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A Social Network Analysis of the Iranian Government

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Abstract

Social networks describe the complex interrelations, both formal and informal, between individuals and groups. Modeling and analysis of social networks has many practical applications across an array of domains. These include government and military applications. An example is considered in detail for the Iranian government decision making process where relevant individuals and groups, their interactions, and their role in the decision-making process are explicitly modeled. This analysis illustrates a flow model representation of social networks. Flow modeling is a robust and powerful tool for social network analysis. This methodology is a result of a three year research effort sponsored by the National Security Agency and National Air Intelligence Center.

Introduction

It is possible to develop predictive models of individual and group behavior based on personality, culture, politics, and other related measures. The ability to understand and predict human behavior and decision making is an age old problem. Fundamentally, every aspect of our

existence, access to resources, and ability to exceed or fail in our endeavors are predicated on interaction with those who make up our environment. To a greater or lesser degree, all people have the ability to influence aspects of their environment and others in that environment.

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

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

cultural norms may vary tremendously across these contexts.

Most people exist in and make decisions based on the influence of many social networks, some of which coincide (i.e., members share more than one social context). Therefore, decisions made in one context (work, for example) are potentially not only influenced by those in the social network for the formal workplace, but the greater social network(s) spanning multiple contexts in the informal structure. "Networking" has long been a verb in business and bureaucratic environments. Going to the "right" school, belonging to the "right" clubs and so forth are all manifestations of this concept. The key point is that to analyze behavior in a social network requires understanding of both the formal and informal social network for the scenario under consideration.

The people and groups operating in a multi-context environment defines a social network. A social network may be depicted as a graph in which individuals are represented as *nodes* and their interrelations are represented by *edges* (Krackhardt, 1996:166). Measures of the strength of connectivity between individuals are termed *social closeness*, where a greater social closeness indicates a stronger influence in the relationship between the individuals. Social closeness is represented as a weight on the edges in a social network graph.

Correctly interpreting a social network assists in predicting behavior and decision making within the social network. This ability to understand and predict behavior of members in a social network allows the analyst to evaluate specific courses of action that will influence the members of a social network in a desirable manner. For example, one may wish to gain more power in the social network or a specific context(s), influence the selection of a particular alternative by the decision

makers in the network, create a more (or less) cooperative environment, weaken (or strengthen) individual's positions within a social environment of interest, or exclude or include people or ideas in the environment depicted by the social network.

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

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

data significantly limits the proper use of appropriate analysis methods applicable.

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

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

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

The focus of this study is to act in concert with existing Social Science research to consider how to expand social network modeling and analysis techniques such that optimization techniques may be applied to Social Science based measures of human interaction. The goal of this research is not to redefine existing Social Science based measures to form new Social Science theory. Rather, an objective is to make existing single dimensional graph based social network analysis more robust by considering multiple dimensions of human interaction in a single graph.

The expansion of existing theory increases the ability to model, understand, describe, and predict behavior in social networks. The origin of social network analysis is found in Sociology and discussed in the next section of this paper as an introduction to the subject.

Background

Social network analysis (SNA) is an accepted methodology applied by Sociologists. SNA theory comes from Sociology, but has been applied across other domains including Organizational Development, Biology, Anthropology, and others (Krackhardt, 1996:161; Brennan, 1999:356). The goal of SNA is to identify "who the key actors are and what positions and actions they are likely to take" (Krackhardt, 1996:161). SNA has been applied to networks of individuals (Krackhardt, 1996:162) as well as networks of organizations (Brennan, 1999:355).

In SNA, interrelations and connections are represented as networks where the nodes are either individuals or organizations with edges representing associations (Krackhardt, 1996:166). The edges may be directed or undirected; undirected edges indicate a mutual relationship. The actual relationships are

traditionally determined through the use of surveys which ask questions such as: "Who among your co-workers do you typically go to for help or advice when you encounter a problem or have a question at work?" or "Check the names of all those who you talk to virtually every day about work-related matters" (Krackhardt, 1996:165, 170).

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

Relationships in a SNA network can be quantified in several ways, allowing further analysis. One measure of "strength" is counting the number of edges incident on the individuals involved. Depending on the survey tool used, other countings may also be possible; for example, counting the number of times pairs of individuals communicate in a fixed time period. For cases where these measures exist, they can be used to weight the edges in the SNA graph.

Using a weighted SNA graph, there are existing techniques utilized by Sociologists to conduct further analysis.

These techniques are described briefly below for reference.

Hierarchical Clustering is a technique that clusters (i.e., groups individuals or objects) in descending order of the strength of the connections in each cluster based on the measure applied (Borgatti, 1994:78). A number of other clustering approaches and distance measures exist. The aim of cluster analysis procedures is to "classify n objects or individuals, upon which t measurements have been taken, into m clusters" (Godehardt, 1990:29). Godehardt notes that there are four broad types of clustering procedures: (1) *disjoint clustering* where n objects are split into a m non-overlapping, disjoint clusters, (2) *non-disjoint clustering* where objects may belong to more than one cluster at the same time, (3) *hierarchical clustering* where objects and groups of objects are arranged in the form of a tree representing the hierarchy, or (4) *quasi-hierarchical clustering* where clusters at each level of the hierarchy may overlap (Godehardt, 1990:42-43).

Inferences based on Hierarchical Clustering must be based on the measure applied. For example, if one used the measure of number of communications then the closest people are those who communicate most frequently and the resulting clusters are those containing people who communicate with each other frequently. This type of analysis does not, however, clarify why these people communicate. Further, Hierarchical Clustering is restricted to the context of the measure applied.

Multidimensional Scaling (MDS) is another SNA technique commonly found in use by Social Scientists. Multidimensional Scaling "provides a visual representation of the pattern of proximities (i.e., similarities or distances) among a set of objects [or people]" (Borgatti, 1996:29). MDS requires

the same data matrix as Hierarchical Clustering and a stress function that measures "the degree of correspondence between distances [or similarities]" (Borgatti, 1996:32). Borgatti suggests the use of the metric Kruskal stress function, which is defined as: $\text{Stress} = ((\sum_i \sum_j a_{ij} - d_{ij}) / (\sum_i \sum_j d_{ij}^2))^{1/2}$ where d_{ij} is the Euclidean distance between points i and j based on the coordinates assigned in the MDS algorithm (Borgatti, 1996:32).

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

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

however, results must be considered in light of these limitations.

Correspondence Analysis is a technique very similar to Multi-Dimensional Scaling for cases where data is non-metric (Anderson, 1992:340). Correspondence analysis, however, only preserves ordinal relationships at most and provides no order relationships when nominal (categorical) data is used (Anderson, 1992:340). Correspondence Analysis, a qualitative technique similar to MDS, is of limited use in extending SNA techniques to analytical Operations Research methods. It has all of the same mathematical problems of MDS and additional problems associated with the non-metric data.

While SNA and related analysis techniques provide a foundation for developing an analytical model, these techniques have several weaknesses where improvement must be made in order to create a robust model. The survey-based approach to collecting data is not practical in all situations. In addition, the questions currently asked are fairly simple and are only taken in one context (problems at work, for example). Further, the survey questions may lead to a bounding of the number of connections (for example, if one is asked to check up to three names of co-workers with whom they associate). In addition, such questions do not capture the relative weight of the relationship. Although SNA can be used to consider either individuals or groups, it is not presently intended to consider both individuals and groups in the same graph. Further, the analysis techniques for SNA graphs described have the noted mathematical problems.

The problems inherent to analysis techniques such as MDS, the most robust of the methods discussed, stem in part from a lack of advantageous properties of the measures applied (they may be non-metric, for example), the dimensionality of the

space may be ill defined, and a lack of multi-context data may lead to higher stress as significant social connections may be neglected (Borgatti, 1996:36). Mapping social network analysis to a flow model representation resolves many of the problems found in existing SNA techniques.

Social Network Analysis Mapped to Flow Problems

The fundamental concept of mapping social network analysis to a classic flow problem is that pairwise measures of social closeness represents the capacity of the potential influence between individuals (Borgatti: 1999, 59). This means that social closeness, distance, similarities, or differences can be represented as capacities on the influence between individuals. Influence measured by social closeness, distance, similarities, or differences are, thus, the commodities flowing over the network where the magnitude of their flow is their relative influence. We define social closeness and similarities to be strictly positive monotonic (greater magnitude implies greater influence). Likewise social distance and differences are defined to be strictly negative monotonic (greater magnitude implies less influence).

These strictly monotonic functions are related as follows. If x and y are both measures of social closeness, and if $x < y$, then $f(x) < f(y)$ where the function f is the relative influence in a particular context. If x and y are both measures of social distance, and if $x < y$, then $g(x) > g(y)$ where the function g is the relative influence in a particular context. Within the same context, then, $f(x) = -g(x)$. In other words, within the same context, g is the inverse function of f (Apostol, 1974:94). If $f(x) \neq -g(x)$, then $f(x)$ and $g(x)$ do not measure the same influence (i.e., one or both of $f(x)$ and $g(x)$ are incomplete measures). It is possible for

different single-criteria measures, even within the same context, that $f(x) \neq -g(x)$; however, for any $f(x)$ or $g(x)$ an inverse function will exist for all ratio type measures used in this study.

For the purpose of the analysis presented in this study, only social closeness measures are considered and are assumed to have positive monotonicity, on a positive-valued scale where zero represents the absence of social closeness (or no relationship whatsoever). For measures not defined on this scale, the stated conditions may be achieved through a simple mathematical transformation without loss of detail or generality. For example, social distance (with negative monotonicity) may be converted to social closeness (with positive monotonicity) by multiplying all values by -1 . Measures that take on negative values may be rescaled to a positive scale. For example, one could simply add any number greater than the absolute value of the smallest valued measure to all measures. For measures where zero does not represent the absence of social closeness, it is also possible to rescale in a similar manner. Such linear transformations are admissible for measures that are at least ratio in nature (Knuze: 1971, 67-68). A discussion of measures violating these assumptions may be found in *Modeling and Analysis of Social Networks* (Renfro, 2001).

Maximum flow problems, with both single and multiple sources and sinks, are useful for the analysis of several issues related to the social networks. Maximum flow problems can address questions such as how much A sources influence B sinks, where sets A and B exist in the set of all nodes in the social network N ($A, B \in N$). The case where A and B have cardinality of 1 is the situation where one person desires to influence only one other person in the network. The case where A has cardinality

of 1 and $B = N - A$ indicates that one person, A in this case, attempts to influence an entire network, $N - A$. Cases where the cardinality of A is greater than 1 represents a combination of people attempting to influence one or more individual in a network. When data is available, achieving specified threshold levels of influence, the effects of predispositions, misunderstanding the message, and other such problems of interested may also be modeled in the flow network representation (Renfro, 2001:86).

We define *Social Closeness*, in general, as a non-metric measure, as follows:

Definition. *Social Closeness* is defined by $s_{ij} \in \mathbf{R}^+$ (where \mathbf{R}^+ is the set of positive real numbers) and is the maximum potential influence one person or group (i) has upon another person or group (j) in a set of N people or groups in a given scenario. The set of N people or groups and their associated s_{ij} measures completely define a *social network* when $s_{ij} = a(s_{kl})$, $a > 0$, $i \neq j$, $k \neq l$, $\forall i, j, k, l \in N$ (i.e., *Social Closeness* is a ratio measure). When $s_{ij} = 0 = 0(s_{kl})$ and $s_{ii} = 0 \forall i$, there exists no potential influence. Since s_{ij} is directed and the network may be asymmetric, $-s_{ij}$ denotes the inverse of flow between i and j and has the property

$-s_{ij} = -a(s_{kl})$, $a > 0$, $i \neq j$, $k \neq l$, $\forall i, j, k, l \in n$. Further, s_{ji} need not equal $|s_{ij}|$. *Social Closeness* is therefore defined as a set denoted S , where S contains $\forall s_{ij}$. S is, thus, a subset of \mathbf{R} .

The underlying assumptions of a linear program are linearity, additivity, proportionality, divisibility, and certainty (Winston, 1994:53-54). Any mathematical program with a linear objective function, linear constraints, and *Social Closeness* measures may be represented as a linear program.

Social Closeness, in network modeling terms, is a capacity on potential influence (Evans, 1992:10). Potential influence may, therefore, be modeled as a commodity (Evans, 1992:10). As such, the flow of influence across a *social network*, as measured by *Social Closeness*, may be appropriately modeled as a traditional network flow problem. Since *Social Closeness* meets the necessary assumptions of classic flow models, *all* such flow models are appropriate for analysis of *social networks* without exception.

Table 1 lays the foundation for mapping social networks to classic flow models.

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

| Social Closeness Terms | Flow Model Properties |
|--|---|
| People or groups | Nodes (sinks, sources, or transshipment) |
| Connectivity or affinity | Capacitated arcs (or edges) between nodes |
| Social Closeness | Capacity |
| Influence | Commodity |
| Potential Influence | Quantity of flow |
| People or groups initiating influence in the network | Source(s) |
| Target people or groups to be influenced | Sink(s) |
| People or groups involved in influencing | Transshipment node(s) |

The flow model mapping has several advantageous theoretical properties:

1. Flow models do not require metric measures (Renfro, 2001:95).
2. Flow models are well defined and accepted.
3. The flow model representation is applicable to multiple problem classes.
4. Formal sensitivity analysis may be conducted.
5. Applicable problem classes may be extended through the use of Goal Programming and other techniques.
6. Lack of fit may only result by improperly defining the network structure.
7. The optimal solution includes both aggregate flow and path information.

This paper describes and demonstrates the single-commodity flow case. Multi-commodity flow model applications follow naturally from the single-commodity development.

Single-Commodity Flow

The single-commodity flow representation of a social network is defined in this section. First, it is necessary to define a notional source node (denoted s) and a notional sink node (denoted t). Node s is then assigned incident notional directed arcs with infinite capacity (or at least large enough capacity so as not to artificially bound the solution) terminating in the actual source nodes under consideration in the problem. An alternative representation is to capacitate the edges from node s based on the ability of the decision-maker to influence the actual source nodes. This alternative representation allows for course of action analysis as part of the flow problem rather than as post-processing analysis.

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

The objective of this problem representation is to maximize the flow (i.e.,

maximize the influence) from s to t . The capacity from node i to node j in the network is d_{ij} where d_{ij} is the selected monotonically increasing social closeness measure between from node i to j . Note that d_{ij} need not necessarily equal d_{ji} for all cases. The actual flow from node i to j is denoted x_{ij} where $x_{ij} \leq d_{ij}$ since no gains are allowed in this formulation. In addition, note that $\sum_j x_{sj} = \sum_i x_{it}$ since no losses are allowed in this formulation. For other scenarios, losses and gains may be used to represent predispositions, miscommunication, mistranslation, and other similar properties (Renfro 2001:86).

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

Let x_{ij} = the flow of influence over the edge from node i to j

Maximize z (where z is the maximum flow)

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

This formulation is demonstrated in the following example.

Social closeness measures may be countings of communications over one or means of communication (phone calls, faxes, emails, meetings, and so on), elicited from people in the social network, or more complex psychological profile based measures. Aggregations (summations, averages, and so on) of social closeness measures, when properly defined, are also social closeness measures. Analysis results may be no more accurate than the input data. When uncertainty exists, traditional sensitivity analysis may be applied as a corrective measure if better data is not available or possible to collect.

To better understand the single-commodity flow representation of a social network, an example based on influencing the Iranian government is considered in detail.

Sample Case: Iranian Government

The purpose of this case study is to understand the relative influence of individuals in the Iranian government. Specifically, this case demonstrates using the flow model representation to determine who among Iran's senior leaders has the greatest ability to influence the key Iranian government decision making bodies. Such an individual might then be considered the best target for an influencing campaign focused at the overall decision-making process of the Iranian government. In other words, the individual with the maximum influence is a *pressure point*. Note that the best operational approach to influencing the target pressure point, a specific individual for example, may or may not be directly applying resources to the target pressure point, depending on access and means available to the decision-maker desiring to influence the given social network. Especially in non-cooperative cases, decision-makers outside the social network may need to work through co-opted intermediaries, for example.

The example used in this paper is a geo-political scenario based on Iran. Sample case data comes from Foundation for Democracy in Iran (FDI) (<http://www.iran.org>). FDI provides data for Iran in 1997 with regard to President Khatami's Cabinet, the Council of Expediency and Discernment, the Council of Guardians, the Judiciary Branch, the Majlis, and the Supreme National Security Council.

In the graphical representation in Figure 1, the membership in organizations other than senior leaders has been

aggregated into their respective organizations. The number of people aggregated into an organizational node is denoted in parentheses below its name. Membership in an organization need not be mutually exclusive (for example, the Executive Branch has 31 members, this includes the 22 Cabinet members, the 8 Vice Presidents, and President Khatami). The weighting of connections is depicted by the width of the edges in the graph. Notional weighting is provided for example purposes based on the following Social Closeness measure:

1. Social Closeness between members of a group they are primarily a member of are three times that of only administrative connections. Secondary group membership is twice as important as administrative connections. Therefore, there is a ratio of 1:2:3 for administrative:secondary:primary connections.

2. Edges are directed based on the rules that: (1) people influence other people and groups down their chain-of-command and (2) groups influence other groups.

This weighting is done for example purposes only. Actual operational weights and measures must be developed from the fusion of open source, expert opinion, and data collected by national technical means. The data, while representative of the 1997 Iranian government, should not be taken as authoritative as FDI is an Iranian opposition group which advocates the overthrow of the existing regime (i.e., the data was not provided by the Iranian government or approved for use by any domestic or foreign government agency). The Iranian government social network is depicted in Figure 1.

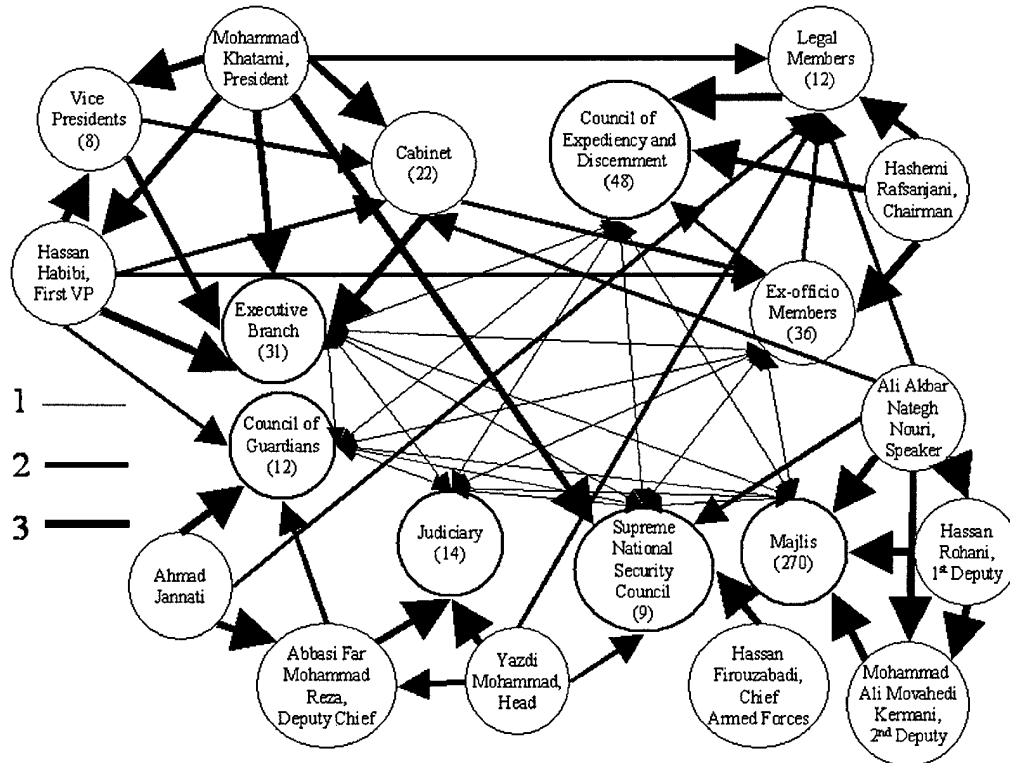


Figure 1. Iranian Government Social Network

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

The results of this analysis are given in Table 2. President Khatami has the maximum flow (indicating maximum potential influence) of 17 in terms of the

non-metric, ratio social closeness measure defined based on primary, secondary, and administrative organizational membership.

Table 2. Iranian Government Influence

| Source | Maximum Flow |
|-------------|--------------|
| Khatami | 17 |
| Rafsanjani | 9 |
| Nouri | 15 |
| Mohammad | 9 |
| Jannati | 8 |
| Firouzabadi | 3 |

The maximum flow solution is depicted graphically in Figure 2.

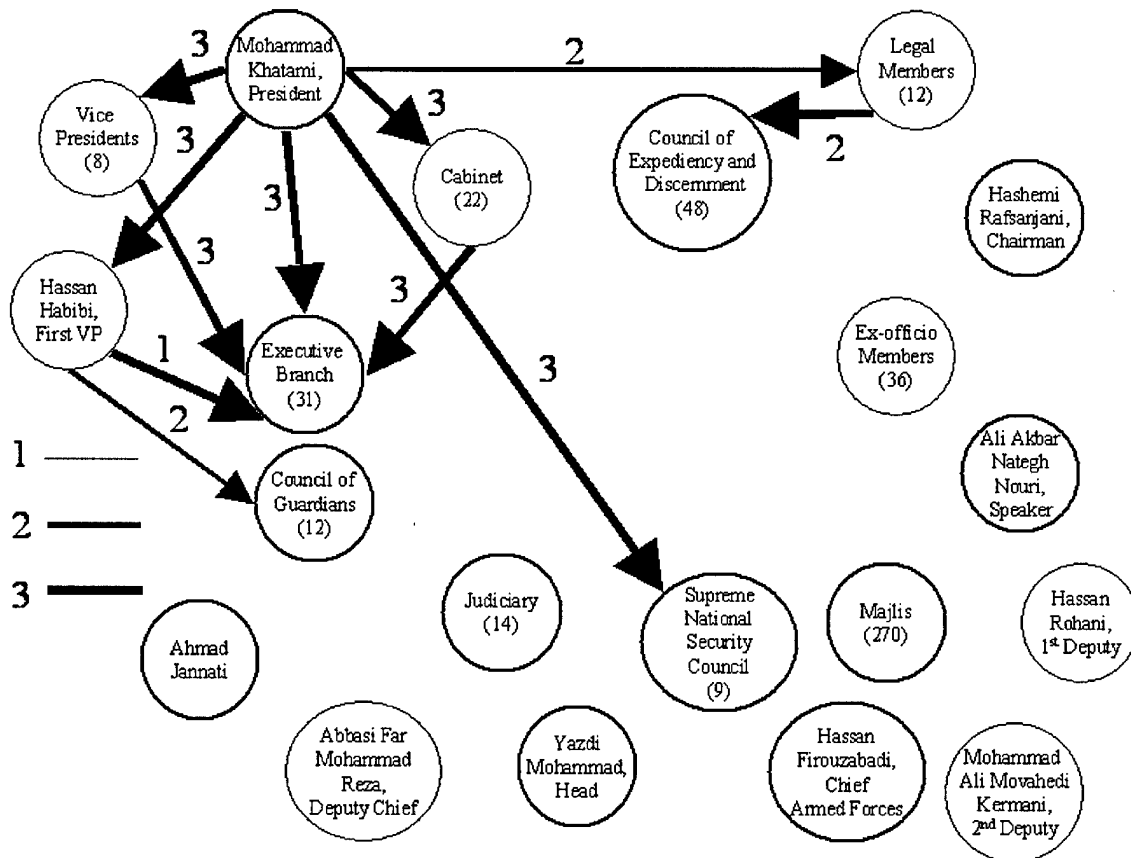


Figure 2. Iranian Government Maximum Flow Solution

The results of this sample problem are not unexpected. The social closeness measure applied essentially represents strength in terms of the given organizational hierarchy. Therefore, the result that President Khatami would exercise the greatest influence in the formal hierarchy of the government of Iran is expected.

As noted, to fully understand influence both formal and informal contexts must be considered. Observe, for example, that Rafsanjani was once the President of Iran, a member of or closely associated with

all of the major governmental departments, and likely informally retains some or all those membership ties. Further, observe that Khatami served under Rafsanjani when he was President. It is now possible to update the Iranian social network with this multiple context data and recalculate the maximum flow problem. For illustrative purposes only, additional notional edges have been added to represent Rafsanjani's influence in the informal context with a weight of 2 on the same scale used in the pervious analysis.

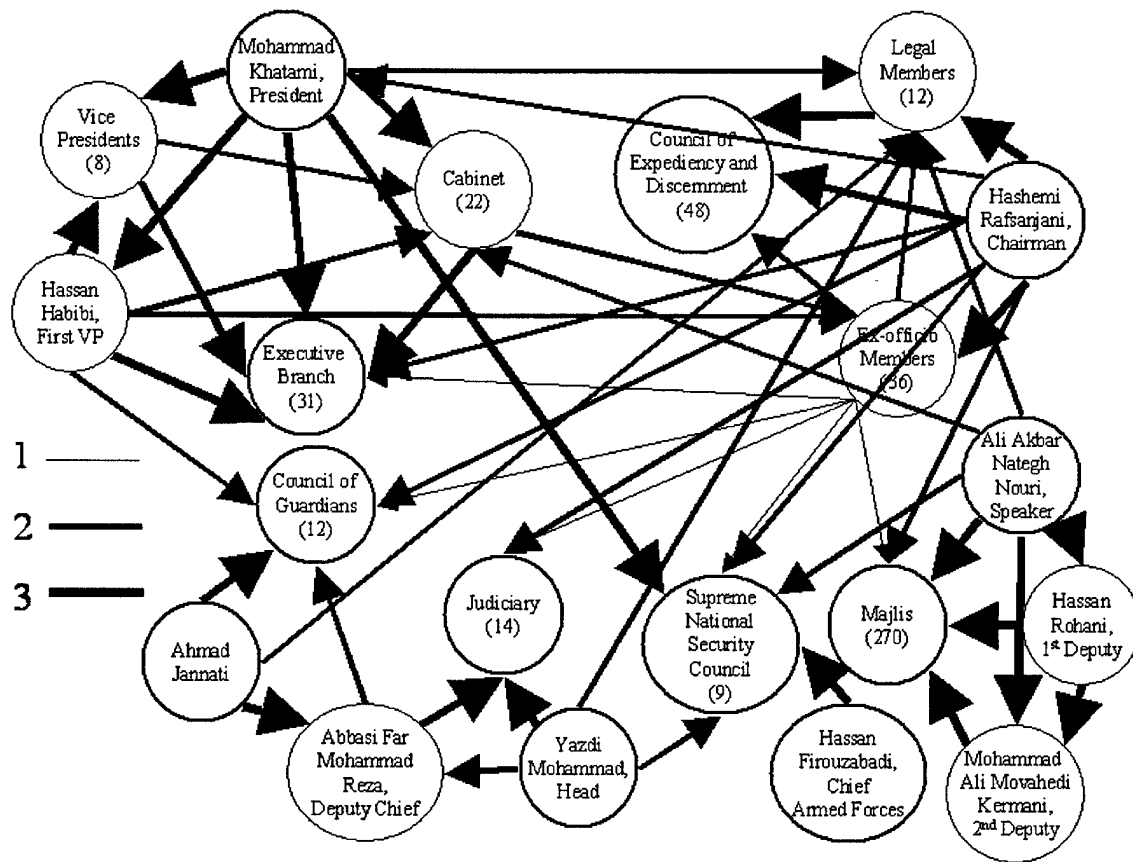


Figure 3. Iranian Government Multi-Context Social Network

The results of the analysis for the Multi-Context problem are given in Table 3.

Table 3. Multi-Context Influence

| <u>Source</u> | <u>Maximum Flow</u> |
|-------------------|---------------------|
| Khatami | 17 |
| Rafsanjani | 21 |
| Nouri | 15 |
| Mohammad | 9 |
| Jannati | 8 |
| Firouzabadi | 3 |

These results indicate that Rafsanjani actually has a greater potential to influence key Iranian government decision-making bodies than Khatami. This result implies that targeting Rafsanjani would result in a greater potential to influence the decisions of the Iranian government than targeting any other individual senior Iranian leader. This maximum flow is depicted graphically in Figure 4.

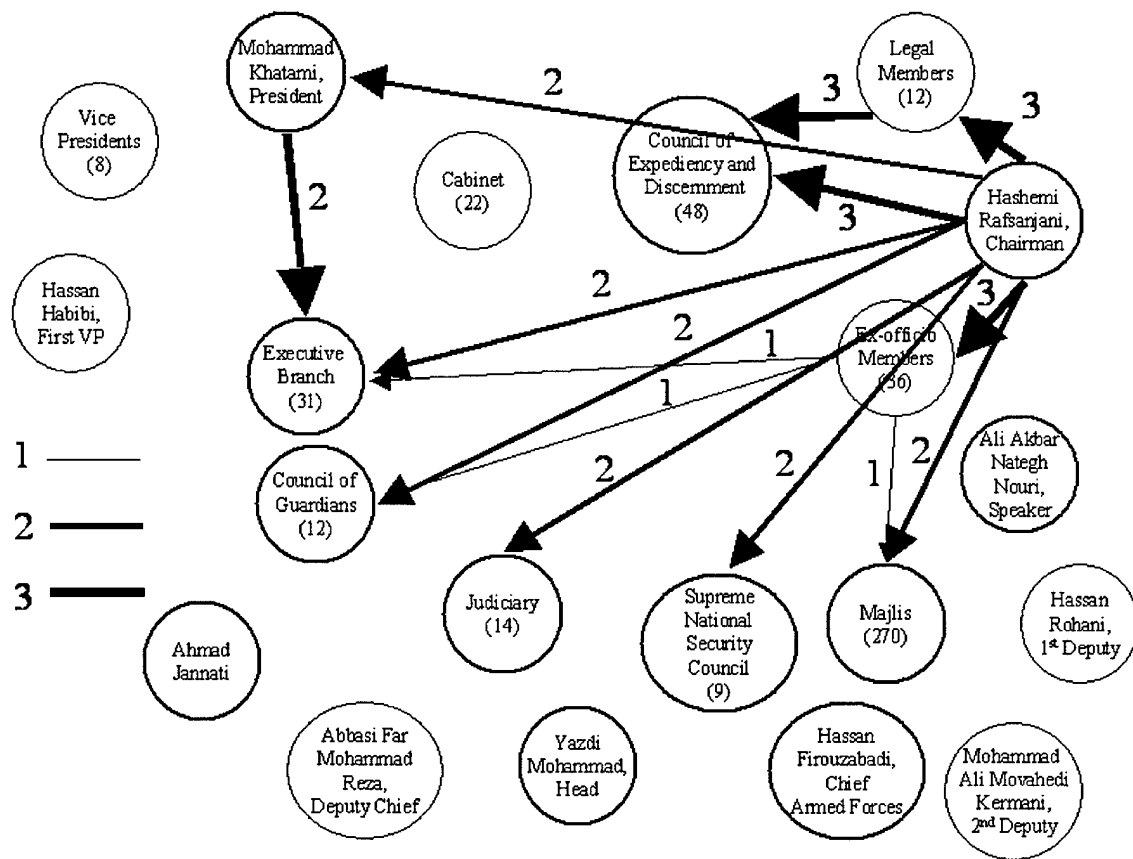


Figure 4. Multi-Context Maximum Flow Solution

While additional data on all of the relevant contexts of influence applicable to the Iranian government social network are needed for a formal analysis, this notional example demonstrates the value of the flow

modeling approach to social network analysis.

Conclusions

The theoretical development of the flow model representation and sample case analysis reinforces the conclusion that mapping social network analysis to a flow model is an analytically correct and very useful methodology. Conceptually, it is easy to conceive that this methodology may be extended to modeling gains and losses to represent predispositions and properties of the communication environment (loss of information, translation problems, misunderstandings, and so on). Maximum flow analysis provides solutions to many relevant problem classes of social network analysis, as discussed and demonstrated. In addition, minimum cost flow analysis may be applied for cases where resource constraints are applicable (for example, communication costs per minute or based on geographic distance). Multi-commodity flow may be used to represent different overlapping contexts with multiple means of influencing (i.e., commodities). Goal programming may be used to model multiple possibly competing objectives (Renfro, 2001:109).

This paper has introduced the concept of social network analysis, discussed the current capabilities of the Social Sciences for modeling social networks, and described areas where

Operations Research may contribute to furthering the ability to describe and predict social network behavior. Social network analysis is of broad interest to both private sector and government analysis. The methods developed in this research adds to the existing capability of social network analysis.

This research began with, and is founded on, the complementary lineage of Psychological, Sociological, Anthropological, and other theories that form a starting point for understanding social networks. The methodological focus of this research was placed on relevant areas of Operations Research, including Graph Theory, Optimization, and Network Models, that may add insight to the analysis of social networks.

The methods described in this research, expand on these existing Operations Research methods by extending them to social network analysis applications. First, the methodology formally defines a class of non-metric measures termed *Social Closeness*. These measures were then mapped to a flow model representation of a social network. The flow model representation provides a robust, transparent, analytically correct problem specification for the analysis of multiple social network problem classes.

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Descriptors

Social network, decision analysis, flow modeling, network flow, maximum flow, terrorists, hackers, information operations, non-cooperative data collection