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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.

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Modeling and Analysis of Clandestine Networks

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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. However, SNA results 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. In this paper, we develop a new proxy measure of pair-wise potential influence between members of a network. The proposed measure 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. Furthermore, the numeric properties of the proposed measure are appropriate for use in operations research network flow models. This is advantageous as it will enable analysts to perform prescriptive analyses focused on specific actions and their outcomes. We apply our methodology to open source data of the Jemaah Islamiah (JI) terrorist networks. Key leaders are identified and leadership profiles are developed. Furthermore, a parametric analysis is performed to compare influence based on individual characteristics, network topology characteristics, and mixtures of network and non-network characteristics.

1. INTRODUCTION

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).

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.

The demand for analysis tools designed to support the analysis of clandestine networks led us to develop a new Social Network Analysis (SNA) technique that is compatible with traditional Operations Research (OR) methods. This was accomplished by developing the Holistic Interpersonal Influence Measure (HIIM) that considers both individual characteristics and network structure in determining influence within clandestine networks. The purpose of this paper is to introduce an analysis process that enables a better understanding of clandestine networks.

Clandestine Networks

Clandestine networks must constantly balance the desire for organizational effectiveness with the need for operational security (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 crime 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).

Operational Definition of Influence

In order to develop a measure of interpersonal influence, it is important to offer a relevant definition. 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.

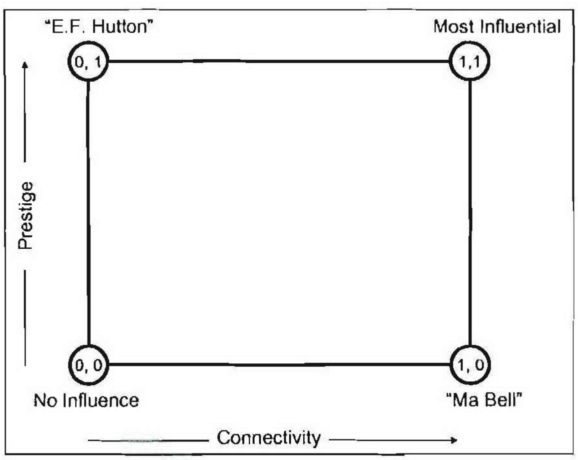

Figure 1-1: Operational Definition of Influence

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 Ma Bell, as well as all other network members.

2. REVIEW OF CURRENT TECHNIQUES

The HIIM uses the theories of Social Network Analysis (SNA), Social Influence Network (SIN) Theory, Multivariate Statistics in its development, and Network Flows and Fuzzy Clique Analysis in its applications. There exists a fair amount of literature available on these topics.

Social Network Analysis

Researchers (ex. Simmel, 1906; Gross, 1980; Geis and Stotland, 1980; Erickson, 1981; Baker and Faulkner, 1993; Klerks, 2001) have conducted 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 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 studies typically focus on a single network and attempts to depict 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). For an exhaustive review of SNA the reader is referred to Wasserman and Faust, 1994. SNA provides descriptive measures focused 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.

SNA results 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 (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).

Social Influence Network Theory

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.

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 two fundamental components. The first component 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). Although the fundamental components of SINs are designed to capture exogenous measures of influence, much of the current work uses endogenous (i.e., network structure) relationships to develop the exogenous measures of initial opinion. This can often result in a purely structural based measure of network influence.

In this paper, we propose the use of discriminant analysis to improve upon the development of exogenous measures of individual influence. In particular, if one can assume that within a network there exists a group of individuals having more influence than ordinary network members, then discriminant analysis may be able to identify the characteristics of this influential group.

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. This paper briefly highlights 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 is 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. Further, an analysis of open source data on the Jemaah Islamiah terrorist network is performed to highlight the benefits of using the HIIM methodology.

3. METHODOLOGY OVERVIEW – Development of the Holistic Interpersonal Influence Measure (HIIM)

Influence Based on Individual Characteristics

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 $\mathbf{E} = \mathbf{XB}$, where $\mathbf{E}$ is an $(n \times 1)$ vector of exogenous influence measures; $\mathbf{X}$ is an $(n \times p)$ matrix of p non-network related characteristics for n group members; and $\mathbf{B}$ 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 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.

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**. 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 is a technique for classifying a set of observations into predefined classes. The purpose is to determine the class of an observation based on a set of variables known as predictors or input variables. A model is built based on a set of observations for which the classes are known (e.g., leadership versus non-leadership). This set of observations is sometimes referred to as the training set. Based on the training set, discriminant analysis constructs a set of linear functions of the predictor variables known as discriminant functions (e.g., $\mathbf{E} = \mathbf{XB}$). Once estimated, these functions can be used to predict an individual's *a posteriori* probability of belonging to a particular group, thus, providing a statistically sound technique for profiling, differentiating, and classifying clandestine network members on the basis of an observed set of characteristic data. Furthermore, the model output can be used as a proxy measure of exogenous influence based on individual characteristics.

Influence Based on Social Network Topology

The development of an appropriate measure of interpersonal influence is critical to 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). Clark (Clark 2004, 3.16-3.23) discusses the different approaches for developing **W**, the pair-wise influence measures for a single network context. The strengths and weaknesses of each approach are briefly summarized in Table 3-1.

Table 3-1: Summary of Pair-wise Influence Measure Techniques

	Network Symmetry	Indirect Connections (attenuation factor)	Computation Complexity
Katz, Hubbell	Appropriate for symmetric and non-symmetric networks	Attenuation factor limited by size of largest eigenvalue of A	Calculation of Inverse, will exist by construction
Stephenson and Zelen	Appropriate for symmetric networks only	Uniform attenuation, inverse of path length	Calculation of Inverse, will exist by construction

The Stephenson-Zelen method is only appropriate for undirected networks. Its ease of calculation and results are comparable to the Katz-Hubbell 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.

As previously noted, because of their need to practice good OPSEC, clandestine networks are built on a foundation of pre-existing, trusted social networks. These pre-existing networks (e.g., family, friends, schoolmates), by their very nature, are two-way relationships. The current literature offers little discussion on the impact of indirect connections in such networks for clandestine groups. It is our opinion that Information Centrality is most appropriate for the development of interpersonal influence measures for clandestine networks.

The informal networks upon which clandestine networks are built are most often undirected networks. Information Centrality, then, can be calculated for these informal networks. Let the matrix **A** denote 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

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

$$B_{ij} = 1 - A_{ij}$$

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

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

where 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 3-1 graphically displays this process:

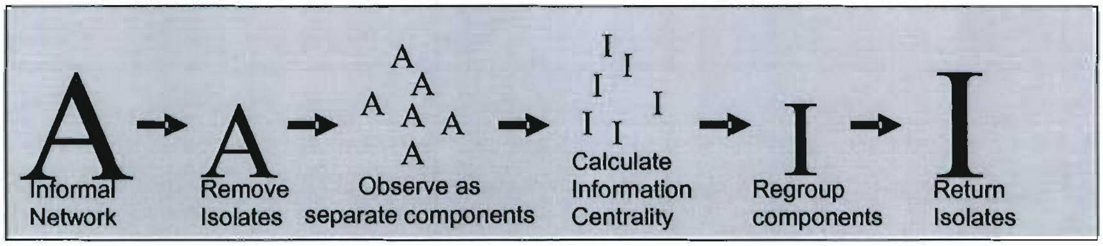

Figure 3-2: Steps to Calculate Information Centrality

Influence Based on Multiple Social Networks

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.

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 $W = \lambda_1 I_1 + \lambda_2 I_2 + ... + \lambda_n I_n$, where $\mathbf{I}_i$ is a matrix of pair-wise interpersonal influences from network i as defined in the previous section, and λ_i is the perceived importance of network context i in determining influence within the group. Furthermore, a constraint is added to the weights such that $\sum \lambda_i = 1$.

There are a variety of elicitation techniques for developing weights based on decision maker opinion or subject matter expertise. von Winterfeldt and Edwards (1986) provide an overview of several techniques used to construct the 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.

Holistic Interpersonal Influence Measure

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 is 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. Our next objective is to combine the information learned into a single network that is appropriate for operations research network flow models, allowing analysts to perform prescriptive rather than descriptive analysis. The final calculations are a modification of the input-output model of social status proposed by (Hubbell, 1965: 381).

Hubbell was concerned with determining ones status based on how many persons "chose a member" as well as the status of the choosers. His model can be summarized by the 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, $\mathbf{W} = [w_{ij}]$, represent the combined pair-wise interpersonal influence measures developed from *each* of the informal social networks of a clandestine network (as developed in the previous section):

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

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

where w_{ij} represents the influence of member i over member j based purely on network topology. Let the vector, $\mathbf{E} = [e_i]$, represent the individual influence measures developed based on the personal characteristics of clandestine network members (i.e. the *a posteriori* probability of belonging to the leadership group). The HIIM network, represented by $\mathbf{H} = [h_{ij}]$, 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.

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 2 implies double the potential flow compared to a cell value of 1. 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.

4. ANALYSIS OF JEMAAH ISLAMIAH

Introduction

The Holistic Interpersonal Influence Measure (HIIM) developed in this paper 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

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.

Description of JI Data – Step 1

The Jemaah Islamiah (JI) data used in this demonstration is a subset of 48 terrorists from Sageman's (Sageman, 2004) Al Qaeda data set. 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 4-1.

Table 4-1: 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 4-2 summarizes the data categories collected by Sageman:

Table 4-2: 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 4-3.

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 4-3: 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.

Analysis Objectives – Step 2

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

Development of Individual Influence Measure – Step 3

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.

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 4-3.

$$\boxed{F_{obs} = 13.4497 \gg F_{.05;(2,29)} = 0.0514}$$

Figure 4-3: 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 4-4 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 4-4: 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 4-4 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.

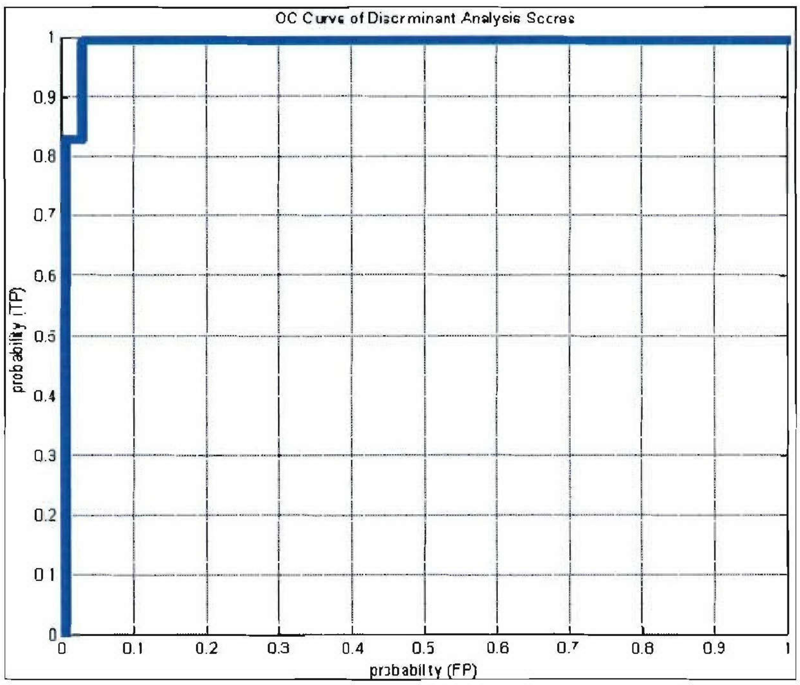

Figure 4-4: Operating Characteristic Curve of "Emir" Discriminant Function

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 4-5 shows the

Discriminant Function coefficients and Discriminant Loadings for the two significant predictor variables.

Table 4-5: 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 4-5 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 4-5 clearly shows the importance of Baasyir and Sungkar, the founders of JI, because they are the religious leaders of the majority of JI.

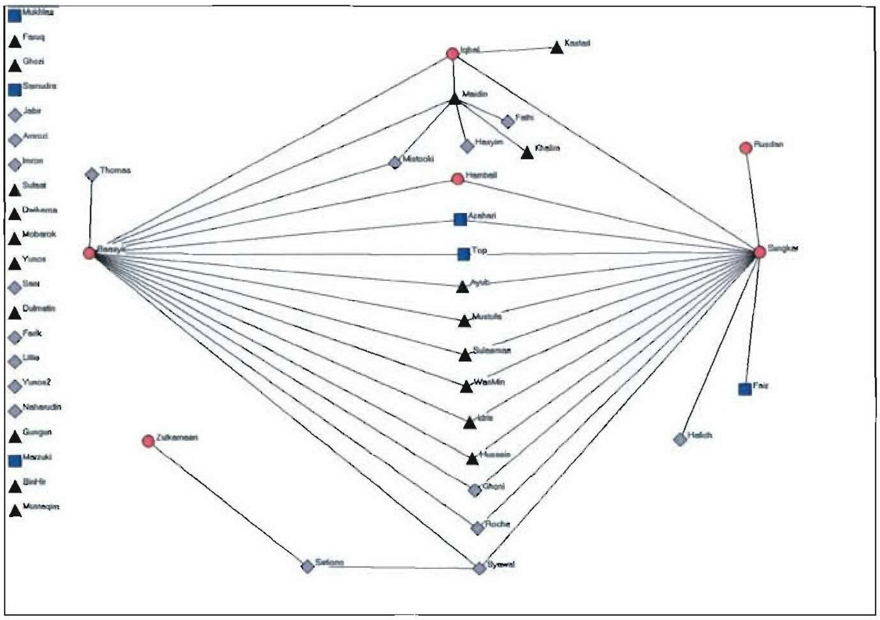

Figure 4-5: JI Religious Leader Network created in UCINET 6

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 4-6 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 4-6: 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				

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. 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.

Development of Interpersonal Influence Measures – Step 4

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 ($\mathbf{A_1}$), Nuclear Family Network ($\mathbf{A_2}$), Relative Network ($\mathbf{A_3}$), Friendship Network ($\mathbf{A_4}$), Teacher-Student Network ($\mathbf{A_5}$), and Religious Leader Network ($\mathbf{A_6}$). 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).

Analysis of Individual Networks

Pair-wise measures of individual influence based on network topology were developed for each informal social network using Information Centrality. 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.

Information Centrality accounts for all direct and indirect connections between network members, and larger scores indicate more connections. Table 4-7 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 4-7: 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 4-6 provides a graphical representation of the interpersonal influences within the Acquaintance Network for the subgroup in Table 4-7. The thickness of the arcs represented in Figure 4-6 represent the level of influence, thicker arcs imply greater influence.

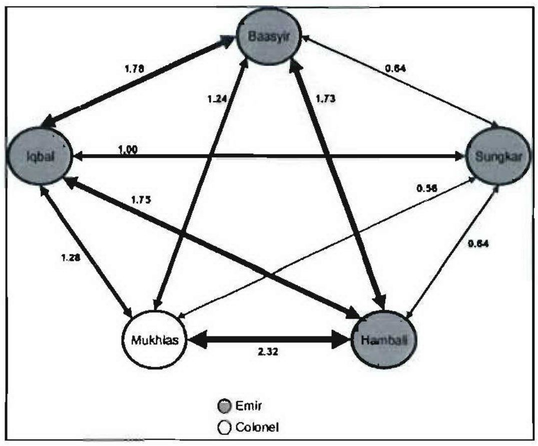

Figure 4-6: Network Representation of Acquaintance Network Interpersonal Influence

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 4-8 contains the pair-wise interpersonal influence measures for the same (5×5) subset of JI members based on the Friendship Network.

Table 4-8: 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 4-8 and Figure 4-7 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.

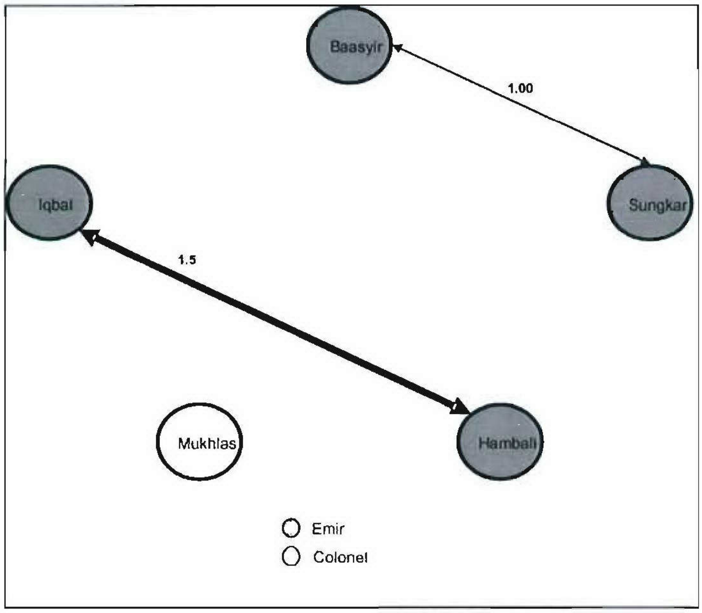

Figure 4-7: Network Representation of Friendship Network of Interpersonal Influence

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 4-9 contains the pair-wise interpersonal influence measures for the (5×5) subset of JI members based on the Teacher-Student Network.

Table 4-9: 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 4-9 and Figure 4-8, again offer a different view of interpersonal influence among JI members.

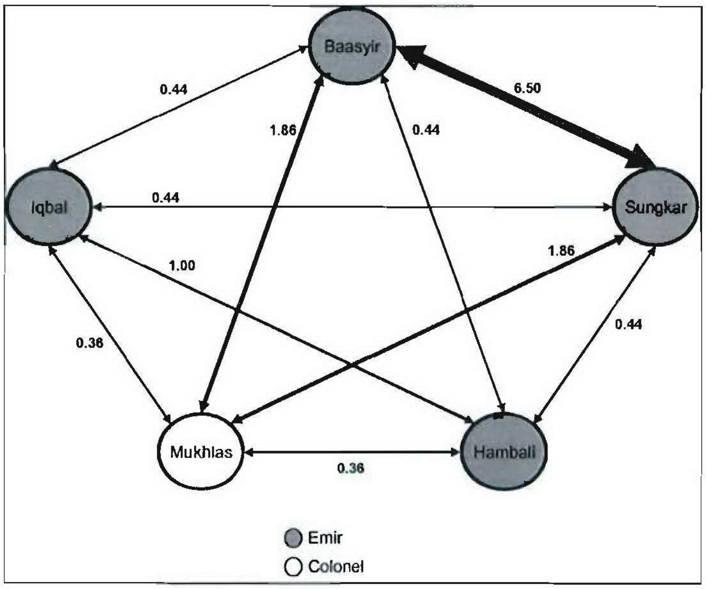

Figure 4-8: Network Representation of Teacher-Student Network of Interpersonal Influence

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.

Development of Network Weights – Step 5

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 4-10 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 4-10: 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 4-9 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 4-10.

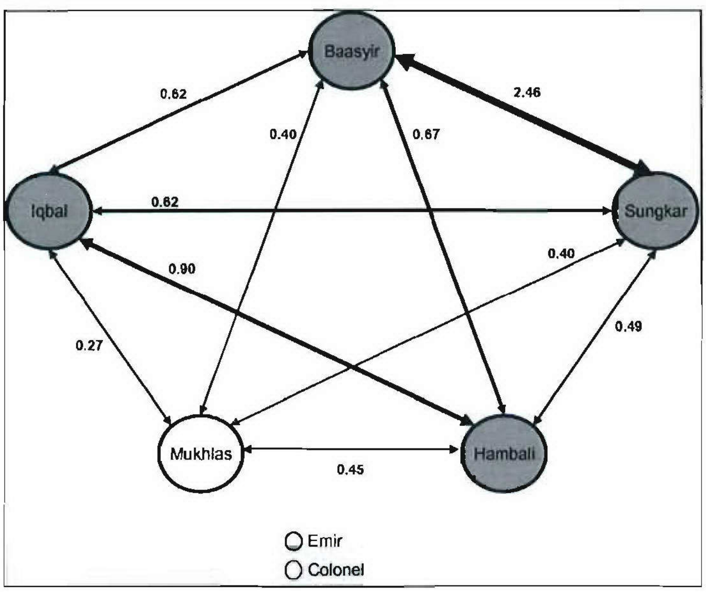

Figure 4-9: Network Representation of Combined Network Interpersonal Influence

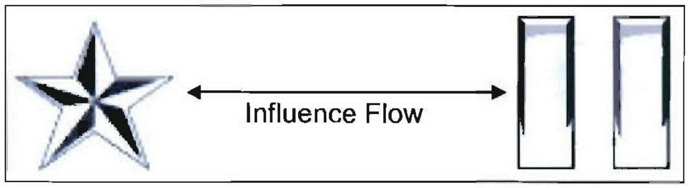

Figure 4-10: Implication of Undirected Influence Arcs

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.

Creation of the Holistic Interpersonal Influence Measure – Step 6

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. Figure 4-11 graphically displays the final calculations necessary to produce the HIIM.

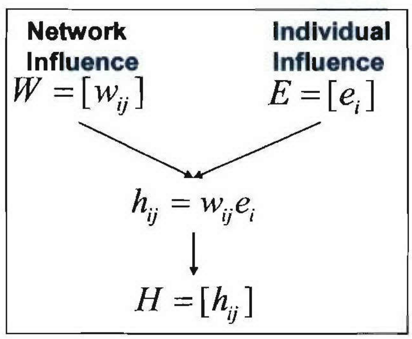

Figure 4-11: Graphical Depiction of HIIM Calculations

A portion of the HIIM network calculated for JI is shown in Table 4-11.

Table 4-11: 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 4-12, 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.

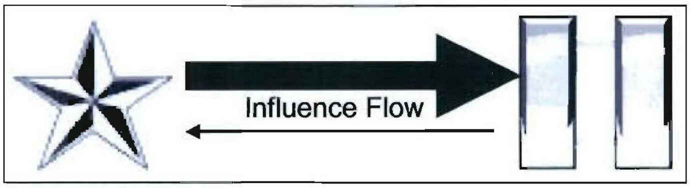

Figure 4-12: Implication of Directed Arcs in the HIIM Network

Figure 4-13 provides a graphical representation of the HIIM network calculated for JI based on Sageman's data for the discussed subgroup.

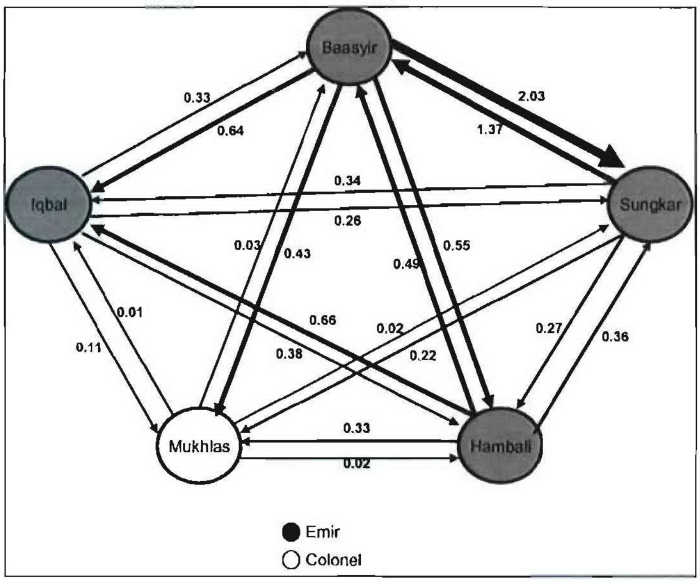

Figure 4-13: Network Representation of the HIIM Network

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.

Single Commodity Flow Model Example – Step 7

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".

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:

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

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

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

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

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 4-12 shows the maximum flows from the "Emirs" to the "Troops" for the JI network.

Table 4-12: 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".

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 4-14 shows the results of a parametric analysis of the maximum flow from the "Emirs" to the "Troops" for $\Theta = 0, 0.1. 0.2,\ldots, 1$.

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.

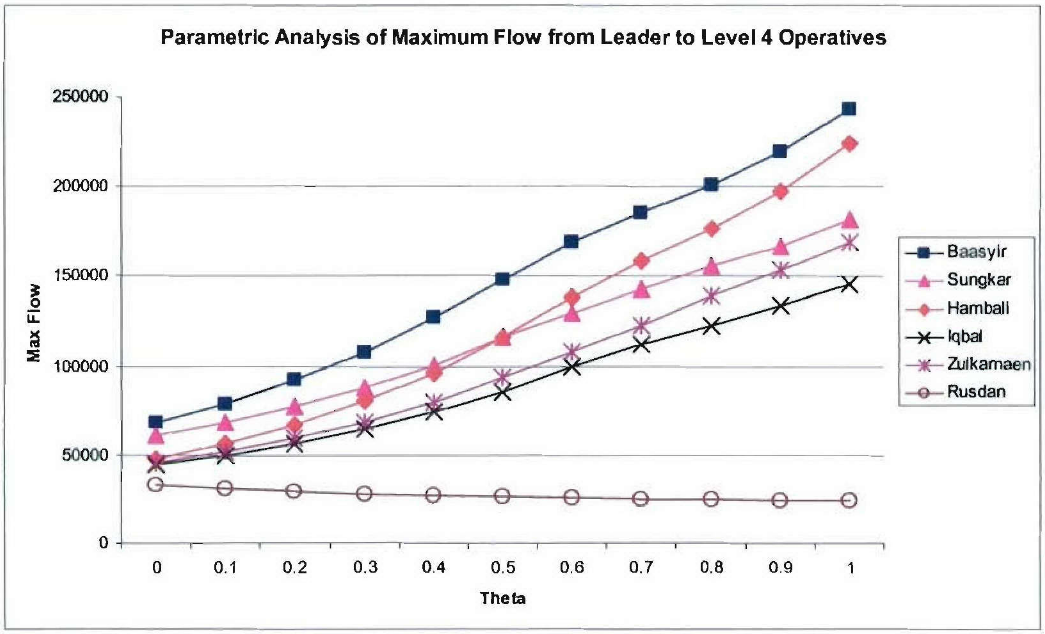

Figure 4-14: Parametric Analysis of Maximum Flow from "Emirs" to "Troops"

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.

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 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 to inaccurate pictures of the influence within JI than if they based their results on the HIIM network.

Fuzzy Clique Analysis – Step 8

One of the major concerns of SNA is the identification and analysis of cohesive subgroups (Wasserman and Faust, 1994: 249). Traditional graph theoretic subgroup detection techniques discussed are *all* limited to binary undirected networks. Further, each of the traditional techniques is 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).

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 the 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 4-13 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 4-13: 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

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

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

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

Table 4-14 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". Figure 4-15 provides a graphical representation of the between group influences within JI based on the clique-clique coefficient.

Table 4-14: 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

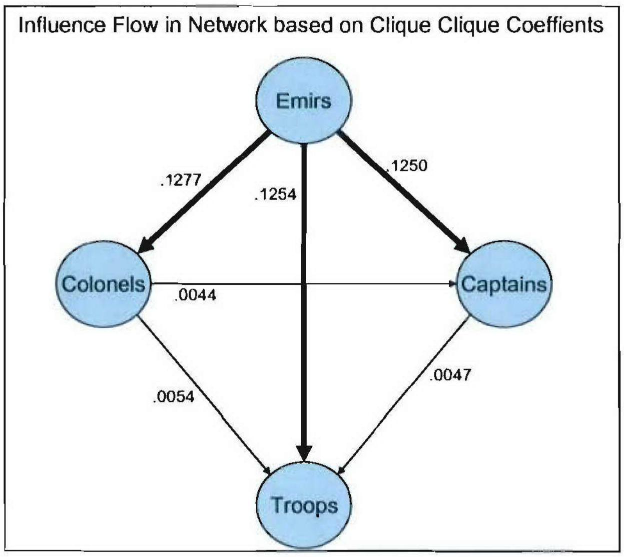

Figure 4-15: Network Representation of JI Influence Structure Based on Clique-Clique Coefficients

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 4-15 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 by Sageman as a friend to both Hambali and Iqbal, 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 4-15 are referred to as the Up-and-Comers.

Table 4-15: 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

Parametric Analysis of Node-Clique Coefficient

To gain a better understanding of the Up-and-Comers, node-clique coefficient results from the previous section were each analyzed parametrically. 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; $\Theta = 0$ will consider influence based solely on network topology, while $\Theta = 1$ will consider influence based solely on individual characteristics. Figure 4-16 shows the results of a parametric analysis of node-clique coefficients for $\Theta = 0, 0.1. 0.2, \ldots, 1$.

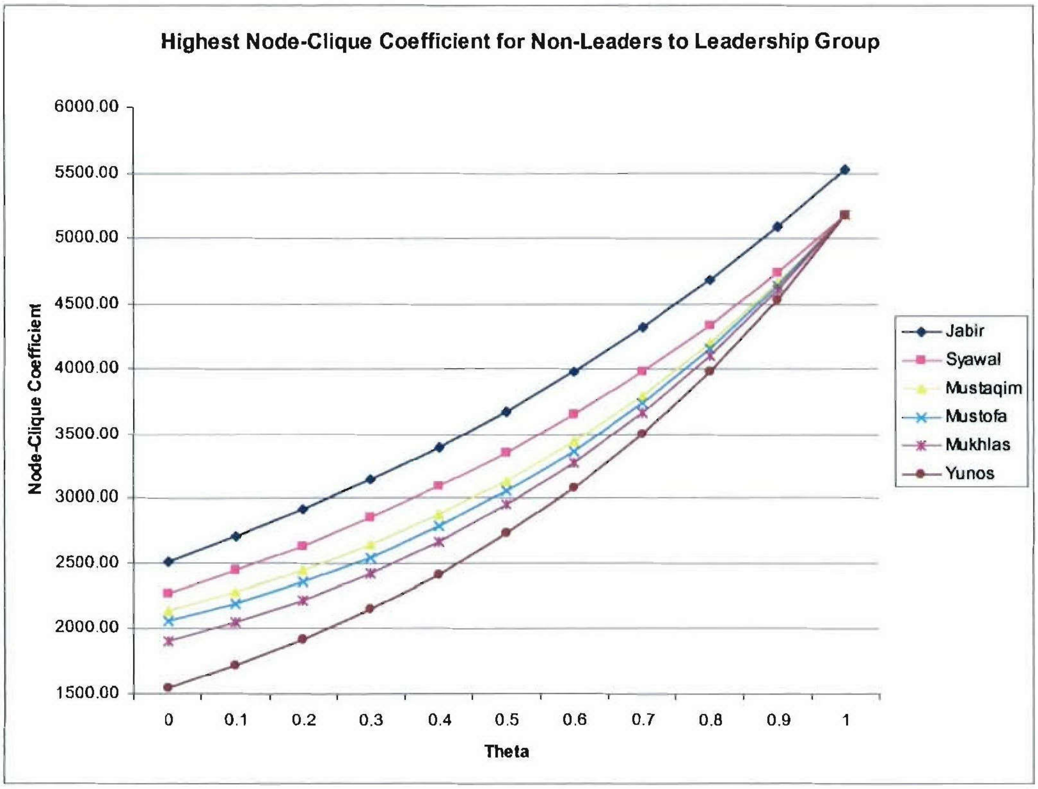

Figure 4-16: Parametric Analysis of Node-Clique Coefficients for JI members to the "Emirs"

Figure 4-16 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. 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 4-16 shows the classification accuracy.

Table 4-16: 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 4-17 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 4-17: 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 4-18 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 4-18: 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

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.

JI Analysis 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 4-17 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.

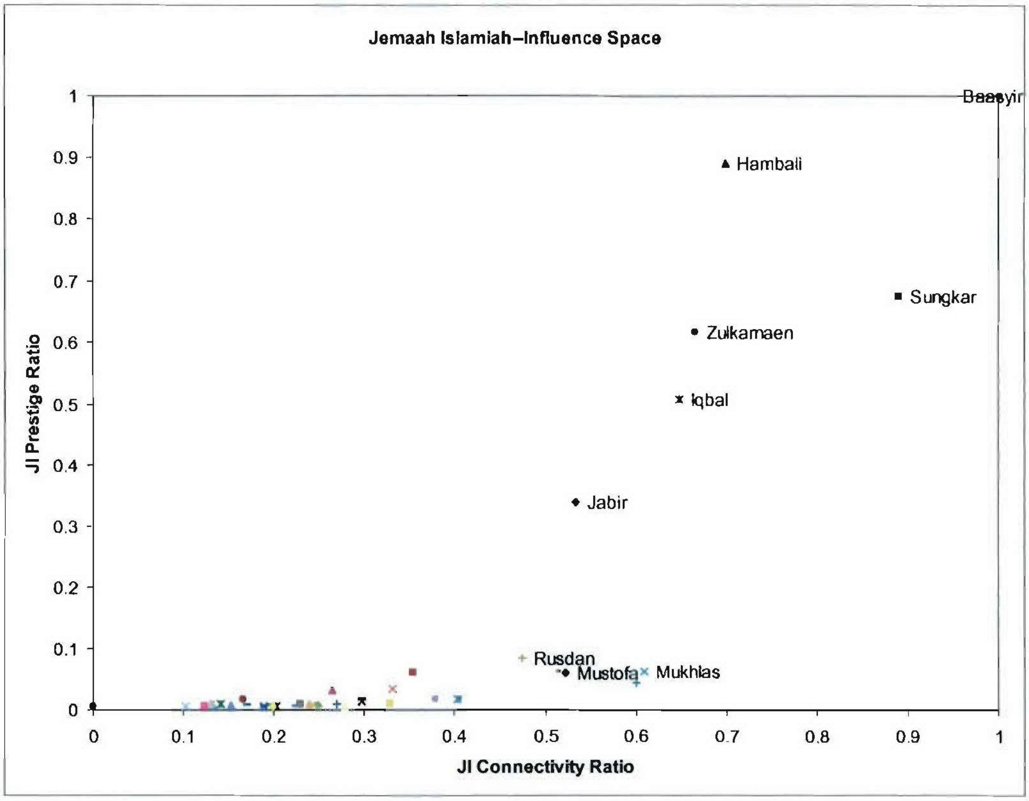

Figure 4-17: Jemaah Islamiah Influence Space

The majority of JI is clustered in the bottom left (least influential) corner of the chart. The operational interpretation of Figure 4-17 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.

5. SUMMARY AND RECOMMENDATIONS

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 paper 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. The potential outputs produced using the HIIM methodology are summarized in Table 5-19.

Table 5-19: 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

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