Technical Report 13-006

Time Series Analysis of Networks: Evaluating the Effectiveness of Sanctions on Iran

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March 2013

United States Military Academy
Network Science Center

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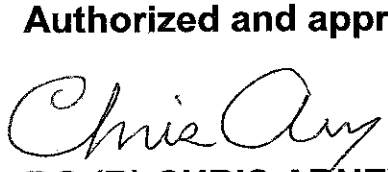

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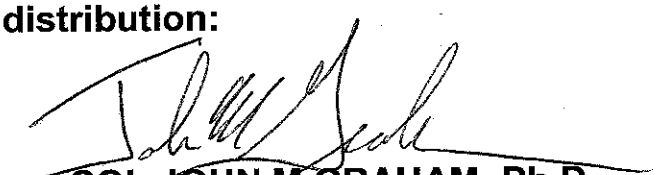

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The team developed a time series analysis method to examine how a network changes over time. Provided time-stamped data is available, a timeline of a network's structure can be built and analyzed using node and network centrality measures. A set of sample data is used to illustrate that analyzing the effectiveness of past sanctions on the Iranian nuclear program can be leveraged to develop more effective sanctions in the future.

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Lauren Kewley and Daniel Evans

Abstract

The team developed a time series analysis method to examine how a network changes over time. Provided time-stamped data is available, a timeline of a network's structure can be built and analyzed using node and network centrality measures. A set of sample data is used to illustrate that analyzing the effectiveness of past sanctions on the Iranian nuclear program can be leveraged to develop more effective sanctions in the future.

Background

Iranian government, financial, and business entities are adapting to, and learning from, each new round of international sanctions. When a sanction is imposed, agents and organizations, predictably, develop creative methods to bypass it in order to continue the pursuit of nuclear weapons production. Based on this scenario, can we quantitatively model the evolution and "learning" of this Iranian Network?

This was the question posed to three summer apprentices at the Network Science Center over the course of their internship during the summer of 2012. Based on team discussions, the group developed three possible methods to formulate and analyze this issue. The following network-based techniques were introduced in a previous paper: standard network analysis, time series analysis, and network flows [1]. This paper is the second in this series.

Introduction

Existing sanctions in place since 1979 have been incrementally broadened by the United States since 2005 after Iran reinstated its nuclear enrichment program [2]. These sanctions have been further reinforced by the United Nations (UN) and by European and Asian nations since 2007. However, some US sanctions, like the 1996 Iran Sanctions Act (ISA), "caused differences of opinion between the United States and its European allies because it mandates US imposition of sanctions against foreign firms"[3]. The objective of the sanctions was to target specific terrorism efforts in Iran as well as dissuade them from continuing their efforts to develop a nuclear weapons program including ballistic missiles by targeting specific Iranian industries. These targeted or "smart" sanctions were not intended to negatively impact ordinary Iranian people. As such, London's International Institute for Strategic Studies (IISS) reported

that “sanctions imposed against Iran have thwarted Tehran’s efforts to develop and produce long-range ballistic missiles capable of striking potential targets in Western Europe and beyond” [4]. However, some contend that sanctions would begin to backfire and damage the Iranian economy. As negative impacts on the Iranian economy have grown with each new round of sanctions, some argue that economic power is becoming consolidated into the hands of the Islamic Revolutionary Guard Corps (IRGC), a special military force with direct ties to the Supreme Leader, Ayatollah Ali Khamenei; giving them an increasing stake in the Iranian economy in order to continue pursuit of the nuclear weapons program as the regime’s top resource priority [5].

Methodology

The team explored the use of a time series analysis in order to analyze how a hypothetical network might react and evolve to the imposition of sanctions. A time-series analysis allows analysts or decision makers to examine a network over several time intervals. This allows them to determine the characteristics of a network before and after an event. When a change is made to a node or link, the network structure is also altered. A change could constitute a deletion, an addition, or an alteration of weight but is not limited to one of these courses of action. By analyzing the network at several time intervals, it is possible to determine how the network reacted to a perturbation. This technique is useful in order to analyze the effectiveness of a sanction or other targeted act, such as military action.

Ultimately, we will compare the network’s structure and its corresponding centrality measures over time. Centrality measures are numerical representations of various attributes of an individual node. For example, if our time step were one year, we would compare the attributes of the 2005 network to the 2006 network. These comparisons lend themselves to sensitivity analyses of the various measures. Thus, we can evaluate changes to the network in response to sanctions over time.

In order to explore this methodology the team selected ten random entities, a mixture of people and organizations, from a list of people and organizations linked to the Iranian nuclear program. The list was compiled using Iran Watch (iranwatch.org), an open data source, and then links were created between the selected nodes to mimic an actual network. This initial network is illustrated in Figure 1.

Figure 1 illustrates the network at *Time 1*. (We have elected to use *Time 1* as our initial network state.) It is an unweighted, directed network meaning each link has a value of one and links are directed from the source to the target.

Time Step 1

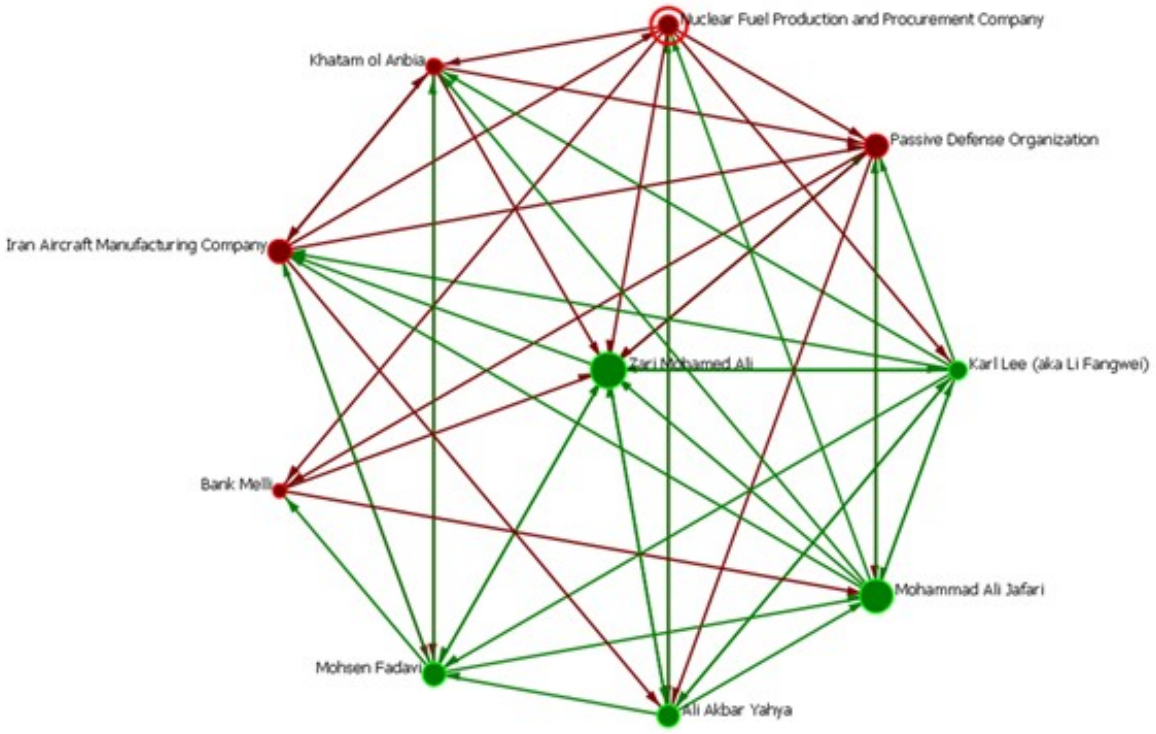

Figure 1: Snapshot of the network at Time 1 oriented such that the node with the highest betweenness is located at the center. Green nodes represent agents and red nodes represent organizations.

The network was then perturbed in two different time steps. In the first step, *Time 1* to *Time 2*, as illustrated in Figure 2, we created a scenario in which the Nuclear Fuel Production and Procurement Company was rendered unable to transfer money wirelessly due to a computer virus. Consequently, the Nuclear Fuel Production and Procurement Company would lose several connections to other nodes in the network.

In the second step, *Time 2* to *Time 3,* as illustrated in Figure 3, we examined the structure of the previous network if a node was removed. In this scenario, we arbitrarily removed Ali Akbar Yahya from the network so that all of his connections within the network would no longer exist. Following this fictional scenario, the team was able to capture the evolution of this network.

Time Step 2

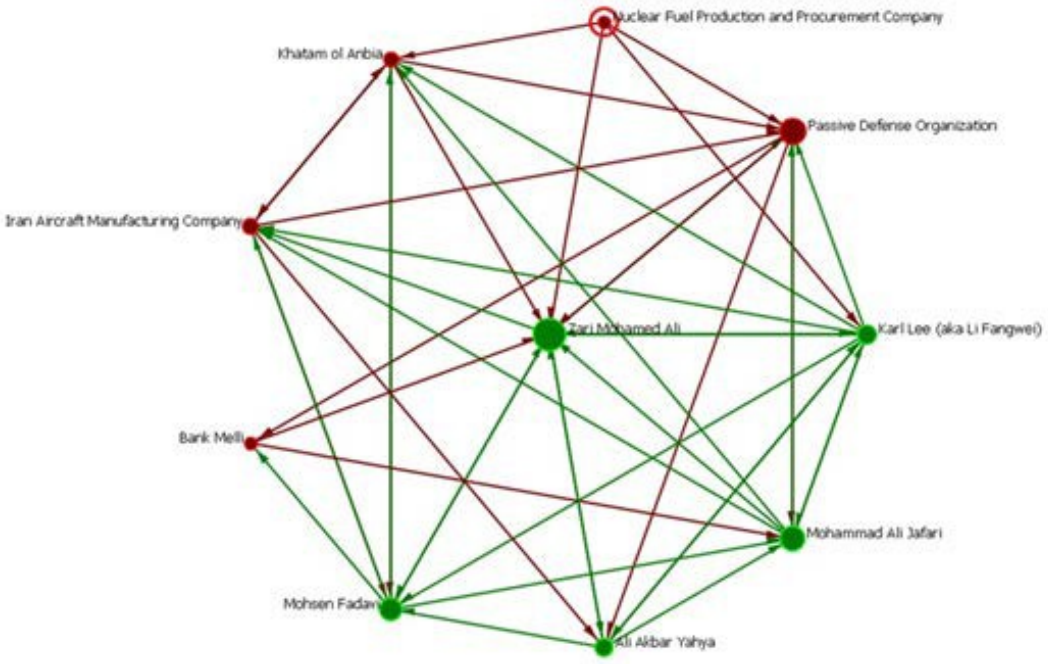

Figure 2. Illustration of the example network at Time 2, after the Nuclear Fuel and Procurement Company links were disrupted.

Time Step 3

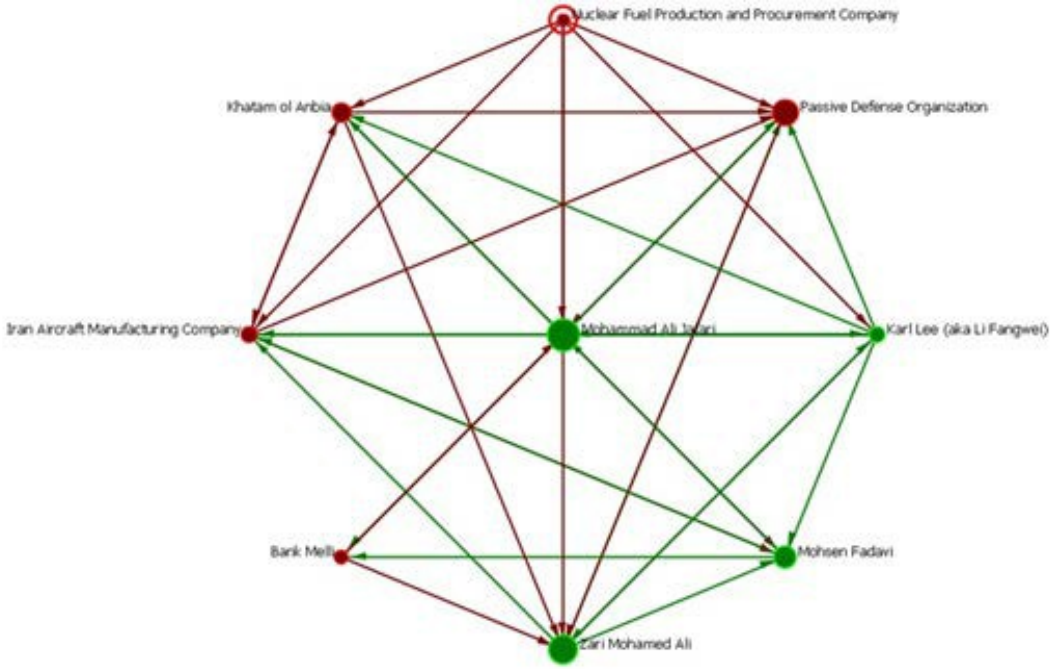

Figure 3. Network structure at Time 3 after removal of Ali Akbar Yahya.

To initiate this time series analysis, the team first calculated several centrality measures of the network across each time step. These centrality measures quantify characteristics of a given node. The team selected the following four commonly used centrality measures: degree, betweenness, closeness, and eigenvector centrality:

- Degree centrality: a measure of how many connections a node has within the network.
- Betweenness centrality: a measure of how often a node acts as an intermediary between other nodes in a network. It represents how many shortest paths go through the given node.
- Closeness centrality: a measure of the average length of the paths from a given node to all other nodes.
- Eigenvector centrality: a measure of the importance of a node based on the number of connections it shares with other important nodes.

All of these measures are normalized to have a value between zero and one. This makes it possible to compare the influence of nodes within the network under analysis. In this situation, it allows us to compare the structure of the network as it changes over time.

Analysis and Results: Node-level Analysis

Table 1 illustrates each node's initial characteristics in terms of the four centrality measures. As visualized in Figure 1, Zari Mohamed Ali is the most central node in the network and also has the highest betweenness value (.124). In fact, the only other node with a similar betweenness value (.113) is Mohammad Ali Jafari. The other nodes in the network have much lower betweenness values. For instance, Mohsen Fadavi's betweenness in the network (.062) is half as much as Mohamed Ali's (.062/.124).

Interestingly, Mohamed Ali does not have the highest closeness value. Karl Lee's value is (.818/.692) almost 1.2 times great that Mohamed Ali's. This finding demonstrates the value of network analysis; a visual inspection would not lead to this discovery.

Mohamed Ali and Ali Jafari both share the same eigenvector value (.507) indicating their connectedness to the other influential nodes in this network. Karl Lee and the Iran Aircraft Manufacturing Company also have high values (.473)-another finding that would likely not be possible without network analysis techniques.

	Degree	Betweenness	Closeness	Eigenvector
Karl Lee (aka Li Fangwei)	0.611	0.036	0.818	0.473
Mohammad Ali Jafari	0.611	0.113	0.750	0.507
Ali Akbar Yahya	0.556	0.055	0.692	0.424
Mohsen Fadavi	0.556	0.062	0.692	0.402
Zari Mohamed Ali	0.722	0.124	0.692	0.507
Bank Melli	0.278	0.004	0.563	0.302
Iran Aircraft Manufacturing Company	0.556	0.058	0.692	0.473
Khatam ol Anbia	0.500	0.018	0.643	0.424
Nuclear Fuel Production and Procurement Company	0.500	0.038	0.750	0.461
Passive Defense Organization	0.556	0.061	0.643	0.461

Table 1. Table of all nodes' four major centrality measures at Time 1.

An innovative way to analyze this network is through the use of a two-dimensional plot comparing two of the centrality measures. In this case, the team selected eigenvector and betweenness centrality because of their different mathematical properties. Betweenness calculates a measure of shortest paths and effectively quantifies how each node connects sub-groups within the network. Eigenvector measures the influence of nodes one link away from the node under analysis and is a measure of real influence in the network. The team has found that the ability to compare these two particular characteristics lend great insight into the holistic character of each node. The graph presented in Figure 4 demonstrates this technique.

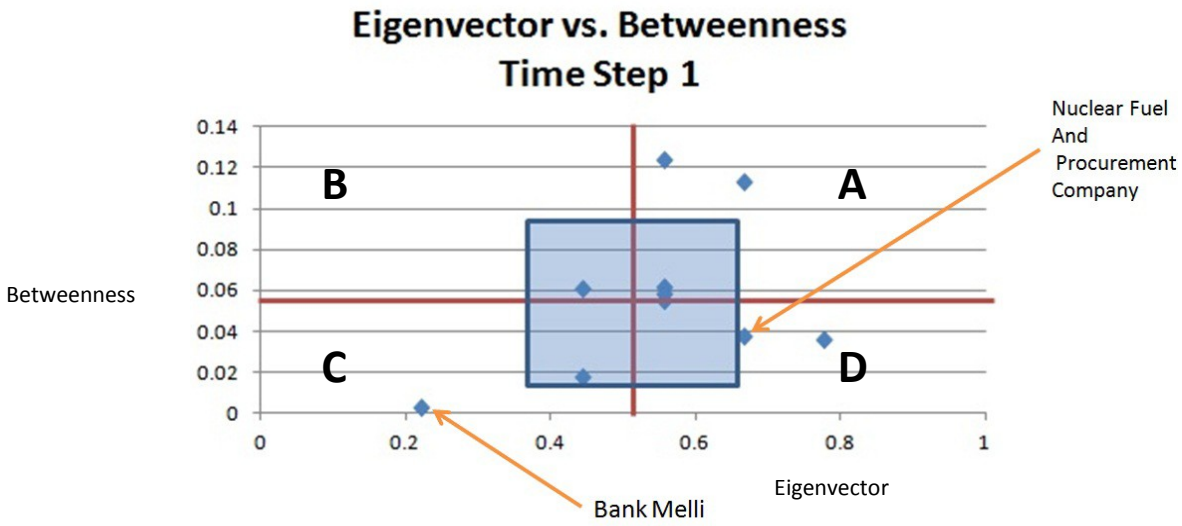

Figure 4. Two-dimensional plot of the mean plus or minus one standard deviation for each measure shown.

The two dimensional plot in Figure 4 is divided into quadrants (labeled A, B, C, and D) by two lines that lie at the mean values of eigenvector (vertical) and betweenness (horizontal) centralities. Each quadrant highlights characteristics particular to the nodes in that quadrant. The nodes within the blue region have centrality values within one standard deviation of the mean. Nodes within this region would be considered less influential because their values are not significantly less than or greater than the mean. The nodes that lie beyond one standard deviation from the mean of the centrality measures are those of interest and deserve a closer analysis.

Nodes that fall within Quadrant B (high in betweeness centrality) tend to connect groups in the network and we have designated them *Gatekeepers*. Nodes in Quadrant D (high in eigenvector centrality) tend to be connected to other influential nodes and we have designated them *Brokers.* The nodes in the Quadrant A (both high in betweenness and eigenvector) are both *Gatekeepers* and *Brokers*. This combination of high values in both of the centrality measures would indicate some of the most influential agents or organizations in the network. Nodes that fall into the lower left quadrant have both low betweenness and eigenvector values and we have designated them *Peripheral Players*. For example, in this model the Nuclear Fuel and Procurement Company is a *Broker* and Bank Melli is a *Peripheral Player*.

As discussed earlier, at Time 2 we simulated that the Nuclear Fuel and Procurement Company is attacked by a computer virus that hinders its ability to transfer money, it might lose its connections, thereby altering the network.

In Figure 2, a red circle surrounds the node corresponding to the Nuclear Fuel Production and Procurement Company. By comparing to Figure 1, a visual inspection verifies that the node has lost all of its incoming links and one of its outgoing links. The loss of links will change the network structure. These changes can be measured using centrality measures.

Table 2 illustrates that every centrality measure decreased for the company from Time 1 to Time 2. The smaller total degree centrality confirms that that there were fewer links at Time 2 than at Time 1. Another measure that should be considered is betweenness centrality as it decreased to zero from Time 1 to Time 2. This shows that the Nuclear Fuel Production and Procurement Company lost its role as an intermediary in the network. The computer virus that was responsible for the loss of the company's connections was successful in severely reducing its importance to flow across the network.

Centrality	Time 1	Time 2
Degree	0.500	0.222
Betweenness	0.038	0.000
Closeness	0.750	0.643
Eigenvector	0.461	0.280

Table 2. Table of the four major centrality measures of the Nuclear Fuel Production and Procurement Company at the first two time steps

We can gain more information about the network's dynamics by again plotting nodes' eigenvector centrality against betweenness centrality (Figure 5)

Figure 5 is structured in the same way as Figure 4. Comparing the two plots, we find that the network experienced major structural changes. The graph of the nodes' centrality measures became more condensed. The nodes cluster around the mean and, unlike Figure 4; there are only three nodes that lie outside the blue region. These are the nodes that should be further investigated. Also, the eigenvector centrality of the Nuclear Fuel and Procurement Company decreased from Time 1 to Time 2 implying that it now has a different role in the network. It has evolved from a *Broke*r role to a *Peripheral Player*. However, even though the degree centrality of Bank Melli decreased, it remained in its original quadrant and therefore its role did not change.

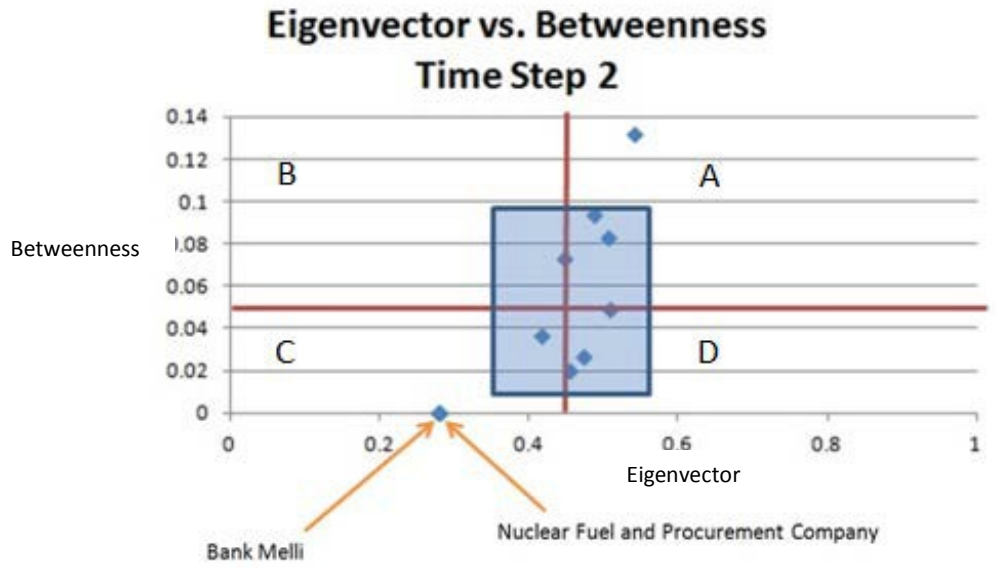

Figure 5. Two dimensional plot of eigenvector centrality vs. betweenness centrality with the means plus or minus one standard deviation identified.

The second time step demonstrated how the loss of several links could affect the network. Another situation to consider is node deletion. As explained in the

Methodology section, the team decided to delete a node at Time Step 3. To analyze the impact of such an event, Ali Akbar Yahya was removed from the network.

Similar to Figures 1 and 2, Figure 3 illustrates a network that is structured so the node with the highest betweenness centrality is located at the center. The removal of Ali Akbar Yahya brought Mohammad Ali Jafari to this position. The network was restructured in response to the perturbation, and as a result, the characteristics of some of the nodes have evolved. Figure 6 illustrates these changes using a 2-D centrality plot similar to Figures 4 and 5.

The removal of a member of the network caused a disruption that affected the centrality measures of all of other nodes. For instance, the Nuclear Fuel and Procurement Company changed from Quadrant D to C. This illustrates that nodes in a network are indirectly connected to other nodes by paths of length greater than one. Even though the Nuclear Fuel and Procurement Company and Ali Akbar Yahya were not adjacent, the Nuclear Fuel and Procurement Company was affected by Ali Akbar Yahya's removal from the network because the nodes were indirectly connected by paths that pass through other intermediary nodes.

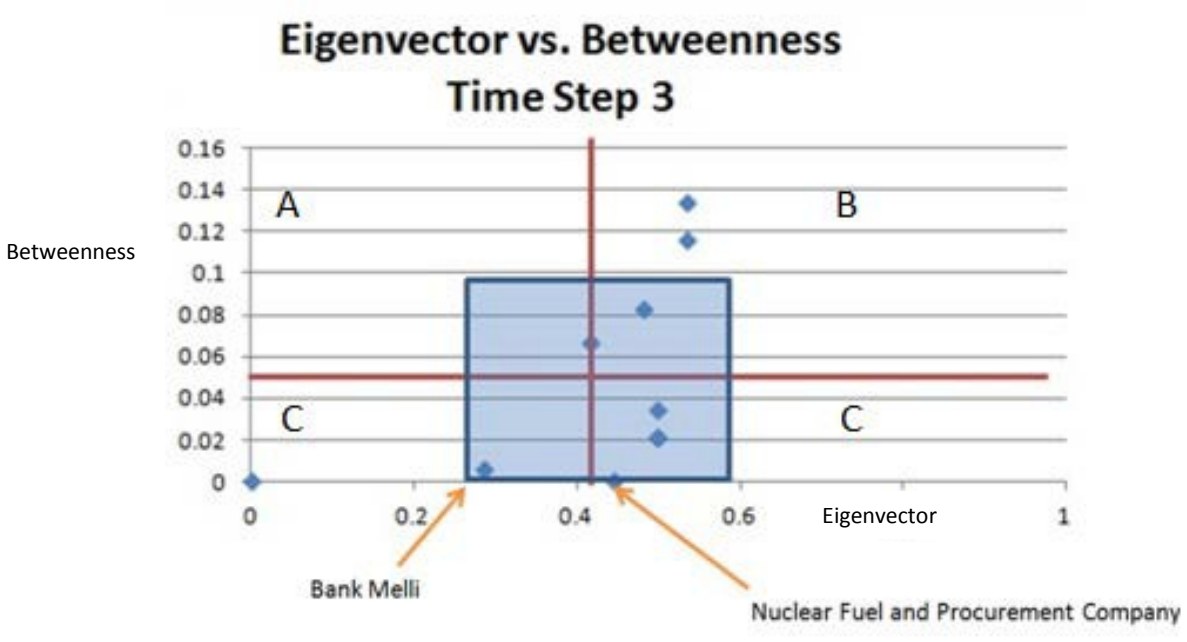

Figure 6. Two Dimensional graph of eigenvector and betweenness centrality measures at Time 3, after Ali Akbar Yahya was removed from the network.

Analysis and Results: Network-level Analysis

When performing a time series analysis it is also valuable to examine measures on the network level, rather than the individual node level. This provides a broader view of the network by providing measures that take into account all present nodes and links. These measures are called network centralization measures. They allow us to compare the same network at different time periods. For example, betweenness centralization measures how susceptible a network is to fracture. Table 3 contains values of this network centralization measure at the three time steps for our demonstration network.

Time Step	Betweenness Centralization
1	0.075
2	0.090
3	0.090

Table 3. Table of betweenness centralization measures over the three described time steps

The betweenness centralization of the example network increased from *Time 1* to *Time 2* indicating that the network became more susceptible to fracture. However, from *Time 2* to *Time 3* the betweenness centralization did not change, implying that whatever changes were made had little effect on the network.

Another measure to consider is network density. This is a measure of how many links are in the network compared to the maximum number of links that could possibly be present. The actual measure for a directed network is defined as the ratio of the number of edges *E* to the number of possible edges or:

$$D = \frac{2E}{\text{}(N - 1)},$$

where N is the total number of nodes present in the network.

Time Step	Density
1	0.544
2	0.489
3	0.528

Table 4. Table of density of example network over three time steps.

Table 4 shows that this particular network maintains a high density because of the small number of nodes combined with the large number of links. The changes observed between time steps are relatively small, but still worth noting as they indicate changes in network structure. Between Time 1 and Time 2 several links were removed. This

resulted in a smaller percentage of possible links and therefore a lower density. Then, a node was removed between Time 2 and Time 3. With fewer nodes present, the number of possible links decreased and led to an increased density.

These network measures allow for an overall view that takes into account all of the nodes and links at once and can be calculated for any network. In turn, decision-makers are able to quickly determine the structure and stability of a data set.

Discussion of Results

This demonstration network analysis illustrates the numerous network analysis methods that can be utilized in order to better understand the impact and effectiveness of sanction imposition.

The node-level analysis techniques allow an analyst to accurately determine the evolution of the network based on the perturbation. For instance, the impact on the Nuclear Fuel and Procurement Company based on the activation of a computer virus (*Time 1* to *Time 2*) is readily apparent. A deeper analysis of this network would include a determination of the nodes that became more, or less, influential in the network based on this event. With improved data, this technique also allows analysts to determine if the affected nodes themselves evolve. For instance, if an organization is impacted by a sanction it might re-organize and effectively become two or more nodes and establish new links.

The network-level analysis techniques enable analysts to better understand the holistic network and determine more effective, focused, sanction strategies. For example, the analysis might recommend targeted sanctions that have a goal of weakening the network at large, which can potentially make it more fragile in the long run. Our colleagues here at West Point have recently developed an example of such a technique. Their algorithm determines nodes in a network to eliminate with a goal of making the network fragile eventually allowing a single action to fracture the network [6].

Conclusion

Network time series analysis is a valuable tool for examining the evolution of networks. Creating a timeline of a network's evolution provides powerful insights into how the network reacts to both negative and positive perturbations. Based on the successful insights gained from this demonstration data set, the team is currently coordinating with several agencies in an attempt to access accurate time-stamped data sets. This data will allow us to more accurately analyze the effectiveness of past sanctions against organizations involved in the Iranian nuclear program. As we refine these analytical techniques, we hope to enable analysts to develop "smarter sanctions" that are more

narrowly targeted and influence the network in order to achieve the desired outcome without the potential collateral impact of broad sanctions.

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