# Network Analysis for Counterterrorism: Leveraging Game Theoretic Centrality and Classical Measures in the 9/11 Case Study

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## ABSTRACT

Identifying key figures within a terrorist network is crucial for thwarting potential attacks, enabling the efficient allocation of surveillance resources or targeted isolation to disrupt network operations. In this study, we implement the approach proposed by [8], which introduces a game theoretic methodology to identify key players in terrorist networks. By adopting this approach, we aim to assess its practical applicability and effectiveness. This methodology allows for the consideration of both the structural aspects of terrorist networks, such as communication patterns, and individual characteristics like financial resources or bomb-making skills. This approach, together with standard centrality measures, will be tested on the 9/11 dataset to see if the key players could have been identified before the tragic events occurred.


## 1 INTRODUCTION

Most remember the 9/11 attack which occurred in the United States of America where the Al-Qaeda terrorist organization, led by Osama bin Laden, coordinated the hijackings of four commercial airplanes which led to the significant destruction of the Twin Towers, extensive damage to the Pentagon and the loss of nearly 3,000 lives [6]. Attacks like this, unfortunately, are not rare, with a lot more happening after that event either by the same organization or by other organizations. As a result, this presents the important question, is there a way to stop this attacks before they occur?

All things being equal, the best way to stop attacks like this would be to maintain 24 hour surveillance on every single person in the terrorist network. However, this is not feasible as surveillance is costly, resources are limited and data is also limited. This in turn causes intelligence agencies to drop surveillance on people who they believe are no longer of interest to focus resources on others who they believe can be of interest. This could be harmful, as pointed out by [4], who mentioned that there were instances of multiple terrorist attacks across Europe where the individuals responsible for the attacks were present in law enforcement suspect databases. Unfortunately, these individuals were not under active surveillance during the attacks due to resource constraints faced by the authorities.

There have been many proposed solutions to solve this problem but the focus of this paper would be on methods which employ social network analysis (a set of techniques which can be used to identify clusters, patterns and hidden structures within social networks [10]) using the 9/11 tragedy as a case study. However, social network analysis (SNA) is most commonly applied in prosecution or investigative cases. In such instances, the attack has already been committed, resulting in loss of lives. We would like to determine if there exists an SNA technique that could be applied to monitor the crucial nodes in a network, given the limited data available. Identifying and neutralizing these principal nodes could disrupt the network significantly and potentially prevent similar attacks, such as the events of 9/11. This leads us to our research question, using the data prior to the investigative efforts after the attack, how could the Al-Qaeda terrorist network best be disrupted well before September 11th, 2001?

## 2 LITERATURE REVIEW

Unlike overt networks, covert networks endeavor to prioritize secrecy over efficiency. Data on nodes and connections are difficult to obtain, as noted by Krebs in [7]. He discovered that data on covert networks will be incomplete due to some nodes and links remaining undiscovered by intelligence agencies. Additionally, these networks often have fuzzy boundaries, making it challenging to determine whom to include or exclude. Moreover, they are dynamic in nature, constantly changing rather than remaining static. However, he was able to gather data around the 19 dead hijackers together with their known associates and the ties which connected each of them like, living together, attending the same school, Las Vegas meeting attendance, etc. With this, he was able to map the covert network and after employing standard centrality measures he was able to identify the key actors in that attack and the group leader.

In [5] a similar but slightly different approach was proffered. Seeing as one of the most important problems for a terrorist organization is the secret procurement and movement of funds, [5] suggested that obtaining the finance manager in the decentralized network would lead to finding the leader whose activity in the network is kept minimal. The finance manager will be the one in charge of activities of the members of the terrorist group around the world and is in-charge of funding their operations. As a result, they presented an algorithm which would find the node in the network who has the highest degree centrality among all other persons and places, who is the closest to all the other nodes in the network and who has the highest betweenness centrality between organizations. This effectively found them combining a lot of the standard centrality measures in order to find the finance manager.

In [8] a game theoretic approach was introduced to identify key players in a terrorist network using Jemaah Islamiyah's Bali bombing and Al Qaeda's 9/11 attack as case studies. They held the belief that standard centrality measures only focused on the structure of social networks, i.e. who communicates with whom, and doesn't include other information. In the context of terrorist networks, these extra information could include (i.) information on individual terrorists e.g. meetings attendance, bomb building skills, financial means, and/or (ii.) information on relationships between terrorists which could range from the frequency of communication between individuals to the quantity of weapons or funds being transported between individuals. Their proposed method combined methods from cooperative game theory and that from social network analysis. This resulted in an approach with which the structure of the network as well as non-network features such as money, skills, etc, could be taken into account, resulting in a more realistic model of identifying key players.

# 3 CENTRALITY

## 3.1 Standard Centrality

In SNA, graphs help in forming a mathematical representation of a social network. This can be represented as a graph $g = (N, E)$, where $N$ represents the set of nodes or persons in the network, and $E$ represents the set of edges that connects the nodes. In this paper, we'll be dealing with directed edges where the relationship between person $i$ and $j$ is denoted by $ij \in E$

Centrality is one of the SNA techniques used to study the properties of social network. The standard centrality measures include degree centrality, betweenness centrality and closeness centrality. Degree centrality looks at the immediate influence of the ego node i.e., what proportion of the nodes in the network are influenced by that ego node. Betweenness centrality favors the nodes that occur most often on the shortest paths between other nodes. In a criminal network, nodes with high betweenness usually indicate the most important or involved actors as they have a greater control over the flow of information in the network. Closeness centrality measures how quickly a node can have access to information through other nodes in the network by looking at the shortest path between the nodes (geodesic distance). This means that a node with high closeness has a high visibility as to what is happening in the network because of the high tendency of information to flow through such a node.

## 3.2 Game Theoretic Centrality

This centrality proposed by [8] studies the situations in which players would benefit by working together, a principle in Cooperative Game Theory. Here, a terrorist organization also consists of individuals that form coalitions in order to achieve a certain goal. A coalition can be seen as a subset $S$ of $N$ where $S \subseteq N$. A cooperative game is a pair $(N, v)$, where $N$ denotes the set of players and a map $v$ assigns a value $v(s)$ to each possible coalition $S \subseteq N$ and this represents the potential power of $S$.

We let the value of each possible coalition be defined by the network structure of that coalition (which is influenced by $g$) as well as weighted by the additional information about the relationships or individuals and is dependent on whether or not the coalition is connected i.e. players in $S$ can communicate. This leads to a weighted connectivity game where the value of each coalition ($v^{conn}(S)$ where the network is represented by a subgraph $S_g$) is defined as[1];

$$v^{conn}(S) = \begin{cases} \sum_{i \in s} w_i & \text{if } S_g \text{ is connected,} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

In allocating a representative and quantitative value to every player in the network, we make use of the Shapley value which is an allocation rule in cooperative game theory. The Shapley value is based on the marginal contributions of a player to the different coalitions in order to measure the power of this player in the coalitions [8]. The Shapley value $\varphi(v)$ of player $i$ is defined as;

$$\varphi(v) = \sum_{S \subseteq N, i \notin S} \frac{|S|!(|N| - 1 - |S|)!}{|N|!} \cdot [v(S \cup i) - v(S)], \tag{2}$$

where $|S|$ is the number of players in coalition $S$. Players with a high Shapley value are ranked on top as it shows that they play an important role in the network. Therefore, our game theoretic centrality of person $i$ is defined by;

$$C_v(i) = \varphi(v) \tag{3}$$

# 4 EXPERIMENTAL DESIGN

The data used for this game theoretic centrality analysis of the 9/11 attacks originates from Kreb's publicly available data [1][7] and from [8], which was the source for our weights. Whilst the source of inspiration for some function definitions comes from [9].

Given the research question, our analysis was only done on the data which was assumed available to the intelligence agencies before the attack i.e. the data on "trusted prior contacts" and "meeting ties"[2]. Results from the game theoretic centrality were combined with that of the standard centrality measures to give us a more informed analysis when comparing with the information available to the investigators after the attack.

# 5 RESULTS AND ANALYSIS

Focusing on the top 5 players as shown in Table 1, we can immediately notice some observations. Both the standard centrality measures and the game theoretic centrality produced a similar, but not the same, set of individuals. H.Hanjour, M.Atta, Z.Jarrah, S.Alhazmi, A.A.Al-Omari, M.Al-Shehhi, H.Alghamdi, N.Alhazmi, W.Alshehri, A.Al Haznawi, A.Alnami and S.Alghamdi all appear in all 4 centrality measures. Although this is important, this is still too much as we have 12 people of interest now.

| Game | Degree | Betweenness | Closeness |
|---|---|---|---|
| Abdul Aziz Al-Omari | Nawaf Alhazmi | Nawaf Alhazmi | Mohamed Atta* |
| Hamza Alghamdi | Hani Hanjour* | Abdul Aziz Al-Omari | Nawaf Alhazmi* |
| Waleed Alshehri | Hamza Alghamdi* | Mohamed Atta | Hani Hanjour• |
| Hani Hanjour | Marwan Al-Shehhi* | Marwan Al-Shehhi | Marwan Al-Shehhi• |
| <u>Marwan Al-Shehhi</u> | Ziad Jarrah• | <u>Waleed Alshehri</u> | Ziad Jarrah |
| Mohamed Atta | Mohamed Atta• | Hamza Alghamdi | Hamza Alghamdi+ |
| Nawaf Alhazmi | Saeed Alghamdi | Hani Hanjour | Salem Alhazmi+ |
| Ziad Jarrah | Ahmed Alnami+ | Ziad Jarrah | <u>Abdul Aziz Al-Omari</u> |
| Mohand Alshehri | Ahmed Al Haznawi+ | Fayez Ahmed | Saeed Alghamdi |
| Khalid Al-Mihdhar | Salem Alhazmi+ | Mohand Alshehri | Ahmed Al Haznawi |
| Ahmed Al Haznawi | Abdul Aziz Al-Omari+ | Ahmed Al Haznawi | Ahmed Alnami¤ |
| Fayez Ahmed | <u>Waleed Alshehri+</u> | Salem Alhazmi | Fayez Ahmed¤ |
| Salem Alhazmi | Wail Alshehri¤ | Saeed Alghamdi | Khalid Al-Mihdhar |
| Saeed Alghamdi | Khalid Al-Mihdhar¤ | Khalid Al-Mihdhar* | Mohand Alshehri |
| Ahmed Alnami | Fayez Ahmed¤ | Ahmed Alghamdi* | Majed Moqed |
| Wail Alshehri* | Mohand Alshehri¤ | Wail Alshehri* | Waleed Alshehri |
| Satam Suqami* | Satam Suqami¤ | Ahmed Alnami* | Ahmed Alghamdi |
| Ahmed Alghamdi | Ahmed Alghamdi° | Majed Moqed* | Wail Alshehri° |
| Majed Moqed | Majed Moqed° | Satam Suqami* | Satam Suqami° |

**Table 1: Shows the ranking of players in descending order according to the centrality measures used. Symbols *,•,+,¤ and °, show players with the same rank under each category.**

[1]Note that this definition is dependent on the network structure and the information available. Also, the definition above is for the 9/11 dataset [8]

[2]Appendix A shows the difference in the networks

Looking at the 4 measures, we can see that betweenness and game theoretic centrality tended to associate a unique value to each player as there are only 5 unique players in their top 5 list. A notable differences between the two kinds of centrality measures is the omission of Mohamed Atta and Nawaf Alhazmi.

This is surprising two reasons, firstly, when it comes to the structure of the network, both players have a key role in the dissipation of information as can be seen by their high ranks in the standard measures of centrality. Secondly, as seen in Table 2, these players had weights >1 attached to them yet, it seems that based on the relationship in the network, they didn't have much marginal coalition power. The only person included in the top 5 of the game theoretic centrality that has a weight >1 is Marwan Al-Shehhi.

The heatmap below (1), shows us the relative value of each player under the 4 centrality measures, sorted in descending order of total normalized value. We can immediately see that only 4 players, H.Hanjour, H.Alghamdi and A.A.Al-Omari and W.Alshehri scored higher than 0.5 under the game centrality measure. This shows the high potential value these players have. This heatmap also puts into perspective the terrible score that N.Alhazmi, M.Atta and M.Al-Shehhi had despite having scored great under the standard centrality measures.

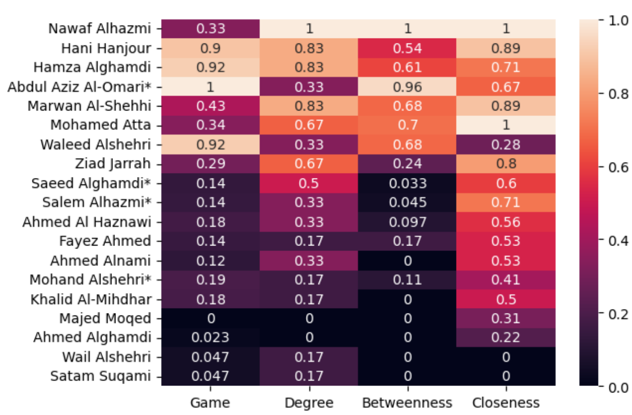


**Figure 1: Heatmap showing the normalized value for each centrality measure. Min-Max normalization was used for each centrality measure**

Therefore, looking at the results from this analysis and also assuming that resources are limited, I'll suggest the main focus of surveillance to be on 5 people. Nawaf Alhazmi and Marwan Al-Shehhi because of their relevance to the structure of the network as displayed by the standard centrality measures. Also focus should be on Hani Hanjour, Hamza Alghamdi and Abdul Aziz Al-Omari because of the high potential value they bring to the possible coalitions.

As you can see from Figure 3 in Appendix A, we didn't pick anyone who would have been on United Airlines Flight 93 which crashed in Pennsylvania. Also, based on information gotten after the attack we missed out on two key people Mohammed Atta, who was a pilot the confirmed to be the leader of that cell which carried out the attack[3], and also Ziad Jarrah who was a pilot on United Airlines Flight 93[2]. However, this method captured two pilots, Hani Hanjour and Marwan Al-Shehhi. Furthermore, despite the failure of this method to capture, M.Atta and Z.Jarrah, focusing surveillance on the selected 5 would have led to the capture of the other pilots, especially M.Atta, given his connection to most of our select 5 as seen in Figure 2 of Appendix A.

## 6 CONCLUSION AND FUTURE WORK

This method proved effective in directing surveillance on Nawaf Alhazmi, Marwan Al-Shehhi, Hani Hanjour, Hamza Alghamdi, and Abdul Aziz Al-Omari of which two were pilots and the rest had the possibility of leading us to the ring leader Mohammed Atta. As suggested by the authors of this method in [8], it proved more effective when combined with the standard measures of centrality.

In a future study, I'd suggest making the implementation of the game theoretic centrality more efficient as it takes into consideration all the possible number of combinations of nodes from the total nodes in the network which increases exponentially with increasing node size. Also, I used assumed that all centralities were equal when sorting my heatmap to show value of players. Multi-criteria decision making methods can be implemented to help come up with an order that best fits our desired preference of measures.

## REFERENCES

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# Appendices

Appendix A: Graph of 9/11 Hijacker Network Before and After the Attack

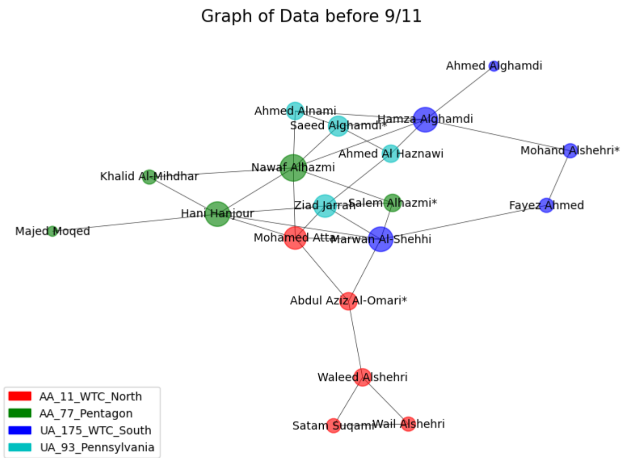


**Figure 2: This shows the hijacker network before the attack. It incorporates "prior contacts" and meeting ties (those present in the Las Vegas meeting). Node size defined by degree centrality**

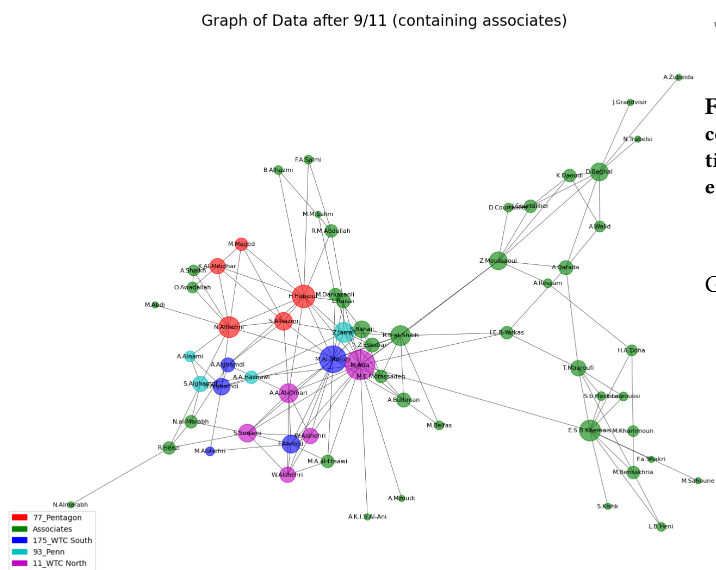


**Figure 3: This shows the hijacker network after the attack. It incorporates "prior contacts", meeting ties, and other associates gotten after investigation. Node size defined by degree centrality.**

Appendix B: Weights Assigned to Hijackers of Al Qaeda's 9/11 Attack[8]

| Person | Total weight | Person | Total weight |
|---|---|---|---|
| Ahmed Alghamdi | 1 | Nawaf Alhazmi | 2 |
| Hamza Alghamdi | 1 | Khalid Al-Mihdhar | 3 |
| Mohand Alshehri | 1 | Hani Hanjour | 1 |
| Fayez Ahmed | 1 | Majed Moqed | 1 |
| Marwan Al-Shehhi | 3 | Mohamed Atta | 4 |
| Ahmed Alnami | 1 | Abdul Aziz Al-Omari | 1 |
| Saeed Alghamdi | 1 | Waleed Alshehri | 1 |
| Ahmed Al-Haznawi | 1 | Satam Suqami | 1 |
| Ziad Jarrah | 4 | Wail Alshehri | 1 |
| Salem Alhazmi | 1 | | |

**Table 2: Gotten from [8] and shows the weights assigned to hijackers of Al Qaeda's 9/11 attack**

Appendix C: Example of Connected and Non-Connected Coalitions

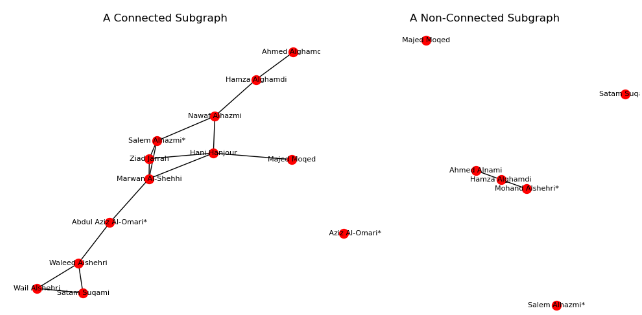


**Figure 4: This shows examples of subgraphs(coalitions) which are connected (12 nodes) and non-connected (7 nodes). Connected coalitions would have a value equal to the total weight as defined in equation 1 while non-connected coalitions would have a value of 0.**

Appendix D: Results of the Standard Centrality Measures and Game Theoretic Centrality

| Hijacker | Game | Degree | Betweenness | Closeness |
|---|---|---|---|---|
| Abdul Aziz Al-Omari* | 6.095702 | 0.166667 | 0.294118 | 0.428571 |
| Hamza Alghamdi | 5.577044 | 0.333333 | 0.188126 | 0.439024 |
| Waleed Alshehri | 5.562229 | 0.166667 | 0.209150 | 0.327273 |
| Hani Hanjour | 5.402611 | 0.333333 | 0.167320 | 0.486486 |
| Marwan Al-Shehhi | 2.202560 | 0.333333 | 0.209695 | 0.486486 |
| Mohamed Atta | 1.600307 | 0.277778 | 0.214161 | 0.514286 |
| Nawaf Alhazmi | 1.569574 | 0.388889 | 0.307516 | 0.514286 |
| Ziad Jarrah | 1.310814 | 0.277778 | 0.075054 | 0.461538 |
| Mohand Alshehri* | 0.630022 | 0.111111 | 0.033660 | 0.360000 |
| Khalid Al-Mihdhar | 0.561184 | 0.111111 | 0.000000 | 0.382979 |
| Ahmed Al Haznawi | 0.496610 | 0.166667 | 0.029739 | 0.400000 |
| Fayez Ahmed | 0.291985 | 0.111111 | 0.051634 | 0.391304 |
| Salem Alhazmi* | 0.280359 | 0.166667 | 0.013725 | 0.439024 |
| Saeed Alghamdi* | 0.233553 | 0.222222 | 0.010022 | 0.409091 |
| Ahmed Alnami | 0.149625 | 0.166667 | 0.000000 | 0.391304 |
| Wail Alshehri | -0.368992 | 0.111111 | 0.000000 | 0.253521 |
| Satam Suqami | -0.368992 | 0.111111 | 0.000000 | 0.253521 |
| Ahmed Alghamdi | -0.535068 | 0.055556 | 0.000000 | 0.310345 |
| Majed Moqed | -0.691128 | 0.055556 | 0.000000 | 0.333333 |

**Table 3: Centrality Measures for Hijackers of Al Qaeda's 9/11 Attack**