Modeling Social Connections in Dynamic Ad Hoc Networks Using Layered Random Matrices

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***Abstract* — We describe a system model for determining decision-making strategies that is based upon the ability to perform data mining and pattern discovery – utilizing open source information from multiple information sources – to prepare for specific events or situations. Within this paper, we discuss the development of a method for determining actionable information. Probabilistic predictions are critical in practice on many decision-making applications because optimizing the user experience requires being able to compute the expected utilities of mutually exclusive pieces of content. Wireless communication technologies are undergoing very rapid advancements. In the past few years, there has been steep growth in research regarding the area of wireless networks in wireless domain. A natural trend is to integrate social networks with mobile devices. Mobile Ad Hoc Networks (MANETs) can extend high-capacity mobile communications over large areas where fixed and tethered-mobile systems are not available. Random matrix theory is useful in simulating network nodes by a Wishart adjacency matrix. Our paper investigates the use of composite sparse random matrices for modeling social networks. We use eigenvectors to characterize activity in the social network. We extend random matrix application to include multi-modal communication channel layer modeling for other communications, such as cell phone, Facebook, and Twitter, etc. We used the Dijkstra algorithm for discovering ad hoc network node connection patterns in random volumes. We use the Poisson process to simulate arrival and departure of social connections for unusual activity. The likelihood of event occurrence is based on unusual activity. The amount of time in system or number of communications is modeled. Additional metrics, such as mean first passage time and rate of batch or group arrival, provide additional indicators of unusual activity.**

Keywords: Social Ad Hoc Networks, Random Matrices, Poisson Process, Decision-making

I. Introduction

Almost all work on mobile ad hoc networks relies on simulations, which, in turn, rely on realistic models for their credibility. Since there is a limited amount of realistic data in the public domain, synthetic models for pattern generation must be used and the most widely used models are currently very simplistic, the focus being ease of implementation rather than soundness of foundation. Mobile networks are social networks after all, since humans usually carry mobile devices and the movement of such devices is necessarily based on human decisions and socialization behavior [17].

One of the most important aspects of cognitive radio (CR) is that it proposes methodologies to drastically increase spectrum efficiency over current capacities by adding the temporal component to spectrum management. One of the highest impact use cases is to let secondary users (those who receive restricted use rights from spectrum owners) access the unused parts of the spectrum for a given geographical space, at a certain time. This requires a certain level of knowledge about the characteristics of the communications environment in the geographical area of interest. If the signal types and communication technologies existing in the area are identified and determined to be spectrally, spatially or temporally orthogonal to secondary user signals, then it will be possible to let the secondary users communicate through the medium in a safe, reliable way with a predetermined acceptable Quality of Service (QoS), that is, without interfering and harming the primary user's communication. Secondly, if the signal type of the primary user is known, alternative methodologies can be applied to allocate for the secondary user. For instance, if the primary user's signal has the frequency hopping property, allocation to secondary users can be done accordingly [10].

Mobile Ad Hoc Networks (MANETs) can extend high-capacity mobile communications over large areas where fixed and tethered-mobile systems are not available. They are valuable in tactical and emergency response operations where fixed infrastructures and pre-planned networks are impractical or of limited utility. As with all modern data communications, the user demands for capacity during these operations is ever increasing and MANETs are subject to the same pressures for capacity growth and spectrum efficiency experienced by other wireless network technologies. In many MANET implementations, the radio nodes use omni-azimuth or hemispherical antennas, which greatly simplify the discovery and network entry functions of the system.

In Figure 1, wireless ad hoc networks are conceptually compared to traditional wireless cellular networks. Wireless multi-hop ad hoc networks are formed by a group of mobile users or mobile devices spread over a certain geographical area. We call the users or devices forming the network the "nodes." The service area of the ad hoc network is the whole geographical area where nodes are distributed. Each node is equipped with a radio transmitter and receiver, which allow it to communicate with the other nodes. As mobile ad hoc networks are self-organized networks, communication in ad hoc network does not require a central base station [12].

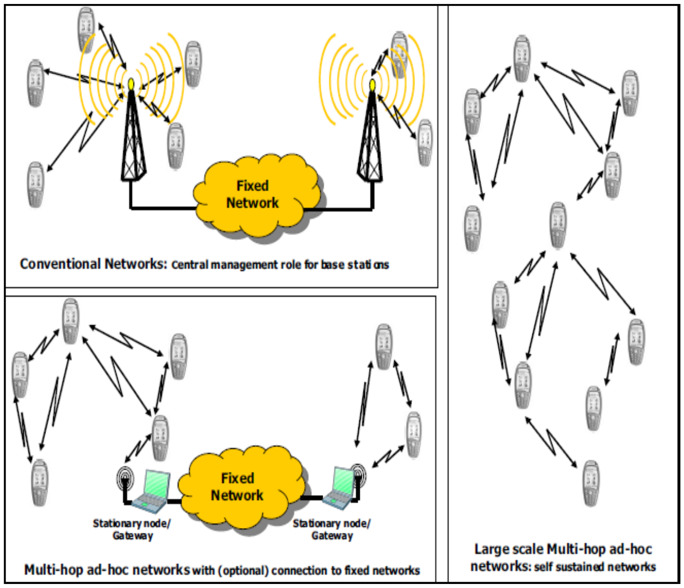

FIG. 1 WIRELESS AD HOC NETWORK [12]

II. SOCIAL NETWORK INFORMATION MANAGEMENT

The Internet has forever changed the way people are able to respond to interconnect with one another. Consider, for example, a collective response to a disaster. Today, a person, business, or organization can create a call to action that generates millions of dollars worth of donations in money, food and even volunteer power in a matter of minutes. This can happen via an email, a button on a website or a YouTube video that goes viral. We have seen this during disastrous events such as Hurricane Katrina, the 2010 earthquake in Haiti or the recent typhoon in the Philippines [13].

The 2014 typhoon in the Philippines has allowed us to witness an exciting change in how crowdsourcing can assist in disaster response. Rather than sit and wait for the heads of organizations and governments to dictate what is needed on the ground, people are able to assist first responders in the very work of saving lives, both directly and indirectly. Through the use of powerful technology, people are able to track weather patterns that are more accurate than anything broadcast on the evening news. Geography buffs are able to use satellite imaging technology to create maps and pinpoint locations where people are stranded and in desperate need of food and water. There are even examples of people who have been able to locate others who were buried under debris. This kind of response is a much more aggressive response to a disaster [13].

The crowdsourcing involved people from all around the world who viewed satellite images from space and provided relief agencies with their knowledge of the changes that had occurred on the ground after the storm passed. Officials from the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) coordinated the effort to get volunteers to help with the aid relief. Doctors without Borders received updated maps generated by more than 1,000 OpenStreetMap volunteers in 82 countries. They identified hospital locations, which buildings were intact and which were damaged, blocked roads and other key infrastructure [14].

Technological advances in sensing, computation, storage and communications are turning the near-ubiquitous mobile phone into a global mobile sensing device. People-centric sensing will help drive this trend by enabling a different way to sense, learn, visualize and share information about ourselves, friends, communities, the way we live and the world we live in. It juxtaposes the traditional view of mesh sensor networks with one in which people, carrying mobile devices, enable opportunistic sensing coverage [3].

Since people-centric sensing began, content provided by ordinary people, so-called "citizen journalists" or individuals with particular agendas has been routinely posted or shared on Social Networks such as Twitter, YouTube, Facebook, MySpace or Flickr, to name but a few. This crowd sourced information has increasingly made it into the channels and services of traditional information providers such as news organizations. New and affordable publishing and distribution tools for ordinary citizens, such as social networks, blogs or services have made this possible. Social networks have more and more become an integral part of the communications mix for all kinds of aims, such as (political) campaigning, and raising awareness [6]. For example, Fox News revamped its newsroom for Shephard Smith reporting on breaking news, such as the December 2013 shooting at Arapahoe High School in Colorado.

The ad hoc network is a network that consists of wireless mobile users only and it does not rely on any backbone infrastructure or special pre-use interventions. The mobile nodes are free to move around as long as they do not go out of the range of the network. In order to provide full interconnectivity, the nodes have two different roles. First, they can be either source or destination for the transferring data. Second, they may need to become routers for some other data source destination stream for situations where the source and the destination are not in the radio range proximity. The ability for users that are not in radio range to exchange data and information is provided via multi-hop paths over one or several intermediate nodes that forward the data toward the destination. The field of ad hoc networks continues to be very popular and challenging when discussing communication networks. The low cost and wide availability of wireless equipment have brought the ad hoc networks closer to the end user and the ever-expanding list of possible applications attracts even more attention. Ad hoc networks provide means for information sharing for a group of users. Thus, care must be taken that a proper model of the end-to-end communication is used. The absence of infrastructure and the on-the-fly establishment are the major reasons for the enormous number of applications for ad hoc networks. The possibilities begin with military use on the battlefield for instant soldier connection, and extend to rescue missions or exploration teams for anywhere, anytime connectivity [9].

The identification of organizational or command and control structures from social data often relies on explicit communication events between group members. Missing or hidden communication channels may affect current search algorithms, resulting in a false or incomplete structure [4].

III. RANDOM MATRIX THEORY

Random matrix theory is currently a popular subject, with applications in many disciplines of science, engineering and finance [8]. In many situations, the nodes of a graph are not fixed but mobile. Many different types of mobility can be considered for the nodes, but it seems natural to allow some room for randomness in the mobility properties. These models can be used to understand properties of communication networks, social networks, ad-hoc networks, sensor networks and also the spread of infectious diseases and rumors. Even though these models are simple, they capture important characteristics of real networks [19].

Our example simulation environment is modeled with 32 nodes. We use an adjacency matrix to describe how users in a MANET or VANET (Vehicular Ad Hoc Network) are connected. We simulate results with a randomly generated Gaussian matrix. In order to get a symmetric Wigner matrix, this matrix is added to its transpose and divided by two. In our example we use an orthogonal Gaussian matrix with elements distributed as N=0 on the diagonal and N=0 or 1 off the diagonal.

Unlike typical wireless ad hoc networks, which focus on propagating collected data to a sink, social ad hoc networks focus on capturing network dynamics at regular intervals. We aim to enable the execution of distributed applications that depend on capturing network dynamics across large-scale, social ad hoc networks. Conservation of the nodes' fixed energy budget is the chief concern in all design decisions, and necessitates that wireless communication is kept to a minimum. In the social settings where our applications will be executing, people are free to join and leave the network, and to move anywhere they please (i.e., make arbitrary changes in the network topology). These dynamic changes to network topology can wreak havoc on many algorithms (e.g., routing and leader election) that assume stable and symmetric connections between nodes. Slots in which the radio is powered up are known as *active* slots, in contrast to inactive or *idle* slots, where the radio is powered down. Our model uses simple TDMA strategy as a parameter of the number of active slots in a frame. This algorithm works well in moderate-traffic networks [7].

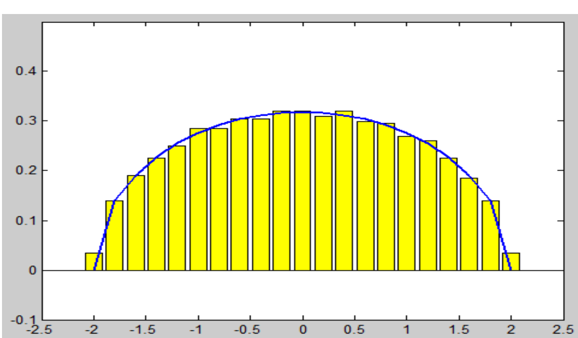

FIG. 2 WIGNER'S SEMI CIRCLE LAW

Wigner originally showed that limiting eigenvalue distribution of simple random symmetric matrices follows a semi-circle distribution. When properly normalized, the curve looks like a semi-circle of radius 2 as shown in Fig 2. This distribution depicts histogram of n eigenvalues of a symmetric random matrix obtained by symmetrizing a matrix of random normals [8]. We can use this method to characterize activity in a social ad hoc network as discussed in next section.

IV. NODE CONNECTIVITY

In wireless multi-hop ad hoc networks, any node may have direct radio links with some other nodes in its vicinity and each node can, if needed, function as a relay station routing traffic to its final destination. Regardless of the radio technology used or the movement pattern of nodes, from the topology point of view, at any instant in time an ad-hoc network can be represented as a graph with a set of vertices consisting of the nodes of network and a set of edges consisting of links between the nodes. The links between nodes are two-way, undirected links. There is a link between two nodes if a signal transmitted from one node is received at another node above a minimum required power threshold [12].

Many important optimization problems can best be analyzed by means of a graphical network representation [21]. We consider the Dijkstra algorithm for shortest or minimum cost network path problems. We assume that each path in the network has a length associated with it. We would like to determine if there is a path that exists between one player of interest and another. The Dijkstra algorithm can be used to find the path from one node to another.

A graph G consist of two sets V and E. The set V is a finite, nonempty set of vertices. The set E is a set of pairs of vertices called edges. The notations $V(G)$ and $E(G)$ represents the sets of vertices and edges respectively, of graph G. We also write $G=(V,E)$ to represent a graph. In an undirected graph, the pair of vertices representing any edge is unordered. Thus, the pairs (u,v) and (v,u) represent the same edge [2].

Graphs can be used to represent a highway structure, with vertices representing cities, and edges representing highway. The edges can then be assigned weights, which may be the distance between the two nodes. The starting vertex of the path is referred to as the source, and the last vertex the destination. Cost Minimization uses the sum of edge weights from source to destination node. The shortest path is the desired output. Figure 3 shows our system flow processing diagram.

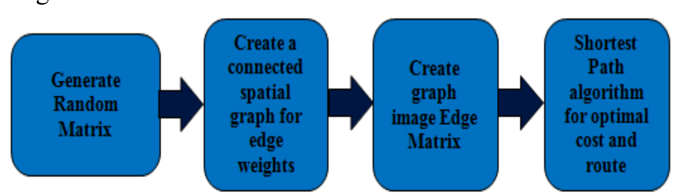

FIG 3 SYSTEM DIAGRAM

In order to generate a graph matrix, each point is assigned an index and a "K" square adjacency matrix is created. Our algorithm is similar to Dijkstra's shortest path algorithm [5]. For a given source node in the graph, the algorithm finds the path with lowest cost or shortest distance between that node and every other node.

The solution for a single cognitive radio may be mathematically tractable but is of little practical use. It assumes that all other radios with which it will communicate will either reason the same solution or will be able to effectively communicate using the reasoning node's solution. This, in turn, assumes all nodes are in a similar radio environment. However, there are many use cases where nodes are in differing environments and the physical layer solution of the network of radios must take into account the requirements of all nodes. For a cognitive network, the required solution must optimize the performance of the network given the constraints of multiple protocol stack layers in potentially diverse radio environments [20].

We model the degree of social interaction between two people using a value in the range [0 or 1]. 0 indicates no interaction; 1 indicates a social interaction. We use a matrix M, which we call Interaction Matrix, to store this information. The generic element $m_{i,j}$ represents the interaction between two individuals i and j. We refer to the elements of the matrix as the interaction indicators. The diagonal elements represent the relationships that an individual has with himself and are set, conventionally, to 0. The matrix is symmetric since, to a first approximation, interactions can be viewed as being symmetric. The first step in this two-level process is the generation of the social network; that is, the generation of the Interaction Matrix, using random distributions [17].

The statistical literature on modeling social networks assumes that there are n entities called actors and information about binary relations between them. Binary relations are represented as a matrix Y, where Yi,j is 1, if actor i is somehow related to j and 0 otherwise. For example, Yi,j = 1 if i considers j to be friend. The entities are usually represented as nodes and the relations as arrows between the nodes. If matrix Y is symmetric, then the relations are represented as undirected arrows. More generally Yi,j can be valued and not just binary, representing the strength (or value) of the relationship between actors i and j [11].

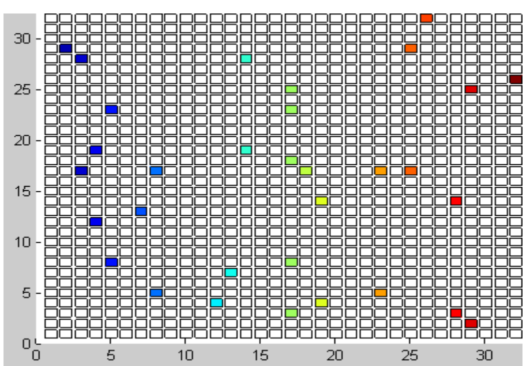

FIG. 4 GRAPH MATRIX

Random matrix techniques can also be used for finding costs of paths from a single source node to a single destination node. Similar to the traveling salesman problem [18], if the nodes of the graph represent cities and edge path costs represent driving distances between pairs of cities connected by a direct road, Dijkstra's algorithm can be used to find the shortest route between one city and all other cities We represent a social network using a graph, by defining associations with each player in the network. Figure 4 shows a graph with the columns representing the source node and the rows representing the destination node. For example, does user 3 talk with user 2? The answer from Dijkstra's algorithm is yes: Path = 3 17 25 29 2.

Figure 5 illustrates destination-source (backward) discovery, showing the shortest path found. The path is determined by looking for sources that can connect to the node 2 destination. In this example, looking at row 2 shows that the only source node with connection to node 2 is node 29. Then, row 29 shows that only nodes 2 and 25 are the only sources able to send to 29. Since 2 is the destination goal, we investigate 25.

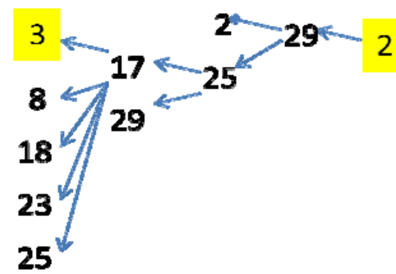

FIG 5: DESTINATION BACKWARD SEARCH

Figure 6 shows the source forward search. Once a node in the potential path repeats, the search goes to the next leaf. Only the first few dead ends are illustrated. Note that there is a path through node 18 to 25, 29 and then to 2. But this is not the shortest path.

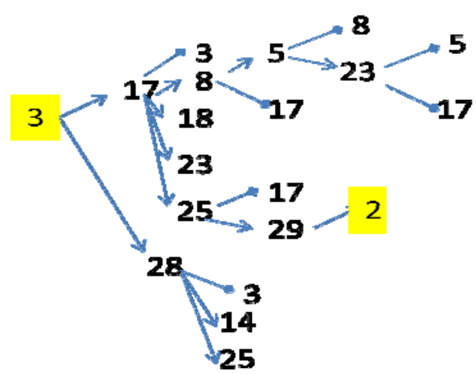

FIG 6: SOURCE FORWARD SEARCH

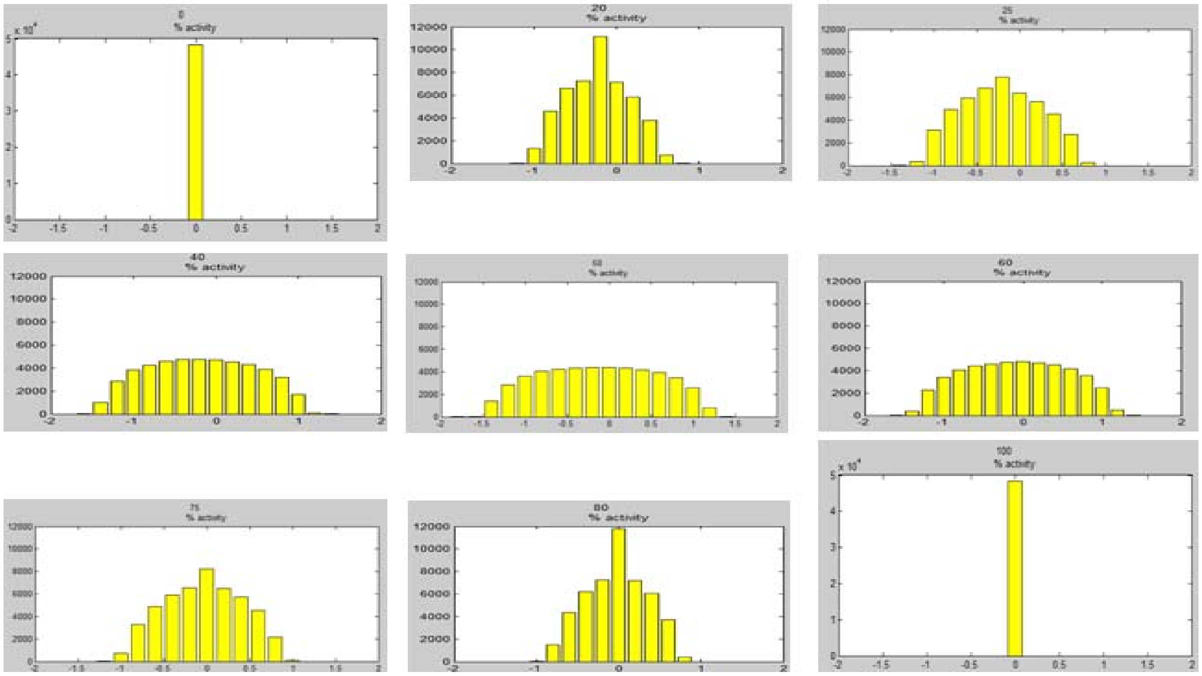

FIG. 7 EIGENVALUES AS A FUNCTION OF SOCIAL NETWORK ACTIVITY

Mobile nodes are more inclined to fail due to energy consumption over time. Work that has been done has determined that the probability that a node changes its behavior is dependent on time. Therefore, the revolution of node behaviors cannot be simply described by a Markov chain because of its time-dependent property. Node behavior model can be modeled by a semi-Markov process, with transition probability of a node's behavior becoming state j from i, and a distribution function of the time spent from state i to j [22].

Figure 7 shows the eigenvalues as a function of network activity. The eigenvalues can be used to characterize unusual activity in a social network. We show histograms for various levels of activity in the social network. It is interesting to note that the Wishart semi-circle law is reproduced in the case where there is 50% network activity as modeled from the generated random matrix data. Our simulation used 10,000 trials. The eigenvalues are used to model unusual activity. No decision is ever 100% correct; however, understanding the effects of algorithmic decisions based upon multiple variables, attributes, or factors and strategies with probability assignments can increase the probability for the best decision for a particular situation.

Digital content generation, combined with ubiquitous platforms, has created the "Big Data" challenge in understanding how to make sense of the information generated through multiple sources. Data can be found everywhere and anywhere, be of any type and be resistant to pattern detection. Human decision-making activities performed with data from disparate sources is difficult and a highly time consuming activity in near real time or on-demand modes. There are additional needs for increased information analysis capabilities demonstrating more accurate decisions, planning factors, resource allocation, risk management and information analysis in near real time

Modeling and analysis of the impact of node misbehaviors to network connectivity of mobile ad hoc networks has been studied. Node behaviors have been classified into four types: Full cooperative, selfish, malicious and failed. A node behavior model has been proposed employing a semi-Markov process. Mobile nodes change their behaviors according to the well-defined transition probability matrix and transition time distribution matrix [22].

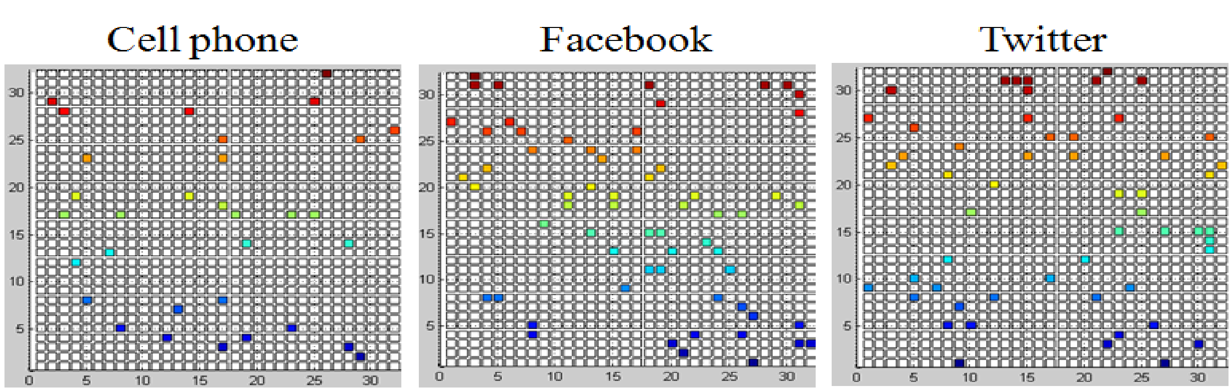

FIG. 8 NON-ERGODIC SOCIAL NETWORK CONNECTIONS

V. NON-ERGODIC SOCIAL NETWORK

This section is about mathematical modeling and better understanding of one the most important fundamental properties in ad hoc networks, the connectivity. From a practical point of view, connectivity is a prerequisite to providing reliable applications to the users of a wireless ad hoc network. To achieve a fully connected ad hoc network there must be a path from any node to any other node. The path between the source and the destination may consist of one hop (when the source and the destination are neighbors) or several hops. When there is no path between at least one source-destination pair, the network is said to be disconnected. A disconnected network may consist of several disconnected islands or clusters [12].

Over the past several years there has been an enormous interest in social networks, such as Facebook, Twitter, YouTube, and LinkedIn, and in various search engines. Concurrent with this surge of social networking, mobile devices such as laptops, PDAs, and cellular (smart) phones have been widely used. A natural trend is to integrate social networks with mobile devices [16]. We further realistically model connections between multiple layers of multi-modal ad hoc networks.

One important question in social networks is who is talking with players of interest. Figure 8 shows a multi-model layered random matrix or random volume. Each matrix was generated as a random matrix. Figure 9 shows a histogram of the number of times a player in the network is communicating. This also can be used to model trends and unusual activity.

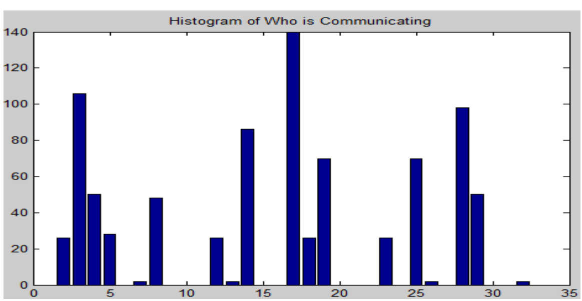

FIG. 9 PLAYER CONNECTIVITY

VI. POISSON MODELING

From the simulation results, we extracted the distribution of the average degree of connectivity. The average is computed using a sample interval equal to 1 second [17].

While real-world tests are crucial for understanding the performance of mobile network protocols, simulation provides an environment with specific advantages over real-world studies. These include repeatable scenarios, isolation of parameters and exploration of a variety of metrics. Repeatable scenarios aid in the development and refinement of networking protocols by allowing the protocol developer to make changes to the protocol and retest the protocol in the same scenario. This aids in deeper understanding of how the changes impact the performance results. Simulation also enables isolation of parameters. Additionally, simulation allows a wide variety of scenarios and network configurations to be evaluated. All of these characteristics are extremely difficult, if not impossible, with real-world experiments. Due to these benefits, simulation has become a popular tool for the development and study of ad hoc networking protocols. The vast majority of networking protocols proposed for ad hoc networks have been evaluated with some simulation tool. [15].

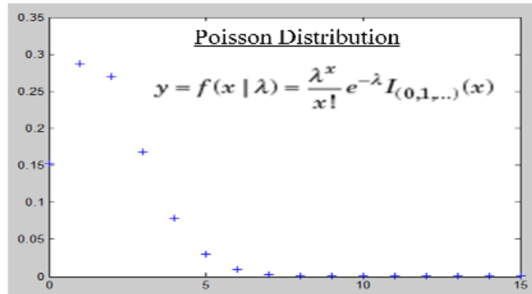

FIG. 10 POISSON DISTRIBUTION

It is possible to choose different distributions according to specific modeling requirements. For example, it is possible to choose a uniform distribution for the generation of equiprobable interaction indicators or a Poisson distribution, shown in Figure 10, to model a scenario where connections are characterized by interaction indicators that are denser around a given value. [17].

Figure 11 shows our simulation results for Monte Carlo generated random matrices for 100 trials. We show the number of players arriving, number of communication connections, and average time in system for a player. Unusual activity will be noticeable when logging performance on a frequent basis.

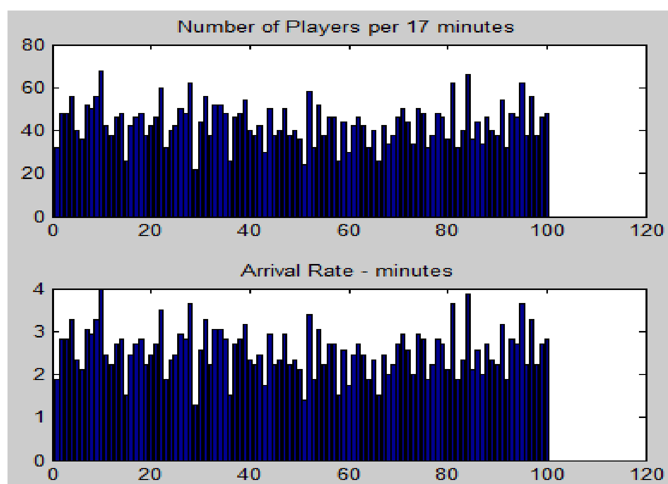

FIG. 11A POISSON SIMULATIONS

An input process is called the arrival process. Arrivals are called players. If more than one arrival occurs at a given instant, it is a group arrival. The average number of players in the system is:

$$L = \lambda w \tag{1}$$

where λ is the rate of arrival and w is the average amount of time a player spends in the system [21].

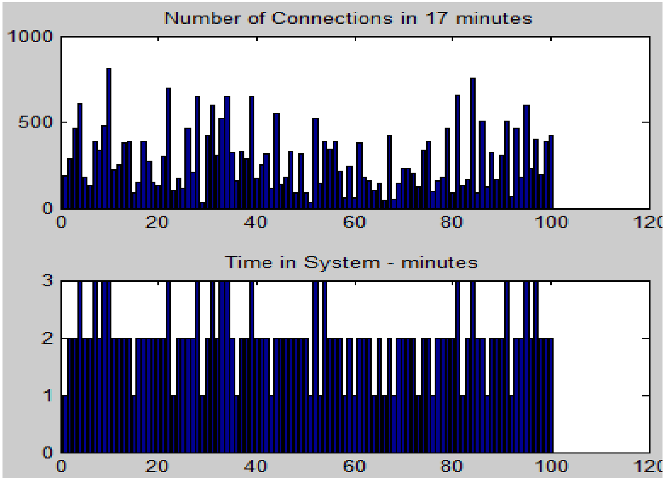

FIG. 11B POISSON SIMULATIONS

It is interesting to note that random matrices provide a good source of data for modeling and simulating social networks. Metrics of unusual activity can be established. The Poisson distribution provides a good statistical framework for modeling the time a player spends in the network for a communication. The Dijkstra algorithm with random matrices provides a good framework for modeling if a player is communicating with another player of interest. Figure 12 shows an example of a connection or relationship graph that can be constructed from the simulations.

VII. CONCLUSION

Many decisions are never 100% correct. However, understanding the effects of algorithmic decisions based upon multiple variables, attributes, or factors and strategies with probability assignments can increase the probability for the best decision for a particular situation or event. We modeled open-source discovery and data mining activities to parse information found from disparate social networks.

We have identified several mathematical applications for optimization. We calculate optimal strategies for path optimization, which increases the likelihood of best decision available. We combine a number of technologies for data fusion/visualization. Our solution is a multi-use application: course of action (COA) planning, strategies, resource management, risk assessment, etc.

Automated processing techniques are needed to augment analysis capabilities by identifying and recognizing patterns, weighting them appropriately, and providing near-real-time objective decisions.

We showed simulation results with composite sparse adjacency random matrices. Use of eigenvectors for characterizing activity is beneficial. We also extended random matrix application to include multi-modal communication channel layer modeling for other communications, such as cell phone, Facebook and Twitter, etc. Random matrix theory is useful in simulating network nodes by a Wishart adjacency matrix. We used the Dijkstra algorithm for discovering ad hoc network node connection patterns in random volumes. Future work is to investigate the optimum time to generate the composite adjacency matrix with different arrival and departure rates.

We used a Poisson Process to simulate arrival and departure of social connections for unusual activity. The likelihood of event occurrence is based on unusual activity. The amount of time in system or number of communications is modeled. Additional metrics such as mean first passage time and rate of batch or group arrival provide additional indicators of unusual activity.

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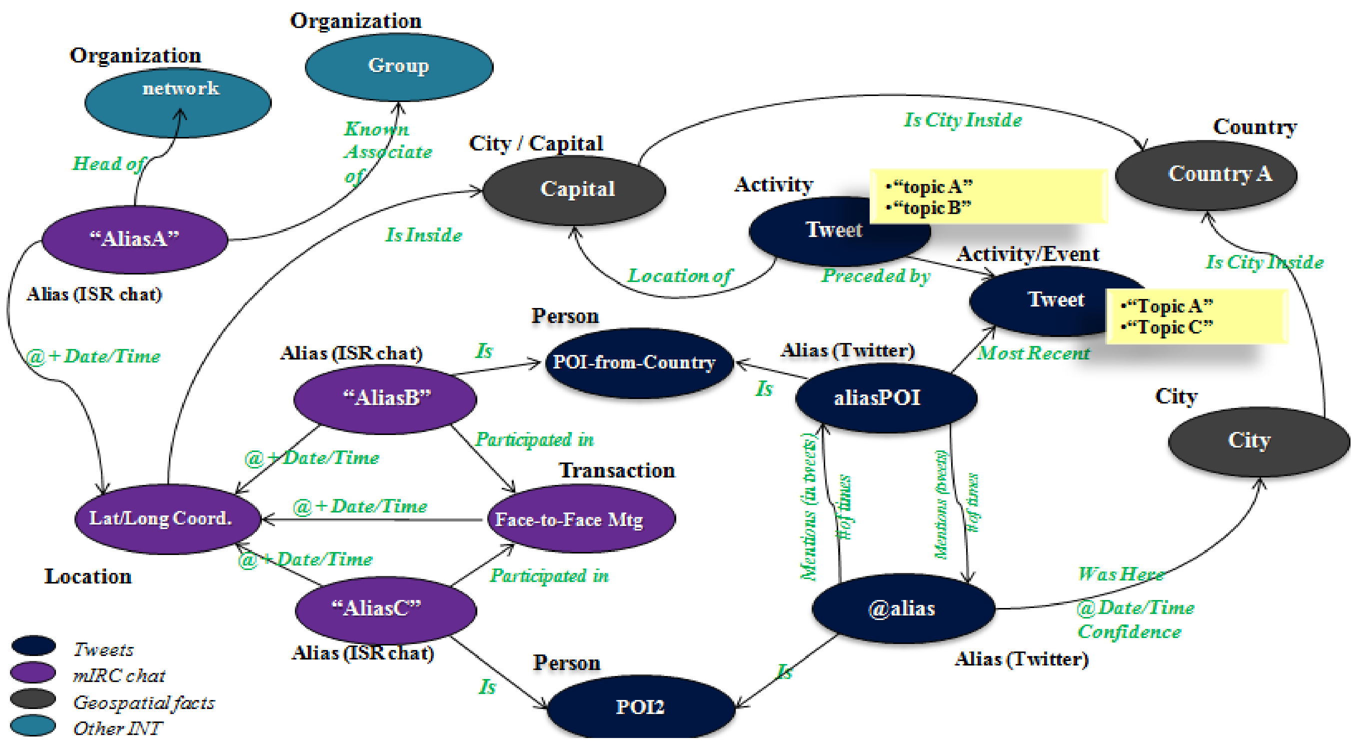

FIG. 12 CONNECTION OR RELATIONSHIP GRAPH