Social network analysis in project management – A case study of analysing stakeholder networks

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SOCIAL NETWORK ANALYSIS

in Project Management - A case study of analysing stakeholder networks.

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• ABSTRACT •

Networks evolve naturally among different relevant entities during the completion of a project. These networks can be of different types; for example, a communication network among project staff or a contact network among project stakeholders. The present literature have documented that a network analysis of such networks can provide valuable insights about the structural embeddedness of those networks that are otherwise not revealed and very crucial for the successful completion of any group effort. A network analysis can reveal, for example, the relations among actors, how actors are positions within a network and how relations are structured into overall network patterns. This article follows a case study approach to explore stakeholder networks using measures and methods of social network analysis. In doing so, it explains the social network measures and methods that have been used and reports the findings from the case study.

1.INTRODUCTION

Projects are inherently complex, so are their management (Pich, Loch, & Meyer, 2002). This complexity requires collaboration among different relevant entities (e.g., project members and stakeholders) of the project during the completion of its different activities. The presence of such collaboration leads to the development of various networks among different entities of the project during its completion phase. Understanding the structural characteristics of these networks can reveal important insights (e.g., which entity is in the central of the network and which one serves a gatekeeper within the network) that are very crucial for the successful completion of the project (Prell, Hubacek, & Reed, 2009). The primary aim of this study is to illustrate how measures and methods of social network analysis (SNA) can be used to examine the structural characteristics of such project networks. To achieve this aim, this study explores two networks that evolve during the course of the completion of a project among its different stakeholders using various methods and measures of SNA.

Although the network analysis approach has long been followed in various research areas as an advanced and robust technique, it has recently been receiving attention in the project management research (Chinowsky, Diekmann, & O'Brien, 2009). Previously, this approach had been used as a key approach to address network organisation issues in management, particularly network characteristics and their effects on business organisation (Tichy, Tushman, & Fombrun, 1979). With the rapid development different network analysis tools, such as UCINET (S. P. Borgatti, Everett, & Freeman, 2002) and PAJEK (De Nooy, Mrvar, & Batagelj, 2011), the network analysis approach has gradually been followed as a key method of hybrid research design to address several important topics in management research, including knowledge transfer and consensus building (Carlsson & Sandström, 2008; Newig, Günther, & Pahl-Wostl, 2010). In response to this trend, the network analysis approach has recently been introduced to the project management research. Since the introduction there is an increasing trend of the adoption of this approach to the project management research. However, this adoption so far remains at a very initial stage. For this reason, this article first explains some SNA measures and methods thoroughly and then explore two project networks using those measures and methods.

2. SOCIAL NETWORK ANALYSIS

A social network can be viewed as a set of actors and a set of links among those actors (S Wasserman & Faust, 2003). In a social network, an actor is a node which represents an entity, such as individual or organisation. The formation of a social network is typically associated with the need for an actor to receive some sort of information or resource from others; thus creating an exchange whereby investments of actors in relationships determined by their level of needs. In a visual illustration of a social network, actors are presented by nodes and relations among actors are presented by links or ties. In **Figure 1**, two nodes are presented by two small circles and a link shows the relation between them. The two nodes and a link between them form a network. Some researcher argued to use the word 'node' to represent an objective entity (e.g., a webpage in the World Wide Web where two webpages are linked if one of them contains the link of the other) and the word 'actor' to represent a subjective entity (e.g., an individual in a mobile communication network). For this reason, this article uses the words 'node' and 'actor' interchangeably.

Social network analysis (SNA) is the mapping, visualising and measuring of relationships among actors in a network (Carrington, Scott, & Wasserman, 2005), which provides both visual and mathematical analysis of networked relations. It has been successfully applied to evaluate the positional influence of actors in networks. The usefulness of applying SNA to a network has been found very useful across many disciplines because of its ability to assess structural patterns and network behaviour (Brandes & Fleischer, 2005). By examining a stakeholder network, for example, in terms of nodes and their relationships, an assessment of the importance of the member stakeholders can be inferred (S. Borgatti, 2005). This will give the corresponding project manager a deeper understanding about the priority of different stakeholders, which is very important for the successful completion of the project. On the other side, there are many SNA tools (e.g., Organisational Risk Analyser (Carley, 2010)) developed for researchers to visualise relations among actors in different contexts; for example, the communication network among the team members of a mega project. The ability to visualise the relations among a networked set of actors and to quantify their structural importance within the network make the SNA very useful to explore many networked systems.

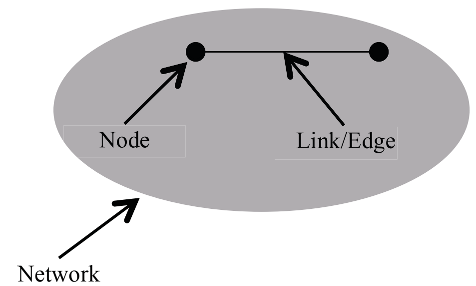

FIGURE 01. Illustration of a social network which has two nodes and an edge.

The origin of social network analysis (SNA) can be traced back in the early 1930s with the sociometric studies of Jacob Moreno at the Hudson School for Girls (L. C. Freeman, White, & Romney, 1992; Hummon & Carley, 1993; Leinhardt, 1977; Marsden & Lin, 1982; S Wasserman & Faust, 2003). Indeed, the year in question is 1934, when the book '*Who Shall Survive*' by Jacob Moreno was published. Clearly, the publication of this book was significant in the introduction of social network analysis. SNA had been further developed regarding its applicability in empirical research with the kinship studies of Elizabeth Bott in England during the 1950s (Nadel, 1957) and the 1950s-1960s urbanisation studies of the University of Manchester group of anthropologists, headed by first Max Gluckman and later by Jams Clyde Mitchell, for exploring community networks in southern Africa, India and United Kingdom (Gluckman, 1973; Mitchell, 1966, 1969). During the era of 1970s, Harrison White and his research team produced an amazing number of important contributions such as '*Block models theory for Social Structure*' to the methodological developments of SNA (Berkowitz, 1982; Mullins & Mullins, 1973; Scott, 1988). According to Freeman (2004), contemporary network analysis methods and measures could never have emerged without their contributions. In brief, SNA was originated in 1930s, had been maturing in empirical research in 1950s-1960s, and in 1970s theoretical research to develop SNA methods and measures was initiated.

Since its inception in 1934, SNA has been gaining significance in diverse range of research areas, including communication studies (Diesner, Frantz, & Carley, 2005), organisational studies (Friedkin, 1982), public health (Uddin, 2016) and social psychology (S. Wasserman & Iacobucci, 1988), and has become a popular topic of speculation and study. In project management, it has recently been receiving attention for research analysis purposes. Prell et al. (2009) followed a SNA approach to analyse stakeholder networks in natural resource management. Crane (2007) used SNA methods and measures to understand the multidimensional determinants and complexity of tobacco use. Similarly, Mok et al. (2017) used basic network centrality measures in identifying key challenges in major engineering projects based on stakeholder concerns. There are many other examples of project management research studies where researchers used SNA methods and measures for research analysis purposes (e.g., Chinowsky et al., 2009; Hagedoorn, 1996; Pryke, 2004). However, the existing SNA studies of the present project management research lack of a comprehensive detail regarding how different SNA measures can reveal different meaningful insights about the structural positions of actors within a network. This study presents a comprehensive illustration about how different SNA approaches can be used in the context of project management by considering a case study.

3. MEASURES OF SOCIAL NETWORK ANALYSIS

Over the time researchers proposed various social network measures. Some of them quantify the structural characteristics of the complete network while some other emphasise the structural influence of individual nodes over the complete network. This section discusses only those SNA measures that are used in the next section to explore the case study.

3.1 NETWORK CENTRALITY AND CENTRALISATION

Centrality is an important concept in studying different social networks and describes structural properties of a node in a network. On the other side, centralisation describes the structural properties of the entire network under consideration. Conceptually, centrality quantifies how central a node is positioned in a network (S Wasserman & Faust, 2003). There are three basic types of centrality measures.

Degree centrality is one of basic measures of the network centrality. For a node, it is the proportion of nodes that are adjacent to that node in a network. It highlights the node with the most links to other nodes in a network and can be defined by the following equation for the node (or actor) in a network having *N* nodes (S Wasserman & Faust, 2003):

$$C_D(n_i) = \frac{d(n_i)}{N-1} \text{...............(1)}$$

Where, the subscript D for 'degree' and $d(n_i)$indicates the number of nodes with whom node *i* is connected. The maximum value for $C_D(n_i)$ is 1 when node *i* is linked with all other nodes in the network. For an isolate node, its value is 0. In **Figure 2**, the node A has three connections with nodes B, C and D. Since there are five nodes in the network, the degree centrality of A will be 0.75 (3/ (5-1) = 0.75).

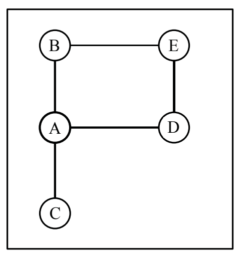

FIGURE 02. An abstract network having five nodes and five links or edges

Closeness centrality, another view of the node centrality which is based on the distance, focuses on how 'close' a node is to all the other nodes in a network (L. Freeman, Roeder, & Mulholland, 1979). The idea is that a node is central if it can quickly interact with all other nodes in a network. In the context of a communication relation, such nodes need not rely on other nodes for the relaying of information. The following equation represents the '*closeness centrality*' for a node *i* in a network having *N* nodes (L. Freeman et al., 1979; S Wasserman & Faust, 2003):

$$C_C(n_i) = \frac{N-1}{\sum_{j=1}^{N} d(n_i, n_j)} \text{.............(2)}$$

Where, the subscript C for '*closeness*', $d(n_i,n_j)$is the number of links in the shortest path between actor *i* and actor *j*, and the sum is taken over all *i* ≠ *j*. A higher value of $C_C(n_i)$ indicates that node *i* is closer to other nodes of the network, and $C_C(n_i)$ will be 1 when node *i* has direct links with all other nodes of the network. In the network of **Figure 2**, node A has a distance of 1 with nodes B, C and D since node A has direct connections with them. It has a distance of 2 with node E since it can reach E through the node D. Therefore, the total distance of node A with the remaining nodes (i.e. B, C, D and E) is 5 (1+1+1+2). Thus, the closeness centrality of the node A is 0.80 (i.e. 4/5).

Betweenness centrality views a node as being in a favoured position to the extent that the node falls on the shortest paths between other pairs of nodes in the network. That is, nodes that occur on many shortest paths between the other pair of nodes have higher *betweenness centrality* than those they do not (L. Freeman, 1978). The *betweenness centrality* for a node n_i (i.e., $C_B(n_i)$) can be represented by the following equation (S Wasserman & Faust, 2003):

$$C_B(n_i) = \frac{\sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}}}{[(N-1)(N-2)]/2} \text{......... (3)}$$

Where, *i* ≠ *j* ≠ *k*, $g_{jk}(n_i)$ represents the number of the shortest paths linking the two nodes that contain node *i* and g_{jk} is the number of the shortest paths linking nodes *j* and *k*. For the central node of a star network as illustrated in **Figure 3**, $C_B(n_i)$ will take its highest value of 1; however, for any peripheral node of a star network $C_B(n_i)$ will take its minimum value of 0.

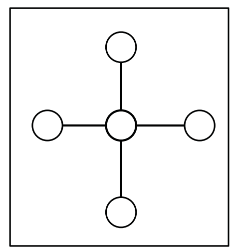

FIGURE 03. A star network having five nodes where A is the central node

In the network of **Figure 2**, consider the node A. Then we need to consider all other remaining nodes (i.e., B, C, D and E) and their all possible pairs (i.e., BC, BD, BE, CD, CE, DE). Now consider the shortest paths for these six pairs. Both BC and CD has only 1 shortest path (i.e., BAC and CAD, respectively) and A is within those paths. There are two shortest paths for CE (i.e., CABE and CADE) and A is within both paths. On the other side, there are two shortest paths (i.e., BAD and BED) for the pair BD but A is within only one path (i.e., BAD). For the shortest paths of remaining two pairs (i.e., BE and DE), A does not fall within those paths.

Thus, the *betweenness centrality* of A

$$= \frac{\frac{1}{1} + \frac{1}{2} + \frac{0}{1} + \frac{1}{1} + \frac{2}{2} + \frac{0}{1}}{\frac{(5-1)\times(5-2)}{2}}$$

$$= \frac{1 + 0.5 + 0 + 1 + 1 + 0}{6}$$

$$= 0.58$$

Centralisation refers to the overall cohesion or integration of a network. A network may, for example, be more or less centralised around particular a node or a set of nodes. A network centralisation measure is an expression of how tightly the network is organised around its most central point (S Wasserman & Faust, 2003). There are three different types of centralisation that are based on the three basic centrality measures.

The set of *degree centralities* (as in equation 1), which represents the collection of *degree* indices of *N* nodes in a network, can be summarised by the following equation to measure the *degree centralisation* (L. Freeman et al., 1979):

$$C_D = \frac{\sum_{i=1}^{N} [C_D(n^*) - C_D(n_i)]}{[(N-1)*(N-2)]} \text{....... (4)}$$

Where, $C_D(n_i)$ are the *degree* indices of *N* nodes and $C_D(n^*)$ is the largest observed value in the *degree* indices. For a network with *N* nodes, the *degree centralisation* (i.e., C_D) reaches its maximum value of 1 when a node chooses all other (*N*-1) nodes and the other (*N*-1) actors interact only with this actor (i.e., the situation in a *star* network as in **Figure 3**). This index attains its minimum value of 0 when all *degrees* are equal (i.e., the situation in a *circle* network as in **Figure 4**). Thus, C_D indicates the varying amount of the centralisation of *degree* compared to both star and *circle* networks.

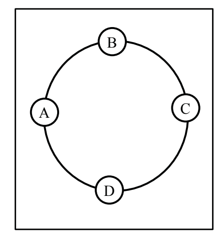

FIGURE 04. A circle network having four nodes and four edges or links

The set of *closeness centralities* (as in equation 2), which represents the collection of *closeness indices* of *N* nodes in a network, can be summarised by the following equation to measure the *closeness centralisation* (L. Freeman et al., 1979):

$$C_C = \frac{\sum_{i=1}^{N}[C_C(n^*) - C_C(n_i)]}{[(N-1)*(N-2)]/(2N-3)} \;\ldots\ldots (5)$$

Where, $C_C(n_i)$ are the closeness indices of *N* nodes and $C_C(n^*)$ is the largest observed value in *closeness* indices. For a network with *N* nodes, the *closeness centralisation* (i.e., C_C) reaches its maximum value of 1 when a node chooses all other (*N*-1) nodes and each of the other (*N*-1) nodes has the *shortest distances* of length 2 to the remaining (*N*-2) actors (i.e., the situation in a star network as in **Figure 3**). This index can attain its minimum value of 0 when lengths of the *shortest distances* are all equal (i.e., the situation in a complete graph as in **Figure 5**). Thus, C_C indicates the varying amount of the centralisation of *closeness* compared to *star* and *complete* networks.

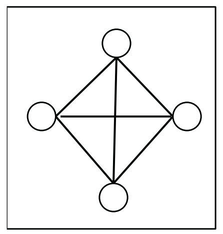

FIGURE 05. A complete network where each node is connected with all other remaining nodes in the network

The set of *betweenness centralities* (as in equation 3), which represents the collection of *betweenness* indices of *N* nodes in a network, can be summarised by the following equation to measure the *betweenness centralisation* (L. Freeman et al., 1979):

$$C_B = \frac{\sum_{i=1}^{N}[C_B(n^*) - C_B(n_i)]}{(N-1)} \;\ldots\ldots\ldots (6)$$

Where, $C_B(n_i)$ are the betweenness indices of *N* nodes and $C_B(n^*)$ is the largest observed value in the betweenness indices. Freeman (1978) demonstrates that betweenness centralisation reaches its maximum value of 1 for the star graph. Its minimum value of 0 occurs when all actors have exactly the same betweenness index.

--- 3.2 NETWORK DENSITY ---

Density is a network-level SNA measure. The *density* of a network represents the proportion of existing ties (or, links) relative to the maximum number of possible ties among all nodes of that network (S Wasserman & Faust, 2003). The *density* value for a network is 1 only when all nodes of that network are connected with each other (i.e., in the case of a complete network as in **Figure 5**). On the other hand, for a completely sparse network, the density value is 0, which indicates there is no link exists between any two nodes of that network. For an undirected network of size *N*, theoretically there are [N*(N-1)]/2 (i.e., $^{N}C_2$) possible links among its *N* nodes. If there are N_t links among its *N* nodes in that network, then, mathematically, *density* can be defined as (S Wasserman & Faust, 2003):

$$\text{Density} = \frac{2 \times N_t}{N \times (N-1)} \;\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

The density of the network as in **Figure 2** is 0.5 (i.e., (2×5)/(5×4) = 0.5) since it has 5 links among its five nodes and there can be maximum 10 links among these 5 nodes. Density describes the general level of cohesion in a network; whereas, centralisation describes the extent to which this cohesion is organised around particular focal nodes. Centralisation and density, therefore, are important complementary measures.

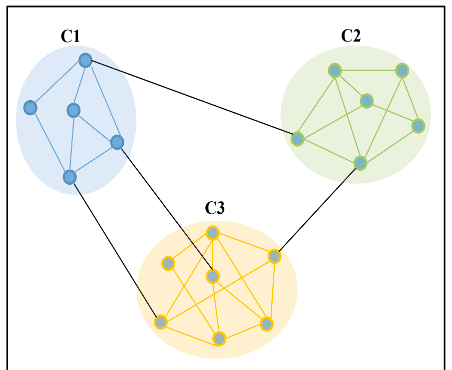

FIGURE 06. AIllustration of the community structure in an abstract network which has three communities (i.e., C1, C2 and C3)

--- 3.3 COMMUNITY STRUCTURE ---

A network is said to have a 'community structure' if the nodes of that network can easily be divided into sets of groups such that each set of nodes is densely connected internally but sparsely connected externally. Each set of nodes is called a 'community'. In the network of **Figure 6**, there are three communities (i.e., C1, C2 and C3). Any node of these communities has more links with other nodes of the same community compared with the number of links with other nodes from other communities. This method is used to conduct a group-level analysis of the underlying social network.

4. STATE TOBACCO CONTROL PROJECTS IN THE UNITED STATES - A CASE STUDY OF NETWORK ANALYSIS

This case study has been considered from the article published by Crane (2007). The network analysis data reported in this case study came from two large-scale multistate projects to evaluate tobacco control programs. These projects were conducted by the Centre for Tobacco Policy Research of the Saint Louis University School of Public Health and had been funded by the American Legacy Foundation and the Chronic Disease Directors Association[1]. The network data is about the connectivity among different stakeholders in two different states (Indiana and Oklahoma). A connection between stakeholders is broadly defined and includes face-to-face meeting, telephone conversations and emails. This network data was collected by surveying different stakeholders in these two states in 2002. Each of these states was rated against some criteria for financial and political climate. According to this rating, which was conducted in 2002, Indiana was found 'strong' for having both positive financial and political climates; whereas, Oklahoma was indexed as 'weak' against these two climate conditions (Crane, 2007). This article first conducts a node-level SNA in order to quantify the importance of different stakeholders within the given stakeholder network. It uses some SNA measures to visually distinguish the importance of different stakeholders within the stakeholder network. Second, it performs a group-level SNA to explore the tendency of stakeholders' preferences to work in small groups. Finally, it conducts a network-level SNA to compare the stakeholder network of Indiana with the stakeholder network of Oklahoma.

The required network analyses for this case study have been conducted using two software tools. The first one is Organizational Risk Analyzer (ORA) which was developed by the Center for Computational Analysis of Social and Organizational System of the Carnegie Mellon University (Carley, 2010). The second one is NodeXL which is a network analysis and visualisation software package for Microsoft Excel (Hansen, Shneiderman, & Smith, 2010).

1. Center for Tobacco Policy Research (2005). Best practices project. Saint Louis University School of Public Health. http://escholarship.org/uc/item/6fs8f7p4

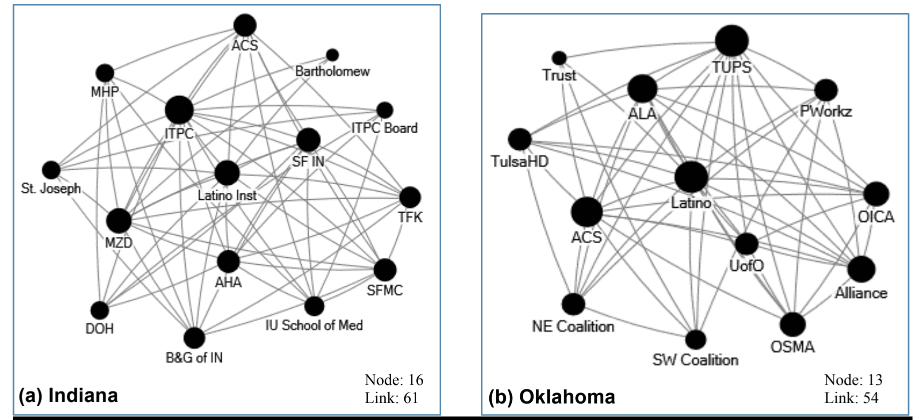

FIGURE 07. Visualisation of stakeholder networks for Indiana (having strong political and financial climate) and Oklahoma (having weak political and financial climate). The size of a node in both networks is proportional to its degree centrality value.

Rank	Indiana			Oklahoma		
	Degree	*Closeness*	*Betweenness*	*Degree*	*Closeness*	*Betweenness*
1	ITPC (1.00)	MHP (0.39)	St. Joseph (0.05)	TUPS (0.92)	Trust (0.36)	ALA (0.07)
2	SF IN (0.57)	DOH (0.26)	ITPC Board (0.03)	Latino (0.85)	ACS (0.32)	ACS (0.05)
3	AHA (0.570	ITPC Board (0.22)	B&G of IN (0.03)	ALA (0.39)	OICA (0.23)	PWorkz (0.04)
4	MZD (0.50)	St. Joseph (0.19)	Latino Inst (0.03)	TulsaHD (0.39)	UofO (0.19)	Alliance (0.02)
5	Latino Inst (0.43)	B&G of IN (0.16)	MZD (0.02)	Alliance (0.31)	OSMA (0.16)	OSMA (0.02)

TABLE 01. List of five top nodes having highest degree, closeness and betweenness centrality values in Indiana and Oklahoma stakeholder networks.

--- 4.1 NODE-LEVEL ---

The stakeholder networks for Indiana and Oklahoma are shown in **Figure 7**. A link connects two stakeholders if they have contact with each other at least once per month. In this figure, the size of a node is proportional to its degree centrality within the network. If a node has a higher degree centrality then its size will be bigger and vice versa. This figure therefore gives a quick visual illustration about the connection(s) that each node has with other network nodes within the network. In the same way, other node-level SNA measures (e.g., closeness centrality) can be used to define the size of a node within a network.

Table 1 shows five top stakeholders in respect to three basic centrality measures (i.e., degree, closeness and betweenness centrality) in both networks. Indiana Tobacco Prevention and Cessation Agency (ITPC) has the highest degree centrality within the stakeholder network of Indiana. In fact, it has a degree centrality of 1, which indicated that ITPC has links with all other nodes and is at the central position within the network. This organisation therefore does not need to rely on other node(s) to establish a direct communication with any of the remaining nodes of the network. Oklahoma State Department of Health Tobacco Use Prevention Service (TUPS) also has a degree centrality of close to 1 (i.e., 0.92) in the Oklahoma stakeholder network. Madison Health Partners (MHP) and Tobacco Settlement and Endowment Trust (Trust) have the highest closeness centrality (0.39 and 0.36, respectively) in Indiana and Oklahoma stakeholder networks, respectively. This indicates that they are the most reachable organisations from any other nodes within the Indiana and Oklahoma stakeholder networks, respectively. A high betweenness centrality (0.07) for the American Lung Association (ALA) in the Oklahoma stakeholder network represents that this organisation has been a gatekeeper or controller of information flow between any pair of other nodes within the network. St. Joseph County (St. Joseph) plays a similar role within the Indiana stakeholder network.

--- 4.2 GROUP-LEVEL ---

Figure 8 shows the community structure for both Indiana and Oklahoma stakeholder networks. The algorithm proposed by Clauset et al. (2004) has been used for this community structure analysis. Nodes with same shape and colour belong to the same community in both stakeholder networks. There are two communities found in the Indiana network. As in **Figure 8(a)**, the first community (represented by black solid circle) has nine members; whereas, the second community (represented by green solid triangle) has six members. Oklahoma network has also two communities with seven and six members, respectively (**Figure 8(b)**).

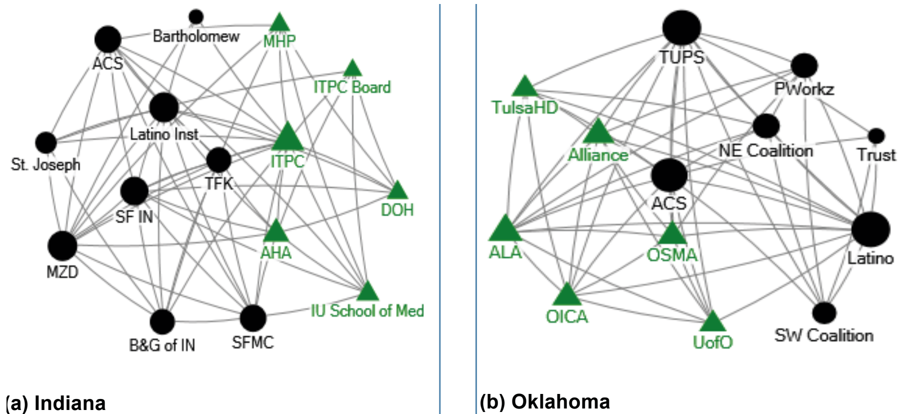

FIGURE 08. Community structure analysis of Indiana and Oklahoma stakeholder networks. Nodes having same colour and shape belong to the same community in both networks. The size of a node in both networks is proportional to its degree centrality value.

Network-level measure	Indiana	Oklahoma
1. Network centralisation		
Degree centralisation	0.24	0.19
Closeness centralisation	0.54	0.46
Betweenness centralisation	0.04	0.06
2. Network density	0.29	0.30

TABLE 02. LValues of different network-level social network analysis measures for Indiana and Oklahoma stakeholder networks.

--- 4.3 NETWORK-LEVEL ---

Based on different network-level SNA measures, a comparison between the stakeholder networks of Indiana and Oklahoma has been presented in **Table 2**. As presented in this table, the stakeholder network of Indiana has higher degree and closeness centralisation values compared with the stakeholder network of Oklahoma. The stakeholder network of Oklahoma has slightly higher betweenness centralisation (0.06 versus 004) and network density values (0.30 versus 0.29) compared with the Indiana stakeholder network. Therefore, the stakeholder network of Indiana has a higher level cohesive network structure compared with the stakeholder network of Oklahoma. Since Indiana and Oklahoma had been indexed as 'strong' and 'weak' for the political and financial climates, respectively when their network datasets were collected, it can be argued that superior network cohesiveness is positively associated with strong political and financial climate.

5. DISCUSSION AND CONCLUSION

This article provides an illustration about the application of SNA measures and methods in the context of project management, particularly for analysing two stakeholder networks. It also shows how two different stakeholder networks that may, or may not, have same member nodes and links among them can be compared using various SNA measures and methods. This type of network analysis can be of help to project managers or other relevant decision makers. They can, for example, figure out which stakeholder is playing the central role within the stakeholder network and allocate the available resources accordingly for the successful completion of the underlying project. Further, by conducting the similar network analysis of the same stakeholder network over the time, they can monitor the ongoing progress of the project.

Any node-level SNA approach usually focuses on questions, such as, "Which organisations are most central in the network?"; "Are the central organisation(s) essential for addressing the needs of a project for its successful completion?"; "Does the network has any connector, information broker and boundary spanner?"; and "If the answer of the previous question is 'yes' then who are the connector(s), information broker(s) and boundary spanner(s) in the network?". The principal focus of a group-level SNA approach is to group a set of nodes based on the similarity of their structural positions within the network. Therefore, the focus of any group-level SNA approach on questions, as like, "Is the network divided into subgroups or cliques?" or "Are there any tendency of actors to work into groups?". The key consideration of the network-level SNA approach is to explore the cohesiveness of the entire network. This cohesiveness can also be used to compare multiple different networks and to answer questions, such as, "How overall sustainability of the network can be enhanced?" or "How the multi-organisational services provided to a client group might be strengthened?".

This article uses few basic level SNA measures (i.e., centrality, centralisation and network density) and methods (i.e., community structure analysis) in exploring two stakeholder networks. Some other advanced level SNA methods can also be used in the context of project management. For example, the network regression can be used to explore the impact of one type of relation among stakeholders on the development of other type of relation among the same group of stakeholders. Application of such advanced level network methods could be the research topic of any future project management research. ◆

• LIST OF ABBREVIATIONS •

ACS → American Cancer Society
AHA → American Heart Association
ALA → American Lung Association
Alliance → Oklahoma Alliance on Health or Tobacco
B&G of IN → Indiana Alliance of Boys and Girls Clubs
Bartholomew → Bartholomew County
DOH → Indiana State Department of Health
ITPC → Indiana Tobacco Prevention and Cessation
ITPC Board → Indiana Tobacco Prevention and Cessation Board
IU School of Med → Indiana University School of Medicine
Latino → Latino Agency
Latino Inst → Indiana Latino Institute
MHP → Madison Health Partners
MZD → MZD Advertising
NE Coalition → Northeast Tobacco Free Oklahoma Coalition
OICA → Oklahoma Institute for Child Advocacy
OSMA → Oklahoma State Medical Association
PWorkz → PreventionWorkz
SF IN → Smoke Free Indiana
SFMC → Smoke Free Marion County
St. Joseph → St. Joseph County
SW Coalition → Southwest Tobacco Free Oklahoma Coalition
TFK → Tobacco Free Kids
Trust → Tobacco Settlement Endowment Trust
TulsaHD → Tulsa City-County Health Department
TUPS → Oklahoma State Department of Health Tobacco Use Prevention Service
UofO → University of Oklahoma Health Sciences Center

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