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Innovative Applications of O.R.

Cooperative game theoretic centrality analysis of terrorist networks: The cases of Jemaah Islamiyah and Al Qaeda

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ABSTRACT

The identification of key players in a terrorist organization aids in preventing attacks, the efficient allocation of surveillance measures, and the destabilization of the corresponding network. In this paper, we introduce a game theoretic approach to identify key players in terrorist networks. In particular we use the Shapley value as a measure of importance in cooperative games that are specifically designed to reflect the context of the terrorist organization at hand. The advantage of this approach is that both the structure of the terrorist network, which usually reflects a communication and interaction structure, as well as non-network features, i.e., individual based parameters such as financial means or bomb building skills, can be taken into account. The application of our methodology to the analysis results in rankings of the terrorists in the network. We illustrate our methodology through two case studies: Jemaah Islamiyah's Bali bombing and Al Qaedas 9/11 attack, which lead to new insights in the operational networks responsible for these attacks.

1. Introduction

The identification of the key players in a terrorist organization is a major problem in targeting top terrorists in counterterrorism practice. Currently key leader engagement is often based on qualitative theories, such as those of charismatic leadership (Jordan, 2009). With the huge increase in digital information gathering, intelligence and law enforcement agencies possess large volumes of raw, heterogeneous, often incomplete and inaccurate data on terrorist networks (McAndrew, 1999; Sparrow, 1991). The use of sophisticated quantitative modeling techniques and procedures to clean and make sense of these data is however limited (Xu and Chen, 2005). One of the quantitative methodologies that is often applied to find the proverbial needle in the haystack in general social networks is *social network analysis* (Wasserman and Faust, 1994). This methodology has also been applied to terrorist networks, see, e.g., Koschade (2006). A common feature of social network analysis is that it only uses the structure of networks. In this paper we introduce a methodology that additionally incorporates information available on a terrorist group in the analysis of the social network underlying the terrorist group. We show that quantitative modeling by means of cooperative game theoretic centrality measures enables the incorporation of such additional information.

Several researchers have shown how complex data on criminal organizations can be analyzed using the *network perspective*, e.g., Sparrow (1991), Peterson (1994) and Klerks (2001). Quantitative analyses of terrorist networks include Carley et al. (2003), Farley (2003) and Lindelauf et al. (2009).

The strength of social network analysis lies in the fact that one takes interrelationships into account when analyzing a group of people (Ressler, 2006). Centrality analyses can be applied to find the most important person in a social network. Clearly, 'most important' depends on the context of the problem under consideration. Hence, many different centrality measures have been proposed. A centrality analysis leads to a ranking of individuals that are active in the social network. Three of the most well-known centrality measures arising in social network analysis are degree centrality, betweenness centrality and closeness centrality (cf. Wasserman and Faust, 1994). In this paper we refer to these three centrality measures as *standard centrality*. Software implementation of standard centrality is found in, for example, Ucinet (Analytic Technologies, 2010). Furthermore, Analyst's Notebook (I2, 2010), a software package used worldwide by law enforcement and intelligence agencies, has recently included standard centrality in its latest update. Unfortunately, most, if not all, centrality measures currently in use in the intelligence and law enforcement domain focus specifically on the social network structure (that is, who

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interacts with whom), and do not incorporate other information often available. In the context of terrorist networks such additional information can be twofold: either information on individual terrorists, like financial means, bomb building skills, attendance of individuals to certain meetings, signs of radicalization or presence at a terrorist training camp, or information on relationships between terrorists, ranging from the frequency and duration of interaction between individuals to the quantities of weapons being transported. Standard centrality is not able to incorporate this kind of data.

In this paper we use cooperative game theory to develop rankings of individuals in terrorist networks based on both the structure of the terrorist network and additional information on the terrorists and their relationships. Cooperative game theory has been used in networks to investigate how power is allocated (cf. Jackson, 2008; Gomez et al., 2003). In this paper we apply cooperative game theory to terrorist networks, which include, in contrast to the networks considered by Jackson and Gomez et al. features that do not only depend on the network structure. Clearly, a terrorist organization can be considered as a social network as it consists of players working together to achieve a goal. A typical example would be a group of insurgents trying to carry out attacks with improvised explosive devices. To successfully launch such attacks several tasks have to be conducted: finances have to be arranged, the bomb material has to be acquired, the bomb has to be built and reconnaissance has to be conducted at the potential attack site. Hence, a terrorist group needs to consist of individuals capable of performing such tasks. Moreover, terrorist groups heavily rely on communication networks to accomplish acts of recruitment and planning (Tsvetovat and Carley, 2005). The structure of a terrorist network, however, differs significantly from a general social network (cf. Lindelauf et al., 2009, 2011). Similar to social networks, we want to determine the key players in terrorist networks. Using game theoretic centrality measures, rankings of players in such a terrorist network can be developed. Because game theoretic models are able to handle additional information by assigning values to coalitions, this approach provides more realistic models to identify key players in a terrorist network.

In this paper we show how cooperative game theory can aid in the identification of key players in a terrorist network. We introduce a weighted connectivity game that is able to take both the structure of the terrorist network as well as information about the individual terrorists into account. Applying a game theoretic centrality measure to the weighted connectivity game leads to a ranking of the players in the terrorist network. This allows for the optimal allocation of scarce observation resources and the destabilization of the terrorist network by the removal of the highest ranking members. To facilitate practical implementation of our methodology we present a general framework that includes three stages: construct the network, define the game theoretic model and analyze the rankings of players. We illustrate this framework through two practical cases: the Jemaah Islamiyah bombing in Bali and the 9/11 attack by Al Qaeda. The analyses of these cases with degree centrality, betweenness centrality and closeness centrality in concurrence with game theoretic connectivity centrality have led to some new results and insights. We therefore state that quantitative centrality analyses provide a valuable contribution to the identification of key players in terrorist networks and hence are useful in combating the violent and disrupting phenomenon called terrorism.

The paper is organized as follows. After recapitulating the basic standard centrality measures in Section 2 we introduce a general framework for game theoretic centrality analysis. We show how law enforcement and intelligence agencies can apply this framework to terrorist networks, in particular when additional information about the terrorist network is available. We also introduce the (weighted) connectivity game and a game theoretic centrality measure. In Section 3 we illustrate the practical use of centrality analyses in two case studies in which we compare the standard centrality measures to case study specific game theoretic centrality measures.

2. Game theoretic centrality

In this section we introduce a game theoretic centrality measure to determine the key player in a terrorist network. Cooperative game theory studies situations in which players can generate benefits by working together. In this view a terrorist organization also consists of individuals that form (opportunity) coalitions in order to achieve a certain goal, e.g., to carry out an attack.

First, however, we briefly recapitulate standard centrality. A (social) network can mathematically be represented by a graph $G = (N, E)$, where the node set N represents the set of persons in the network and the set of edges E consists of all relationships that exist between these persons. A relationship between person i and j is denoted by $ij \in E$.

The idea behind degree centrality (Proctor and Loomis, 1951) is that the more people one knows the more important one is. The *normalized degree centrality* of person i is expressed as the fraction of the network with which person i is directly related:

$$C_{\text{degree}}(i) = \frac{d(i)}{|N| - 1}, \tag{1}$$

where $d(i)$ represents the number of direct relations of person i and $|N|$ is the total number of persons in the network. Observe that $0 \leqslant C_{\text{degree}}(i) \leqslant 1$.

Betweenness centrality was first introduced by Freeman (1977). The idea is that a person is important when he enables the flow of information between other persons in the network. Betweenness centrality is measured by counting the number of shortest paths (i.e., a path that uses a minimal number of links) between two persons that pass through another person. Let s_{kj} denote the total number of shortest paths between person k and j and let s_{kij} denote the number of shortest paths between k and j that pass through person i. The *normalized betweenness centrality* of person i is then defined through

$$C_{\text{between}}(i) = \frac{2}{(|N| - 1)(|N| - 2)} \cdot \sum_{\substack{k,j \in N \setminus \{i\} \\ k < j}} \frac{s_{kij}}{s_{kj}}. \tag{2}$$

Again, it follows that $0 \leqslant C_{\text{between}}(i) \leqslant 1$.

Finally, closeness centrality quantifies the distance from a certain person to all other persons in the network. The *normalized closeness centrality* of person i is defined by

$$C_{\text{close}}(i) = \frac{|N| - 1}{\sum_{j \in N} l_{ij}}, \tag{3}$$

where l_{ij} denotes the shortest distance between person i and j. Again, observe that $0 \leqslant C_{\text{close}}(i) \leqslant 1$. Borgatti and Everett (2006) argue that the essence of closeness centrality is *time-until-arrival* of entities that flow through a network, whereas betweenness centrality measures the *frequency-of-arrival* of flows in a network.

Note that the actual standard centrality values are not important to us, only the resulting ordinal rankings of the persons involved are of interest. The following example illustrates the use of standard centrality.

2.1. Example: standard centrality measures

Consider the social network depicted in Fig. 1. The nodes represent seven persons, denoted by letters A to G, that are part of the

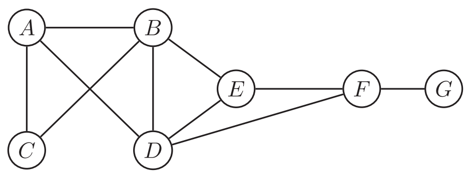

Fig. 1. Example of a network.

Table 1
Standard and game theoretic centrality for network in Fig. 1.

Person	Degree	Betweenness	Closeness	Wconn1	Wconn2	Wconn3
A	0.5000	0.0778	0.6000	1.1833	1.3190	18.3333
B	0.6667	0.2222	0.6667	0.3667	3.3190	6.2333
C	0.3333	0	0.4615	1.0500	1.3357	18.3500
D	0.6667	0.3222	0.7500	0.5500	2.6190	6.6833
E	0.5000	0.1111	0.6667	0.2167	6.6190	15.7333
F	0.5000	0.3333	0.6000	1.0333	6.4024	18.4667
G	0.1667	0	0.4000	−0.4000	−1.6143	−3.8000

Table 2
Rankings for network in Fig. 1 based on standard and game theoretic centrality.

Degree	Betweenness	Closeness	Wconn1	Wconn2	Wconn3
*B**	*F*	*D*	*A*	*E*	*F*
*D**	*D*	*B**	*C*	*F*	*C*
A•	*B*	*E**	*F*	*B*	*A*
E•	*E*	*A*•	*D*	*D*	*E*
F•	*A*	*F*•	*B*	*C*	*D*
C	*C**	*C*	*E*	*A*	*B*
G	*G**	*G*	*G*	*G*	*G*

network. The 10 links represent relationships between these seven persons, a relationship being bidirectional.

Applying Eqs. (1)–(3), standard centrality can be computed for all persons in the network. Table 1 summarizes these results in columns 2–4.[1] Since only the ordinal rankings of the persons involved are of interest to us, these rankings are presented in Table 2. In this latter table, the rankings are presented in descending order with an asterisk ($*$) and bullet ($\bullet$) indicating equal rank.

It follows that different centrality measures yield different rankings of individuals, which is a direct result of the difference in context that these centrality measures try to capture.

Note that standard centrality only considers network *structure* and does not take additional information into account. Newman (2004) does consider weighted networks (i.e., a network where the relationships have assigned weights) by mapping a weighted network to its unweighted counterpart and applying standard centrality measures. However, this method still only analyzes the structure of the network and is not able to include information about (groups of) persons and their relationships. This motivates the need for a centrality measure that enables the use of such additional information.

Before we introduce game theoretic centrality measures, we recall the definition of a cooperative game. A cooperative game is a pair (N, v), where N denotes the set of players. These players can cooperate and form different coalitions. A map v assigns a value $v(S)$ to each possible coalition $S \subseteq N$, which reflects the potential power of coalition S. By definition $v(\emptyset) = 0$. We let the value for each possible coalition be defined by the network structure of the coalition as well as by additional information that is available for the coalition. To do so, we introduce a class of weighted connectivity games. It seems natural to adopt a game that reflects the structural position of players in a network. Let the subgraph S_G consist of the players in coalition S and the lines of communication between them. If the players in coalition S are able to communicate using only the relationships present within coalition S we say that S_G is connected and assign a value of 1 to coalition S. Otherwise we say that S_G is not connected and assign value 0 to this coalition. A coalition consisting of a single person obtains a value of 0 by definition. Henceforth, the connectivity game v^{conn} (cf. Amer and Giminez, 2004) is defined as

$$v^{\text{conn}}(S) = \begin{cases} 1 & \text{if } S_G \text{ is connected,} \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

2.2. Example: connectivity game

Consider the network in Fig. 1. The subgraph corresponding to, for example, coalition $\{D, E, F, G\}$ is connected, see Fig. 2, whereas the subgraph corresponding to coalition $\{D, E, G\}$ is not, see Fig. 3. Hence, $v^{\text{conn}}(\{D, E, F, G\}) = 1$ and $v^{\text{conn}}(\{D, E, G\}) = 0$.

Besides the structural positions of the individuals in the terrorist network, we would also like to model additional information that is available on these individuals and their relationships. For example, intelligence analysis may show that a certain person has access to weapons, has financial means to set up an attack or attended a terrorist training camp. On the other hand, surveillance may show that the frequency of communication between two persons is much higher than the communication between other individuals in the network. This additional information can be obtained through discussions and expert meetings with domain experts. We acknowledge that there could be practical difficulties in this regard, however, once obtained it makes for much more realistic rankings. Such additional information should be used to modify the value of coalitions in which these persons take part. A weighted connectivity game v^{wconn} enables the modeling of network structure as well as additional information.

Next, we need to allocate the power of the coalition of all players in the network. The Shapley value (Shapley, 1953) can be viewed as the most prominent 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. Calculating a weighted average of these marginal contributions results in a ranking of the players in the network. A player that on average contributes more than another player when added to a coalition, will have more power and thus will play a more important role in the network. This is reflected in the computation of the Shapley value $\varphi_i(v)$ of player i:

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

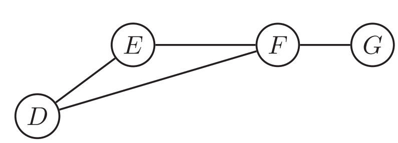

Fig. 2. Subgraph for coalition $\{D, E, F, G\}$.

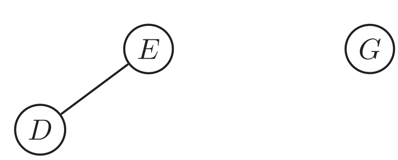

Fig. 3. Subgraph for coalition $\{D, E, G\}$.

[1] Column 5–7 contain the game theoretic centrality measures that will be introduced later on.

Players with higher Shapley values are ranked on top. In this paper, the game theoretic centrality of person i is defined by

$$C_v(i) = \varphi_i(v). \tag{5}$$

Clearly, the weighted connectivity game used should reflect the problem at hand. Hence, in practice each new case leads to a new weighted connectivity game. To illustrate the definition of a weighted connectivity game and the ranking of players in a network we give three examples. The first one uses additional information about relationships between individuals. The second example uses personal information about individuals. The third example combines information about relationships with personal information.

2.3. Example: weighted connectivity game using information about relationships

Consider the network in Fig. 1. Assume that surveillance results in additional information about relationship AC. For example, it is found that person A and person C communicate more frequently with one another than any other pair of individuals in the network. Therefore, the involved counterterrorism analyst assigns a weight of 4 to relationship AC, whereas all other relationships are assigned a weight of 1.[2] Let the weighted connectivity game v^{wconn1} on the resulting weighted graph be defined as follows.[3] The value of coalition S is equal to the maximum weight of the relationships that are present in coalition S if the underlying subgraph is connected and 0 in all other cases; i.e.,

$$v^{\text{wconn1}}(S) = \begin{cases} \max\limits_{\substack{i,j \in S \\ i \neq j}} f_{ij} & \text{if } S_G \text{ is connected}, \\ 0 & \text{otherwise}, \end{cases} \tag{6}$$

where f_{ij} is the weight assigned to relationship ij in the network, with $f_{ij} = 0$ if $ij \notin E$. The choice for this specific game may be motivated by a terrorist cell structure in which there are many lines of communication and we need to focus on the most prominent lines in order to filter out the key players in the network. Using such weighted connectivity game v^{wconn1} the game theoretic centrality value $C_{v^{\text{wconn1}}}(i)$ can be computed for each player i. The centrality values and the corresponding ranking of the players are presented in the columns denoted by *Wconn1* in Tables 1 and 2.

Consider columns *Degree*, *Betweenness*, *Closeness* and *Wconn1* of Table 2. First, notice that it is not immediately clear who the key player in the network is. Person B, D and F score high in most rankings, but only person F attains a top 3 ranking for all four centrality measures. Second, it can be seen that game theoretic centrality is better able to distinguish individuals than standard centrality. In other words, there are less persons of equal game theoretic rank than there are for standard centrality ranks. This observation is strengthened by the results obtained in Section 3 for the cases of Jemaah Islamiyah and Al Qaeda. Third, the use of additional information clearly affects the rankings. In this example, person A and C are both ranked on top in the game theoretic centrality ranking (i.e., Wconn1). Fourth, comparing the rankings generated by standard centrality and game theoretic centrality leads to new insights in identifying the key players and the less important persons in a network. For example, without additional information person C is found to play an insignificant role in the network. Using additional data on the relationship AC person C scores higher on the game theoretic centrality ranking (i.e., Wconn1). This last observation is also supported by the results of our case studies in Section 3.

2.4. Example: weighted connectivity game using information about individuals

Assume that intelligence analysis shows that person E took part in a previous attack and that persons C and E both have sufficient financial means to support a potential attack. To model this additional information, C is assigned a weight of 4 and E a weight of 11, whereas all other persons are assigned a weight of 1. The weighted connectivity game v^{wconn2} is defined as follows. The value of coalition S is equal to the sum of the weights of the players that are part of coalition S if the underlying subgraph is connected and 0 otherwise; i.e.,

$$v^{\text{wconn2}}(S) = \begin{cases} \sum\limits_{i \in S} w_i & \text{if } S_G \text{ is connected}, \\ 0 & \text{otherwise}, \end{cases} \tag{7}$$

where w_i is the weight assigned to person i in the network. The choice for this specific game may be motivated by the idea that the probability of launching a successful attack dramatically increases when experienced terrorists and terrorists with financial means or other useful skills team up. Using the weighted connectivity game v^{wconn2} in Eq. (7) the game theoretic centrality value $C_{v^{\text{wconn2}}}(i)$ can be computed for each player i. The centrality values and the corresponding ranking of the players are presented in the columns denoted by *Wconn2* in Tables 1 and 2.

Consider columns *Degree*, *Betweenness*, *Closeness* and *Wconn2* of Table 2. It follows that both person B and person F attain a top 3 ranking for all these four centrality measures. Second, it can be seen that game theoretic centrality is again better able to distinguish individuals than standard centrality. Third, the use of additional information affects the ranking of E and C. This effect is more profound for E, since he is ranked on top (in Wconn2), whereas C is only assigned a slightly higher position in the ranking when compared to standard centrality. Fourth, comparing the game theoretic centrality ranking with the standard centrality rankings leads to new insights. For example, comparing the positions of person E in the various rankings calls for a further analysis of his role in the network.

2.5. Example: weighted connectivity game using information about relationships and individuals

Combining the information gathered at the previous two examples leads to a model that incorporates additional information about relationships between individuals as well as personal information about individuals. To illustrate we asssign relationship AC a weight of 4 and all other relationships a weight of 1. Furthermore, we assign C a weight of 4, E a weight of 11 and all other persons a weight of 1. The weighted connectivity game v^{wconn3} is defined as follows. The value of coalition S is equal to the product of the sum of the weights of the players and the maximum weight of the relationships that are part of coalition S if the underlying subgraph is connected and 0 otherwise; i.e.,

$$v^{\text{wconn3}}(S) = \begin{cases} \left(\sum\limits_{i \in S} w_i\right) \cdot \max\limits_{\substack{i,j \in S \\ i \neq j}} f_{ij} & \text{if } S_G \text{ is connected}, \\ 0 & \text{otherwise}. \end{cases} \tag{8}$$

The choice for this specific game may be motivated by a terrorist cell in which we need to focus on the most prominent lines of communication between individuals as well as on the individuals

[2] The weight of 4 is chosen arbitrarily in this example, just to illustrate how to incorporate additional information. Experts should provide more realistic values for the weights.

[3] Note that the game used in this example differs from the game used in the Bali bombing case, see Section 3. The latter game is chosen to better fit the context of the problem at hand.

with most experience or financial means or other useful skills. Using the weighted connectivity game v^{wconn3} in Eq. (8) the game theoretic centrality value $C_{v^{\text{wconn3}}}(i)$ can be computed for each player i. The centrality values and the corresponding ranking of the players are presented in the columns denoted by *Wconn3* in Tables 1 and 2. As expected, the additional information used ensures that persons C, A and E attain a high ranking. Notice, however, that the data used indirectly affects the position of person F in the ranking, identifying him as the key player. This calls for further analysis of the role of person F in the network.

Identifying key players in a terrorist network by means of game theoretic centrality is based on both the structural position of each person as well as additional information about the individuals in the network and their relationships. In the previous three examples we presented three possible approaches to assign weights and construct a weighted connectivity game. These are illustrative of how the available information can be taken into account in modeling that situation. These are certainly not the only approaches. Each operational context under consideration will call for its own specific game. Important steps in a practical implementation of our methodology consist of gathering information about the terrorist network (input), weighing the available data, defining a game theoretic model (modeling) and analyzing the game theoretic and standard centrality rankings (output). In practice, these steps may overlap one another and the execution of the steps may follow a cyclic pattern. In addition we recognize that weighing of the data is as much an art as a science and should be done in close cooperation with domain experts. We propose to use the following framework.

2.6. General framework

The application of game theoretic centrality to a terrorist network includes the following three stages.

1. *Construct the network (input)*. Model a terrorist network by a weighted graph. The nodes of this graph represent the persons involved in the terrorist network and the links in the graph represent the known relationships present between these persons. Furthermore, weights may be assigned to individuals and their relationships. The obtained data could originate from publicly available sources or from classified intelligence analysis. Experts in the counterterrorism and security domain are responsible for weighing each bit of information. Hence, the result of the first stage is a weighted graph representing the terrorist network.
2. *Define the game theoretic model (modeling)*. When applying game theoretic centrality, the weighted graph is considered to be a given input. The behavior of persons in the terrorist network, how they interact and how they cooperate, has to be modeled in a weighted connectivity game. Hence, each new terrorist network calls for the selection or development of the most suitable game. In practice, it is advisable to construct several weighted connectivity games, in order to model a variety of possible scenarios. In the weighted connectivity game the value of each coalition of persons should be expressed in terms of the weights assigned to the persons and their relationships that are part of the coalition. Customization can be obtained through a suitable construction of the game. Therefore, both quantitative and intelligence experts play a crucial role in the construction of the game theoretic models.
3. *Analyze the rankings of players (output)*. Using a game theoretic centrality measure, its value can be computed for the previously defined weighted connectivity game. A ranking of persons in the network is obtained and key players can be identified. It is advisable to compute standard centrality as well, since comparing the rankings obtained by standard and game theoretic centrality may lead to new insights in identifying the most important players in a terrorist network. Hence, the result of the third stage is a ranking based on the game theoretic centrality measure. This ranking may be used for reassessment of allocation of scarce observation resources.

3. The cases of Jemaah Islamiyah and Al Qaeda

We illustrate now the application of game theoretic centrality to two terrorist networks: the operational network of Jemaah Islamiyah's Bali bombing and the network of hijackers of Al Qaeda's 9/11 attack. For each of these networks we define a case specific weighted connectivity game that incorporates additional information about the individuals and relationships involved.

3.1. Case 1: Jemaah Islamiyah in Bali

On October 12th 2002, one of the deadliest attacks in Indonesia's history took place on the island of Bali. 202 persons died as a result. After a long trial a number of members of the extremist group Jemaah Islamiyah (JI) were found guilty of planning and perpetrating this attack.

JI was officially founded in 1993 in Malaysia, with the goal of creating an Islamic state in Indonesia (Wise, 2005). In 1998 JI started the so-called *uhud* project aimed at removing Christians as well as Hindus from regions in Indonesia, so that pure Islamic enclaves could be founded that were guided by the Sharia (Abuza, 2003). In addition JI started a series of attacks in 2000. The 2002 Bali attack was the most prominent.

The tactical operation in Bali was conducted by the JI's Indonesian cell, headed by Hambali. A suicide terrorist detonated an explosive vest in Paddy's bar. This caused many people to flee into the streets. A second explosion followed, caused by a so-called vehicle borne improvised explosive (VBIED): an L300 van filled with about 1000 kilograms of TNT and ammonium nitrate, resulting in 202 deaths.

In order to apply a game theoretic centrality analysis to the Bali attack we need information about the operational cell responsible for this attack. We have used data available from scientific literature, in particular data from a social network analysis of JI by Koschade (2006). In his paper, Koschade not only defines the network structure, but also assigns weights to relationships between cell members. However, these weights are not used in his analysis of the operational network. We show how game theoretic centrality can incorporate this additional information in its analysis. Our analysis follows the three stages of the framework in Section 2.

1. *Construct the network*. We consider the operational network of the Bali attack as presented by Koschade. The corresponding network is depicted in Fig. 4. The operational cell conducting the attack consisted of three teams: a team of bomb builders (gray), a support team (lightgray) and a team responsible for coordinating the attack (white). The team of bomb builders consisted of Patek, Ali Imron, Azahari, Dulmatin, Ghoni, Sarijo; later on, Feri was added to this team. The persons responsible for the support of the operation (team Lima) were Octavia, Junaedi, Hidayat, Abdul Rauf and Arnasan. The remaining persons, i.e., Samudra, Idris, Muklas, Amrozi and Mubarok, were in charge of coordinating the attack. These 17 cell members and their 63 relationships define the structure of the operational network. To determine the strength of existing relationships in the network, interactions (like text messages, financial transactions and face-to-face contact) between the 17 cell members were recorded from October 6 to October 11. Weighing these recordings using the criteria *transactional content* and *frequency*

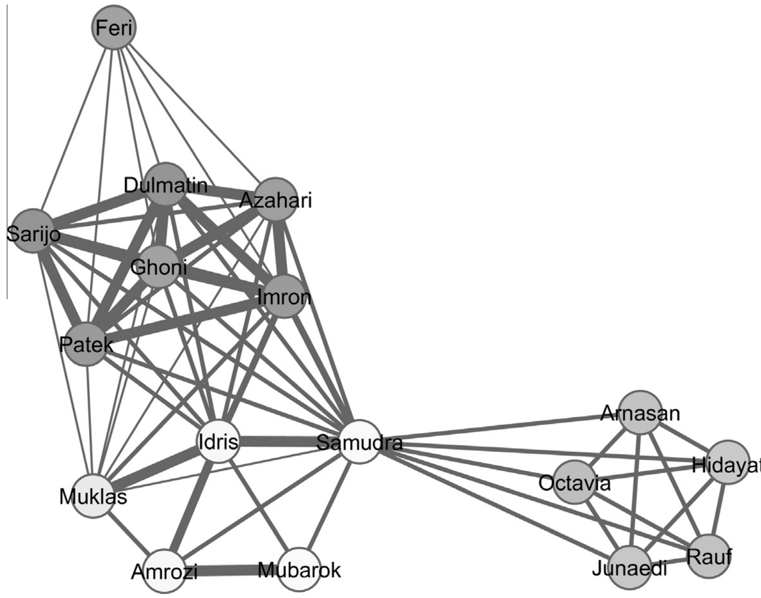

Fig. 4. Operational network of JI's Bali attack. Coordination team (white), support team (lightgray) and bomb building team (gray).

and duration of interaction, each relationship *ij* was assigned a weight f_{ij} between 0 and 5 (Koschade, 2006). A weight of 0 implies there is no relationship at all between two individuals (based on the recordings), whereas a weight of 5 means that there is highly frequent interaction of long duration between cell members. In Fig. 4 these weights are visualized by the thickness of the lines connecting the cell members; i.e., the thicker the line, the higher the weight assigned to the corresponding relationship.

2. *Define the game theoretic model.* At this stage we need to define a weighted connectivity game that uses the available data and reflects the context of the problem at hand; i.e., a terrorist cell that tries to prevent discovery during the planning and execution phase of an attack. A terrorist organization will try to shield its important players by keeping the frequency and duration of their interaction with others to a minimum. However, to be able to coordinate and control the attack an important player needs to maintain relationships with other individuals in the network. This is a well known trade-off dilemma of covert organizations (cf. Lindelauf et al., 2009). The power of a coalition is therefore defined by the total number of relationships that exist within that coalition divided by the sum of the weights (representing frequency and duration of interaction) on those relationships; i.e.,

$$v^{\mathrm{wconn}}(S) = \begin{cases} \dfrac{\sum_{i,j\in S,\ i\neq j} I_{ij}}{\sum_{i,j\in S,\ i\neq j} f_{ij}} & \text{if } S_G \text{ is connected,} \\ 0 & \text{otherwise,} \end{cases} \tag{9}$$

where f_{ij} is the weight assigned to relationship *ij* in the network, with $f_{ij} = 0$ if $ij \notin E$. If relationship *ij* is present in the network (i.e., if $ij \in E$) then $I_{ij} = 1$, else $I_{ij} = 0$. To clarify the idea behind Eq. (9), consider all coalitions with a low frequency and duration of interaction. If a certain player facilitates communication between individuals in many such coalitions (i.e., he makes the underlying subgraphs connected) then this player will attain a high ranking. Note that if $f_{ij} = 1$ for all relationships $ij \in E$ then Eq. (9) equals the definition of the connectivity game v^{conn} in Eq. (4). It can thus be seen that the weighted connectivity game not only takes the structure of the terrorist network into account but it also models additional information that is available on the relationships between cell members.

Table 3
Rankings for the JI network based on standard and game theoretic centrality.

Degree	Betweenness	Closeness	Wconn
Samudra	Samudra	Samudra	Samudra
Idris	Idris	Idris	Muklas
Muklas*	Muklas	Muklas*	Feri
Ali Imron*	Ali Imron*	Ali Imron*	Azahari
Dulmatin*	Dulmatin*	Dulmatin*	Sarijo
Azahari*	Azahari*	Azahari*	Patek
Patek*	Patek*	Patek*	Dulmatin
Ghoni*	Ghoni*	Ghoni*	Idris
Sarijo*	Sarijo*	Sarijo*	Ghoni
Feri	Amrozi	Arnasan•	Octavia*
Arnasan•	Feri•	Junaedi•	Abdul Rauf*
Junaedi•	Arnasan•	Abdul Rauf•	Hidayat*
Abdul Rauf•	Junaedi•	Octavia•	Arnasan*
Octavia•	Abdul Rauf•	Hidayat•	Junaedi*
Hidayat•	Octavia•	Amrozi	Amrozi
Amrozi	Hidayat•	Mubarok	Mubarok
Mubarok	Mubarok•	Feri	Ali Imron

3. *Analyze the rankings of players.* The game theoretic centrality value of each cell member is computed for the game v^{wconn} in Eq. (9). The resulting rankings for standard as well as game theoretic centrality are presented in Table 3. In this table the ranking is presented in descending order with an asterisk ($*$) and bullet ($\bullet$) indicating equal rank.
In practice capacity for surveillance is limited. We therefore focus on the top 5 of highest ranked cell members at each centrality measure, as indicated by the bars in Table 3. Note that there may be more than five persons in the top 5 due to ties in rankings. Analyzing the different rankings leads to the following observations. First, we conclude that Samudra was the key player in this operation. Each centrality measure defines him as the most important person in the operational network. Second, if only the network structure is taken into account, the rankings of the five most important persons are ambiguous. With capacity of surveillance limited to a total of five individuals, it is not clear which persons to watch more closely. Only game theoretic centrality is able to distinguish between the top ranking players in the network. Third, we observe that the

game theoretic ranking introduces a new person in the top 5, when compared with standard centrality; i.e., Feri attains a top 5 ranking. In particular, the way Feri advances from an insignificant position in the standard centrality rankings to a third place in the game theoretic ranking calls for a further analysis of his role in the operational network.

It is safe to say that Samudra's removal from the network would have had a pronounced effect on the Bali operation. This is in concordance with a ruling by judge Sudewi (The New Zealand Herald, 2003):

> "*Judge Isa Sudewi told the court today the prosecution had proven Samudra, an engineering graduate, played a key role in the bombings. 'The defendant worked behind the scenes as the coordinator so the panel of judges has an opinion that the defendant is the intellectual actor behind the bomb explosions,' she said.*"

From our analysis it follows that if additional information is added to the network structure, other persons turn up as high ranking cell members. Feri, for example, conducted an important task during the Bali bombing. He arrived on October 10th, 2 days prior to the attack, and was recruited to be the suicide bomber of Paddy's bar. Another cell member that is identified by game theoretic centrality is Azahari. He was JI's bomb expert and is considered to have been one of the 'brains' behind the Bali operation (Council on Foreign Relations, 2009). If Feri's or Azahari's role would have been detected or recognized in time, the feasibility of the operation would have been seriously hampered. It thus follows that taking additional information into account (in this case study weights on the relationships between cell members) the results of a game theoretic centrality analysis can lead to new insights in a terrorist network. As a result, surveillance can more effectively be allocated due to the increased ability to distinguish between the importance of different individuals.

3.2. Case 2: Al Qaeda and 9/11

On Tuesday morning September 11th 2001, the world was shocked by two planes flying into the Twin Towers of the World Trade Center in New York. A third plane flew into the Pentagon and a fourth plane crashed somewhere in Pennsylvania. It turned out that 19 hijackers, most of whom were from Saudi Arabia, were directly responsible for the execution of the operation. The events leading up to this day have been described meticulously in popular media and the academic literature, e.g., Kean et al. (2002).

Three and a half years before the infamous 9/11 attack Osama Bin Laden issued a *fatwa* calling on all Muslims "to kill the Americans, both civilian and military, in every country in which it was possible to do so..." (Al Quds Al Arabi, 1998). Already in 1996 he issued a *declaration of jihad* against the United States (Al Islah, 1996). Furthermore, Bin Laden expressed his wish that the United States would withdraw from Saudi Arabia. He argued that the presence of American troops on the Arabian peninsula was an insult to the Islamic community.

During a presentation in Tora Bora, Khalid Sheikh Mohammed proposed an operation with trained pilots flying into buildings (Kean et al., 2002). This proposal finally culminated in the 9/11 attack. Note that Khalid Sheikh Mohammed was also in contact with Hambali, JI's Indonesian cell leader. During the summer and autumn of 2000, the hijackers were selected by Bin Laden and his followers. These hijackers arrived in the United States in April 2001. The specific date of September 11th was probably only determined somewhere in August 2001. Several days before the actual attack the hijackers relocated to hotels close to their designated airports and the remaining finances were transferred.

The data we use in our game theoretic centrality analysis of the 9/11 attack originates from two publicly available sources: a social network analysis of the hijackers by Krebs (2002) and the 9/11 commission report by Kean et al. (2002). Again, we follow the three stages of the framework in Section 2.

1. *Construct the network*. To conduct a centrality analysis of the network responsible for the 9/11 operation we used network data gathered by Krebs (2002). He obtained data on the hijackers from open sources, like major newspapers. The network corresponding to our data is depicted in Fig. 5. The colors in the network refer to the different flights of American Airlines (AA) and United Airlines (UA); i.e., AA-77 (white), AA-11 (lightgray), UA-93 (gray) and UA-175 (darkgray).
   The power of game theoretic centrality analysis is the ability to incorporate additional information in the analysis of a terrorist network. There are many ways to obtain such additional information. For example, in the case study of JI's Bali attack we used additional information that reflected the frequency and duration of interaction between cell members. A first look at the publicly available data on Al Qaeda's 9/11 attack shows that it only contains binary network information. Reports on the 9/11 attack, however, reveal more information on the individuals that perpetrated this attack. Using the 9/11 commission report of Kean et al. (2002), we were able to obtain additional information on some of the hijackers, which we characterized under indicators like affiliation and signs of radicalization. Table 4 presents the additional data extracted from the 9/11 commission report. Note that, in general, a thorough analysis of historical sources will shed more light on the persons involved in an attack.
   We determine the weight w_i of each person i as follows. First, every person in the network is assigned a weight of 1. Next, for each person it is determined which indicators are relevant and the weight assigned to this person is increased accordingly. As

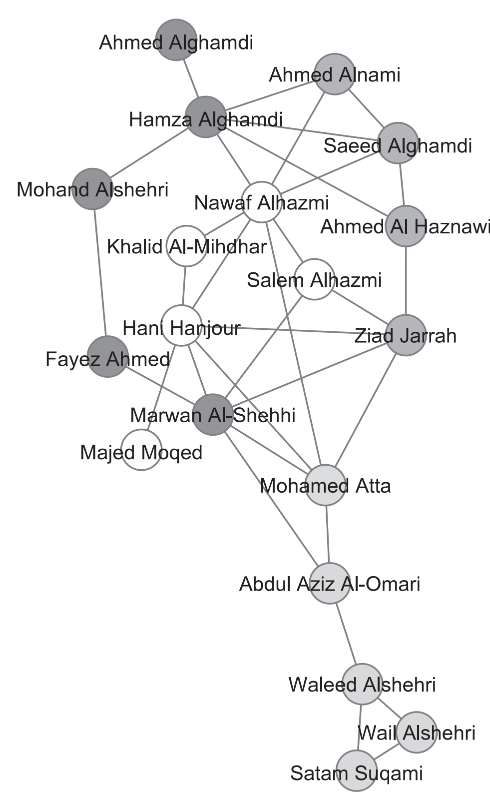

Fig. 5. Operational network of hijackers of Al Qaeda's 9/11 attack. AA-77 (white), AA-11 (lightgray), UA-93 (gray) and UA-175 (darkgray).

Table 4
Example of some indicators and assigned weights.

Description indicator	Example(s)	Person(s)	Weight
Attending meetings on terror attack planning	Kuala Lumpur meeting January 2000	Nawaf Al-Hazmi Khalid Al-Midhar	+1
Signs of radicalization	Antisemitic and anti-American speech, talk about jihad and martyrdom, writing a will	Mohamed Atta Marwan Al-Shehhi Ziad Jarrah	+1
Affiliations	Al-Quds mosque Hamburg	Mohamed Atta Ziad Jarrah	+1
Accomplice to previous attacks	Attack on USS Cole	Khalid Al-Midhar	+1
Attending terrorist training camps	Traveling to training camps in Pakistan and Afghanistan	Mohamed Atta Marwan Al-Shehhi Ziad Jarrah	+1

Table 5
Weights assigned to hijackers of Al Qaeda's 9/11 attack.

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 4 indicates, we have chosen to let each relevant indicator increase the person's weight by 1. For example, Mohamed Atta is assigned a weight of 4, whereas Majed Moqed is assigned a weight of only 1. Table 5 presents the total weight of each hijacker when considering the indicators defined in Table 4.

2. *Define the game theoretic model*. Given the network of hijackers and the weights assigned to each hijacker we want to identify the key players. Therefore, we need to define a weighted connectivity game.
   Individuals that score high on the indicators defined in Table 4 play an important part in the operation. When such individuals team up, they have a significant effect on the potential success of the operation. We therefore define the value of a coalition to be the sum of the weights of its players if the underlying subgraph is connected and 0 otherwise, see Eq. (7).
3. *Analyze the rankings of players*. The game theoretic centrality value of each hijacker is computed for the game v^{wconn2} in Eq. (7). The resulting rankings for standard as well as game theoretic centrality are presented in Table 6. In this table ranking is presented in descending order with players that attain equal rank indicated by the symbols $*$, $\bullet$, $\diamondsuit$, $\star$ and $\circ$.
   We again focus on the top 5 of highest ranked individuals at each centrality measure, as indicated by the bars in Table 6. Analyzing the different rankings leads to the following observations. First, we conclude that standard and game theoretic centrality identify a different key player; i.e. Nawaf Alhazmi versus Abdul Aziz Al-Omari. The destabilizing effect to the network after the removal of Nawaf Alhazmi is only minor. Since Abdul Aziz Al-Omari forms a *bridge* between two parts of the network the destabilizing effect of his removal is more profound, see Fig. 5. However we note that Al-Omari being a disconnecting link might be a choice by the organizers to compartmentalize functions. Second, there are other hijackers that form bridges in the network, for instance Hamza Alghamdi. Together with Marwan Al-Shehhi he links United Airlines flight 175 with the remaining hijackers. Additionally it can be seen that Abdul Aziz Al-Omari and Waleed Alshehri are essential in linking American Airlines flight 11 to the remainder of the network. This is why these hijackers are ranked high according to game theoretic centrality. Third, when considering only network structure the rankings of hijackers are ambiguous. Only game theoretic centrality is able to distinguish between all hijackers (with the exception of the two symmetric players Satam Suqami and Wail Alshehri).

Table 6
Rankings for Al Qaeda's 9/11 network based on standard and game theoretic centrality.

Degree	Betweenness	Closeness	Wconn2
N. Alhazmi	N. Alhazmi	N. Alhazmi*	A. Aziz Al-Omari
M. Al-Shehhi*	A. Aziz Al-Omari	M. Atta*	H. Alghamdi
H. Alghamdi*	M. Atta	M. Al-Shehhi$^{\bullet}$	Wd. Alshehri
H. Hanjour*	M. Al-Shehhi	H. Hanjour$^{\bullet}$	H. Hanjour
M. Atta$^{\bullet}$	<u>Wd. Alshehri</u>	Z. Jarrah	<u>M. Al-Shehhi</u>
Z. Jarrah$^{\bullet}$	H. Alghamdi	H. Alghamdi$^{\diamondsuit}$	M. Atta
S. Alghamdi	H. Hanjour	S. Alhazmi$^{\diamondsuit}$	N. Alhazmi
A. Aziz Al-Omari$^{\diamondsuit}$	Z. Jarrah	<u>A. Aziz Al-Omari</u>	Z. Jarrah
Wd. Alshehri$^{\diamondsuit}$	F. Ahmed	S. Alghamdi	M. Alshehri
A. Al-Haznawi$^{\diamondsuit}$	M. Alshehri	A. Al-Haznawi	K. Al-Midhar
S. Alhazmi$^{\diamondsuit}$	A. Al-Haznawi	F. Ahmed*	A. Al-Haznawi
<u>A. Alnami</u>$^{\diamondsuit}$	S. Alhazmi	A. Alnami*	F. Ahmed
F. Ahmed*	S. Alghamdi*	K. Al-Midhar	S. Alhazmi
M. Alshehri*	A. Alnami*	M. Alshehri	S. Alghamdi
K. Al-Midhar*	K. Al-Midhar*	M. Moqed	A. Alnami
S. Suqami*	S. Suqami*	Wd. Alshehri	S. Suqami*
W. Alshehri*	W. Alshehri*	A. Alghamdi	W. Alshehri*
A. Alghamdi$^{\circ}$	A. Alghamdi*	W. Alshehri$^{\circ}$	A. Alghamdi
M. Moqed$^{\circ}$	M. Moqed*	S. Suqami$^{\circ}$	M. Moqed

The difference between the suggested key players Nawaf Alhazmi and Abdul Aziz Al-Omari calls for a further analysis of their role in the network of hijackers. Nawaf Alhazmi was known to be regularly in contact with Mohamed Atta during the summer of 2001. It is assumed that the latter had an important role in planning the operational part of the attack (Los Angeles Times, 2002). Abdul Aziz Al-Omari, together with Mohamed Atta, constituted the link between the hijackers of American Airlines flight 11 and the remainder of the network. Using only a marginal amount of additional information has led to more insight in the role of and the relationship between Nawaf Alhazmi and Abdul Aziz Al-Omari and the destabilizing effect that would be invoked by the removal of these hijackers from the network responsible for the 9/11 attack. Hence, even in case of limited additional information we can profit from the comparison between standard centrality and game theoretic centrality.

4. Conclusions

We have introduced a quantitative methodology to identify key players in terrorist networks. Our methodology combines solution concepts from cooperative game theory with social network analysis. The advantage of our game theoretic approach is that both the

Table 7
Characteristics of standard and game theoretic centrality measures.

Centrality measure	Network structure	Additional information	Level of differentiation
Degree	Direct relationships	–	–
Betweenness	Connection between individuals	–	+
Closeness	Distance between individuals	–	+
Game theoretic	Coalitions of individuals	+	++

structure of a terrorist network as well as non-network features, such as money and bomb building skills, can be taken into account. Since game theoretic models are able to handle such additional information our approach provides more encompassing models to identify key players. We illustrated our methodology through two case studies: Jemaah Islamiyah's Bali bombing and Al Qaeda's 9/11 attack. This has led to new insights about the operational networks responsible for these attacks.

Centrality measures can be used to construct rankings of important players in terrorist networks. In the case studies of Jemaah Islamiyah and Al Qaeda we applied both standard centrality and game theoretic case specific centrality measures to construct rankings of the terrorists involved. Our analyses included three stages: construct the network (input), define the game theoretic model (modeling) and analyze the rankings of players (output). The characteristics of each centrality measure, from the results of our case studies, are presented in Table 7.

Table 7 should be interpreted as follows. Game theoretic centrality, for example, considers all possible coalitions of terrorists in a given network (*network structure*). Furthermore, personal information about terrorists and their interrelationships can be taken into account (*additional information*). Finally, the centrality measure is able to distinguish individuals when ranking terrorists in order of their importance to the network (*level of differentiation*).

Game theoretic centrality contributes to social network analysis by facilitating the incorporation of additional information when constructing rankings of the players in a terrorist network. This leads to more informative rankings and, when compared to standard centrality rankings, may lead to new insights in the terrorist network under consideration.

Note that all data used in this paper originate from publicly available resources. It is to be expected that the quality of quantitative analyses of terrorists networks increases when more accurate and trustworthy (classified) data are available. Nevertheless, using only publicly available data sets, game theoretic centrality analysis provides valuable new insights in the operational networks of Jemaah Islamiyah and Al Qaeda.

Finally, this paper focuses on constructing rankings of players in a terrorist network. When key players have been identified, the next step is to determine how to act in order to maximize damage to the terrorist organization. For example, does a key player need to be put under extra surveillance in order to gain more information about the organization as a whole or should this player be eliminated from the network in order to destabilize the lines of communication? To answer this question further quantitative analysis of the network is needed. In addition, a possible further stage in our framework could be the inclusion of assessing resources based on rankings. Here, for instance, the idea of disposition matrices (?) could be further investigated. In such a matrix the names of suspects are arrayed against the resources being marshaled to track them down.

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