military to continue to develop and exploit JI susceptibilities and vulnerabilities until we are certain they no longer pose a threat to the nation and our allies.

5.3. Description of JI Data

The Jemaah Islamiah (JI) data used in this demonstration is a subset of 48 terrorists from Sageman's (Sageman, 2004) Al Qaeda data set described in Chapter 4. Terrorists were identified as JI members by appropriate Department of Defense (DOD) subject matter experts (SMEs). Further, because this study focuses on influence based partly on leadership characteristics, the SMEs also developed a leadership classification scale to which they assigned JI members. The leadership classifications are summarized in Table 5-1.

Table 5-1: Jemaah Islamiah Member Classifications

Leadership Level	Description of Members
1	Emir Types (Senior Leaders/Founders)
2	Trusted Second Tier/ Key Counselors and Facilitators / Leadership Council
3	Regional/District Leaders / Key Operatives / Unit Commanders / Liaisons
4	Operatives who provide support or followers who often risk arrest, physical injury or death; i.e.. execute missions / foot soldiers

For the remainder of this chapter JI members classified as Level 1 (6 members) are referred to as the *"Emirs"*, Level 2 JI (6 members) are referred to as the *"Colonels"*, Level 3 JI (19 members) are referred to as the *"Captains"*, and the Level 4 (17 members) are referred to as *"Troops"*.

Sageman's data set consists of demographic data, affiliation data from pre-existing informal networks, and affiliation data from networks formed after "joining the Jihad" for 48 JI members. Sageman, however, was unable to gather complete information for every JI member in his data set. Incomplete demographic data for JI members are referred to as Missing Data. Table 4-1 summarizes the data categories collected by Sageman:

Table 5-2: Data Categories Collected by Sageman (2004)

Demographic Data		Social Network
Continuous	**Categorical**	**Affiliations**
Age joining the jihad	Children	Acquaintance
Date of birth	Country Joined the Jihad	Friendship
Year joined the jihad	Educational achievement	Links Post Joining
	Family Socioeconomic Status	Nuclear Family
	Marital Status	Operation involvement
	Occupation	Place joined the jihad
	Place of birth	Relatives (not Nuclear Fam)
	Religious Background	Teacher-Student Network
	Role in Organization	Religious Leader
	Social background	Ties not in sample
	Type of education	
	Youth National Status	

The JI dataset contains 94 predictor variables, 3 continuous, 12 categorical (23 columns when Dummy Coded), and 17 networks and network combinations (4 centrality measures for each) which must each be evaluated for their potential to discriminate between groups. The Dummy Variable coding scheme applied to the categorical JI data is shown in Table 5-3.

The large number of variables makes Forward Stepwise Variable Selection (FSVS) an attractive exploratory analysis tool. FSVS is the most widely used automatic search technique, and is recommended when there are 40 or more predictor variables under consideration (Neter, *et al*., 1996: 347). In order to quickly perform an exploratory analysis of the JI data to identify potential variables for inclusion in a Discriminant Function, a FSVS was employed.

FSVS has several weaknesses; it only identifies a single "best" model instead of several "good" models, it can potentially identify a poor model, and it can overestimate the significance of variable coefficients (Neter, *et al*., 1996: 348). FSVS should only be used as exploratory analysis tool to identify potential variables for inclusion in ones model. The potential variables should then be used in a confirmatory analysis to verify their importance in discriminating between groups. During this analysis FSVS was used strictly as an exploratory analysis tool.

Table 5-3: Dummy Variable Coding Scheme for Sageman JI Data

Dummy Variable Coding Scheme for JI Data						
Youth National Status	**Column 1**	**Column 2**		**Socio-Eco Status**	**Column 1**	**Column 2**
Native	0	0		Lower	0	0
2nd Generation/Minority	1	0		Middle	1	0
Immigrant	0	1		Upper	0	1
Religious Background	**Column 1**	**Column 2**		**School**	**Column 1**	**Column 2**
non-Muslim	0	0		Christian	0	0
Secular	1	0		Secular	1	0
Religious	0	1		Madrassa	0	1
Occupation	**Column 1**	**Column 2**		**Married**	**Column 1**	
Unskilled	0	0		Not Married	0	
Semi-prof	1	0		Married	1	
Profesional	0	1				
Education Type	**Column 1**	**Column 2**	**Column 3**		**Kids**	**Column 1**
HS or Vocational	0	0	0		No	0
Hum	1	0	0		Yes	1
Soc Sci	0	1	0			
Tech/Nat Sci	0	0	1			
Criminal Background	**Column 1**	**Column 2**	**Column 3**			
None	0	0	0			
Criminal	1	0	0			
Political Activism	0	1	0			
Both	0	0	1			
Education	**Column 1**	**Column 2**	**Column 3**	**Column 4**	**Column 5**	
Less than High School	0	0	0	0	0	
High School Grad	1	0	0	0	0	
Some College	0	1	0	0	0	
Bachelor's	0	0	1	0	0	
Master's	0	0	0	1	0	
Doctorate	0	0	0	0	1	

It should be noted that Sageman's JI data set only contains data for 48 members, many of whom have been arrested or killed. Further, the data set was last updated in 2003. The reader is cautioned against the extension of these results to current operations directed against the JI network based on the small sample size and age of the data. The results presented in this chapter are done so strictly for the purpose of demonstration. The approach outlined here, however, could be applied to a current data set *if* and *when* available.

5.4. Analysis Objectives

The analysis in this chapter is presented to demonstrate the application of the HIIM to improve ones understanding of clandestine networks. The primary objectives of the analysis conducted this chapter are to determine:

- Which JI "Emir" is most influential
- Which JI members (non-"Emir") are likely to succeed the current leaders
- How JI subgroups are interrelated

In addition to the primary objectives, the secondary objectives were develop:

- Operational profile for JI leaders
- Operational profile for JI rank and file

5.5. Development of Individual Influence Measure

In this section, Discriminant Analysis is used to develop a measure of individual influence for JI members based on individual characteristics. The reader is reminded that in addition to developing a measure of influence, Discriminant Analysis can also be used to differentiate between groups, build an operational profile of a group, and build a classifier that can be used to determine to which group newly identified members belong.

5.5.1. Discriminant Analysis of "Emir" Group

To perform a Discriminant Analysis of the "Emir" group, the JI data was divided into two groups, G1 ("Emirs") and G2 (Rest of JI). The Discriminant Function built for the "Emirs" required only two predictor variables, Acquaintance Network degree centrality and Religious Leader Network degree centrality, to produce a statistically significant classifier. To determine if the Discriminant Function produced a significant difference between the average discriminant scores of G1 and G2, Hotelling's T-test was performed (Lattin *et al.*, 2003: 447-448). The null hypothesis for this test is that the mean of G1 is equal to the mean of G2; the alternative is that they are different:

$$H_o : \mu_1 = \mu_2$$
$$H_a : \mu_1 \neq \mu_2$$

The hypothesis test results are summarized in Figure 5-1.

$$\boxed{F_{obs} = 13.4497 \;\; >> \; \mathrm{F}_{.05;\,(2,29)} \; = 0.0514}$$

Figure 5-1: Hotelling's T-test results for JI "Emir" Discriminant Function

Based on Hotelling's T-test, the Discriminant Function was determined to be significant at the $\alpha = 0.5$ level. In addition to the T-test, overall classification accuracy of the Discriminant Function was evaluated to determine its quality. Table 5-4 shows the classification accuracy of the Discriminant Function. The two misclassified leaders, Iqbal and Rusdan are discussed in greater detail later in the chapter.

Table 5-4: Classification Accuracy of Discriminant Function Built for "Emirs"

Classification Accuracy for Predicting Level 1			
		Predicted Membership	
		Level 1	Other
Actual	Level 1	4	2
Membership	Other	0	42
Overall Classification Accuracy 95.8%			

Figure 5-2 shows the Operating Characteristic (OC) curve for the Discriminant Function. The OC curve can enable decision makers to perform risk tradeoffs based on the number of correctly classified "Emirs" to the number of incorrectly classified non-"Emirs" by changing the membership threshold. Based on this example, one could adjust the membership threshold such that the Discriminant Function correctly classifies all “Emirs” with 2% of non-“Emirs” misclassified.

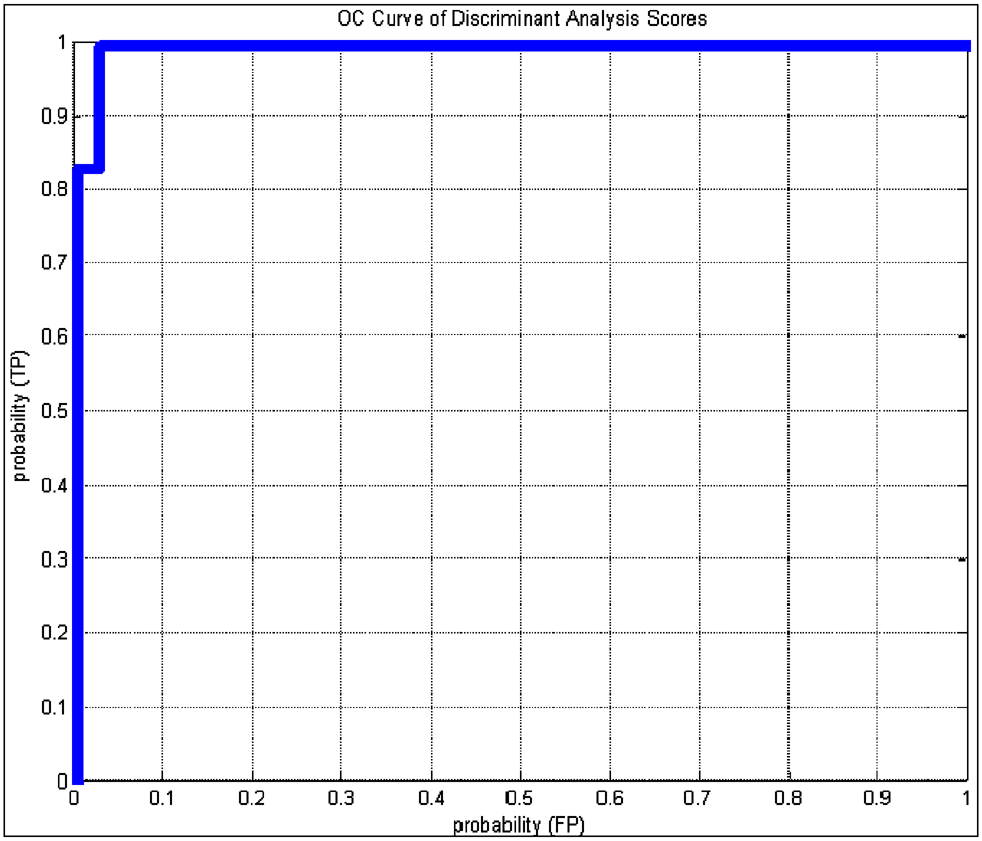

Figure 5-2: Operating Characteristic Curve of “Emir” Discriminant Function

Based on the T-test results and the overall classification accuracy of the Discriminant Function one is justified in developing an operational profile of the “Emirs” based on the beta coefficients and Discriminant Loadings for the predictor variables. However, based on the sample size and age of the data set it is not recommended that these profiles be extended for use in current operations. Table 5-5 shows the Discriminant Function coefficients and Discriminant Loadings for the two significant predictor variables.

Table 5-5: Beta Coefficients and Discriminant Loadings of Significant Predictor Variables

Variable Contribution for Level 1 Members			
Characteristic	**beta**	**Discriminant Loading**	**p-value**
Acquaintance--Degree	0.3095	0.6551	< 0.0001
Religious Leader--Degree	0.1505	0.6858	< 0.0001

Positive coefficients in the Discriminant Function indicate that the “Emirs” degree centrality values for both networks were larger than the remainder of JI, indicating that the “Emirs” in general have more direct contact with network members than other JI members. Figure 5-3 graphically depicts the “Religious Leader” network for JI. “Emirs” are indicated by circles, “Colonels” are indicated by squares, “Captains” are indicated by triangles, and “Troops” are indicated by diamonds. Figure 5-3 clearly shows the importance of Baasyir and Sungkar, the founders of JI, because they are the religious leaders of the majority of JI.

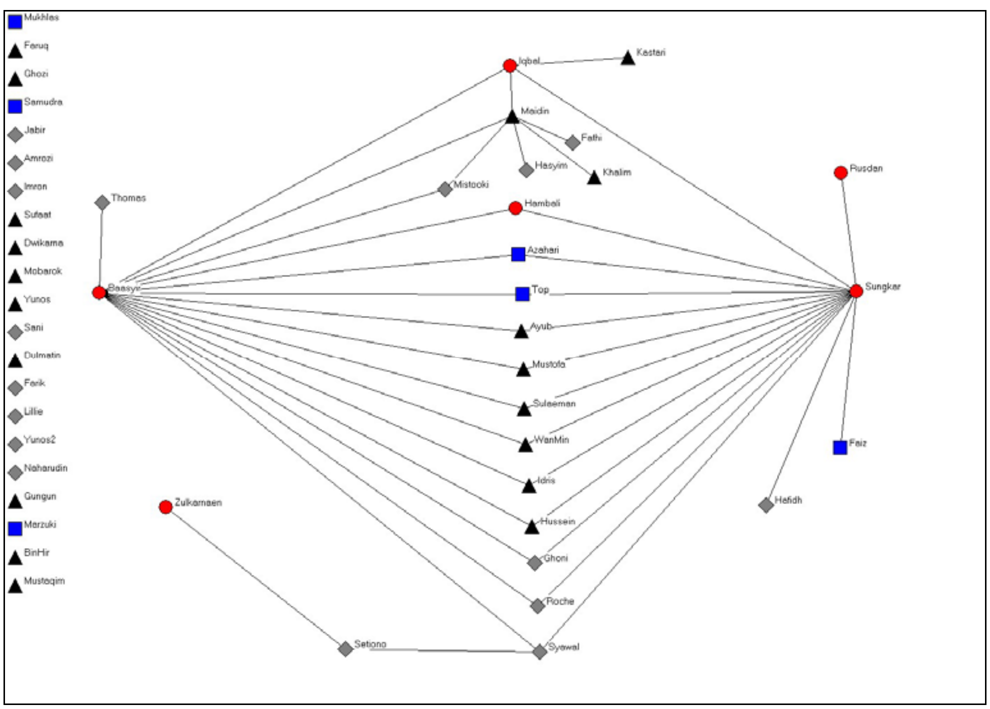

Figure 5-3: JI Religious Leader Network created in UCINET 6

The Discriminant Function produced to discriminate between the "Emir" group and the Rest of JI was ultimately used to produce posterior probabilities of membership in the leadership group. Because the individual influence measure developed in this thesis is based on ones possession of leadership characteristics, the posterior probabilities listed in Table 5-6 serve as a proxy measure of individual influence that are used in the final development of the HIIM network. Remembering that the elements of $\mathbf{H} = [h_{ij}]$ are defined as:

$$h_{ij} = w_{ij} e_i \,,$$

the posterior probabilities form the vector $\mathbf{E} = [e_i]$, where e_i is the posterior probability of member i. Because probabilities are ratio type numbers the influence measures can be easily interpreted, for example Baaysir (0.8236) has approximately twice as much individual influence as Iqbal (0.4189)

Table 5-6: Posterior Probability of Membership in "Emir" Group

Member	Classification	a priori group	Predicted Group	Posterior Probabililty
Baasyir	1	1	1	0.8236
Sungkar	1	1	1	0.5557
Hambali	1	1	1	0.7325
Mukhlas	2	0	0	0.0509
Iqbal**	1	1	0**	0.4189
Faruq	3	0	0	0.0142
Syawal	4	0	0	0.0362
Ghozi	3	0	0	0.0038
Samudra	2	0	0	0.0038
Jabir	4	0	0	0.2789
Amrozi	4	0	0	0.0038
Imron	4	0	0	0.0038
Sufaat	3	0	0	0.0038
Dwikarna	3	0	0	0.0074
Mobarok	3	0	0	0.0142
Yunos	3	0	0	0.027
Mistooki	4	0	0	0.0073
Faiz	2	0	0	0.0053
Hasyim	4	0	0	0.0053
Sulaeman	3	0	0	0.0073
Hussein	3	0	0	0.0073
Ayub	3	0	0	0.0265
Azahari	2	0	0	0.0139
Zulkarnaen	1	1	1	0.5072
Ghoni	4	0	0	0.0073
Top	2	0	0	0.0139
Idris	3	0	0	0.0139
Mustofa	3	0	0	0.0501
WanMin	3	0	0	0.0501
Maidin	3	0	0	0.0256
Sani	4	0	0	0.0038
Dulmatin	3	0	0	0.0038
Farik	4	0	0	0.0074
Lillie	4	0	0	0.0074
Yunos2	4	0	0	0.0038
Naharudin	4	0	0	0.0038
Gungun	3	0	0	0.0038
Marzuki	2	0	0	0.0038
Kastari	3	0	0	0.0053
Hafidh	4	0	0	0.0101
Setiono	4	0	0	0.0073
BinHir	3	0	0	0.0038
Rusdan**	1	1	0**	0.0688
Mustaqim	3	0	0	0.0509
Fathi	4	0	0	0.0053
Khalim	3	0	0	0.0053
Roche	4	0	0	0.0073
Thomas	4	0	0	0.0053

** indicates misclassified by Discriminant Function

5.5.2. Discriminant Analysis of the "Troops"

Because this analysis has been focused on measuring influence based on leadership characteristics, Discriminant Analysis has only been used to discriminate the leadership group from other subgroups. Discriminant Analysis, however, is a flexible analysis technique that can be used to develop a profile for any subgroup of interest. This section briefly highlights the results of a Discriminant Analysis performed to illustrate the creation of a profile of the "Troops" in JI.

The Discriminant Function built was significant at the $\alpha = 0.5$ level. Table 5-7 shows the classification accuracy of the Discriminant Function.

Table 5-7: Classification Accuracy of Discriminant Function built for "Troops"

Classification Accuracy for Predicting Level 4			
		Predicted Membership	
		Level 4	Other
Actual	Level 4	15	2
Membership	Other	1	30
Overall Classification Accuracy 93.75%			

The quality of the Discriminant Function makes building an operational profile appropriate, however the reader is cautioned against extending these results based on the size and age of the data set. Table 5-8 contains the Discriminant Function coefficients and Discriminant Loadings for the key variables used to discriminate between the "Troops" and the Rest of JI.

Table 5-8: Discriminant Function Coefficients and Discriminant Loadings for "Troops"

Variable Contribution for Level 4 Members			
Characteristic	**beta**	**Discriminant Loading**	**p-value**
Youth National Status--Immigrant	7.285	0.2409	0.023
Occupation--SemiProfessional	-11.6518	-0.2067	< 0.0001
Occupation--Professional	-8.8457	-0.2887	< 0.0001
Year Joined JI	0.593	0.2553	0.029
Friendship--Closeness	3.1366	0.1296	<0.0001

In general, "Troops" were immigrants who grew up in countries that they did not call home. The negative coefficients on Occupation indicate that the "Troops" tend to have non-professional jobs. Further, the "Troops" joined JI later than the other groups. The positive coefficient for Friendship Network closeness centrality indicates that the "Troops" are generally groups of friends. Figure 5-4 graphically displays the "Friendship" network for JI. "Emirs" are indicated by circles, "Colonels" are indicated by squares, "Captains" are indicated by triangles, and "Troops" are indicated by diamonds. Figure 5-4 highlights the various pre-existing friendship groups within JI. The graph reveals that about two-thirds of the "Troops" permeate the Friendship network. Further, Figure 5-4 reveals that Jabir (Troop) is a common friend to both Hambali ("Emir") and Iqbal ("Emir"); the potential importance of Jabir is discussed later in this chapter.

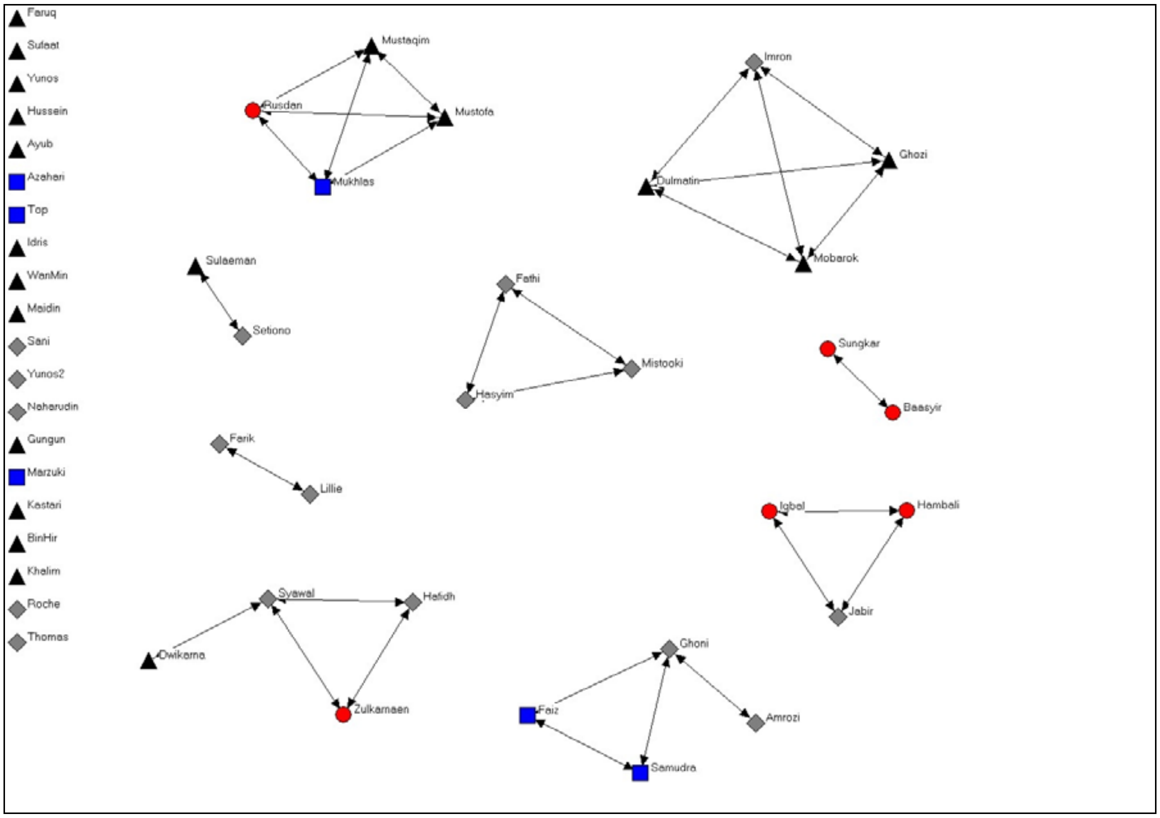

Figure 5-4: Graphical Representation of JI Friendship Network created in UCINET 6

5.5.3. Section Summary

The Discriminant Analysis results presented in this section highlighted the development of a proxy measure of individual influence for the members of JI. The development of a meaningful measure of non-network influence is critical to the development of the HIIM network and the modeling of network influence in general. The influence measures produced in this section are used to develop the final HIIM network in Section 5.8. In addition, the Discriminant Analysis results presented in this section satisfied the secondary analysis objectives of developing operational profiles of the “Emirs” and “Troops” of JI. The development of the HIIM network requires both non-network and network measures of influence. The next section describes the development of pair-wise measures of interpersonal influence based solely on network topology.

5.6. Development of Interpersonal Influence Measures

By definition clandestine networks are organizations that must operate in secrecy. Erickson (Erickson, 1981: 188) states that "risk enforces recruitment along lines of trust," which causes clandestine networks to use pre-existing networks of relationships. The trust premium paid by clandestine organizations is their reliance on pre-existing networks. In this section, pair-wise measures of interpersonal influence are developed for each of JI's informal networks based on Sageman's data. The networks considered were the Acquaintance Network ($\mathbf{I_1}$), Nuclear Family Network ($\mathbf{I_2}$), Relative Network ($\mathbf{I_3}$), Friendship Network ($\mathbf{I_4}$), Teacher-Student Network ($\mathbf{I_5}$), and Religious Leader Network ($\mathbf{I_6}$). For the purposes of this demonstration it was assumed that the affiliation data is complete and correct. For a discussion on the impacts of missing affiliation data, the reader is referred to Sterling (Sterling, 2004: 133-146).

5.6.1. Analysis of Individual Networks

Pair-wise measures of individual influence based on network topology were developed for each informal social network using the Information Centrality methodology developed in Chapter 3. This section briefly discusses the results of applying the Information Centrality methodology to three informal JI networks. Due to the size of the resultant matrices (48×48), only a small portion of each network is highlighted. The results highlighted, however, are representative of the results for the entire network. The complete results are available in Appendix A.

Information Centrality accounts for all direct and indirect connections between network members, and larger scores indicate more connections. Table 5-9 contains the pair-wise interpersonal influence measures for a (5×5) subset of JI members based on the Acquaintance Network. The values in each cell are ratio numbers and can easily be interpreted. The influence between Baasyir and Hambali (1.73) is approximately three times larger than the influence between Baasyir and Sungkar (0.64), based on Sageman's data for this particular network. In addition, because it was assumed that each network was based on undirected arcs, the resultant matrix of interpersonal influence values is symmetric.

Table 5-9: Subsection of Acquaintance Network Pair-wise Influence Measures based on Information Centrality

Acquaintance Network					
	Baasyir	**Sungkar**	**Hambali**	**Mukhlas**	**Iqbal**
Baasyir	0.00	0.64	1.73	1.24	1.78
Sungkar	0.64	0.00	0.64	0.56	1.00
Hambali	1.73	0.64	0.00	2.32	1.75
Mukhlas	1.24	0.56	2.32	0.00	1.28
Iqbal	1.78	1.00	1.75	1.28	0.00

Figure 5-5 provides a graphical representation of the interpersonal influences within the Acquaintance Network for the subgroup in Table 5-9. The thickness of the arcs represented in Figure 5-5 represent the level of influence, thicker arcs imply greater influence.

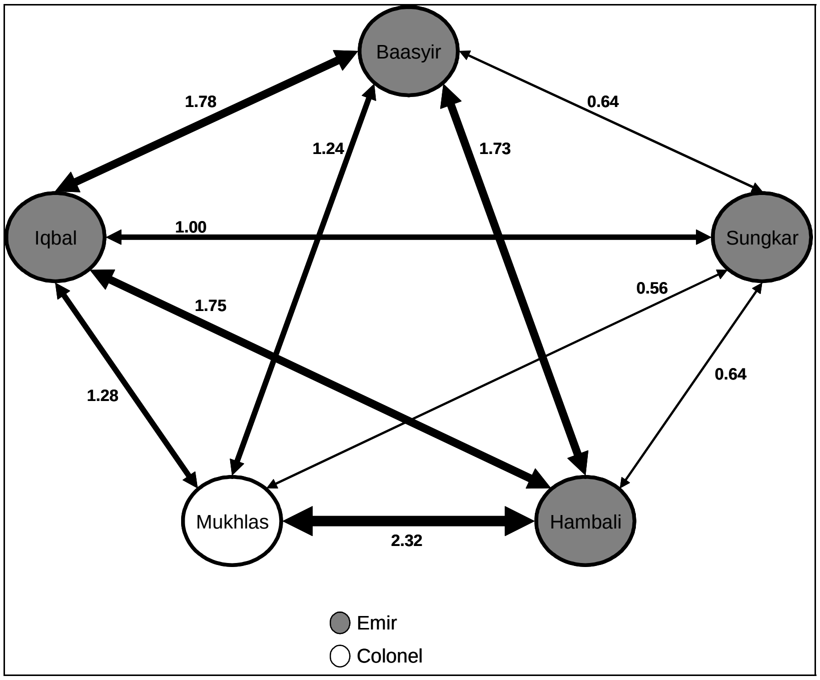

Figure 5-5: Network Representation of Acquaintance Network Interpersonal Influence

The Acquaintance Network was shown to be an indicator of JI leadership based on Discriminant Analysis, and as such, analysis of this network *may* provide a reasonable representation of the network. However, a tenet of this study is that multiple networks should be considered simultaneously. Analysis of JI's Friendship Network provides a very different picture of JI's interpersonal influence. Table 5-10 contains the pair-wise interpersonal influence measures for the same (5×5) subset of JI members based on the Friendship Network.

Table 5-10: Subsection of Friendship Network Pair-wise Influence Measures based on Information Centrality

Friendship Network					
	Baasyir	**Sungkar**	**Hambali**	**Mukhlas**	**Iqbal**
Baasyir	0.00	1.00	0.00	0.00	0.00
Sungkar	1.00	0.00	0.00	0.00	0.00
Hambali	0.00	0.00	0.00	0.00	1.50
Mukhlas	0.00	0.00	0.00	0.00	0.00
Iqbal	0.00	0.00	1.50	0.00	0.00

Table 5-10 and Figure 5-6 offer a very different representation of influence among the subset if JI highlighted. In this network there are much fewer connections, as well as dramatic changes in the amount of influence between members. The difference in these network structures highlights the very real possibility that an analysis focused on a single network context can result in inappropriate conclusions about influence within a clandestine network.

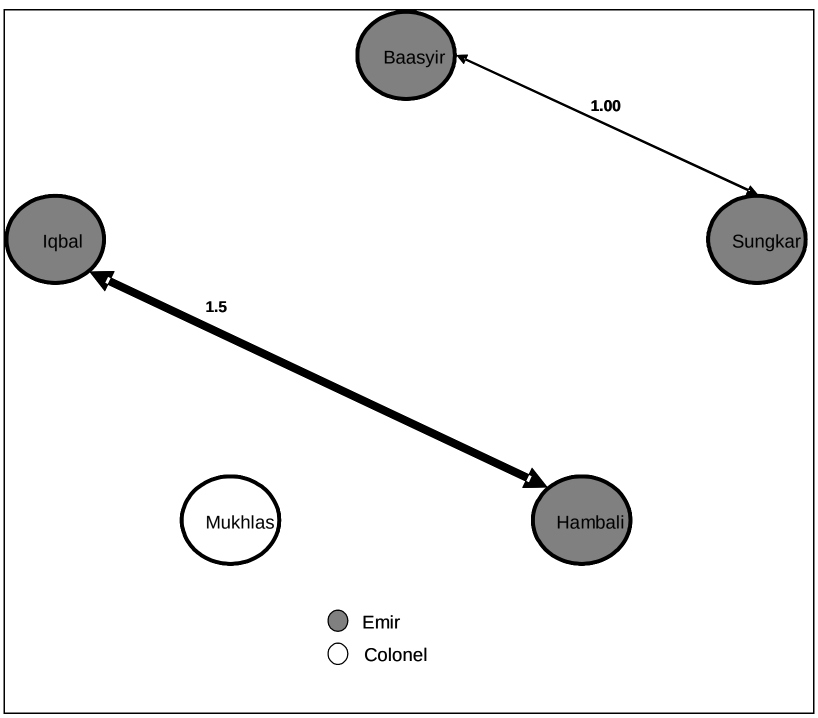

Figure 5-6: Network Representation of Friendship Network of Interpersonal Influence

Finally, the results based on the Teacher-Student Network are offered to highlight the vastly different relationship structures that exist in multiple network levels. Table 5-11 contains the pair-wise interpersonal influence measures for the (5×5) subset of JI members based on the Teacher-Student Network.

Table 5-11: Subsection of Teacher-Student Network Pair-wise Influence Measures based on Information Centrality

Teacher-Student Network					
	Baasyir	**Sungkar**	**Hambali**	**Mukhlas**	**Iqbal**
Baasyir	0.00	6.50	0.44	1.86	0.44
Sungkar	6.50	0.00	0.44	1.86	0.44
Hambali	0.44	0.44	0.00	0.36	1.00
Mukhlas	1.86	1.86	0.36	0.00	0.36
Iqbal	0.44	0.44	1.00	0.36	0.00

Table 5-11 and Figure 5-7, again offer a different view of interpersonal influence among JI members.

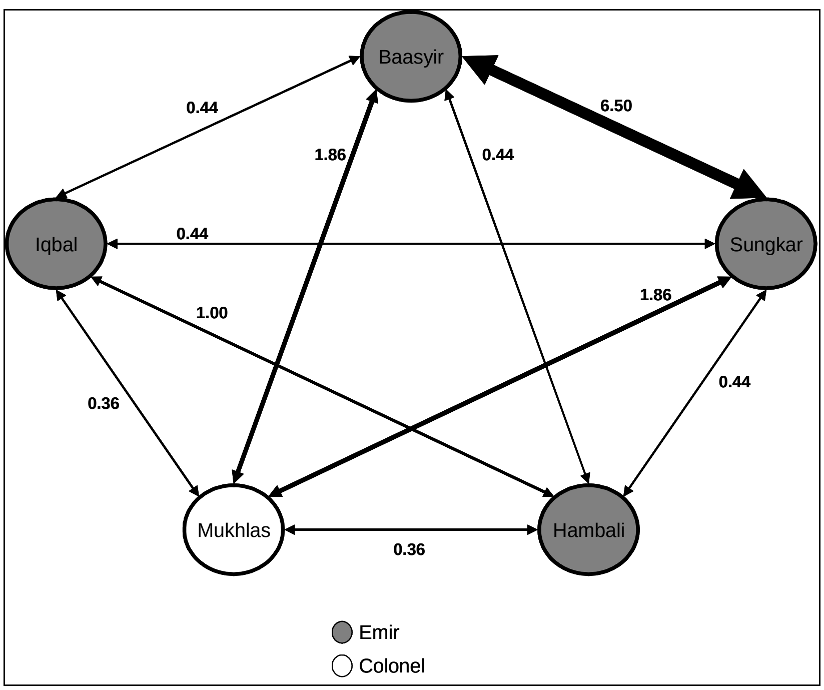

Figure 5-7: Network Representation of Teacher-Student Network of Interpersonal Influence

5.6.2. Section Summary

This section has highlighted the results of computing pair-wise measures of interpersonal influence for the informal networks of JI based on the Sageman data. The results clearly show the differences in influence relationships between network members in different contexts. While it *may* be possible to accurately model a clandestine network on the basis of a single network context, these results indicate that it may be more appropriate to consider each network simultaneously.

5.7. Development of Network Weights

The combined network of interpersonal influences was defined in Chapter 3 as a linear combination of the interpersonal influences from *each* informal network to which clandestine network members belong. The multi-layered influence measure for JI is represented by:

$$W = \lambda_1 I_1 + \lambda_2 I_2 + \lambda_3 I_3 + \lambda_4 I_4 + \lambda_5 I_5 + \lambda_6 I_6$$

$$\sum_{i=1}^{6} \lambda_i = 1$$

where $\mathbf{I_i}$ is the matrix of pair-wise interpersonal influences from network *i* as defined in the previous section, and w_i is the perceived importance of network context *i* in determining influence within JI.

Proper weighting of each network is *critical*; however an analysis of appropriate weighting techniques is beyond the scope of this research. Analysts are cautioned to carefully consider the impact and appropriateness of network weights and weighting techniques for their decision problem. For the purposes of this demonstration the networks were assigned equal weights, λ_i = 1/6. Based on this weighting scheme the combined network of interpersonal influences was created. Table 5-12 contains the pair-wise interpersonal influence measures for the (5×5) subset of JI members based on the linear combination of *each* informal network.

Table 5-12: Subsection of Combined Network Pair-wise Influence Measures based on Information Centrality

Combined Network					
	Baasyir	**Sungkar**	**Hambali**	**Mukhlas**	**Iqbal**
Baasyir	0.00	2.46	0.67	0.52	0.78
Sungkar	2.46	0.00	0.49	0.40	0.62
Hambali	0.67	0.49	0.00	0.45	0.90
Mukhlas	0.52	0.40	0.45	0.00	0.27
Iqbal	0.78	0.62	0.90	0.27	0.00

The combined influence measures w_{ij} in each cell represent the average overall influence between JI members based *solely* on network topology. The values are ratio type numbers, and can be interpreted as such. For example, the influence between Baasyir and Sungkar (2.46) is approximately four times larger than the influence between Baasyir and Hambali (0.67). Figure 5-8 provides a graphical representation of combined interpersonal influence based on each informal JI network in Sageman's data.

The combined network, **W**, provides an average measure of influence between JI network members based on *each* informal network to which they belong. This measure is limited however, because it is based on connections within undirected networks. The implication of these undirected connections is that members will have equal influence over one another as shown in Figure 5-9.

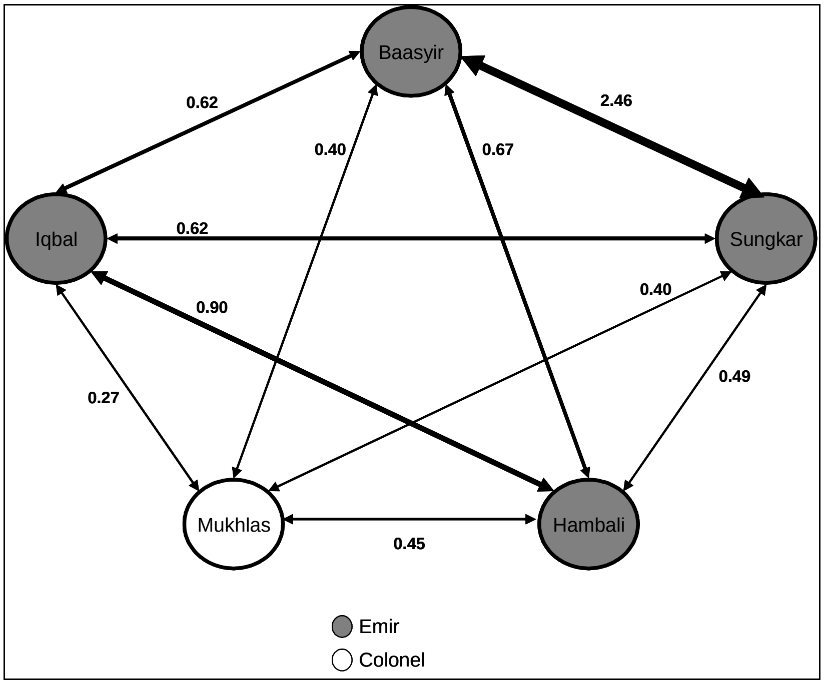

Figure 5-8: Network Representation of Combined Network Interpersonal Influence

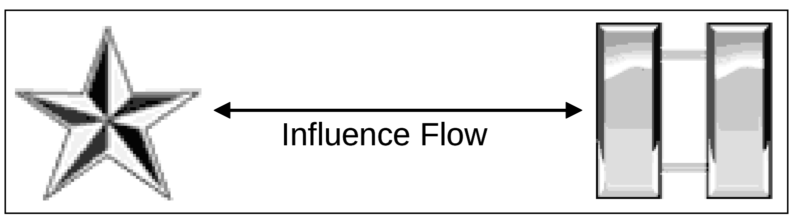

Figure 5-9: Implication of Undirected Influence Arcs

Further, this symmetry will hold for all network members. To provide greater insight into the network, the interpersonal influence measures must be considered with the individual influence measures.

5.8. Creation of the Holistic Interpersonal Influence Measure

The Holistic Interpersonal Influence Measure (HIIM) was defined in Chapter 3 as the matrix $\mathbf{H} = [h_{ij}] = [w_{ij}e_i]$ where h_{ij} represents the average pair-wise interpersonal influence of member *i* over member *j*. A portion of the HIIM network calculated for JI is shown in Table 5-13.

Table 5-13: Subsection of Holistic Interpersonal Influence Measure (HIIM) Network for JI

HIIM Network					
	Baasyir	**Sungkar**	**Hambali**	**Mukhlas**	**Iqbal**
Baasyir	0.00	2.03	0.55	0.43	0.64
Sungkar	1.37	0.00	0.27	0.22	0.34
Hambali	0.49	0.36	0.00	0.33	0.66
Mukhlas	0.03	0.02	0.02	0.00	0.01
Iqbal	0.33	0.26	0.38	0.11	0.00

The HIIIM network is a directed network of ratio type numbers that offer simple interpretations, where larger numbers indicate greater influence. Baasyir's influence over Iqbal (0.64) is approximately twice Iqbal's influence over Baasyir (0.33). Further, Baasyir's influence over Sungkar (2.03) is approximately four times greater than Baasyir's influence over Hambali (0.55).

The implication of the directed arcs in the HIIM network, as shown in Figure 5-10, suggest that it is possible to accurately represent both network topology based influence as well as individual characteristic based influence. The HIIM network enables a more accurate picture of influence than either network or non-network measures alone.

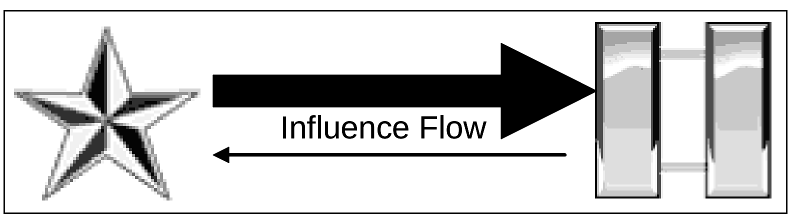

Figure 5-10: Implication of Directed Arcs in the HIIM Network

Figure 5-11 provides a graphical representation of the HIIM network calculated for JI based on Sageman's data for the discussed subgroup.

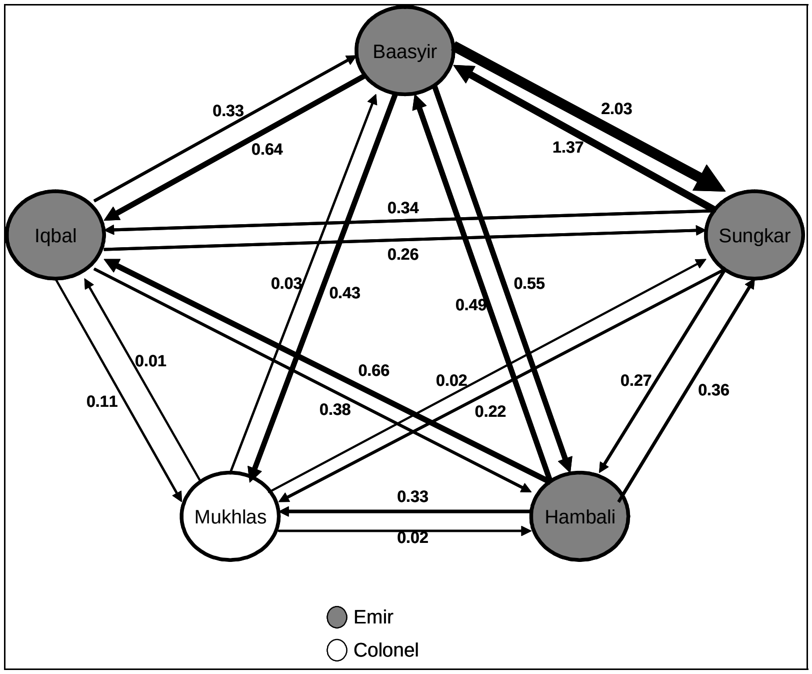

Figure 5-11: Network Representation of the HIIM Network

The HIIM network provides the analyst insight into the influence relationships between JI members. In addition, because of the measurement properties of the influence arcs, the HIIM network is appropriate for use in a variety of analysis techniques. The next two sections will demonstrate applications of the HIIM network using various analysis techniques. Individual importance is considered in a Single Commodity Network Flow model, and cohesive subgroups are analyzed using Fuzzy Clique analysis techniques.

5.9. Single Commodity Flow Model Example

One of the primary goals of SNA is the identification of the "most important" actors within a social network (Wasserman and Faust, 1994: 169). SNA results, however, are limited due to the "lack of advantageous properties" of the relationship measures applied to the arcs in a social network (Renfro, 2001; Renfro and Deckro, 2004). Renfro and Deckro (Renfro, 2001; Renfro and Deckro, 2004) state that Operations Research (OR) techniques can extend and refine SNA with results that are "measurable, quantifiable, and organized in a manner that allows for specific courses of action to be evaluated."

The HIIM network offers an alternative to traditional SNA techniques by enabling simultaneous consideration of multiple network and non-network characteristics. Further, the relationship arcs within the HIIM network are appropriate for Operations Research (OR) Network Flow models. To identify the "Emir" with the most influence over JI operations, the HIIM network was mapped to a Single Commodity Network Flow model. This section highlights the results of calculating the maximum flow of influence from each JI "Emir" to the "Troops".

5.9.1. Maximum Flow Mapping

Renfro (Renfro, 2001: 95) offers a taxonomy of social network concepts mapped to network flow modeling; the mapping offered in this section is based on Renfro's work. In a capacitated network, a maximum flow problem attempts to send as much flow as possible between a source node, *s*, and a sink node *t* (Ahuja et al., 1993: 166). Let arc x_{ij} represent the magnitude of potential influence flow between members *i* and *j*. Let h_{ij} represent the capacity of arc x_{ij} such that

$$0 \le x_{ij} \le h_{ij} \, .$$

The maximum flow problem can formally be stated as follows:

Maximize: z

Subject to:

$$\sum_j x_{sj} - z = 0$$

$$\sum_j x_{ij} - \sum_j x_{ji} = 0, \forall i$$

$$z - \sum_i x_{it} = 0$$

$$0 \le x_{ij} \le h_{ij}, \forall i, j$$

5.9.2. Maximum Flow Results

To determine which of the six "Emirs" has the most potential influence over the "Troops", six separate maximum flow problems were solved. In each of the problems one of the "Emirs" was identified as the source node, *s*. Further, because the maximum influence flow to all "Troops" was desired a super sink node, *t*, was created along with infinite capacity arcs emanating from each Troop and terminating at node *t*. The greatest maximum flow from a source node found in these problems will correspond to the "Emir" able to exert the greatest potential influence over the "Troops" based on Sageman's data.

Table 5-14 shows the maximum flows from the "Emirs" to the "Troops" for the JI network.

Table 5-14: Maximum Flow from "Emirs" to "Troops"

Maximum Potential Influence Flow from Level 1 Emirs to Level 4 Troops	
Leader	**Flow**
Baasyir	9.00
Sungkar	6.15
Hambali	5.86
Iqbal	3.74
Zulkarnaen	4.47
Rusdan	0.55

The maximum flow results reveal that Baasyir has the most potential influence over the "Troops" based on Sageman's data. In general, maximum flow results will identify persons to neutralize or marginalize. Further, because of strong duality, by solving the maximum flow problem from *s* to *t*, one has solved the complementary minimum *s*-*t* cut problem (Ahuja et al., 1993: 167). An *s*-*t* cut separates a network into two components such that *s* and *t* are in different components; a minimum *s*-*t* cut is the *s*-*t* cut whose capacity is the minimum among all *s*-*t* cuts. The arcs identified in the *s*-*t* cut represent the set of connections that, when removed, will isolate the "Emir" from the "Troops".

5.9.3. Parametric Analysis of Maximum Flow

To determine the influence of the "Emirs" over the "Troops" based on different weightings of network and non-network influences, Θ (theta), was varied from 0 to 1; $\Theta = 0$ will consider influence based solely on network topology, while $\Theta = 1$ will consider influence based solely on individual characteristics. Figure 5-12 shows the results of a parametric analysis of the maximum flow from the "Emirs" to the "Troops" for $\Theta = 0$, 0.1. 0.2,…, 1.

The results of the parametric analysis offer more insight into the importance of each "Emir" in JI. Baasyir has the greatest potential influence over the "Troops" across all levels of Θ. As the problem transitions from considering strictly network based influence to non-network influence Hambali becomes more influential than Sungkar. This shift helps to indicate the nature of Hambali's and Sungkar's power base. The results could be interpreted by inferring that Sungkar is better connected, but Hambali is more revered. Further, if current intelligence estimates indicated Hambali was more influential within JI, these results would suggest choosing a value a Θ greater than 0.5 to accurately model influence within JI.

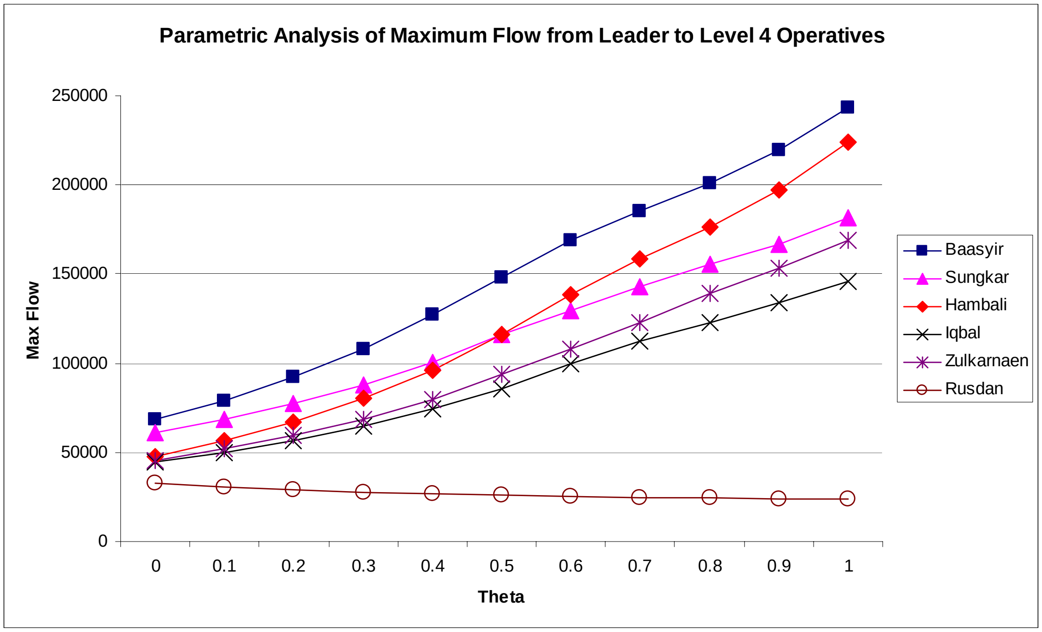

Figure 5-12: Parametric Analysis of Maximum Flow from "Emirs" to "Troops"

The "Emir" identified as least influential, Rusdan, stands out because his profile is very different from the others. Rusdan's maximum flow profile has many possible operational interpretations. First, his profile could suggest that there is inadequate information available to accurately model his influence. Second, he may have been misclassified originally as an "Emir", and these results in combination with the Discriminant Analysis performed earlier could be used to change his classification. Finally, if Rusdan is an "Emir", his profile suggests he may be the least revered in the group. If one wanted to neutralize an "Emir" without creating a martyr, the results of the analysis indicate that Rusdan may be the appropriate target. Again, the results would be used by knowledgeable intelligence analysts and other knowledgeable operators to focus their efforts.

5.9.4. Section Summary

This section has highlighted the results of mapping the HIIM network created for JI into a single commodity maximum flow problem. The results indicate that Baasyir is the most influential "Emir". These results could easily be extended to identify the minimum arc, node, or mixed cut set that would separate each "Emir" from the "Troops". Further, post optimality analysis of the results could be performed to determine the changes in h_{ij} that would change the results, that is someone other than Baasyir being most influential. The parametric analysis offers further insight into the JI network. Baasyir was shown to be the most influential "Emir" across all values of Θ. It was also shown, however, that as network characteristics or non-network characteristics are weighed more heavily, the level of influence of Sungkar and Hambali flip. Given a complete and up to date data set, cut-sets and post optimality analysis results could be utilized as a part of a campaign to neutralize or marginalize any of the "Emirs".

Although no explicit comparison has been made to traditional SNA measures, it has been shown implicitly that key individuals identified based on analysis of the HIIM network are more likely to be representative of actual leadership within the group of interest. Discriminant Analysis results from Section 5.5 identified degree centrality in the Acquaintance and Religious Leader networks as discriminating characteristics for JI "Emirs". Other networks and centrality measures, however, by their absence from the Discriminant Function suggest they are not likely to identify the leaders of JI. Analysts attempting to identify JI leadership using traditional SNA measures are more likely produce inaccurate pictures of the influence within JI than if they based their results on the HIIM network.

5.10. Fuzzy Clique Analysis

One of the major concerns of SNA is the identification and analysis of cohesive subgroups (Wasserman and Faust, 1994: 249). The traditional graph theoretic subgroup detection techniques discussed in Chapter 2 are *all* limited to binary undirected networks. Further, each of the traditional techniques are limited to evaluating a single network. It has been argued throughout this paper that informal networks should be evaluated simultaneously. Traditional SNA subgroup analysis techniques applied to JI for this demonstration, however, produce results with limited applicability; for example a 3-clique within JI produces a single group with 42 (of 48) members, and a 3-plex identifies 16762 subgroups.

The fuzzy clique analysis techniques developed by Yan (Yan, 1987), however, enable analysts to evaluate subgroups based on the interpersonal influence measures developed in the HIIM. To evaluate the relationships between the SME identified subgroups in JI, Yan's fuzzy clique analysis techniques were employed. This section highlights the results of the fuzzy clique analysis of JI. Note that the SME classifications do not satisfy the mathematical definition of clique; however, the subgroups are appropriate for Yan's measures. For further discussion on creation of subgroups when SMEs are not able to provide them, the reader is referred to *Aggregation Techniques to Characterize Social Networks* (Sterling, 2004).

5.10.1. Node Membership Value

The membership value of a node, m_i, is a measure of how important a node is within its own clique. Yan's definition of membership value is based on distance, and therefore members who are close to many members will have a higher membership value. Yan's definition can be modified to model influence by changing to definition of *n'* to the number of nodes in the clique over whom *i*'s influence is greater than some threshold D. Define $|A|$ as the number of directed edges in a particular clique. For the purposes of this demonstration D is defined as the average influence flow between subgroup members:

$$D = \frac{\sum_{(i,j)} h_{ij}}{|A|} .$$

Table 5-15 shows the membership values for each member of the "Emir" group. Based on these results Baasyir and Hambali are the most important members of the "Emir" group, followed by Sungkar. This implies that Baasyir and Hambali have above average influence over four out of the 5 other members in the "Emir" group, while Sungkar has above average influence over only one other "Emir". Operationally, these results suggest that Baasyir and Hambali are the core of JI's leadership.

Table 5-15: Membership Values for Members of the "Emir" Group

Node Membership Value for Emir Group	
Baasyir	0.8
Sungkar	0.2
Hambali	0.8
Iqbal	0
Zulkarnaen	0
Rusdan	0

5.10.2. Clique-Clique Coefficient

The clique-clique coefficient, c_{mn} is a measure of the relationship between two separate cliques. Yan's clique-clique coefficient definition, again, is based on distance, however, the definition can be modified to model influence by defining Q_{ij} as the influence of node *i*, in clique *m*, over a node *j* in clique *n*. The node-clique formulation then becomes

$$c_{mn} = \frac{\sum_{i \in c_m} \sum_{j \in c_n} Q_{ij}}{|c_m||c_n|}$$

$$Q_{ij} = h_{ij} .$$

shows the clique-clique coefficients between JI groups based on influence outflow. These results indicate that the "Emirs" are the key operational players in the JI network because they have the predominant amount of influence over every other subgroup. The identified influence structure is surprising, because the relationships are counter to traditional military or hierarchical network relationships. A traditional influence flow would be from the "Emirs" to the "Colonels", from the "Colonels" to the "Captains", and then from the "Captains" to the "Troops". Table 5-16 shows the clique-clique coefficient scores between each pair of JI subgroups. Figure 5-13 provides a graphical representation of the between group influences within JI based on the clique-clique coefficient.

Table 5-16: Clique-Clique Coefficients for JI Subgroups

Clique-Clique Coefficients for JI Levels		
From Level	To Level	Clique-Clique Coefficient
1	2	0.1277
1	3	0.1250
1	4	0.1254
2	3	0.0044
2	4	0.0054
3	4	0.0047

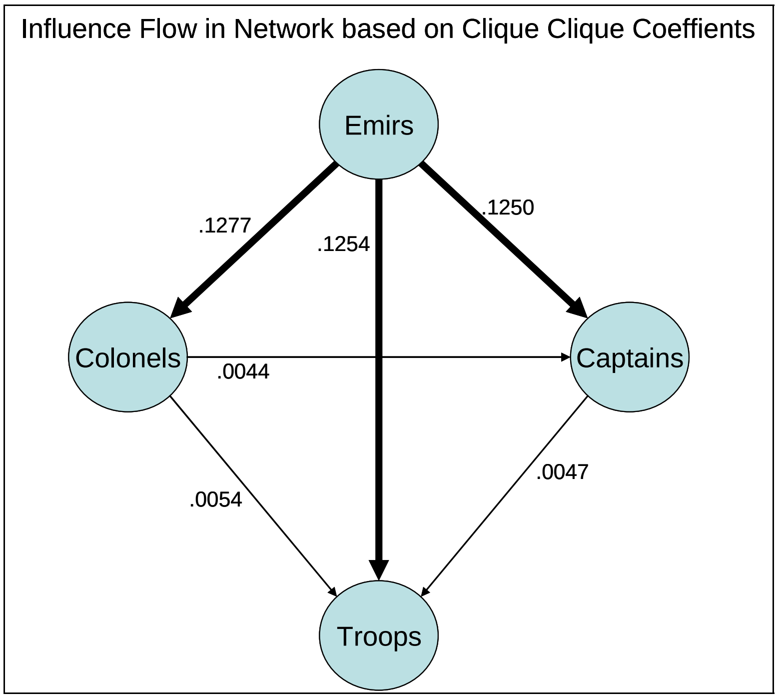

Figure 5-13: Network Representation of JI Influence Structure Based on Clique-Clique Coefficients

5.10.3. Node-Clique Coefficient

The node-clique coefficient, n_{ic}, is a measure of node i's relationship to a clique c of which i is *not a member*. Yan's node-clique coefficient definition is again based on distance; however, the definition can be modified to model influence by defining Q_{ij} as the influence of node *i*, not in clique *c*, over a node *j* in *c*. The node-clique formulation then becomes

$$n_{ic} = \sum_{j=1}^{m} (Q_{ij}) / |c|$$

$$Q_{ij} = h_{ij} .$$

Table 5-17 shows the non-"Emirs" with the highest node-clique coefficients for the "Emir" group. These results suggest that the six identified members have the most influence with the "Emir" group based on Sageman's data. Jabir, identified as a friend to both Hambali and Iqbal in Figure 5-6, has the highest node-clique coefficient. There are several interpretations of these results. Each of these individuals clearly warrant closer inspection based on their relationships with the "Emir" group. Further, these results *may* indicate that these individuals are key deputies outside of the "Emir" subgroup. For the remainder of this study, the JI members identified in Table 5-17 are referred to as the Up-and-Comers.

Table 5-17: Node-Clique Coefficients for non-"Emirs" to the "Emir" Group

Node-Clique Coefficients for non-Level 1 Members		
Name	**Classification**	**Node-Clique Coefficient**
Jabir	4	0.3548
Syawal	4	0.3112
Mustaqim	3	0.2692
Mustofa	3	0.2503
Mukhlas	2	0.2366
Yunos	3	0.2057

5.10.4. Parametric Analysis of Node-Clique Coefficient

The fuzzy clique analysis results from the previous section were each analyzed parametrically, however only the node-clique coefficient results are highlighted in this section. Parametric analysis results for Node Membership Value and Clique-Clique Coefficient are provided in Appendix A. To determine the node-clique coefficients of JI members to the "Emir" group based on different weightings of network and non-network influences, Θ (theta), was varied from 0 to 1; Θ = 0 will consider influence based solely on network topology, while Θ = 1 will consider influence based solely on individual characteristics. Figure 5-14 shows the results of a parametric analysis of node-clique coefficients for Θ = 0, 0.1. 0.2,…, 1.

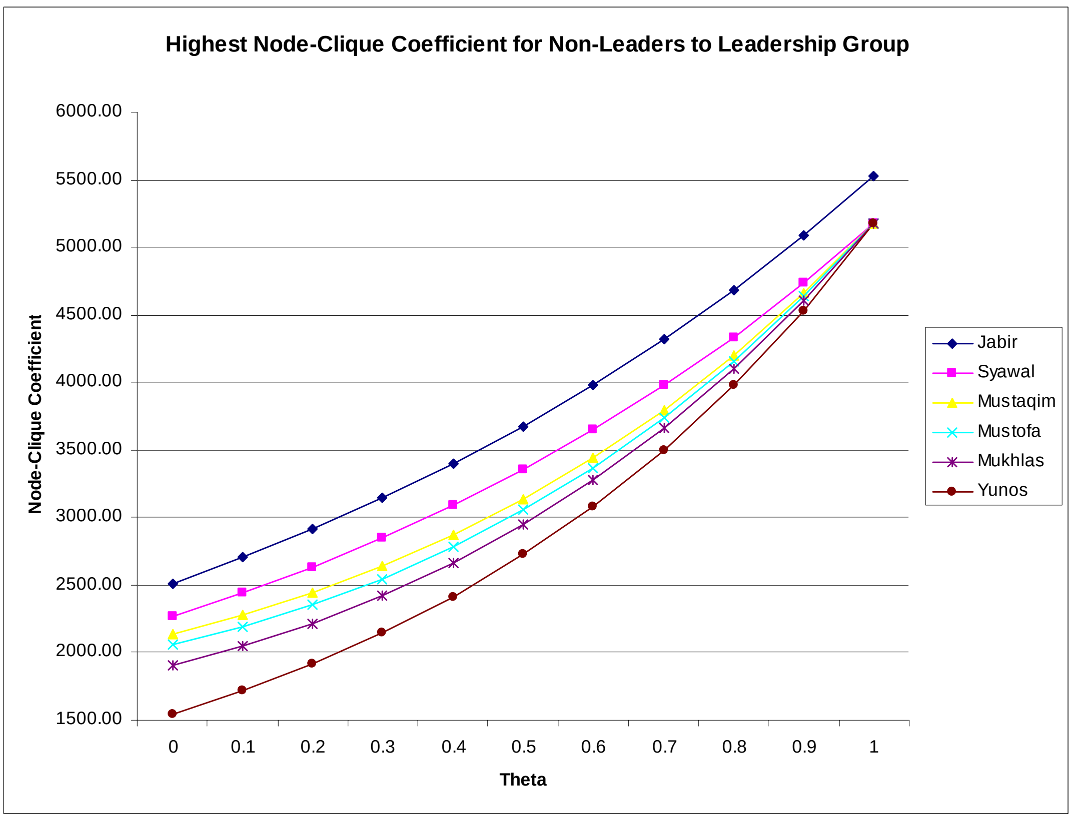

Figure 5-14: Parametric Analysis of Node-Clique Coefficients for JI members to the "Emirs"

Figure 5-14 reveals that Jabir has the most influence with the “Emir” group across all values of Θ. Jabir’s higher node-clique coefficient value is likely based on his pre-existing friendships with Hambali and Iqbal as shown in Figure 5-6. Further, as Θ transitions from zero to one, the node-clique coefficient values of the other five Up-and-Comers identified converge. When only non-network characteristics are considered, these five members have identical node-clique coefficient values. This result suggests that the Up-and-Comers have similar personal characteristics.

A Discriminant Function was built for the Up-and-Comers to determine if there were individual characteristics that distinguished them from the Rest of JI; Table 5-18 shows the classification accuracy.

Table 5-18: Classification Accuracy of Discriminant Function for Up-and-Comers

Classification Accuracy for Predicting Up-and-Comers			
		Predicted Membership	
		Up-and-Comer	Other
Actual	**U-&-C**	4	2
Membership	**Other**	1	41
Overall Classification Accuracy 95.8%			

Table 5-19 shows the misclassified JI members based on the Discriminant Function built for the Up-and-Comers. The classification of Rusdan (“Emir”) as an Up-and-Comer suggests that his individual characteristics are more similar to the Up-and-Comers than the Rest of JI.

Table 5-19: Misclassifications of Up-and-Comers

Misclassified Members	
Name	**SME Classification**
Rusdan	1
Yunos	3
Syawal	4

All of the previous analysis suggested that Rusdan was the least influential "Emir". These results suggest, however, that Rusdan may be part of a new generation of JI leadership. According to Agence France-Presse, Rusdan was appointed acting JI "Emir" after the arrests of Baasyir and Hambali (Agence, 2003). The results of this analysis indicate that it may be possible to build a profile of the next group of JI leaders.

Table 5-20 shows the Discriminant Function coefficients as well as the discriminant loadings for the Up-and-Comers. The discriminant loadings suggest that the Up-and-Comers were political activists prior to joining JI. In addition, the coefficients for the social networks indicate that the Up-and-Comers are connected to central members in the Acquaintance and Friendship networks, whereas they posses fewer direct connections themselves. In short, it appears that the Up-and-Comers are outspoken individuals connected to the right people.

Table 5-20: Beta Coefficients and Discriminant Loadings for Up-and-Comers

Variable Contribution for Up-and-Comers			
Characteristic	**beta**	**Discriminant Loading**	**p-value**
Criminal Background--Political Activisim	10.8921	0.37	0.036
Acq-Friend--Eigenvector	0.6047	0.6566	< 0.0001
Acquaintance--Degree	-1.5081	0.3917	0.0005

5.10.5. Section Summary

This section has highlighted the results of analyzing JI subgroups. Based on node membership value, Baasyir and Hambali were identified as the core members of the "Emir" group. In addition, the relationships between each JI subgroup was evaluated using the clique-clique coefficient. The clique-clique coefficient revealed that the influence of the "Emir" group dominates JI relationships. This *may* suggest that JI operations are run directly from the top.

The node-clique coefficient was used to identify JI members with the most influence with the "Emir" group. Jabir, who is the friend of both Hambali and Iqbal, was shown to have the most influence with the "Emir" group across all values of Θ, which *may* indicate that he is in line to be promoted to a leadership position within JI. The node-clique coefficients of the other Up-and-Comers were shown to be identical when only non-network characteristics were considered. A Discriminant Function was developed to identify the distinguishing characteristics of the Up-and-Comers. The least influential "Emir", Rusdan, was misclassified as an Up-and-Comer, suggesting that he *may* have been the first of the Up-and-Comers to be promoted. These Up-and-Comers warrant further investigation based on their relationships with the leadership group. In addition, the node-clique coefficient values *may* indicate that the Up-and-Comers are the key deputies and potential future leaders of JI.

The results from the section have highlighted the influence within, between, and amongst JI subgroups. Given a complete and up to date data set, as well as key intelligence analysis and SMEs, these techniques could be used to support operations against any clandestine network.

5.11. Chapter Summary

This chapter has demonstrated the potential of the HIIM to support the modeling and analysis of clandestine networks. It was shown that the elements of the HIIM network could be mapped to a maximum flow formulation to identify key individuals within a clandestine network. Mapping the HIIM network to Operations Research (OR) Network Flow models enables researchers to provide prescriptive analysis focused on specific operational outcomes. Further, because network flow models enable analysts to quickly identify alternate optimal solutions and perform post optimality analysis, the HIIM network will provide added utility to traditional SNA analysis that provides single point solutions.

In addition, the HIIM network was used to perform a fuzzy clique analysis, providing measures of influence within, amongst, and between subgroups. It was shown that these techniques could highlight the core group leaders, potentially identify the next generation of leaders, and uncover the influence relationships between the various subgroups within a clandestine network.

Finally, Figure 5-15 is offered to demonstrate the nature of influence within JI that was captured by the HIIM, in reference to the definition of influence provided in Chapter 1. The x-axis represents the ratio of each members topology based influence to the maximum influence within the network. The y-axis represents the ratio each members non-network based influence to the maximum influence within the network.

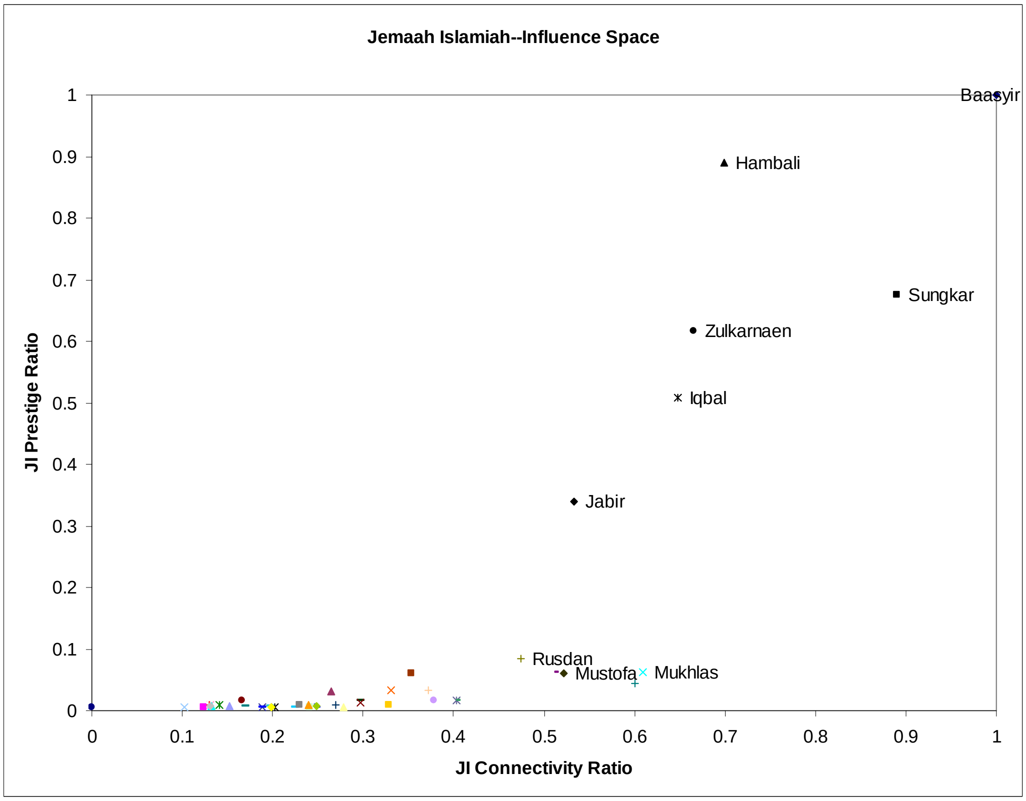

Figure 5-15: Jemaah Islamiah Influence Space

The majority of JI is clustered in the bottom left (least influential) corner of the chart. The operational interpretation of Figure 5-15 is that the JI members who stand out warrant continued and perhaps increased attention. These "most influential" members should represent an initial candidate set of JI personnel to be targeted through a neutralization or marginalization campaign. Due to the size and age of this data set, the results produced in this chapter are not intended for operational use and are provided only as a demonstration. Given sufficient data, however, this methodology could be applied to various groups of interest to support operations against clandestine networks, aiding an analysts search for key pressure points and vulnerabilities.

6. Summary and Recommendations

6.1. Introduction

This chapter will summarize the academic and operational contributions of the research conducted for this thesis. In addition, this chapter summarizes the analysis results presented in Chapters 4 and 5, and suggests recommendations for future research.

6.2. Contributions of the Research

The major contribution of this research is the development of a meaningful measure of interpersonal influence within clandestine networks, which considers both the *personal characteristics of individuals* and the *topology of each informal network* to which clandestine network members belong. The Discriminant Analysis methodology provides one of the first adequate discussions of the development of a non-network measure of influence compatible with Social Influence Network (SIN) theory. The linear combination of multiple network contexts provides an original, yet simple way to simultaneously evaluate influence from multiple network layers. Finally, because the influence measure is a ratio number it can be extended for use in a variety of analysis techniques.

The numeric properties of the Holistic Interpersonal Influence Measure (HIIM) are appropriate for use in a variety of analysis tools including Operations Research Network Flow models. Analysis of clandestine networks using Network Flow models enables analysts to provide *prescriptive* analysis results focused on specific actions and their outcomes, in contrast to traditional Social Network Analysis (SNA) *descriptive* results.

The capability to identify key leaders with the HIIM was implicitly compared to traditional SNA individual centrality measures. Typical SNA studies focus on a single informal social network; those studies that consider multiple networks consider each network independently. By considering *each* informal social network simultaneously the HIIM is much less likely to inappropriately identify non-leaders as leaders. In addition, it was shown that the Discriminant Analysis methodology can be used to validate the results of traditional SNA centrality measures.

The analysis methodology in this thesis provides a robust alternative to traditional SNA techniques. In general, the HIIM introduces no new data requirements over traditional SNA studies. In addition, because the intermediate steps required to develop the HIIM for a clandestine network are relatively straight forward to perform, the HIIM will provide a relatively firm basis to develop a user-friendly analysis tool, or can be easily integrated into tools currently in use by military and intelligence analysts.

6.3. Results of the Research

The HIIM analysis provides potentially meaningful operational results. It develops leadership profiles, identifies key leaders and potential next generation leaders. The HIIM methodology was applied to open source Al Qaeda data graciously provided by Dr. Marc Sageman (Sageman, 2004). The analysis was conducted in two phases. First, a Discriminant Analysis of Al Qaeda was used to develop an operational profile of Al Qaeda leadership. Second, the complete HIIM methodology was applied to the Jemaah Islamiah (JI) terror network.

Analysis results indicate that the leadership of Al Qaeda can be distinguished from the rank and file members. In addition, a statistically significant Discriminant

Function for the Sageman data was produced that was able to provide a profile for Al Qaeda leadership and accurately predict group membership. Further, analysis of misclassifications highlighted the ability of the Discriminant Function to uncover previously unidentified leaders within Al Qaeda. These results suggest that given appropriate data, one could develop an operational profile for any group of interest.

The JI analysis highlighted the broad spectrum of operational questions that could the HIIM could support. First, Discriminant Analysis was used to develop statistically significant operational profiles of both the top-level leadership group and the low-level operatives of JI. Mapping the HIIM to a Network Flow model and computing maximum flows from the top-level leadership to the low-level operatives identified the most influential JI leaders. Based on the maximum flow results, minimum arc-, node-, and mixed-cut-sets could quickly be identified that would isolate any JI leader from the low-level operatives. Further, using fuzzy clique analysis techniques, it was possible to identify the core of JI's leadership group. Fuzzy clique analysis also enabled the identification of potential next-generation leaders of JI. Parametric analysis of the results provided further insight into the nature of interpersonal influence within JI using non-network based influence, network topology based influence, and mixtures of non-network and network influences. The potential outputs produced using the HIIM methodology are summarized in Table 6-1. While provided for illustrative purposes only, the examples do indicate that the approach developed in this thesis can assist intelligence and counter terrorist analysts in identifying key factors and personnel for further analysis.

Table 6-1: Overview of HIIM Potential Outputs

Discriminant Analysis	Operational profiles; Classification rule (prediction); Measure of individual influence Validation of SNA Centrality Measures
Information Centrality	Measure of Interpersonal Influence based on network topology
Linear Combination, Network Weighting	Consideration of ***each*** informal network simultaneously
Holistic Interpersonal Influence Measure (HIIM)	Measure of interpersonal influence based on individual characteristics ***and*** network topology
Network Flow (Maximum Flow)	Identify members with greatest potential influence; Post optimality analysis; Alternate optimals
Fuzzy Clique Analysis	Identify core of subgroup; Identify members with influence over key subgroups; Highlight relationships between groups

6.4. Recommendations for Future Research

This research offers a starting point for the modeling and analysis of clandestine networks based on interpersonal influence between members. There are, however, many fruitful areas of future research. Since two year old open source data was used to demonstrate the methodology, most of these terrorists have been captured or killed; it would be useful to test the methodology on current, operationally relevant data.

The HIIM is appropriate for use in Network Flow models, however, only a maximum flow solution was presented in this thesis. There remain many Network Flow problem classes such as cut-sets, minimum cost network flow, and p-centers that are also applicable. Mapping Network Flow problem classes to specific operational problems involving clandestine networks could prove very beneficial.

Network topology based measures of influence may be improved by applying General Linear Modeling (GLM) theory. GLM and Designs of Experiments (DOE) can provide a convenient structure to evaluate social networks. GLM concepts such as the Hat Matrix, $\mathbf{H} = [h_{ij}]$, can provide a statistics based measure of influence with confidence bounds (Neter, *et al.*, 1996: 203). DOE can be used to improve the modeling of multiple network contexts by directly accounting for interactions between networks. Further, the aliasing structure in Designed Experiments may be useful in evaluating the impact of missing information.

The network topology based measures of influence discussed in this thesis considered the impact of all direct and indirect connections. The techniques considered all paths, dependent and independent. There are many cases, however, when only independent paths should be considered. Graph Theory provides techniques to identify all pair-wise independent paths. Measures of influence based on pair-wise independent paths may provide a more accurate representation of topology based influence.

Simultaneous evaluation of multiple network contexts will require a robust methodology to appropriately assign network importance weightings. A variety of techniques are available to facilitate solicitation of weights from subject matter experts (SME). The network weights will likely vary based on group culture. The field of Anthropology offers a rich discussion of the impacts of culture on group activities. Researchers are encouraged to consider the works of Anthropologists in addition to traditional value modeling literature.

Finally, there are a variety of software packages that support social network visualization. Network visualization is a powerful aid when performing exploratory analysis. In general, current network visualization tools are designed to display only a single network context. Social networks, as shown in this thesis, must be considered in multiple contexts simultaneously. Development of a multi-layered network visualization tool will be critical to future analysis. The images produced by any network visualization tool must be useful to analysts. An optimization study focused on maximizing desirable qualities within a graph while minimizing undesired qualities would be beneficial for single and multi-layered networks.

6.5. Conclusions

Modeling and analysis of clandestine networks using the HIIM provides a robust alternative to traditional SNA techniques. The research in this thesis can be used by military and intelligence analysts as an aid in understanding the influence relationships within a clandestine network, as well as aid in the planning and implementing of influence campaigns designed to disrupt clandestine network operations.

Appendix A: Jemaah Islamiah Outputs

A.1. Introduction

The analysis of Jemaah Islamiah presented in Chapter 5 was limited to a subset of the network because of the size of the resultant matrices. This appendix contains the complete Jemaah Islamiah analysis results performed during this study.

A.2. Topology Based Influence Measures

Information Centrality (Stephenson and Zelen, 1989) was used to calculate pair-wise measures of interpersonal influence for each of the six informal networks provided in the Sageman data. This section contains the complete (48x48) matrices created during this analysis.

A.2.1. Acquaintance Network

	Baasyir	Sungkar	Hambali	Mukhlas	Iqbal	Faruq	Syawal	Ghozi	Samudra	Jabir	Amrozi
Baasyir	0.0000	0.6404	1.7276	1.2420	1.7808	0.8483	0.8483	0.0000	0.0000	1.7276	0.0000
Sungkar	0.6404	0.0000	0.6365	0.5612	1.0000	0.4606	0.4606	0.0000	0.0000	0.6365	0.0000
Hambali	1.7276	0.6365	0.0000	2.3249	1.7508	1.4286	1.2500	0.0000	0.0000	3.3333	0.0000
Mukhlas	1.2420	0.5612	2.3249	0.0000	1.2787	0.9708	0.9708	0.0000	0.0000	2.3249	0.0000
Iqbal	1.7808	1.0000	1.7508	1.2787	0.0000	0.8539	0.8539	0.0000	0.0000	1.7508	0.0000
Faruq	0.8483	0.4606	1.4286	0.9708	0.8539	0.0000	1.4286	0.0000	0.0000	1.2500	0.0000
Syawal	0.8483	0.4606	1.2500	0.9708	0.8539	1.4286	0.0000	0.0000	0.0000	1.4286	0.0000
Ghozi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Samudra	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jabir	1.7276	0.6365	3.3333	2.3249	1.7508	1.2500	1.4286	0.0000	0.0000	0.0000	0.0000
Amrozi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Imron	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sufaat	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dwikarna	0.6404	0.5000	0.6365	0.5612	1.0000	0.4606	0.4606	0.0000	0.0000	0.6365	0.0000
Mobarok	0.6500	0.4025	0.7867	0.7040	0.6736	0.5344	0.5344	0.0000	0.0000	0.7867	0.0000
Yunos	1.3402	0.6436	2.1577	1.3879	1.8056	0.9403	0.9403	0.0000	0.0000	2.1577	0.0000
Mistooki	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Faiz	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hasyim	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sulaeman	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hussein	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Ayub	0.3939	0.2870	0.4403	0.4131	0.4025	0.3483	0.3483	0.0000	0.0000	0.4403	0.0000
Azahari	0.3565	0.2644	0.4115	0.5000	0.3594	0.3300	0.3300	0.0000	0.0000	0.4115	0.0000
Zulkarnae	1.8571	0.6736	3.6879	2.3780	2.0635	1.1479	1.1479	0.0000	0.0000	3.6879	0.0000
Ghoni	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Top	0.3565	0.2644	0.4115	0.5000	0.3594	0.3300	0.3300	0.0000	0.0000	0.4115	0.0000
Idris	0.2826	0.2230	0.3057	0.2924	0.2870	0.2583	0.2583	0.0000	0.0000	0.3057	0.0000
Mustofa	1.2420	0.5612	2.3249	1.5000	1.2787	0.9708	0.9708	0.0000	0.0000	2.3249	0.0000
WanMin	0.5540	0.3594	0.6992	1.0000	0.5612	0.4926	0.4926	0.0000	0.0000	0.6992	0.0000
Maidin	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sani	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dulmatin	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Farik	0.6334	0.3889	1.0000	0.6992	0.6365	0.5882	0.5556	0.0000	0.0000	0.7692	0.0000
Lillie	0.6334	0.3889	1.0000	0.6992	0.6365	0.5882	0.5556	0.0000	0.0000	0.7692	0.0000
Yunos2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Naharudin	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Gungun	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Marzuki	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Kastari	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hafidh	0.6404	0.5000	0.6365	0.5612	1.0000	0.4606	0.4606	0.0000	0.0000	0.6365	0.0000
Setiono	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BinHir	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rusdan	1.9403	0.6103	2.6396	1.6318	1.5663	1.0216	1.0216	0.0000	0.0000	2.6396	0.0000
Mustaqim	1.9403	0.6103	2.6396	1.6318	1.5663	1.0216	1.0216	0.0000	0.0000	2.6396	0.0000
Fathi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Khalim	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Roche	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Thomas	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

	Imron	Sufaat	Dwikarna	Mobarok	Yunos	Mistooki	Faiz	Hasyim	Sulaeman	Hussein	Ayub	Azahari
Baasyir	0.0000	0.0000	0.6404	0.6500	1.3402	0.0000	0.0000	0.0000	0.0000	0.0000	0.3939	0.3565
Sungkar	0.0000	0.0000	0.5000	0.4025	0.6436	0.0000	0.0000	0.0000	0.0000	0.0000	0.2870	0.2644
Hambali	0.0000	0.0000	0.6365	0.7867	2.1577	0.0000	0.0000	0.0000	0.0000	0.0000	0.4403	0.4115
Mukhlas	0.0000	0.0000	0.5612	0.7040	1.3879	0.0000	0.0000	0.0000	0.0000	0.0000	0.4131	0.5000
Iqbal	0.0000	0.0000	1.0000	0.6736	1.8056	0.0000	0.0000	0.0000	0.0000	0.0000	0.4025	0.3594
Faruq	0.0000	0.0000	0.4606	0.5344	0.9403	0.0000	0.0000	0.0000	0.0000	0.0000	0.3483	0.3300
Syawal	0.0000	0.0000	0.4606	0.5344	0.9403	0.0000	0.0000	0.0000	0.0000	0.0000	0.3483	0.3300
Ghozi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Samudra	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jabir	0.0000	0.0000	0.6365	0.7867	2.1577	0.0000	0.0000	0.0000	0.0000	0.0000	0.4403	0.4115
Amrozi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Imron	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sufaat	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dwikarna	0.0000	0.0000	0.0000	0.4025	0.6436	0.0000	0.0000	0.0000	0.0000	0.0000	0.2870	0.2644
Mobarok	0.0000	0.0000	0.4025	0.0000	0.6599	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.2924
Yunos	0.0000	0.0000	0.6436	0.6599	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.3976	0.3676
Mistooki	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Faiz	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hasyim	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sulaeman	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hussein	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Ayub	0.0000	0.0000	0.2870	1.0000	0.3976	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2262
Azahari	0.0000	0.0000	0.2644	0.2924	0.3676	0.0000	0.0000	0.0000	0.0000	0.0000	0.2262	0.0000
Zulkarnaen	0.0000	0.0000	0.6736	1.0000	1.9403	0.0000	0.0000	0.0000	0.0000	0.0000	0.5000	0.4131
Ghoni	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Top	0.0000	0.0000	0.2644	0.2924	0.3676	0.0000	0.0000	0.0000	0.0000	0.0000	0.2262	0.5000
Idris	0.0000	0.0000	0.2230	0.5000	0.2845	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.1845
Mustofa	0.0000	0.0000	0.5612	0.7040	1.3879	0.0000	0.0000	0.0000	0.0000	0.0000	0.4131	0.3750
WanMin	0.0000	0.0000	0.3594	0.4131	0.5812	0.0000	0.0000	0.0000	0.0000	0.0000	0.2924	1.0000
Maidin	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sani	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dulmatin	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Farik	0.0000	0.0000	0.3889	0.4403	0.6833	0.0000	0.0000	0.0000	0.0000	0.0000	0.3057	0.2915
Lillie	0.0000	0.0000	0.3889	0.4403	0.6833	0.0000	0.0000	0.0000	0.0000	0.0000	0.3057	0.2915
Yunos2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Naharudin	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Gungun	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Marzuki	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Kastari	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hafidh	0.0000	0.0000	0.5000	0.4025	0.6436	0.0000	0.0000	0.0000	0.0000	0.0000	0.2870	0.2644
Setiono	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BinHir	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rusdan	0.0000	0.0000	0.6103	0.7345	1.5663	0.0000	0.0000	0.0000	0.0000	0.0000	0.4235	0.3827
Mustaqim	0.0000	0.0000	0.6103	0.7345	1.5663	0.0000	0.0000	0.0000	0.0000	0.0000	0.4235	0.3827
Fathi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Khalim	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Roche	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Thomas	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

	Zulkarnaer	Ghoni	Top	Idris	Mustofa	WanMin	Maidin	Sani	Dulmatin	Farik	Lillie	Yunos2
Baasyir	1.8571	0.0000	0.3565	0.2826	1.2420	0.5540	0.0000	0.0000	0.0000	0.6334	0.6334	0.0000
Sungkar	0.6736	0.0000	0.2644	0.2230	0.5612	0.3594	0.0000	0.0000	0.0000	0.3889	0.3889	0.0000
Hambali	3.6879	0.0000	0.4115	0.3057	2.3249	0.6992	0.0000	0.0000	0.0000	1.0000	1.0000	0.0000
Mukhlas	2.3780	0.0000	0.5000	0.2924	1.5000	1.0000	0.0000	0.0000	0.0000	0.6992	0.6992	0.0000
Iqbal	2.0635	0.0000	0.3594	0.2870	1.2787	0.5612	0.0000	0.0000	0.0000	0.6365	0.6365	0.0000
Faruq	1.1479	0.0000	0.3300	0.2583	0.9708	0.4926	0.0000	0.0000	0.0000	0.5882	0.5882	0.0000
Syawal	1.1479	0.0000	0.3300	0.2583	0.9708	0.4926	0.0000	0.0000	0.0000	0.5556	0.5556	0.0000
Ghozi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Samudra	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jabir	3.6879	0.0000	0.4115	0.3057	2.3249	0.6992	0.0000	0.0000	0.0000	0.7692	0.7692	0.0000
Amrozi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Imron	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sufaat	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dwikarna	0.6736	0.0000	0.2644	0.2230	0.5612	0.3594	0.0000	0.0000	0.0000	0.3889	0.3889	0.0000
Mobarok	1.0000	0.0000	0.2924	0.5000	0.7040	0.4131	0.0000	0.0000	0.0000	0.4403	0.4403	0.0000
Yunos	1.9403	0.0000	0.3676	0.2845	1.3879	0.5812	0.0000	0.0000	0.0000	0.6833	0.6833	0.0000
Mistooki	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Faiz	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hasyim	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sulaeman	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hussein	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Ayub	0.5000	0.0000	0.2262	1.0000	0.4131	0.2924	0.0000	0.0000	0.0000	0.3057	0.3057	0.0000
Azahari	0.4131	0.0000	0.5000	0.1845	0.3750	1.0000	0.0000	0.0000	0.0000	0.2915	0.2915	0.0000
Zulkarnaer	0.0000	0.0000	0.4131	0.3333	2.3780	0.7040	0.0000	0.0000	0.0000	0.7867	0.7867	0.0000
Ghoni	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Top	0.4131	0.0000	0.0000	0.1845	0.3750	1.0000	0.0000	0.0000	0.0000	0.2915	0.2915	0.0000
Idris	0.3333	0.0000	0.1845	0.0000	0.2924	0.2262	0.0000	0.0000	0.0000	0.2341	0.2341	0.0000
Mustofa	2.3780	0.0000	0.3750	0.2924	0.0000	0.6000	0.0000	0.0000	0.0000	0.6992	0.6992	0.0000
WanMin	0.7040	0.0000	1.0000	0.2262	0.6000	0.0000	0.0000	0.0000	0.0000	0.4115	0.4115	0.0000
Maidin	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sani	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dulmatin	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Farik	0.7867	0.0000	0.2915	0.2341	0.6992	0.4115	0.0000	0.0000	0.0000	0.0000	0.5000	0.0000
Lillie	0.7867	0.0000	0.2915	0.2341	0.6992	0.4115	0.0000	0.0000	0.0000	0.5000	0.0000	0.0000
Yunos2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Naharudin	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Gungun	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Marzuki	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Kastari	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hafidh	0.6736	0.0000	0.2644	0.2230	0.5612	0.3594	0.0000	0.0000	0.0000	0.3889	0.3889	0.0000
Setiono	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BinHir	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rusdan	2.7660	0.0000	0.3827	0.2975	1.6318	0.6200	0.0000	0.0000	0.0000	0.7252	0.7252	0.0000
Mustaqim	2.7660	0.0000	0.3827	0.2975	1.6318	0.6200	0.0000	0.0000	0.0000	0.7252	0.7252	0.0000
Fathi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Khalim	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Roche	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Thomas	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

	Naharudin	Gungun	Marzuki	Kastari	Hafidh	Setiono	BinHir	Rusdan	Mustaqim	Fathi	Khalim	Roche	Thomas
Baasyir	0.0000	0.0000	0.0000	0.0000	0.6404	0.0000	0.0000	1.9403	1.9403	0.0000	0.0000	0.0000	0.0000
Sungkar	0.0000	0.0000	0.0000	0.0000	0.5000	0.0000	0.0000	0.6103	0.6103	0.0000	0.0000	0.0000	0.0000
Hambali	0.0000	0.0000	0.0000	0.0000	0.6365	0.0000	0.0000	2.6396	2.6396	0.0000	0.0000	0.0000	0.0000
Mukhlas	0.0000	0.0000	0.0000	0.0000	0.5612	0.0000	0.0000	1.6318	1.6318	0.0000	0.0000	0.0000	0.0000
Iqbal	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	1.5663	1.5663	0.0000	0.0000	0.0000	0.0000
Faruq	0.0000	0.0000	0.0000	0.0000	0.4606	0.0000	0.0000	1.0216	1.0216	0.0000	0.0000	0.0000	0.0000
Syawal	0.0000	0.0000	0.0000	0.0000	0.4606	0.0000	0.0000	1.0216	1.0216	0.0000	0.0000	0.0000	0.0000
Ghozi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Samudra	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jabir	0.0000	0.0000	0.0000	0.0000	0.6365	0.0000	0.0000	2.6396	2.6396	0.0000	0.0000	0.0000	0.0000
Amrozi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Imron	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sufaat	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dwikarna	0.0000	0.0000	0.0000	0.0000	0.5000	0.0000	0.0000	0.6103	0.6103	0.0000	0.0000	0.0000	0.0000
Mobarok	0.0000	0.0000	0.0000	0.0000	0.4025	0.0000	0.0000	0.7345	0.7345	0.0000	0.0000	0.0000	0.0000
Yunos	0.0000	0.0000	0.0000	0.0000	0.6436	0.0000	0.0000	1.5663	1.5663	0.0000	0.0000	0.0000	0.0000
Mistooki	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Faiz	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hasyim	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sulaeman	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hussein	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Ayub	0.0000	0.0000	0.0000	0.0000	0.2870	0.0000	0.0000	0.4235	0.4235	0.0000	0.0000	0.0000	0.0000
Azahari	0.0000	0.0000	0.0000	0.0000	0.2644	0.0000	0.0000	0.3827	0.3827	0.0000	0.0000	0.0000	0.0000
Zulkarnae	0.0000	0.0000	0.0000	0.0000	0.6736	0.0000	0.0000	2.7660	2.7660	0.0000	0.0000	0.0000	0.0000
Ghoni	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Top	0.0000	0.0000	0.0000	0.0000	0.2644	0.0000	0.0000	0.3827	0.3827	0.0000	0.0000	0.0000	0.0000
Idris	0.0000	0.0000	0.0000	0.0000	0.2230	0.0000	0.0000	0.2975	0.2975	0.0000	0.0000	0.0000	0.0000
Mustofa	0.0000	0.0000	0.0000	0.0000	0.5612	0.0000	0.0000	1.6318	1.6318	0.0000	0.0000	0.0000	0.0000
WanMin	0.0000	0.0000	0.0000	0.0000	0.3594	0.0000	0.0000	0.6200	0.6200	0.0000	0.0000	0.0000	0.0000
Maidin	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sani	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dulmatin	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Farik	0.0000	0.0000	0.0000	0.0000	0.3889	0.0000	0.0000	0.7252	0.7252	0.0000	0.0000	0.0000	0.0000
Lillie	0.0000	0.0000	0.0000	0.0000	0.3889	0.0000	0.0000	0.7252	0.7252	0.0000	0.0000	0.0000	0.0000
Yunos2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Naharudin	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Gungun	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Marzuki	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Kastari	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hafidh	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.6103	0.6103	0.0000	0.0000	0.0000	0.0000
Setiono	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BinHir	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rusdan	0.0000	0.0000	0.0000	0.0000	0.6103	0.0000	0.0000	0.0000	2.0000	0.0000	0.0000	0.0000	0.0000
Mustaqim	0.0000	0.0000	0.0000	0.0000	0.6103	0.0000	0.0000	2.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Fathi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Khalim	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Roche	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Thomas	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

A.2.2. Friendship Network

	Baasyir	Sungkar	Hambali	Mukhlas	Iqbal	Faruq	Syawal	Ghozi	Samudra	Jabir	Amrozi
Baasyir	0	1	0	0	0	0	0	0	0	0	0
Sungkar	1	0	0	0	0	0	0	0	0	0	0
Hambali	0	0	0	0	1.5	0	0	0	0	1.5	0
Mukhlas	0	0	0	0	0	0	0	0	0	0	0
Iqbal	0	0	1.5	0	0	0	0	0	0	1.5	0
Faruq	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	0	0	0	0	0	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0.6
Jabir	0	0	1.5	0	1.5	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0	0	0.6	0	0
Imron	0	0	0	0	0	0	0	2	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	1	0	0	0	0
Mobarok	0	0	0	0	0	0	0	2	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	1.5	0	0.6
Hasyim	0	0	0	0	0	0	0	0	0	0	0
Sulaeman	0	0	0	0	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0
Zulkarnaen	0	0	0	0	0	0	1.5	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	1.5	0	1
Top	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	2	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	2	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	1.5	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	2	0	0	0	0	0	0	0
Mustaqim	0	0	0	2	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0

	Imron	Sufaat	Dwikarna	Mobarok	Yunos	Mistooki	Faiz	Hasyim	Sulaeman	Hussein	Ayub	Azahari
Baasyir	0	0	0	0	0	0	0	0	0	0	0	0
Sungkar	0	0	0	0	0	0	0	0	0	0	0	0
Hambali	0	0	0	0	0	0	0	0	0	0	0	0
Mukhlas	0	0	0	0	0	0	0	0	0	0	0	0
Iqbal	0	0	0	0	0	0	0	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	0	1	0	0	0	0	0	0	0	0	0
Ghozi	2	0	0	2	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	1.5	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0.6	0	0	0	0	0
Imron	0	0	0	2	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	2	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	1.5	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	0	0	1.5	0	0	0	0	0	0
Sulaeman	0	0	0	0	0	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0	0
Zulkarnae	0	0	0.6	0	0	0	0	0	0	0	0	0
Ghoni	0	0	0	0	0	0	1.5	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	2	0	0	2	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0.6	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	1	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	0	0	0	0	0	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	1.5	0	1.5	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0	0

	Zulkarnaer	Ghoni	Top	Idris	Mustofa	WanMin	Maidin	Sani	Dulmatin	Farik	Lillie	Yunos2
Baasyir	0	0	0	0	0	0	0	0	0	0	0	0
Sungkar	0	0	0	0	0	0	0	0	0	0	0	0
Hambali	0	0	0	0	0	0	0	0	0	0	0	0
Mukhlas	0	0	0	0	2	0	0	0	0	0	0	0
Iqbal	0	0	0	0	0	0	0	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	1.5	0	0	0	0	0	0	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	2	0	0	0
Samudra	0	1.5	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	1	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	2	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0.6	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	2	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	1.5	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	0	0	0	0	0	0	0	0	0
Sulaeman	0	0	0	0	0	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0	0
Zulkarnae	0	0	0	0	0	0	0	0	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	1	0
Lillie	0	0	0	0	0	0	0	0	0	1	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0	0
Hafidh	1.5	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	2	0	0	0	0	0	0	0
Mustaqim	0	0	0	0	2	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0	0

	Naharudin	Gungun	Marzuki	Kastari	Hafidh	Setiono	BinHir	Rusdan	Mustaqim	Fathi	Khalim	Roche	Thomas
Baasyir	0	0	0	0	0	0	0	0	0	0	0	0	0
Sungkar	0	0	0	0	0	0	0	0	0	0	0	0	0
Hambali	0	0	0	0	0	0	0	0	0	0	0	0	0
Mukhlas	0	0	0	0	0	0	0	2	2	0	0	0	0
Iqbal	0	0	0	0	0	0	0	0	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	0	0	0	1.5	0	0	0	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0.6	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	1.5	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	0	0	0	0	0	0	1.5	0	0	0
Sulaeman	0	0	0	0	0	1	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0	0	0
Zulkarnaen	0	0	0	0	1.5	0	0	0	0	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	2	2	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	2	0	0	0	0
Mustaqim	0	0	0	0	0	0	0	2	0	0	0	0	0
Fathi	0	0	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0	0	0

A.2.3. Nuclear Family Network

	Baasyir	Sungkar	Hambali	Mukhlas	Iqbal	Faruq	Syawal	Ghozi	Samudra	Jabir	Amrozi
Baasyir	0	0	0	0	0	0	0	0	0	0	0
Sungkar	0	0	0	0	0	0	1	0	0	0	0
Hambali	0	0	0	0	0	0	0	0	0	0	0
Mukhlas	0	0	0	0	0	0	0	0	0	0	1.5
Iqbal	0	0	0	0	0	0	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	1	0	0	0	0	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	1.5	0	0	0	0	0	0	0
Imron	0	0	0	1.5	0	0	0	0	0	0	1.5
Sufaat	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	0	0	0	0	0	0	0	0
Sulaeman	0	0	0	0	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0
Zulkarnaen	0	0	0	0	0	0	0	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	1	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	0	0	0	0	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0

	Imron	Sufaat	Dwikarna	Mobarok	Yunos	Mistooki	Faiz	Hasyim	Sulaeman	Hussein	Ayub	Azahari
Baasyir	0	0	0	0	0	0	0	0	0	0	0	0
Sungkar	0	0	0	0	0	0	0	0	0	0	0	0
Hambali	0	0	0	0	0	0	0	0	0	0	0	0
Mukhlas	1.5	0	0	0	0	0	0	0	0	0	0	0
Iqbal	0	0	0	0	0	0	0	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	0	0	0	0	0	0	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0	0
Amrozi	1.5	0	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	0	0	0	0	0	1	0	0	0
Sulaeman	0	0	0	0	0	0	0	1	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	1	0
Ayub	0	0	0	0	0	0	0	0	0	1	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0	0
Zulkarnae	0	0	0	0	0	0	0	0	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	0	0	0	0	0	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0	1	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0	0

	Zulkarnaer	Ghoni	Top	Idris	Mustofa	WanMin	Maidin	Sani	Dulmatin	Farik	Lillie	Yunos2
Baasyir	0	0	0	0	0	0	0	0	0	0	0	0
Sungkar	0	0	0	0	0	0	0	0	0	0	0	0
Hambali	0	0	0	0	0	0	0	0	0	0	0	0
Mukhlas	0	0	0	0	0	0	0	0	0	0	0	0
Iqbal	0	0	0	0	0	0	0	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	0	0	0	0	0	0	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	0	0	0	0	0	0	0	0	0
Sulaeman	0	0	0	0	0	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0	0
Zulkarnae	0	0	0	0	0	0	0	0	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	0	0	0	0	0	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0	0

	Naharudin	Gungun	Marzuki	Kastari	Hafidh	Setiono	BinHir	Rusdan	Mustaqim	Fathi	Khalim	Roche	Thomas
Baasyir	0	0	0	0	0	0	0	0	0	0	0	0	0
Sungkar	0	0	0	0	0	0	0	0	0	0	0	0	0
Hambali	0	1	0	0	0	0	0	0	0	0	0	0	0
Mukhlas	0	0	0	0	0	0	0	0	0	0	0	0	0
Iqbal	0	0	0	0	0	0	0	0	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	0	0	0	0	0	0	0	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	1	0	0	0
Hasyim	0	0	0	0	0	0	0	0	0	0	0	0	0
Sulaeman	0	0	0	0	0	0	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0	0	0
Zulkarnae	0	0	0	0	0	0	0	0	0	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	0	0	0	0	0	0	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0	0	0

A.2.4. Relative Network

	Baasyir	Sungkar	Hambali	Mukhlas	Iqbal	Faruq	Syawal	Ghozi	Samudra	Jabir	Amrozi
Baasyir	0	0	0	0	0	0	0	0	0	0	0
Sungkar	0	0	0	0	0	0	0	0	0	0	0
Hambali	0	0	0	0	0	0	0	0	0	0	0
Mukhlas	0	0	0	0	0	0	0	0	0	0	0
Iqbal	0	0	0	0	0	0	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	0	0	0	0	0	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	2.142857	0	0	0	0	0	0	0
Sulaeman	0	0	0	2.142857	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	2.5	0	0	0	0	0	0	0
Zulkarnae	0	0	0	0	0	0	0	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	2.5	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	0	0	0	0	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0

	Imron	Sufaat	Dwikarna	Mobarok	Yunos	Mistooki	Faiz	Hasyim	Sulaeman	Hussein	Ayub	Azahari
Baasyir	0	0	0	0	0	0	0	0	0	0	0	0
Sungkar	0	0	0	0	0	0	0	0	0	0	0	0
Hambali	0	0	0	0	0	0	0	0	0	0	0	0
Mukhlas	0	0	0	0	0	0	0	2.142857	2.142857	0	0	2.5
Iqbal	0	0	0	0	0	0	0	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	0	0	0	0	0	0	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	0	0	0	0	0	1.5	0	0	2.142857
Sulaeman	0	0	0	0	0	0	0	1.5	0	0	0	2.142857
Hussein	0	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	2.142857	2.142857	0	0	0
Zulkarnae	0	0	0	0	0	0	0	0	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	2.142857	2.142857	0	0	2.5
Idris	0	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	0	0	0	0	0	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0	0

	Zulkarnaen	Ghoni	Top	Idris	Mustofa	WanMin	Maidin	Sani	Dulmatin	Farik	Lillie	Yunos2
Baasyir	0	0	0	0	0	0	0	0	0	0	0	0
Sungkar	0	0	0	0	0	0	0	0	0	0	0	0
Hambali	0	0	0	0	0	0	0	0	0	0	0	0
Mukhlas	0	0	2.5	0	0	0	0	0	0	0	0	0
Iqbal	0	0	0	0	0	0	0	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	0	0	0	0	0	0	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	2.142857	0	0	0	0	0	0	0	0	0
Sulaeman	0	0	2.142857	0	0	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	2.5	0	0	0	0	0	0	0	0	0
Zulkarnae	0	0	0	0	0	0	0	0	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	0	0	0	0	0	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0	0

	Naharudin	Gungun	Marzuki	Kastari	Hafidh	Setiono	BinHir	Rusdan	Mustaqim	Fathi	Khalim	Roche	Thomas
Baasyir	0	0	0	0	0	0	0	0	0	0	0	0	0
Sungkar	0	0	0	0	0	0	0	0	0	0	0	0	0
Hambali	0	0	0	0	0	0	0	0	0	0	0	0	0
Mukhlas	0	0	0	0	0	0	0	0	0	0	0	0	0
Iqbal	0	0	0	0	0	0	0	0	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	0	0	0	0	0	0	0	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	0	0	0	0	0	0	0	0	0	0
Sulaeman	0	0	0	0	0	0	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0	0	0
Zulkarnaen	0	0	0	0	0	0	0	0	0	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	0	0	0	0	0	0	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0	0	0

A.2.5. Teacher-Student Network

	Baasyir	Sungkar	Hambali	Mukhlas	Iqbal	Faruq	Syawal	Ghozi	Samudra	Jabir	Amrozi
Baasyir	0	6.5	0.436975	1.857143	0.436975	0	0.65	1.857143	1.857143	1.857143	1.857143
Sungkar	6.5	0	0.436975	1.857143	0.436975	0	0.65	1.857143	1.857143	1.857143	1.857143
Hambali	0.436975	0.436975	0	0.363636	1	0	1.333333	0.363636	0.363636	0.363636	0.363636
Mukhlas	1.857143	1.857143	0.363636	0	0.363636	0	0.5	1	1	1	1
Iqbal	0.436975	0.436975	1	0.363636	0	0	1.333333	0.363636	0.363636	0.363636	0.363636
Faruq	0	0	0	0	0	0	0	0	0	0	0
Syawal	0.65	0.65	1.333333	0.5	1.333333	0	0	0.5	0.5	0.5	0.5
Ghozi	1.857143	1.857143	0.363636	1	0.363636	0	0.5	0	1	1	1
Samudra	1.857143	1.857143	0.363636	1	0.363636	0	0.5	1	0	1	1
Jabir	1.857143	1.857143	0.363636	1	0.363636	0	0.5	1	1	0	1
Amrozi	1.857143	1.857143	0.363636	1	0.363636	0	0.5	1	1	1	0
Imron	1.857143	1.857143	0.363636	1	0.363636	0	0.5	1	1	1	1
Sufaat	0.393939	0.393939	1.333333	0.333333	1.333333	0	1	0.333333	0.333333	0.333333	0.333333
Dwikarna	0	0	0	0	0	0	0	0	0	0	0
Mobarok	1.857143	1.857143	0.363636	1	0.363636	0	0.5	1	1	1	1
Yunos	0.776119	0.776119	0.666667	0.571429	0.666667	0	1.333333	0.571429	0.571429	0.571429	0.571429
Mistooki	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	0	0	0	0	0	0	0	0
Sulaeman	0	0	0	0	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0
Zulkarnaen	1.857143	1.857143	0.571429	1	0.571429	0	1	1	1	1	1
Ghoni	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0
Sani	1.857143	1.857143	0.363636	1	0.363636	0	0.5	1	1	1	1
Dulmatin	0.776119	0.776119	0.666667	0.571429	0.666667	0	1.333333	0.571429	0.571429	0.571429	0.571429
Farik	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0
Yunos2	1.857143	1.857143	0.363636	1	0.363636	0	0.5	1	1	1	1
Naharudin	1.857143	1.857143	0.363636	1	0.363636	0	0.5	1	1	1	1
Gungun	1.857143	1.857143	0.363636	1	0.363636	0	0.5	1	1	1	1
Marzuki	1	0.866667	0.304094	0.65	0.304094	0	0.393939	0.65	0.65	0.65	0.65
Kastari	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	1.857143	1.857143	0.363636	1	0.363636	0	0.5	1	1	1	1
Fathi	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0

	Imron	Sufaat	Dwikarna	Mobarok	Yunos	Mistooki	Faiz	Hasyim	Sulaeman	Hussein	Ayub	Azahari
Baasyir	1.857143	0.393939	0	1.857143	0.776119	0	0	0	0	0	0	0
Sungkar	1.857143	0.393939	0	1.857143	0.776119	0	0	0	0	0	0	0
Hambali	0.363636	1.333333	0	0.363636	0.666667	0	0	0	0	0	0	0
Mukhlas	1	0.333333	0	1	0.571429	0	0	0	0	0	0	0
Iqbal	0.363636	1.333333	0	0.363636	0.666667	0	0	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0.5	1	0	0.5	1.333333	0	0	0	0	0	0	0
Ghozi	1	0.333333	0	1	0.571429	0	0	0	0	0	0	0
Samudra	1	0.333333	0	1	0.571429	0	0	0	0	0	0	0
Jabir	1	0.333333	0	1	0.571429	0	0	0	0	0	0	0
Amrozi	1	0.333333	0	1	0.571429	0	0	0	0	0	0	0
Imron	0	0.333333	0	1	0.571429	0	0	0	0	0	0	0
Sufaat	0.333333	0	0	0.333333	0.571429	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	1	0.333333	0	0	0.571429	0	0	0	0	0	0	0
Yunos	0.571429	0.571429	0	0.571429	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	0	0	0	0	0	0	0	0	0
Sulaeman	0	0	0	0	0	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0	0
Zulkarnaen	1	0.5	0	1	1.333333	0	0	0	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0	0
Sani	1	0.333333	0	1	0.571429	0	0	0	0	0	0	0
Dulmatin	0.571429	0.571429	0	0.571429	1	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	1	0.333333	0	1	0.571429	0	0	0	0	0	0	0
Naharudin	1	0.333333	0	1	0.571429	0	0	0	0	0	0	0
Gungun	1	0.333333	0	1	0.571429	0	0	0	0	0	0	0
Marzuki	0.65	0.282609	0	0.65	0.436975	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	1	0.333333	0	1	0.571429	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0	0

	Zulkarnaen	Ghoni	Top	Idris	Mustofa	WanMin	Maidin	Sani	Dulmatin	Farik	Lillie	Yunos2
Baasyir	1.857142857	0	0	0	0	0	0	1.857143	0.776119	0	0	1.857143
Sungkar	1.857142857	0	0	0	0	0	0	1.857143	0.776119	0	0	1.857143
Hambali	0.571428571	0	0	0	0	0	0	0.363636	0.666667	0	0	0.363636
Mukhlas	1	0	0	0	0	0	0	1	0.571429	0	0	1
Iqbal	0.571428571	0	0	0	0	0	0	0.363636	0.666667	0	0	0.363636
Faruq	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	1	0	0	0	0	0	0	0.5	1.333333	0	0	0.5
Ghozi	1	0	0	0	0	0	0	1	0.571429	0	0	1
Samudra	1	0	0	0	0	0	0	1	0.571429	0	0	1
Jabir	1	0	0	0	0	0	0	1	0.571429	0	0	1
Amrozi	1	0	0	0	0	0	0	1	0.571429	0	0	1
Imron	1	0	0	0	0	0	0	1	0.571429	0	0	1
Sufaat	0.5	0	0	0	0	0	0	0.333333	0.571429	0	0	0.333333
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	1	0	0	0	0	0	0	1	0.571429	0	0	1
Yunos	1.333333333	0	0	0	0	0	0	0.571429	1	0	0	0.571429
Mistooki	0	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	0	0	0	0	0	0	0	0	0
Sulaeman	0	0	0	0	0	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0	0
Zulkarnaen	0	0	0	0	0	0	0	1	1.333333	0	0	1
Ghoni	0	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0	0
Sani	1	0	0	0	0	0	0	0	0.571429	0	0	1
Dulmatin	1.333333333	0	0	0	0	0	0	0.571429	0	0	0	0.571429
Farik	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	1	0	0	0	0	0	0	1	0.571429	0	0	0
Naharudin	1	0	0	0	0	0	0	1	0.571429	0	0	1
Gungun	1	0	0	0	0	0	0	1	0.571429	0	0	1
Marzuki	0.65	0	0	0	0	0	0	0.65	0.436975	0	0	0.65
Kastari	0	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	1	0	0	0	0	0	0	1	0.571429	0	0	1
Fathi	0	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0	0

	Naharudin	Gungun	Marzuki	Kastari	Hafidh	Setiono	BinHir	Rusdan	Mustaqim	Fathi	Khalim	Roche	Thomas
Baasyir	1.857142857	1.857143	1	0	0	0	0	0	1.857143	0	0	0	0
Sungkar	1.857142857	1.857143	0.866667	0	0	0	0	0	1.857143	0	0	0	0
Hambali	0.363636364	0.363636	0.304094	0	0	0	0	0	0.363636	0	0	0	0
Mukhlas	1	1	0.65	0	0	0	0	0	1	0	0	0	0
Iqbal	0.363636364	0.363636	0.304094	0	0	0	0	0	0.363636	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0.5	0.5	0.393939	0	0	0	0	0	0.5	0	0	0	0
Ghozi	1	1	0.65	0	0	0	0	0	1	0	0	0	0
Samudra	1	1	0.65	0	0	0	0	0	1	0	0	0	0
Jabir	1	1	0.65	0	0	0	0	0	1	0	0	0	0
Amrozi	1	1	0.65	0	0	0	0	0	1	0	0	0	0
Imron	1	1	0.65	0	0	0	0	0	1	0	0	0	0
Sufaat	0.333333333	0.333333	0.282609	0	0	0	0	0	0.333333	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	1	1	0.65	0	0	0	0	0	1	0	0	0	0
Yunos	0.571428571	0.571429	0.436975	0	0	0	0	0	0.571429	0	0	0	0
Mistooki	0	0	0	0	0	0	0	0	0	0	0	0	0
Faiz	0	0	0	0	0	0	0	0	0	0	0	0	0
Hasyim	0	0	0	0	0	0	0	0	0	0	0	0	0
Sulaeman	0	0	0	0	0	0	0	0	0	0	0	0	0
Hussein	0	0	0	0	0	0	0	0	0	0	0	0	0
Ayub	0	0	0	0	0	0	0	0	0	0	0	0	0
Azahari	0	0	0	0	0	0	0	0	0	0	0	0	0
Zulkarnaen	1	1	0.65	0	0	0	0	0	1	0	0	0	0
Ghoni	0	0	0	0	0	0	0	0	0	0	0	0	0
Top	0	0	0	0	0	0	0	0	0	0	0	0	0
Idris	0	0	0	0	0	0	0	0	0	0	0	0	0
Mustofa	0	0	0	0	0	0	0	0	0	0	0	0	0
WanMin	0	0	0	0	0	0	0	0	0	0	0	0	0
Maidin	0	0	0	0	0	0	0	0	0	0	0	0	0
Sani	1	1	0.65	0	0	0	0	0	1	0	0	0	0
Dulmatin	0.571428571	0.571429	0.436975	0	0	0	0	0	0.571429	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	1	1	0.65	0	0	0	0	0	1	0	0	0	0
Naharudin	0	1	0.65	0	0	0	0	0	1	0	0	0	0
Gungun	1	0	0.65	0	0	0	0	0	1	0	0	0	0
Marzuki	0.65	0.65	0	0	0	0	0	0	0.65	0	0	0	0
Kastari	0	0	0	0	0	0	0	0	0	0	0	0	0
Hafidh	0	0	0	0	0	0	0	0	0	0	0	0	0
Setiono	0	0	0	0	0	0	0	0	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0	0	0	0	0	0	0	0
Mustaqim	1	1	0.65	0	0	0	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0	0	0	0	0	0	0	0
Khalim	0	0	0	0	0	0	0	0	0	0	0	0	0
Roche	0	0	0	0	0	0	0	0	0	0	0	0	0
Thomas	0	0	0	0	0	0	0	0	0	0	0	0	0

A.2.6. Religious-Leader Network

	Baasyir	Sungkar	Hambali	Mukhlas	Iqbal	Faruq	Syawal	Ghozi	Samudra	Jabir	Amrozi
Baasyir	0	6.615385	1.859459	0	2.457143	0	1.859459	0	0	0	0
Sungkar	6.615385	0	1.859459	0	2.263158	0	1.859459	0	0	0	0
Hambali	1.859459	1.859459	0	0	1.127869	0	1	0	0	0	0
Mukhlas	0	0	0	0	0	0	0	0	0	0	0
Iqbal	2.457143	2.263158	1.127869	0	0	0	1.127869	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0
Syawal	1.859459	1.859459	1	0	1.127869	0	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0
Mistooki	1.622642	1.34375	0.875318	0	1.162162	0	0.875318	0	0	0	0
Faiz	0.868687	1	0.650284	0	0.693548	0	0.650284	0	0	0	0
Hasyim	0.68254	0.637037	0.50514	0	0.646617	0	0.50514	0	0	0	0
Sulaeman	1.859459	1.859459	1	0	1.127869	0	1	0	0	0	0
Hussein	1.859459	1.859459	1	0	1.127869	0	1	0	0	0	0
Ayub	1.859459	1.859459	1	0	1.127869	0	1	0	0	0	0
Azahari	1.859459	1.859459	1	0	1.127869	0	1	0	0	0	0
Zulkarnae	0.394044	0.394044	0.333333	0	0.346425	0	0.5	0	0	0	0
Ghoni	1.859459	1.859459	1	0	1.127869	0	1	0	0	0	0
Top	1.859459	1.859459	1	0	1.127869	0	1	0	0	0	0
Idris	1.859459	1.859459	1	0	1.127869	0	1	0	0	0	0
Mustofa	1.859459	1.859459	1	0	1.127869	0	1	0	0	0	0
WanMin	1.859459	1.859459	1	0	1.127869	0	1	0	0	0	0
Maidin	2.15	1.755102	1.020772	0	1.829787	0	1.020772	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0
Kastari	0.710744	0.693548	0.530046	0	1	0	0.530046	0	0	0	0
Hafidh	0.868687	1	0.650284	0	0.693548	0	0.650284	0	0	0	0
Setiono	0.650284	0.650284	0.5	0	0.530046	0	1	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0.868687	1	0.650284	0	0.693548	0	0.650284	0	0	0	0
Mustaqim	0	0	0	0	0	0	0	0	0	0	0
Fathi	0.68254	0.637037	0.50514	0	0.646617	0	0.50514	0	0	0	0
Khalim	0.68254	0.637037	0.50514	0	0.646617	0	0.50514	0	0	0	0
Roche	1.859459	1.859459	1	0	1.127869	0	1	0	0	0	0
Thomas	1	0.868687	0.650284	0	0.710744	0	0.650284	0	0	0	0

	Imron	Sufaat	Dwikarna	Mobarok	Yunos	Mistooki	Faiz	Hasyim	Sulaeman	Hussein	Ayub	Azahari
Baasyir	0	0	0	0	0	1.622642	0.868687	0.68254	1.859459	1.859459	1.859459	1.859459
Sungkar	0	0	0	0	0	1.34375	1	0.637037	1.859459	1.859459	1.859459	1.859459
Hambali	0	0	0	0	0	0.875318	0.650284	0.50514	1	1	1	1
Mukhlas	0	0	0	0	0	0	0	0	0	0	0	0
Iqbal	0	0	0	0	0	1.162162	0.693548	0.646617	1.127869	1.127869	1.127869	1.127869
Faruq	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	0	0	0	0	0.875318	0.650284	0.50514	1	1	1	1
Ghozi	0	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0	0	0	0.573333	0.618705	0.875318	0.875318	0.875318	0.875318
Faiz	0	0	0	0	0	0.573333	0	0.38914	0.650284	0.650284	0.650284	0.650284
Hasyim	0	0	0	0	0	0.618705	0.38914	0	0.50514	0.50514	0.50514	0.50514
Sulaeman	0	0	0	0	0	0.875318	0.650284	0.50514	0	1	1	1
Hussein	0	0	0	0	0	0.875318	0.650284	0.50514	1	0	1	1
Ayub	0	0	0	0	0	0.875318	0.650284	0.50514	1	1	0	1
Azahari	0	0	0	0	0	0.875318	0.650284	0.50514	1	1	1	0
Zulkarnae	0	0	0	0	0	0.318224	0.282662	0.251278	0.333333	0.333333	0.333333	0.333333
Ghoni	0	0	0	0	0	0.875318	0.650284	0.50514	1	1	1	1
Top	0	0	0	0	0	0.875318	0.650284	0.50514	1	1	1	1
Idris	0	0	0	0	0	0.875318	0.650284	0.50514	1	1	1	1
Mustofa	0	0	0	0	0	0.875318	0.650284	0.50514	1	1	1	1
WanMin	0	0	0	0	0	0.875318	0.650284	0.50514	1	1	1	1
Maidin	0	0	0	0	0	1.622642	0.637037	1	1.020772	1.020772	1.020772	1.020772
Sani	0	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0.5375	0.409524	0.392694	0.530046	0.530046	0.530046	0.530046
Hafidh	0	0	0	0	0	0.573333	0.5	0.38914	0.650284	0.650284	0.650284	0.650284
Setiono	0	0	0	0	0	0.466757	0.394044	0.33561	0.5	0.5	0.5	0.5
BinHir	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0	0	0.573333	0.5	0.38914	0.650284	0.650284	0.650284	0.650284
Mustaqim	0	0	0	0	0	0	0	0	0	0	0	0
Fathi	0	0	0	0	0	0.618705	0.38914	0.5	0.50514	0.50514	0.50514	0.50514
Khalim	0	0	0	0	0	0.618705	0.38914	0.5	0.50514	0.50514	0.50514	0.50514
Roche	0	0	0	0	0	0.875318	0.650284	0.50514	1	1	1	1
Thomas	0	0	0	0	0	0.618705	0.464865	0.40566	0.650284	0.650284	0.650284	0.650284

	Zulkarnaen	Ghoni	Top	Idris	Mustofa	WanMin	Maidin	Sani	Dulmatin	Farik	Lillie	Yunos2
Baasyir	0.394043528	1.859459	1.859459	1.859459	1.859459	1.859459	2.15	0	0	0	0	0
Sungkar	0.394043528	1.859459	1.859459	1.859459	1.859459	1.859459	1.755102	0	0	0	0	0
Hambali	0.333333333	1	1	1	1	1	1.020772	0	0	0	0	0
Mukhlas	0	0	0	0	0	0	0	0	0	0	0	0
Iqbal	0.346424975	1.127869	1.127869	1.127869	1.127869	1.127869	1.829787	0	0	0	0	0
Faruq	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0.5	1	1	1	1	1	1.020772	0	0	0	0	0
Ghozi	0	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0.318223867	0.875318	0.875318	0.875318	0.875318	0.875318	1.622642	0	0	0	0	0
Faiz	0.282662284	0.650284	0.650284	0.650284	0.650284	0.650284	0.637037	0	0	0	0	0
Hasyim	0.251278305	0.50514	0.50514	0.50514	0.50514	0.50514	1	0	0	0	0	0
Sulaeman	0.333333333	1	1	1	1	1	1.020772	0	0	0	0	0
Hussein	0.333333333	1	1	1	1	1	1.020772	0	0	0	0	0
Ayub	0.333333333	1	1	1	1	1	1.020772	0	0	0	0	0
Azahari	0.333333333	1	1	1	1	1	1.020772	0	0	0	0	0
Zulkarnaei	0	0.333333	0.333333	0.333333	0.333333	0.333333	0.33561	0	0	0	0	0
Ghoni	0.333333333	0	1	1	1	1	1.020772	0	0	0	0	0
Top	0.333333333	1	0	1	1	1	1.020772	0	0	0	0	0
Idris	0.333333333	1	1	0	1	1	1.020772	0	0	0	0	0
Mustofa	0.333333333	1	1	1	0	1	1.020772	0	0	0	0	0
WanMin	0.333333333	1	1	1	1	0	1.020772	0	0	0	0	0
Maidin	0.335609756	1.020772	1.020772	1.020772	1.020772	1.020772	0	0	0	0	0	0
Sani	0	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0	0
Kastari	0.257292446	0.530046	0.530046	0.530046	0.530046	0.530046	0.646617	0	0	0	0	0
Hafidh	0.282662284	0.650284	0.650284	0.650284	0.650284	0.650284	0.637037	0	0	0	0	0
Setiono	1	0.5	0.5	0.5	0.5	0.5	0.50514	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0.282662284	0.650284	0.650284	0.650284	0.650284	0.650284	0.637037	0	0	0	0	0
Mustaqim	0	0	0	0	0	0	0	0	0	0	0	0
Fathi	0.251278305	0.50514	0.50514	0.50514	0.50514	0.50514	1	0	0	0	0	0
Khalim	0.251278305	0.50514	0.50514	0.50514	0.50514	0.50514	1	0	0	0	0	0
Roche	0.333333333	1	1	1	1	1	1.020772	0	0	0	0	0
Thomas	0.282662284	0.650284	0.650284	0.650284	0.650284	0.650284	0.68254	0	0	0	0	0

	Naharudin	Gungun	Marzuki	Kastari	Hafidh	Setiono	BinHir	Rusdan	Mustaqim	Fathi	Khalim	Roche	Thomas
Baasyir	0	0	0	0.710744	0.868687	0.650284	0	0.868687	0	0.68254	0.68254	1.859459	1
Sungkar	0	0	0	0.693548	1	0.650284	0	1	0	0.637037	0.637037	1.859459	0.868687
Hambali	0	0	0	0.530046	0.650284	0.5	0	0.650284	0	0.50514	0.50514	1	0.650284
Mukhlas	0	0	0	0	0	0	0	0	0	0	0	0	0
Iqbal	0	0	0	1	0.693548	0.530046	0	0.693548	0	0.646617	0.646617	1.127869	0.710744
Faruq	0	0	0	0	0	0	0	0	0	0	0	0	0
Syawal	0	0	0	0.530046	0.650284	1	0	0.650284	0	0.50514	0.50514	1	0.650284
Ghozi	0	0	0	0	0	0	0	0	0	0	0	0	0
Samudra	0	0	0	0	0	0	0	0	0	0	0	0	0
Jabir	0	0	0	0	0	0	0	0	0	0	0	0	0
Amrozi	0	0	0	0	0	0	0	0	0	0	0	0	0
Imron	0	0	0	0	0	0	0	0	0	0	0	0	0
Sufaat	0	0	0	0	0	0	0	0	0	0	0	0	0
Dwikarna	0	0	0	0	0	0	0	0	0	0	0	0	0
Mobarok	0	0	0	0	0	0	0	0	0	0	0	0	0
Yunos	0	0	0	0	0	0	0	0	0	0	0	0	0
Mistooki	0	0	0	0.5375	0.573333	0.466757	0	0.573333	0	0.618705	0.618705	0.875318	0.618705
Faiz	0	0	0	0.409524	0.5	0.394044	0	0.5	0	0.38914	0.38914	0.650284	0.464865
Hasyim	0	0	0	0.392694	0.38914	0.33561	0	0.38914	0	0.5	0.5	0.50514	0.40566
Sulaeman	0	0	0	0.530046	0.650284	0.5	0	0.650284	0	0.50514	0.50514	1	0.650284
Hussein	0	0	0	0.530046	0.650284	0.5	0	0.650284	0	0.50514	0.50514	1	0.650284
Ayub	0	0	0	0.530046	0.650284	0.5	0	0.650284	0	0.50514	0.50514	1	0.650284
Azahari	0	0	0	0.530046	0.650284	0.5	0	0.650284	0	0.50514	0.50514	1	0.650284
Zulkarnae	0	0	0	0.257292	0.282662	1	0	0.282662	0	0.251278	0.251278	0.333333	0.282662
Ghoni	0	0	0	0.530046	0.650284	0.5	0	0.650284	0	0.50514	0.50514	1	0.650284
Top	0	0	0	0.530046	0.650284	0.5	0	0.650284	0	0.50514	0.50514	1	0.650284
Idris	0	0	0	0.530046	0.650284	0.5	0	0.650284	0	0.50514	0.50514	1	0.650284
Mustofa	0	0	0	0.530046	0.650284	0.5	0	0.650284	0	0.50514	0.50514	1	0.650284
WanMin	0	0	0	0.530046	0.650284	0.5	0	0.650284	0	0.50514	0.50514	1	0.650284
Maidin	0	0	0	0.646617	0.637037	0.50514	0	0.637037	0	1	1	1.020772	0.68254
Sani	0	0	0	0	0	0	0	0	0	0	0	0	0
Dulmatin	0	0	0	0	0	0	0	0	0	0	0	0	0
Farik	0	0	0	0	0	0	0	0	0	0	0	0	0
Lillie	0	0	0	0	0	0	0	0	0	0	0	0	0
Yunos2	0	0	0	0	0	0	0	0	0	0	0	0	0
Naharudin	0	0	0	0	0	0	0	0	0	0	0	0	0
Gungun	0	0	0	0	0	0	0	0	0	0	0	0	0
Marzuki	0	0	0	0	0	0	0	0	0	0	0	0	0
Kastari	0	0	0	0	0.409524	0.346425	0	0.409524	0	0.392694	0.392694	0.530046	0.415459
Hafidh	0	0	0	0.409524	0	0.394044	0	0.5	0	0.38914	0.38914	0.650284	0.464865
Setiono	0	0	0	0.346425	0.394044	0	0	0.394044	0	0.33561	0.33561	0.5	0.394044
BinHir	0	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0.409524	0.5	0.394044	0	0	0	0.38914	0.38914	0.650284	0.464865
Mustaqim	0	0	0	0	0	0	0	0	0	0	0	0	0
Fathi	0	0	0	0.392694	0.38914	0.33561	0	0.38914	0	0	0.5	0.50514	0.40566
Khalim	0	0	0	0.392694	0.38914	0.33561	0	0.38914	0	0.5	0	0.50514	0.40566
Roche	0	0	0	0.530046	0.650284	0.5	0	0.650284	0	0.50514	0.50514	0	0.650284
Thomas	0	0	0	0.415459	0.464865	0.394044	0	0.464865	0	0.40566	0.40566	0.650284	0

A.3. Combined Topology Based Influence Measures

	Baasyir	Sungkar	Hambali	Mukhlas	Iqbal	Faruq	Syawal	Ghozi	Samudra	Jabir	Amrozi
Baasyir	0.0000	2.4593	0.6707	0.5165	0.7792	0.1414	0.5596	0.3095	0.3095	0.5975	0.3095
Sungkar	2.4593	0.0000	0.4888	0.4030	0.6167	0.0768	0.6617	0.3095	0.3095	0.4156	0.3095
Hambali	0.6707	0.4888	0.0000	0.4481	0.8965	0.2381	0.5972	0.0606	0.0606	0.8662	0.0606
Mukhlas	0.5165	0.4030	0.4481	0.0000	0.2737	0.1618	0.2451	0.1667	0.1667	0.5541	0.4167
Iqbal	0.7792	0.6167	0.8965	0.2737	0.0000	0.1423	0.5525	0.0606	0.0606	0.6024	0.0606
Faruq	0.1414	0.0768	0.2381	0.1618	0.1423	0.0000	0.2381	0.0000	0.0000	0.2083	0.0000
Syawal	0.5596	0.6617	0.5972	0.2451	0.5525	0.2381	0.0000	0.0833	0.0833	0.3214	0.0833
Ghozi	0.3095	0.3095	0.0606	0.1667	0.0606	0.0000	0.0833	0.0000	0.1667	0.1667	0.1667
Samudra	0.3095	0.3095	0.0606	0.1667	0.0606	0.0000	0.0833	0.1667	0.0000	0.1667	0.2667
Jabir	0.5975	0.4156	0.8662	0.5541	0.6024	0.2083	0.3214	0.1667	0.1667	0.0000	0.1667
Amrozi	0.3095	0.3095	0.0606	0.4167	0.0606	0.0000	0.0833	0.1667	0.2667	0.1667	0.0000
Imron	0.3095	0.3095	0.0606	0.4167	0.0606	0.0000	0.0833	0.5000	0.1667	0.1667	0.4167
Sufaat	0.0657	0.0657	0.2222	0.0556	0.2222	0.0000	0.1667	0.0556	0.0556	0.0556	0.0556
Dwikarna	0.1067	0.0833	0.1061	0.0935	0.1667	0.0768	0.2434	0.0000	0.0000	0.1061	0.0000
Mobarok	0.4179	0.3766	0.1917	0.2840	0.1729	0.0891	0.1724	0.5000	0.1667	0.2978	0.1667
Yunos	0.3527	0.2366	0.4707	0.3266	0.4120	0.1567	0.3789	0.0952	0.0952	0.4549	0.0952
Mistooki	0.2704	0.2240	0.1459	0.0000	0.1937	0.0000	0.1459	0.0000	0.0000	0.0000	0.0000
Faiz	0.1448	0.1667	0.1084	0.0000	0.1156	0.0000	0.1084	0.0000	0.2500	0.0000	0.1000
Hasyim	0.1138	0.1062	0.0842	0.3571	0.1078	0.0000	0.0842	0.0000	0.0000	0.0000	0.0000
Sulaeman	0.3099	0.3099	0.1667	0.3571	0.1880	0.0000	0.1667	0.0000	0.0000	0.0000	0.0000
Hussein	0.3099	0.3099	0.1667	0.0000	0.1880	0.0000	0.1667	0.0000	0.0000	0.0000	0.0000
Ayub	0.3756	0.3577	0.2401	0.0689	0.2551	0.0580	0.2247	0.0000	0.0000	0.0734	0.0000
Azahari	0.3693	0.3540	0.2353	0.5000	0.2479	0.0550	0.2217	0.0000	0.0000	0.0686	0.0000
Zulkarnaen	0.6847	0.4875	0.7655	0.5630	0.4969	0.1913	0.6913	0.1667	0.1667	0.7813	0.1667
Ghoni	0.3099	0.3099	0.1667	0.0000	0.1880	0.0000	0.1667	0.0000	0.2500	0.0000	0.1667
Top	0.3693	0.3540	0.2353	0.5000	0.2479	0.0550	0.2217	0.0000	0.0000	0.0686	0.0000
Idris	0.3570	0.3471	0.2176	0.0487	0.2358	0.0431	0.2097	0.0000	0.0000	0.0510	0.0000
Mustofa	0.5169	0.4034	0.5541	0.5833	0.4011	0.1618	0.3285	0.0000	0.0000	0.3875	0.0000
WanMin	0.4022	0.3698	0.2832	0.1667	0.2815	0.0821	0.2488	0.0000	0.0000	0.1165	0.0000
Maidin	0.3583	0.2925	0.1701	0.0000	0.3050	0.0000	0.1701	0.0000	0.0000	0.0000	0.0000
Sani	0.3095	0.3095	0.0606	0.1667	0.0606	0.0000	0.0833	0.1667	0.1667	0.1667	0.1667
Dulmatin	0.1294	0.1294	0.1111	0.0952	0.1111	0.0000	0.2222	0.4286	0.0952	0.0952	0.0952
Farik	0.1056	0.0648	0.1667	0.1165	0.1061	0.0980	0.0926	0.0000	0.0000	0.1282	0.0000
Lillie	0.1056	0.0648	0.1667	0.1165	0.1061	0.0980	0.0926	0.0000	0.0000	0.1282	0.0000
Yunos2	0.3095	0.3095	0.0606	0.1667	0.0606	0.0000	0.0833	0.1667	0.1667	0.1667	0.1667
Naharudin	0.3095	0.3095	0.0606	0.1667	0.0606	0.0000	0.0833	0.1667	0.1667	0.1667	0.1667
Gungun	0.3095	0.3095	0.2273	0.1667	0.0606	0.0000	0.0833	0.1667	0.1667	0.1667	0.1667
Marzuki	0.1667	0.1444	0.0507	0.1083	0.0507	0.0000	0.0657	0.1083	0.1083	0.1083	0.1083
Kastari	0.1185	0.1156	0.0883	0.0000	0.1667	0.0000	0.0883	0.0000	0.0000	0.0000	0.0000
Hafidh	0.2515	0.2500	0.2145	0.0935	0.2823	0.0768	0.4351	0.0000	0.0000	0.1061	0.0000
Setiono	0.1084	0.1084	0.0833	0.0000	0.0883	0.0000	0.1667	0.0000	0.0000	0.0000	0.0000
BinHir	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rusdan	0.4682	0.2684	0.5483	0.6053	0.3766	0.1703	0.2786	0.0000	0.0000	0.4399	0.0000
Mustaqim	0.6329	0.4112	0.5005	0.7720	0.3217	0.1703	0.2536	0.1667	0.1667	0.6066	0.1667
Fathi	0.1138	0.1062	0.0842	0.0000	0.1078	0.0000	0.0842	0.0000	0.0000	0.0000	0.0000
Khalim	0.1138	0.1062	0.0842	0.0000	0.1078	0.0000	0.0842	0.0000	0.0000	0.0000	0.0000
Roche	0.3099	0.3099	0.1667	0.0000	0.1880	0.0000	0.1667	0.0000	0.0000	0.0000	0.0000
Thomas	0.1667	0.1448	0.1084	0.0000	0.1185	0.0000	0.1084	0.0000	0.0000	0.0000	0.0000

	Imron	Sufaat	Dwikarna	Mobarok	Yunos	Mistooki	Faiz	Hasyim	Sulaeman	Hussein	Ayub	Azahari
Baasyir	0.3095	0.0657	0.1067	0.4179	0.3527	0.2704	0.1448	0.1138	0.3099	0.3099	0.3756	0.3693
Sungkar	0.3095	0.0657	0.0833	0.3766	0.2366	0.2240	0.1667	0.1062	0.3099	0.3099	0.3577	0.3540
Hambali	0.0606	0.2222	0.1061	0.1917	0.4707	0.1459	0.1084	0.0842	0.1667	0.1667	0.2401	0.2353
Mukhlas	0.4167	0.0556	0.0935	0.2840	0.3266	0.0000	0.0000	0.3571	0.3571	0.0000	0.0689	0.5000
Iqbal	0.0606	0.2222	0.1667	0.1729	0.4120	0.1937	0.1156	0.1078	0.1880	0.1880	0.2551	0.2479
Faruq	0.0000	0.0000	0.0768	0.0891	0.1567	0.0000	0.0000	0.0000	0.0000	0.0000	0.0580	0.0550
Syawal	0.0833	0.1667	0.2434	0.1724	0.3789	0.1459	0.1084	0.0842	0.1667	0.1667	0.2247	0.2217
Ghozi	0.5000	0.0556	0.0000	0.5000	0.0952	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Samudra	0.1667	0.0556	0.0000	0.1667	0.0952	0.0000	0.2500	0.0000	0.0000	0.0000	0.0000	0.0000
Jabir	0.1667	0.0556	0.1061	0.2978	0.4549	0.0000	0.0000	0.0000	0.0000	0.0000	0.0734	0.0686
Amrozi	0.4167	0.0556	0.0000	0.1667	0.0952	0.0000	0.1000	0.0000	0.0000	0.0000	0.0000	0.0000
Imron	0.0000	0.0556	0.0000	0.5000	0.0952	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sufaat	0.0556	0.0000	0.0000	0.0556	0.0952	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dwikarna	0.0000	0.0000	0.0000	0.0671	0.1073	0.0000	0.0000	0.0000	0.0000	0.0000	0.0478	0.0441
Mobarok	0.5000	0.0556	0.0671	0.0000	0.2052	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0487
Yunos	0.0952	0.0952	0.1073	0.2052	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0663	0.0613
Mistooki	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0956	0.3531	0.1459	0.1459	0.1459	0.1459
Faiz	0.0000	0.0000	0.0000	0.0000	0.0000	0.0956	0.0000	0.0649	0.1084	0.1084	0.1084	0.1084
Hasyim	0.0000	0.0000	0.0000	0.0000	0.0000	0.3531	0.0649	0.0000	0.5009	0.0842	0.0842	0.4413
Sulaeman	0.0000	0.0000	0.0000	0.0000	0.0000	0.1459	0.1084	0.5009	0.0000	0.1667	0.1667	0.5238
Hussein	0.0000	0.0000	0.0000	0.0000	0.0000	0.1459	0.1084	0.0842	0.1667	0.0000	0.3333	0.1667
Ayub	0.0000	0.0000	0.0478	0.1667	0.0663	0.1459	0.1084	0.0842	0.1667	0.3333	0.0000	0.2044
Azahari	0.0000	0.0000	0.0441	0.0487	0.0613	0.1459	0.1084	0.4413	0.5238	0.1667	0.2044	0.0000
Zulkarnaen	0.1667	0.0833	0.2123	0.3333	0.5456	0.0530	0.0471	0.0419	0.0556	0.0556	0.1389	0.1244
Ghoni	0.0000	0.0000	0.0000	0.0000	0.0000	0.1459	0.3584	0.0842	0.1667	0.1667	0.1667	0.1667
Top	0.0000	0.0000	0.0441	0.0487	0.0613	0.1459	0.1084	0.4413	0.5238	0.1667	0.2044	0.6667
Idris	0.0000	0.0000	0.0372	0.0833	0.0474	0.1459	0.1084	0.0842	0.1667	0.1667	0.3333	0.1974
Mustofa	0.0000	0.0000	0.0935	0.1173	0.2313	0.1459	0.1084	0.0842	0.1667	0.1667	0.2355	0.2292
WanMin	0.0000	0.0000	0.0599	0.0689	0.0969	0.1459	0.1084	0.0842	0.1667	0.1667	0.2154	0.3333
Maidin	0.0000	0.0000	0.0000	0.0000	0.0000	0.2704	0.1062	0.1667	0.1701	0.1701	0.1701	0.1701
Sani	0.1667	0.0556	0.0000	0.1667	0.0952	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dulmatin	0.4286	0.0952	0.0000	0.4286	0.1667	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Farik	0.0000	0.0000	0.0648	0.0734	0.1139	0.0000	0.0000	0.0000	0.0000	0.0000	0.0510	0.0486
Lillie	0.0000	0.0000	0.0648	0.0734	0.1139	0.0000	0.0000	0.0000	0.0000	0.0000	0.0510	0.0486
Yunos2	0.1667	0.0556	0.0000	0.1667	0.0952	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Naharudin	0.1667	0.0556	0.0000	0.1667	0.0952	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Gungun	0.1667	0.0556	0.0000	0.1667	0.0952	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Marzuki	0.1083	0.0471	0.0000	0.1083	0.0728	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Kastari	0.0000	0.0000	0.0000	0.0000	0.0000	0.0896	0.0683	0.0654	0.0883	0.0883	0.0883	0.0883
Hafidh	0.0000	0.0000	0.1833	0.0671	0.1073	0.0956	0.0833	0.0649	0.1084	0.1084	0.1562	0.1524
Setiono	0.0000	0.0000	0.0000	0.0000	0.0000	0.0778	0.0657	0.0559	0.2500	0.0833	0.0833	0.0833
BinHir	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rusdan	0.0000	0.0000	0.1017	0.1224	0.2610	0.0956	0.0833	0.0649	0.1084	0.1084	0.1790	0.1722
Mustaqim	0.1667	0.0556	0.1017	0.2891	0.3563	0.0000	0.0000	0.0000	0.0000	0.0000	0.0706	0.0638
Fathi	0.0000	0.0000	0.0000	0.0000	0.0000	0.3531	0.2315	0.3333	0.0842	0.0842	0.0842	0.0842
Khalim	0.0000	0.0000	0.0000	0.0000	0.0000	0.1031	0.0649	0.0833	0.0842	0.0842	0.0842	0.0842
Roche	0.0000	0.0000	0.0000	0.0000	0.0000	0.1459	0.1084	0.0842	0.1667	0.1667	0.1667	0.1667
Thomas	0.0000	0.0000	0.0000	0.0000	0.0000	0.1031	0.0775	0.0676	0.1084	0.1084	0.1084	0.1084

	Zulkarnaen	Ghoni	Top	Idris	Mustofa	WanMin	Maidin	Sani	Dulmatin	Farik	Lillie	Yunos2
Baasyir	0.6847	0.3099	0.3693	0.3570	0.5169	0.4022	0.3583	0.3095	0.1294	0.1056	0.1056	0.3095
Sungkar	0.4875	0.3099	0.3540	0.3471	0.4034	0.3698	0.2925	0.3095	0.1294	0.0648	0.0648	0.3095
Hambali	0.7655	0.1667	0.2353	0.2176	0.5541	0.2832	0.1701	0.0606	0.1111	0.1667	0.1667	0.0606
Mukhlas	0.5630	0.0000	0.5000	0.0487	0.5833	0.1667	0.0000	0.1667	0.0952	0.1165	0.1165	0.1667
Iqbal	0.4969	0.1880	0.2479	0.2358	0.4011	0.2815	0.3050	0.0606	0.1111	0.1061	0.1061	0.0606
Faruq	0.1913	0.0000	0.0550	0.0431	0.1618	0.0821	0.0000	0.0000	0.0000	0.0980	0.0980	0.0000
Syawal	0.6913	0.1667	0.2217	0.2097	0.3285	0.2488	0.1701	0.0833	0.2222	0.0926	0.0926	0.0833
Ghozi	0.1667	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.4286	0.0000	0.0000	0.1667
Samudra	0.1667	0.2500	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0952	0.0000	0.0000	0.1667
Jabir	0.7813	0.0000	0.0686	0.0510	0.3875	0.1165	0.0000	0.1667	0.0952	0.1282	0.1282	0.1667
Amrozi	0.1667	0.1667	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0952	0.0000	0.0000	0.1667
Imron	0.1667	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.4286	0.0000	0.0000	0.1667
Sufaat	0.0833	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0556	0.0952	0.0000	0.0000	0.0556
Dwikarna	0.2123	0.0000	0.0441	0.0372	0.0935	0.0599	0.0000	0.0000	0.0000	0.0648	0.0648	0.0000
Mobarok	0.3333	0.0000	0.0487	0.0833	0.1173	0.0689	0.0000	0.1667	0.4286	0.0734	0.0734	0.1667
Yunos	0.5456	0.0000	0.0613	0.0474	0.2313	0.0969	0.0000	0.0952	0.1667	0.1139	0.1139	0.0952
Mistooki	0.0530	0.1459	0.1459	0.1459	0.1459	0.1459	0.2704	0.0000	0.0000	0.0000	0.0000	0.0000
Faiz	0.0471	0.3584	0.1084	0.1084	0.1084	0.1084	0.1062	0.0000	0.0000	0.0000	0.0000	0.0000
Hasyim	0.0419	0.0842	0.4413	0.0842	0.0842	0.0842	0.1667	0.0000	0.0000	0.0000	0.0000	0.0000
Sulaeman	0.0556	0.1667	0.5238	0.1667	0.1667	0.1667	0.1701	0.0000	0.0000	0.0000	0.0000	0.0000
Hussein	0.0556	0.1667	0.1667	0.1667	0.1667	0.1667	0.1701	0.0000	0.0000	0.0000	0.0000	0.0000
Ayub	0.1389	0.1667	0.2044	0.3333	0.2355	0.2154	0.1701	0.0000	0.0000	0.0510	0.0510	0.0000
Azahari	0.1244	0.1667	0.6667	0.1974	0.2292	0.3333	0.1701	0.0000	0.0000	0.0486	0.0486	0.0000
Zulkarnaen	0.0000	0.0556	0.1244	0.1111	0.4519	0.1729	0.0559	0.1667	0.2222	0.1311	0.1311	0.1667
Ghoni	0.0556	0.0000	0.1667	0.1667	0.1667	0.1667	0.1701	0.0000	0.0000	0.0000	0.0000	0.0000
Top	0.1244	0.1667	0.0000	0.1974	0.2292	0.3333	0.1701	0.0000	0.0000	0.0486	0.0486	0.0000
Idris	0.1111	0.1667	0.1974	0.0000	0.2154	0.2044	0.1701	0.0000	0.0000	0.0390	0.0390	0.0000
Mustofa	0.4519	0.1667	0.2292	0.2154	0.0000	0.2667	0.1701	0.0000	0.0000	0.1165	0.1165	0.0000
WanMin	0.1729	0.1667	0.3333	0.2044	0.2667	0.0000	0.1701	0.0000	0.0000	0.0686	0.0686	0.0000
Maidin	0.0559	0.1701	0.1701	0.1701	0.1701	0.1701	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sani	0.1667	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0952	0.0000	0.0000	0.1667
Dulmatin	0.2222	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0952	0.0000	0.0000	0.0000	0.0952
Farik	0.1311	0.0000	0.0486	0.0390	0.1165	0.0686	0.0000	0.0000	0.0000	0.0000	0.2500	0.0000
Lillie	0.1311	0.0000	0.0486	0.0390	0.1165	0.0686	0.0000	0.0000	0.0000	0.2500	0.0000	0.0000
Yunos2	0.1667	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0952	0.0000	0.0000	0.0000
Naharudin	0.1667	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0952	0.0000	0.0000	0.1667
Gungun	0.1667	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0952	0.0000	0.0000	0.1667
Marzuki	0.1083	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1083	0.0728	0.0000	0.0000	0.1083
Kastari	0.0429	0.0883	0.0883	0.0883	0.0883	0.0883	0.1078	0.0000	0.0000	0.0000	0.0000	0.0000
Hafidh	0.4094	0.1084	0.1524	0.1455	0.2019	0.1683	0.1062	0.0000	0.0000	0.0648	0.0648	0.0000
Setiono	0.1667	0.0833	0.0833	0.0833	0.0833	0.0833	0.0842	0.0000	0.0000	0.0000	0.0000	0.0000
BinHir	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rusdan	0.5081	0.1084	0.1722	0.1580	0.7137	0.2117	0.1062	0.0000	0.0000	0.1209	0.1209	0.0000
Mustaqim	0.6277	0.0000	0.0638	0.0496	0.6053	0.1033	0.0000	0.1667	0.0952	0.1209	0.1209	0.1667
Fathi	0.0419	0.0842	0.0842	0.0842	0.0842	0.0842	0.1667	0.0000	0.0000	0.0000	0.0000	0.0000
Khalim	0.0419	0.0842	0.0842	0.0842	0.0842	0.0842	0.1667	0.0000	0.0000	0.0000	0.0000	0.0000
Roche	0.0556	0.1667	0.1667	0.1667	0.1667	0.1667	0.1701	0.0000	0.0000	0.0000	0.0000	0.0000
Thomas	0.0471	0.1084	0.1084	0.1084	0.1084	0.1084	0.1138	0.0000	0.0000	0.0000	0.0000	0.0000

	Naharudin	Gungun	Marzuki	Kastari	Hafidh	Setiono	BinHir	Rusdan	Mustaqim	Fathi	Khalim	Roche	Thomas
Baasyir	0.3095	0.3095	0.1667	0.1185	0.2515	0.1084	0.0000	0.4682	0.6329	0.1138	0.1138	0.3099	0.1667
Sungkar	0.3095	0.3095	0.1444	0.1156	0.2500	0.1084	0.0000	0.2684	0.4112	0.1062	0.1062	0.3099	0.1448
Hambali	0.0606	0.2273	0.0507	0.0883	0.2145	0.0833	0.0000	0.5483	0.5005	0.0842	0.0842	0.1667	0.1084
Mukhlas	0.1667	0.1667	0.1083	0.0000	0.0935	0.0000	0.0000	0.6053	0.7720	0.0000	0.0000	0.0000	0.0000
Iqbal	0.0606	0.0606	0.0507	0.1667	0.2823	0.0883	0.0000	0.3766	0.3217	0.1078	0.1078	0.1880	0.1185
Faruq	0.0000	0.0000	0.0000	0.0000	0.0768	0.0000	0.0000	0.1703	0.1703	0.0000	0.0000	0.0000	0.0000
Syawal	0.0833	0.0833	0.0657	0.0883	0.4351	0.1667	0.0000	0.2786	0.2536	0.0842	0.0842	0.1667	0.1084
Ghozi	0.1667	0.1667	0.1083	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0000	0.0000	0.0000	0.0000
Samudra	0.1667	0.1667	0.1083	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0000	0.0000	0.0000	0.0000
Jabir	0.1667	0.1667	0.1083	0.0000	0.1061	0.0000	0.0000	0.4399	0.6066	0.0000	0.0000	0.0000	0.0000
Amrozi	0.1667	0.1667	0.1083	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0000	0.0000	0.0000	0.0000
Imron	0.1667	0.1667	0.1083	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0000	0.0000	0.0000	0.0000
Sufaat	0.0556	0.0556	0.0471	0.0000	0.0000	0.0000	0.0000	0.0000	0.0556	0.0000	0.0000	0.0000	0.0000
Dwikarna	0.0000	0.0000	0.0000	0.0000	0.1833	0.0000	0.0000	0.1017	0.1017	0.0000	0.0000	0.0000	0.0000
Mobarok	0.1667	0.1667	0.1083	0.0000	0.0671	0.0000	0.0000	0.1224	0.2891	0.0000	0.0000	0.0000	0.0000
Yunos	0.0952	0.0952	0.0728	0.0000	0.1073	0.0000	0.0000	0.2610	0.3563	0.0000	0.0000	0.0000	0.0000
Mistooki	0.0000	0.0000	0.0000	0.0896	0.0956	0.0778	0.0000	0.0956	0.0000	0.3531	0.1031	0.1459	0.1031
Faiz	0.0000	0.0000	0.0000	0.0683	0.0833	0.0657	0.0000	0.0833	0.0000	0.2315	0.0649	0.1084	0.0775
Hasyim	0.0000	0.0000	0.0000	0.0654	0.0649	0.0559	0.0000	0.0649	0.0000	0.3333	0.0833	0.0842	0.0676
Sulaeman	0.0000	0.0000	0.0000	0.0883	0.1084	0.2500	0.0000	0.1084	0.0000	0.0842	0.0842	0.1667	0.1084
Hussein	0.0000	0.0000	0.0000	0.0883	0.1084	0.0833	0.0000	0.1084	0.0000	0.0842	0.0842	0.1667	0.1084
Ayub	0.0000	0.0000	0.0000	0.0883	0.1562	0.0833	0.0000	0.1790	0.0706	0.0842	0.0842	0.1667	0.1084
Azahari	0.0000	0.0000	0.0000	0.0883	0.1524	0.0833	0.0000	0.1722	0.0638	0.0842	0.0842	0.1667	0.1084
Zulkarnaen	0.1667	0.1667	0.1083	0.0429	0.4094	0.1667	0.0000	0.5081	0.6277	0.0419	0.0419	0.0556	0.0471
Ghoni	0.0000	0.0000	0.0000	0.0883	0.1084	0.0833	0.0000	0.1084	0.0000	0.0842	0.0842	0.1667	0.1084
Top	0.0000	0.0000	0.0000	0.0883	0.1524	0.0833	0.0000	0.1722	0.0638	0.0842	0.0842	0.1667	0.1084
Idris	0.0000	0.0000	0.0000	0.0883	0.1455	0.0833	0.0000	0.1580	0.0496	0.0842	0.0842	0.1667	0.1084
Mustofa	0.0000	0.0000	0.0000	0.0883	0.2019	0.0833	0.0000	0.7137	0.6053	0.0842	0.0842	0.1667	0.1084
WanMin	0.0000	0.0000	0.0000	0.0883	0.1683	0.0833	0.0000	0.2117	0.1033	0.0842	0.0842	0.1667	0.1084
Maidin	0.0000	0.0000	0.0000	0.1078	0.1062	0.0842	0.0000	0.1062	0.0000	0.1667	0.1667	0.1701	0.1138
Sani	0.1667	0.1667	0.1083	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0000	0.0000	0.0000	0.0000
Dulmatin	0.0952	0.0952	0.0728	0.0000	0.0000	0.0000	0.0000	0.0000	0.0952	0.0000	0.0000	0.0000	0.0000
Farik	0.0000	0.0000	0.0000	0.0000	0.0648	0.0000	0.0000	0.1209	0.1209	0.0000	0.0000	0.0000	0.0000
Lillie	0.0000	0.0000	0.0000	0.0000	0.0648	0.0000	0.0000	0.1209	0.1209	0.0000	0.0000	0.0000	0.0000
Yunos2	0.1667	0.1667	0.1083	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0000	0.0000	0.0000	0.0000
Naharudin	0.0000	0.1667	0.1083	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0000	0.0000	0.0000	0.0000
Gungun	0.1667	0.0000	0.1083	0.0000	0.0000	0.0000	0.0000	0.0000	0.1667	0.0000	0.0000	0.0000	0.0000
Marzuki	0.1083	0.1083	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1083	0.0000	0.0000	0.0000	0.0000
Kastari	0.0000	0.0000	0.0000	0.0000	0.0683	0.0577	0.0000	0.0683	0.0000	0.0654	0.0654	0.0883	0.0692
Hafidh	0.0000	0.0000	0.0000	0.0683	0.0000	0.0657	0.0000	0.1851	0.1017	0.0649	0.0649	0.1084	0.0775
Setiono	0.0000	0.0000	0.0000	0.0577	0.0657	0.0000	0.0000	0.0657	0.0000	0.0559	0.0559	0.0833	0.0657
BinHir	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rusdan	0.0000	0.0000	0.0000	0.0683	0.1851	0.0657	0.0000	0.0000	0.6667	0.0649	0.0649	0.1084	0.0775
Mustaqim	0.1667	0.1667	0.1083	0.0000	0.1017	0.0000	0.0000	0.6667	0.0000	0.0000	0.0000	0.0000	0.0000
Fathi	0.0000	0.0000	0.0000	0.0654	0.0649	0.0559	0.0000	0.0649	0.0000	0.0000	0.0833	0.0842	0.0676
Khalim	0.0000	0.0000	0.0000	0.0654	0.0649	0.0559	0.0000	0.0649	0.0000	0.0833	0.0000	0.0842	0.0676
Roche	0.0000	0.0000	0.0000	0.0883	0.1084	0.0833	0.0000	0.1084	0.0000	0.0842	0.0842	0.0000	0.1084
Thomas	0.0000	0.0000	0.0000	0.0692	0.0775	0.0657	0.0000	0.0775	0.0000	0.0676	0.0676	0.1084	0.0000

A.4. Holistic Interpersonal Influence Measures

	Baasyir	Sungkar	Hambali	Mukhlas	Iqbal	Faruq	Syawal	Ghozi	Samudra	Jabir	Amrozi
Baasyir	0	2.025479	0.552389	0.425389	0.641749	0.116457	0.460887	0.254904	0.254904	0.492101	0.254904
Sungkar	1.366633	0	0.271626	0.223947	0.3427	0.042678	0.367707	0.171989	0.171989	0.230949	0.171989
Hambali	0.491288	0.358046	0	0.328233	0.656686	0.174408	0.437449	0.04439	0.04439	0.634492	0.04439
Mukhlas	0.02629	0.020513	0.022808	0	0.013931	0.008236	0.012476	0.008485	0.008485	0.028204	0.02121
Iqbal	0.326407	0.258336	0.375544	0.114653	0	0.059609	0.231442	0.025385	0.025385	0.252345	0.025385
Faruq	0.002008	0.001091	0.003381	0.002298	0.002021	0	0.003381	0	0	0.002958	0
Syawal	0.020258	0.023954	0.021619	0.008873	0.020001	0.008619	0	0.003015	0.003015	0.011635	0.003015
Ghozi	0.001176	0.001176	0.00023	0.000633	0.00023	0	0.000317	0	0.000633	0.000633	0.000633
Samudra	0.001176	0.001176	0.00023	0.000633	0.00023	0	0.000317	0.000633	0	0.000633	0.001013
Jabir	0.166643	0.115911	0.241583	0.154538	0.168009	0.058095	0.089638	0.046493	0.046493	0	0.046493
Amrozi	0.001176	0.001176	0.00023	0.001583	0.00023	0	0.000317	0.000633	0.001013	0.000633	0
Imron	0.001176	0.001176	0.00023	0.001583	0.00023	0	0.000317	0.0019	0.000633	0.000633	0.001583
Sufaat	0.00025	0.00025	0.000844	0.000211	0.000844	0	0.000633	0.000211	0.000211	0.000211	0.000211
Dwikarna	0.00079	0.000616	0.000785	0.000692	0.001234	0.000568	0.001801	0	0	0.000785	0
Mobarok	0.005934	0.005348	0.002722	0.004033	0.002455	0.001265	0.002448	0.0071	0.002367	0.004229	0.002367
Yunos	0.009523	0.006388	0.012709	0.008818	0.011124	0.004231	0.01023	0.00257	0.00257	0.012282	0.00257
Mistooki	0.001974	0.001635	0.001065	0	0.001414	0	0.001065	0	0	0	0
Faiz	0.000767	0.000884	0.000575	0	0.000613	0	0.000575	0	0.001325	0	0.00053
Hasyim	0.000603	0.000563	0.000446	0.001893	0.000571	0	0.000446	0	0	0	0
Sulaeman	0.002262	0.002262	0.001217	0.002607	0.001372	0	0.001217	0	0	0	0
Hussein	0.002262	0.002262	0.001217	0	0.001372	0	0.001217	0	0	0	0
Ayub	0.009953	0.009479	0.006363	0.001826	0.00676	0.001537	0.005955	0	0	0.001945	0
Azahari	0.005133	0.004921	0.003271	0.00695	0.003446	0.000765	0.003082	0	0	0.000954	0
Zulkarnaen	0.34728	0.24726	0.388262	0.285554	0.252028	0.097027	0.350627	0.08455	0.08455	0.396275	0.08455
Ghoni	0.002262	0.002262	0.001217	0	0.001372	0	0.001217	0	0.001825	0	0.001217
Top	0.005133	0.004921	0.003271	0.00695	0.003446	0.000765	0.003082	0	0	0.000954	0
Idris	0.004962	0.004825	0.003025	0.000677	0.003278	0.000599	0.002915	0	0	0.000709	0
Mustofa	0.025897	0.02021	0.02776	0.029223	0.020095	0.008106	0.016458	0	0	0.019414	0
WanMin	0.02015	0.018527	0.014188	0.008352	0.014103	0.004113	0.012465	0	0	0.005837	0
Maidin	0.009172	0.007488	0.004355	0	0.007808	0	0.004355	0	0	0	0
Sani	0.001176	0.001176	0.00023	0.000633	0.00023	0	0.000317	0.000633	0.000633	0.000633	0.000633
Dulmatin	0.000492	0.000492	0.000422	0.000362	0.000422	0	0.000844	0.001629	0.000362	0.000362	0.000362
Farik	0.000781	0.00048	0.001234	0.000862	0.000785	0.000725	0.000685	0	0	0.000949	0
Lillie	0.000781	0.00048	0.001234	0.000862	0.000785	0.000725	0.000685	0	0	0.000949	0
Yunos2	0.001176	0.001176	0.00023	0.000633	0.00023	0	0.000317	0.000633	0.000633	0.000633	0.000633
Naharudin	0.001176	0.001176	0.00023	0.000633	0.00023	0	0.000317	0.000633	0.000633	0.000633	0.000633
Gungun	0.001176	0.001176	0.000864	0.000633	0.00023	0	0.000317	0.000633	0.000633	0.000633	0.000633
Marzuki	0.000633	0.000549	0.000193	0.000412	0.000193	0	0.00025	0.000412	0.000412	0.000412	0.000412
Kastari	0.000628	0.000613	0.000468	0	0.000884	0	0.000468	0	0	0	0
Hafidh	0.00254	0.002525	0.002166	0.000944	0.002851	0.000776	0.004395	0	0	0.001072	0
Setiono	0.000791	0.000791	0.000608	0	0.000645	0	0.001217	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0.032212	0.018466	0.037723	0.041645	0.02591	0.011717	0.019168	0	0	0.030265	0
Mustaqim	0.032215	0.02093	0.025475	0.039295	0.016375	0.008668	0.012908	0.008485	0.008485	0.030876	0.008485
Fathi	0.000603	0.000563	0.000446	0	0.000571	0	0.000446	0	0	0	0
Khalim	0.000603	0.000563	0.000446	0	0.000571	0	0.000446	0	0	0	0
Roche	0.002262	0.002262	0.001217	0	0.001372	0	0.001217	0	0	0	0
Thomas	0.000884	0.000767	0.000575	0	0.000628	0	0.000575	0	0	0	0

	Imron	Sufaat	Dwikarna	Mobarok	Yunos	Mistooki	Faiz	Hasyim	Sulaeman	Hussein	Ayub	Azahari
Baasyir	0.254904	0.054111	0.087878	0.344182	0.290484	0.222701	0.119257	0.093726	0.255234	0.255234	0.309344	0.304155
Sungkar	0.171989	0.036509	0.04629	0.209277	0.131479	0.124477	0.092635	0.059015	0.172211	0.172211	0.198774	0.196718
Hambali	0.04439	0.162762	0.077718	0.14042	0.344788	0.106872	0.079403	0.061677	0.122108	0.122108	0.175873	0.172357
Mukhlas	0.02121	0.00283	0.004759	0.014456	0.016624	0	0	0.018176	0.018176	0	0.003507	0.02545
Iqbal	0.025385	0.09308	0.069831	0.072428	0.172587	0.081141	0.048425	0.045157	0.078753	0.078753	0.106861	0.103845
Faruq	0	0	0.001091	0.001265	0.002225	0	0	0	0	0	0.000824	0.000781
Syawal	0.003015	0.006035	0.008811	0.006241	0.013716	0.005282	0.003924	0.003048	0.006035	0.006035	0.008134	0.008026
Ghozi	0.0019	0.000211	0	0.0019	0.000362	0	0	0	0	0	0	0
Samudra	0.000633	0.000211	0	0.000633	0.000362	0	0.00095	0	0	0	0	0
Jabir	0.046493	0.015507	0.029591	0.083056	0.126872	0	0	0	0	0	0.020471	0.019133
Amrozi	0.001583	0.000211	0	0.000633	0.000362	0	0.00038	0	0	0	0	0
Imron	0	0.000211	0	0.0019	0.000362	0	0	0	0	0	0	0
Sufaat	0.000211	0	0	0.000211	0.000362	0	0	0	0	0	0	0
Dwikarna	0	0	0	0.000497	0.000794	0	0	0	0	0	0.000354	0.000326
Mobarok	0.0071	0.00079	0.000953	0	0.002914	0	0	0	0	0	0.002367	0.000692
Yunos	0.00257	0.00257	0.002897	0.00554	0	0	0	0	0	0	0.00179	0.001655
Mistooki	0	0	0	0	0	0	0.000698	0.002578	0.001065	0.001065	0.001065	0.001065
Faiz	0	0	0	0	0	0.000507	0	0.000344	0.000575	0.000575	0.000575	0.000575
Hasyim	0	0	0	0	0	0.001871	0.000344	0	0.002655	0.000446	0.000446	0.002339
Sulaeman	0	0	0	0	0	0.001065	0.000791	0.003657	0	0.001217	0.001217	0.003824
Hussein	0	0	0	0	0	0.001065	0.000791	0.000615	0.001217	0	0.002433	0.001217
Ayub	0	0	0.001267	0.004418	0.001757	0.003866	0.002873	0.002231	0.004418	0.008832	0	0.005417
Azahari	0	0	0.000613	0.000677	0.000852	0.002028	0.001507	0.006134	0.007281	0.002317	0.002841	0
Zulkarnae	0.08455	0.04225	0.107679	0.16905	0.276728	0.026882	0.023889	0.021252	0.0282	0.0282	0.07045	0.063096
Ghoni	0	0	0	0	0	0.001065	0.002616	0.000615	0.001217	0.001217	0.001217	0.001217
Top	0	0	0.000613	0.000677	0.000852	0.002028	0.001507	0.006134	0.007281	0.002317	0.002841	0.009267
Idris	0	0	0.000517	0.001158	0.000659	0.002028	0.001507	0.00117	0.002317	0.002317	0.004633	0.002744
Mustofa	0	0	0.004684	0.005877	0.011588	0.00731	0.005431	0.004218	0.008352	0.008352	0.011799	0.011483
WanMin	0	0	0.003001	0.003452	0.004855	0.00731	0.005431	0.004218	0.008352	0.008352	0.010792	0.016698
Maidin	0	0	0	0	0	0.006922	0.002719	0.004268	0.004355	0.004355	0.004355	0.004355
Sani	0.000633	0.000211	0	0.000633	0.000362	0	0	0	0	0	0	0
Dulmatin	0.001629	0.000362	0	0.001629	0.000633	0	0	0	0	0	0	0
Farik	0	0	0.00048	0.000543	0.000843	0	0	0	0	0	0.000377	0.00036
Lillie	0	0	0.00048	0.000543	0.000843	0	0	0	0	0	0.000377	0.00036
Yunos2	0.000633	0.000211	0	0.000633	0.000362	0	0	0	0	0	0	0
Naharudin	0.000633	0.000211	0	0.000633	0.000362	0	0	0	0	0	0	0
Gungun	0.000633	0.000211	0	0.000633	0.000362	0	0	0	0	0	0	0
Marzuki	0.000412	0.000179	0	0.000412	0.000277	0	0	0	0	0	0	0
Kastari	0	0	0	0	0	0.000475	0.000362	0.000347	0.000468	0.000468	0.000468	0.000468
Hafidh	0	0	0.001851	0.000678	0.001084	0.000966	0.000841	0.000655	0.001095	0.001095	0.001578	0.001539
Setiono	0	0	0	0	0	0.000568	0.00048	0.000408	0.001825	0.000608	0.000608	0.000608
BinHir	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0.006997	0.008421	0.017957	0.006577	0.005731	0.004465	0.007458	0.007458	0.012315	0.011847
Mustaqim	0.008485	0.00283	0.005177	0.014715	0.018136	0	0	0	0	0	0.003594	0.003247
Fathi	0	0	0	0	0	0.001871	0.001227	0.001766	0.000446	0.000446	0.000446	0.000446
Khalim	0	0	0	0	0	0.000546	0.000344	0.000441	0.000446	0.000446	0.000446	0.000446
Roche	0	0	0	0	0	0.001065	0.000791	0.000615	0.001217	0.001217	0.001217	0.001217
Thomas	0	0	0	0	0	0.000546	0.000411	0.000358	0.000575	0.000575	0.000575	0.000575

	Zulkarnaen	Ghoni	Top	Idris	Mustofa	WanMin	Maidin	Sani	Dulmatin	Farik	Lillie	Yunos2
Baasyir	0.56391892	0.255234	0.304155	0.294025	0.425719	0.331252	0.295096	0.254904	0.106574	0.086972	0.086972	0.254904
Sungkar	0.27090375	0.172211	0.196718	0.192883	0.224169	0.205498	0.162542	0.171989	0.071908	0.036009	0.036009	0.171989
Hambali	0.56072875	0.122108	0.172357	0.159392	0.405878	0.207444	0.124598	0.04439	0.081381	0.122108	0.122108	0.04439
Mukhlas	0.0286567	0	0.02545	0.002479	0.02969	0.008485	0	0.008485	0.004846	0.00593	0.00593	0.008485
Iqbal	0.20815141	0.078753	0.103845	0.098777	0.168021	0.11792	0.127765	0.025385	0.04654	0.044445	0.044445	0.025385
Faruq	0.00271646	0	0.000781	0.000612	0.002298	0.001166	0	0	0	0.001392	0.001392	0
Syawal	0.02502506	0.006035	0.008026	0.007591	0.011892	0.009007	0.006158	0.003015	0.008044	0.003352	0.003352	0.003015
Ghozi	0.00063346	0	0	0	0	0	0	0.000633	0.001629	0	0	0.000633
Samudra	0.00063346	0.00095	0	0	0	0	0	0.000633	0.000362	0	0	0.000633
Jabir	0.21790457	0	0.019133	0.014224	0.108074	0.032492	0	0.046493	0.026551	0.035755	0.035755	0.046493
Amrozi	0.00063346	0.000633	0	0	0	0	0	0.000633	0.000362	0	0	0.000633
Imron	0.00063346	0	0	0	0	0	0	0.000633	0.001629	0	0	0.000633
Sufaat	0.00031654	0	0	0	0	0	0	0.000211	0.000362	0	0	0.000211
Dwikarna	0.00157102	0	0.000326	0.000275	0.000692	0.000443	0	0	0	0.00048	0.00048	0
Mobarok	0.00473286	0	0.000692	0.001183	0.001666	0.000978	0	0.002367	0.006086	0.001042	0.001042	0.002367
Yunos	0.0147312	0	0.001655	0.00128	0.006245	0.002616	0	0.00257	0.004501	0.003075	0.003075	0.00257
Mistooki	0.0003869	0.001065	0.001065	0.001065	0.001065	0.001065	0.001974	0	0	0	0	0
Faiz	0.00024963	0.0019	0.000575	0.000575	0.000575	0.000575	0.000563	0	0	0	0	0
Hasyim	0.00022207	0.000446	0.002339	0.000446	0.000446	0.000446	0.000884	0	0	0	0	0
Sulaeman	0.00040588	0.001217	0.003824	0.001217	0.001217	0.001217	0.001242	0	0	0	0	0
Hussein	0.00040588	0.001217	0.001217	0.001217	0.001217	0.001217	0.001242	0	0	0	0	0
Ayub	0.00368085	0.004418	0.005417	0.008832	0.006241	0.005708	0.004508	0	0	0.001352	0.001352	0
Azahari	0.00172916	0.002317	0.009267	0.002744	0.003186	0.004633	0.002364	0	0	0.000676	0.000676	0
Zulkarnae	0	0.0282	0.063096	0.05635	0.229204	0.087695	0.028352	0.08455	0.1127	0.066494	0.066494	0.08455
Ghoni	0.00040588	0	0.001217	0.001217	0.001217	0.001217	0.001242	0	0	0	0	0
Top	0.00172916	0.002317	0	0.002744	0.003186	0.004633	0.002364	0	0	0.000676	0.000676	0
Idris	0.00154429	0.002317	0.002744	0	0.002994	0.002841	0.002364	0	0	0.000542	0.000542	0
Mustofa	0.02264019	0.008352	0.011483	0.010792	0	0.013362	0.008522	0	0	0.005837	0.005837	0
WanMin	0.00866229	0.008352	0.016698	0.01024	0.013362	0	0.008522	0	0	0.003437	0.003437	0
Maidin	0.00143104	0.004355	0.004355	0.004355	0.004355	0.004355	0	0	0	0	0	0
Sani	0.00063346	0	0	0	0	0	0	0	0.000362	0	0	0.000633
Dulmatin	0.00084436	0	0	0	0	0	0	0.000362	0	0	0	0.000362
Farik	0.00097014	0	0.00036	0.000289	0.000862	0.000508	0	0	0	0	0.00185	0
Lillie	0.00097014	0	0.00036	0.000289	0.000862	0.000508	0	0	0	0.00185	0	0
Yunos2	0.00063346	0	0	0	0	0	0	0.000633	0.000362	0	0	0
Naharudin	0.00063346	0	0	0	0	0	0	0.000633	0.000362	0	0	0.000633
Gungun	0.00063346	0	0	0	0	0	0	0.000633	0.000362	0	0	0.000633
Marzuki	0.00041154	0	0	0	0	0	0	0.000412	0.000277	0	0	0.000412
Kastari	0.00022737	0.000468	0.000468	0.000468	0.000468	0.000468	0.000571	0	0	0	0	0
Hafidh	0.00413494	0.001095	0.001539	0.00147	0.002039	0.0017	0.001073	0	0	0.000654	0.000654	0
Setiono	0.00121691	0.000608	0.000608	0.000608	0.000608	0.000608	0.000615	0	0	0	0	0
BinHir	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0.03495728	0.007458	0.011847	0.01087	0.049103	0.014565	0.007307	0	0	0.008318	0.008318	0
Mustaqim	0.03194993	0	0.003247	0.002525	0.03081	0.005258	0	0.008485	0.004846	0.006154	0.006154	0.008485
Fathi	0.00022207	0.000446	0.000446	0.000446	0.000446	0.000446	0.000884	0	0	0	0	0
Khalim	0.00022207	0.000446	0.000446	0.000446	0.000446	0.000446	0.000884	0	0	0	0	0
Roche	0.00040588	0.001217	0.001217	0.001217	0.001217	0.001217	0.001242	0	0	0	0	0
Thomas	0.00024963	0.000575	0.000575	0.000575	0.000575	0.000575	0.000603	0	0	0	0	0

	Naharudin	Gungun	Marzuki	Kastari	Hafidh	Setiono	BinHir	Rusdan	Mustaqim	Fathi	Khalim	Roche	Thomas
Baasyir	0.2549042	0.254904	0.137294	0.097597	0.207135	0.089278	0	0.38561	0.521256	0.093726	0.093726	0.255234	0.137294
Sungkar	0.17198915	0.171989	0.080243	0.064239	0.138925	0.060238	0	0.14915	0.228504	0.059015	0.059015	0.172211	0.080465
Hambali	0.0443895	0.166497	0.037138	0.06468	0.157121	0.061017	0	0.40163	0.366616	0.061677	0.061677	0.122108	0.079403
Mukhlas	0.00848503	0.008485	0.005512	0	0.004759	0	0	0.03081	0.039295	0	0	0	0
Iqbal	0.02538534	0.025385	0.021238	0.069831	0.118255	0.036989	0	0.157758	0.13476	0.045157	0.045157	0.078753	0.04964
Faruq	0	0	0	0	0.001091	0	0	0.002418	0.002418	0	0	0	0
Syawal	0.00301546	0.003015	0.002378	0.003196	0.015751	0.006035	0	0.010085	0.00918	0.003048	0.003048	0.006035	0.003924
Ghozi	0.00063346	0.000633	0.000412	0	0	0	0	0	0.000633	0	0	0	0
Samudra	0.00063346	0.000633	0.000412	0	0	0	0	0	0.000633	0	0	0	0
Jabir	0.04649263	0.046493	0.030205	0	0.029591	0	0	0.122688	0.169181	0	0	0	0
Amrozi	0.00063346	0.000633	0.000412	0	0	0	0	0	0.000633	0	0	0	0
Imron	0.00063346	0.000633	0.000412	0	0	0	0	0	0.000633	0	0	0	0
Sufaat	0.00021128	0.000211	0.000179	0	0	0	0	0	0.000211	0	0	0	0
Dwikarna	0	0	0	0	0.001356	0	0	0.000753	0.000753	0	0	0	0
Mobarok	0.00236714	0.002367	0.001538	0	0.000953	0	0	0.001738	0.004105	0	0	0	0
Yunos	0.0025704	0.00257	0.001966	0	0.002897	0	0	0.007047	0.00962	0	0	0	0
Mistooki	0	0	0	0.000654	0.000698	0.000568	0	0.000698	0	0.002578	0.000753	0.001065	0.000753
Faiz	0	0	0	0.000362	0.000441	0.000348	0	0.000441	0	0.001227	0.000344	0.000575	0.000411
Hasyim	0	0	0	0.000347	0.000344	0.000296	0	0.000344	0	0.001766	0.000441	0.000446	0.000358
Sulaeman	0	0	0	0.000645	0.000791	0.001825	0	0.000791	0	0.000615	0.000615	0.001217	0.000791
Hussein	0	0	0	0.000645	0.000791	0.000608	0	0.000791	0	0.000615	0.000615	0.001217	0.000791
Ayub	0	0	0	0.00234	0.004139	0.002207	0	0.004744	0.001871	0.002231	0.002231	0.004418	0.002873
Azahari	0	0	0	0.001227	0.002118	0.001158	0	0.002394	0.000887	0.00117	0.00117	0.002317	0.001507
Zulkarnaeı	0.08455024	0.08455	0.05493	0.021759	0.207648	0.08455	0	0.257708	0.318369	0.021252	0.021252	0.0282	0.023889
Ghoni	0	0	0	0.000645	0.000791	0.000608	0	0.000791	0	0.000615	0.000615	0.001217	0.000791
Top	0	0	0	0.001227	0.002118	0.001158	0	0.002394	0.000887	0.00117	0.00117	0.002317	0.001507
Idris	0	0	0	0.001227	0.002022	0.001158	0	0.002196	0.000689	0.00117	0.00117	0.002317	0.001507
Mustofa	0	0	0	0.004424	0.010115	0.004173	0	0.035756	0.030326	0.004218	0.004218	0.008352	0.005431
WanMin	0	0	0	0.004424	0.008432	0.004173	0	0.010606	0.005175	0.004218	0.004218	0.008352	0.005431
Maidin	0	0	0	0.00276	0.002719	0.002156	0	0.002719	0	0.004268	0.004268	0.004355	0.002913
Sani	0.00063346	0.000633	0.000412	0	0	0	0	0	0.000633	0	0	0	0
Dulmatin	0.00036176	0.000362	0.000277	0	0	0	0	0	0.000362	0	0	0	0
Farik	0	0	0	0	0.00048	0	0	0.000895	0.000895	0	0	0	0
Lillie	0	0	0	0	0.00048	0	0	0.000895	0.000895	0	0	0	0
Yunos2	0.00063346	0.000633	0.000412	0	0	0	0	0	0.000633	0	0	0	0
Naharudin	0	0.000633	0.000412	0	0	0	0	0	0.000633	0	0	0	0
Gungun	0.00063346	0	0.000412	0	0	0	0	0	0.000633	0	0	0	0
Marzuki	0.00041154	0.000412	0	0	0	0	0	0	0.000412	0	0	0	0
Kastari	0	0	0	0	0.000362	0.000306	0	0.000362	0	0.000347	0.000347	0.000468	0.000367
Hafidh	0	0	0	0.00069	0	0.000664	0	0.00187	0.001027	0.000655	0.000655	0.001095	0.000783
Setiono	0	0	0	0.000421	0.00048	0	0	0.00048	0	0.000408	0.000408	0.000608	0.00048
BinHir	0	0	0	0	0	0	0	0	0	0	0	0	0
Rusdan	0	0	0	0.004699	0.012735	0.00452	0	0	0.045869	0.004465	0.004465	0.007458	0.005332
Mustaqim	0.00848503	0.008485	0.005512	0	0.005177	0	0	0.033935	0	0	0	0	0
Fathi	0	0	0	0.000347	0.000344	0.000296	0	0.000344	0	0	0.000441	0.000446	0.000358
Khalim	0	0	0	0.000347	0.000344	0.000296	0	0.000344	0	0.000441	0	0.000446	0.000358
Roche	0	0	0	0.000645	0.000791	0.000608	0	0.000791	0	0.000615	0.000615	0	0.000791
Thomas	0	0	0	0.000367	0.000411	0.000348	0	0.000411	0	0.000358	0.000358	0.000575	0

A.5. Fuzzy Clique Parametric Analysis

This section contains the results of the fuzzy clique parametric analysis of the Jemaah Islamiah terrorist network.

A.5.1. Node Membership Value

	Theta										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Baaysir	0.4	0.8	0.8	0.8	0.8	1	1	1	1	1	1
Sungkar	0.2	0.2	0.2	0.2	0.4	0.6	0.6	0.6	0.8	0.8	0.4
Hambali	0.4	0.6	0.6	0.6	0.8	1	1	1	1	1	1
Iqbal	0.4	0.4	0.4	0.4	0.6	0.6	0.6	0.6	0.6	0.6	0.4
Zulkarnaen	0.2	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.6	0.6	0.4
Rusdan	0	0	0	0	0.2	0.4	0.4	0.4	0.4	0.4	0.4

A.5.2. Clique-Clique Coefficient

		Theta										
From	**To**	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
Emir	**Colonel**	1786.732	1765.114	1805.752	1909.347	2080.002	2325.448	2657.543	3093.068	3654.908	4373.71	5330.5
Emir	**Captain**	1751.561	1736.985	1780.065	1881.656	2045.672	2279.284	2593.347	3003.096	3529.144	4198.89	5348.412
Emir	**Troop**	1605.949	1600.291	1656.37	1774.619	1959.572	2220.089	2569.945	3028.817	3623.743	4391.197	5415.539
Colonel	**Captain**	735.9033	626.0168	537.2387	465.1891	406.4635	358.4055	318.9343	286.4136	259.5517	237.3254	323.2456
Colonel	**Troop**	775.9103	642.625	540.4923	462.3347	402.8744	358.2491	325.6643	303.1442	289.3555	283.4863	390.3725
Captain	**Troop**	576.1588	492.87	427.9529	377.4519	338.436	308.7421	286.7933	271.4679	262.0098	257.9665	408.2848

B.1. Introduction

As discussed in Chapter 3, multidimensional centrality (MDC) can be used to evaluate individual importance across multiple social networks based solely on network topology. This appendix details the calculation of MDC for a simple example.

B.2. Multidimensional Centrality Sample Problem

An example situation in which MDC can provide added insight is given in Figure B-0-1. Consider three individuals A, B, and C, in three separate network contexts; work (1), members on same sports teams (2), and members of same professional society (3).

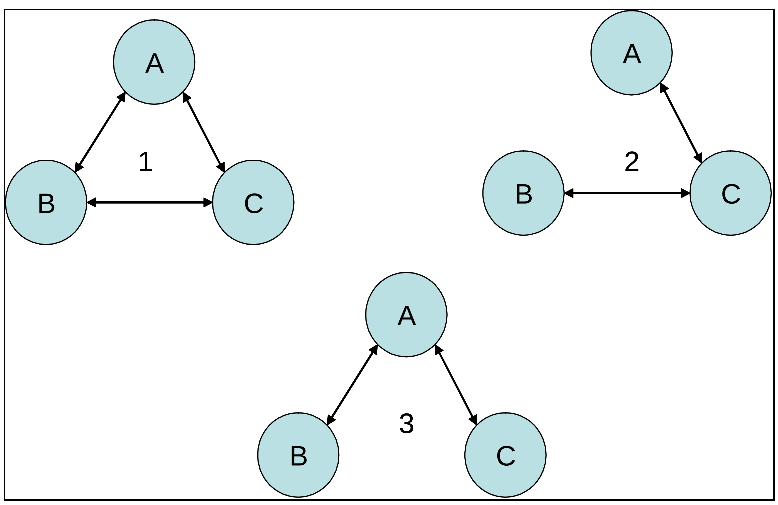

Figure B-0-1: Multiple Network Contexts--Example Situation

This situation can be represented by a hypergraph using a node-arc incidence matrix. Create the matrix, **E**, where the rows represent arcs and the columns represent the nodes and the network contexts. There are six columns in this matrix, 3 for nodes *A*, *B*, and *C*, and 3 for the three network contexts, as shown in Table B-1

Table B-1: Node-Arc Incidence Matrix with Hyperedges

	Node			Network		
	A	**B**	**C**	**1**	**2**	**3**
arc a-b	1	1	0	1	0	1
arc a-c	1	0	1	1	1	1
arc b-c	0	1	1	1	1	0

This yields the following node-arc incidence matrix:

$$E = \begin{bmatrix} 1 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 & 0 \end{bmatrix}$$

Once a hypergraph has been represented in a node-arc incidence matrix, MDC can be calculated. MDC is an extension of eigenvector centrality applied to hypergraphs. To calculate, let $M = E^T E$, then solve the eigenvector-eigenvalue problem for M. Node and network multidimensional centrality scores are given by the eigenvector associated with the largest eigenvalue of **M**.

For the sample situation in Figure B-0-1,

$$M = E^T E = \begin{bmatrix} 2 & 1 & 1 & 2 & 1 & 2 \\ 1 & 2 & 1 & 2 & 1 & 1 \\ 1 & 1 & 2 & 2 & 2 & 1 \\ 2 & 2 & 2 & 3 & 2 & 2 \\ 1 & 1 & 2 & 2 & 2 & 1 \\ 2 & 1 & 1 & 2 & 1 & 2 \end{bmatrix}$$

Table B-2 gives the MDC scores for the three network contexts:

Table B-2: Individual Multidimensional Centrality Scores

Node	MDC
A	0.3816
B	0.3381
C	0.3816

As expected, with this simple network, the scores are very similar. The MDC scores for the individuals do highlight the difference between node B and nodes A and C. It is clear to see that across the three networks node B is the least connected, while nodes A and C have the same number of connections.

B.3. Limitations

The reader is reminded that MDC can be misleading. When analyzing clandestine networks it is likely that individuals for whom we have the most data *may* be of little importance to the network under study. If one assumes key network members are practicing better OPSEC, it is likely less data will be available. Nodes with more connections identified, however, will score highly on multidimensional centrality. This “easy” to monitor individual, however, may be of little importance to the question under consideration for the clandestine network. In addition, MDC is only shown to work for undirected networks. Therefore, results of multidimensional centrality must be carefully considered with regards to the situation before recommending further action.

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14. ABSTRACT

Since Sept. 11, 2001, there has been great interest in the military and intelligence communities in using Social Network Analysis (SNA) to support the disruption and destruction of global terrorist networks. SNA results, however, tend to be descriptive and are limited due to the lack of advantageous properties of the relationship measures applied to the arcs in a social network. Further, SNA techniques generally focus on a single network context while real relationships are based in multiple contexts. This thesis develops a new proxy measure of pair-wise potential influence between members of a network, a Holistic Interpersonal Influence Measure (HIIM). The HIIM considers the topology of the multiple formal and informal networks to which group members belong as well as non-network characteristics such as age and education level that may indicate potential influence. The HIIM, once constructed results in a network of pair-wise potential influence between group members. Further, the numeric properties of the HIIM are appropriate for use in Operations Research Network Flow models, which will enable analysts to provide prescriptive analysis focused on specific actions and their outcomes. In addition to an overall measure of influence, the HIIM methodology provides important intermediate results such as the development of operational group profiles.
The methodology is applied to open source data on both Al Qaeda and the Jemaah Islamiah (JI) terrorist networks. Key leaders are identified, and leadership profiles are developed. Further, a parametric analysis is performed to compare influence based on individual characteristics, network topology characteristics, and mixtures of network and non-network characteristics.

15. SUBJECT TERMS
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