Abstract—Mobility is one of the most challenging issues in mobile ad-hoc networks and has a significant impact on performance of network protocols. Different kinds of mobility models have been proposed to represent the movement pattern of mobile nodes in mobile ad-hoc networks. These models attempt to capture various mobility characteristics existing in real movement of mobile nodes. In this paper, a new framework called Fuzzy Mobility Analyzer has been proposed to evaluate mobility models. At first, our framework categorizes mobility models based on their mobility characteristics into five classes; subsequently it uses mobility metrics to capture the mobility and graph connectivity characteristics of mobile nodes in each class; finally it specifies the similarity degree between mobility classes and real world movements of mobile nodes by using the fuzzy set theory. Experimental results on well known mobility models with real world mobility traces is presented to verify our claims.

I. INTRODUCTION

A mobile ad-hoc network (MANET) is a self organized network that is created and maintained by collections of wireless mobile nodes without using any infrastructure. Due to the ease of deployment, many practical applications have been developed for these networks. Mobile classrooms, battlefield communications and disaster relief are some applications of MANETs [1]. One of the inherent characteristics of these networks is the movement of nodes. This characteristic has a significant impact on the performance of protocols in MANETs.

In real world scenarios, the movements of mobile nodes capture the following mobility characteristics.

1) Temporal dependency of movement for a mobile node during the time.
2) Spatial dependency of neighboring nodes movements in group movements.
3) Existence of obstacles or predefined maps which confine mobile node movements.
4) Existence of social context points where mobile nodes spend a considerable amount of time.

Mobility models were proposed to emulate the movement pattern of mobile nodes in a specific area. Mobility models determine how nodes change their location, velocity and acceleration against time. Since mobility patterns play a significant role on protocol performance, it is desirable for mobility models to emulate the movement pattern of real world scenarios. Otherwise, the observations made and the conclusions drawn from the simulation studies may be misleading. Thus, when evaluating MANET protocols, it is necessary to choose the proper underlying mobility model.

In recent years, a wide variety of mobility models have been proposed that only consider some of the mobility characteristics. In this paper, we propose the Fuzzy Mobility Analyzer for evaluation of mobility models.

The fuzzy mobility analyzer provides a categorization of mobility models based on their mobility characteristics which has been categorized into five classes. Subsequently, mobility metrics are used to capture the characteristics of the mobility and graph connectivity metrics among mobile nodes. We propose new metrics which capture geographic restrictions and social context points. In addition, we introduce inter contact time which captures graph connectivity characteristics of mobile nodes. Finally, a novel method is proposed to evaluate mobility models based on the mobility metrics. To the best of our knowledge, Fuzzy mobility analyzer is the first framework for evaluating mobility models.

The rest of this paper is organized as follows. Section II categorizes mobility model and briefly describes each mobility class. Section III introduces the mobility metrics. Section IV presents our proposed method. Section V is devoted to simulation results. Finally, conclusions are presented in section VI.

II. MOBILITY MODELS

The mobility models have been categorized based on their mobility characteristics into five classes: Random Models, Random Variants Models, Group Models, Geographic Models and Social Models (Fig. 1).

For some mobility models, mobile nodes select waypoints randomly and independent of their neighbors. This mobility class is called a Random model. Random walk [2], Random
Waypoint [2], Random Direction [2] and Levy walk [3], are important examples of random models. Random variants models are a slight modification of random models. In this class, each node selects mobility parameters such as velocity and direction according to their previous movement. Gauss-Markov [2], Smooth random [4] and Semi-Markov Smooth model [5] are most important examples of random variants models. There are some situations where mobile nodes move together, Group mobility models refer to mobility models that describe the movement pattern in these situations. Reference point Group Mobility model [6], Column [2], Pursue [2] and Nomadic Community [2] are examples of group models. Geographic models are another class of mobility models. These models have been introduced to emulate the movement pattern in geographic areas. Manhattan [1], Freeway [1] and Obstacle [7] are examples of geographic models. The last class of mobility models is the social model. This class contains nodes which are not in transmission range of each other at time slots. Moreover, these nodes are not in transmission range of each other at time $t$. Manhattan [1], Freeway [1] and Obstacle [7] are examples of social models.

### III. Mobility Metrics

In order to evaluate mobility models, in this section, we introduce mobility metrics which capture the mobility and graph connectivity characteristics of mobile nodes.

**Average Degree of Temporal Dependency.** This metric has been proposed to capture the temporal dependency. Degree of temporal dependency for a mobile node at two time slots $t_1$, $t_2$ is defined as: $RD(t_1,t_2)$, where $RD(t_1,t_2) = \cos(\theta)$, $\theta$ is the angle between velocity at time slots $t_1$, $t_2$ time slots; $SR(t_1,t_2) = \frac{\min(v(t_1),v(t_2))}{\max(v(t_1),v(t_2))}$ is speed ratio at time slots $t_1$, $t_2$. Average degree of temporal dependency is obtained by taking average over temporal dependency of all nodes [1].

**Average Degree of Spatial Dependency.** This metric has been proposed to capture the spatial dependency. The degree of spatial dependency between two mobile node $i$ and $j$ is defined as: $RD(i,j) = \cos(\theta)$, where $RD(i,j) = \cos(\theta)$, $\theta$ is the angle between velocity of mobile node $i$ and $j$; $SR(i,j) = \frac{\min(v(i),v(j))}{\max(v(i),v(j))}$ is speed ratio of two mobile nodes $i$ and $j$. Average degree of spatial dependency is obtained by taking average over spatial dependency of all pairs [1].

**Average Degree of Freedom.** This metric was proposed to capture geographical restrictions. Degree of freedom at each point is number of directions which mobile nodes can select for the next movement. The value of this metric is low when nodes movement is restricted to predefined paths or obstacles. For measuring degree of freedom, the entire simulation area is logically divided into a number of equal grids (length and height of grids are set according to the simulation area). For a given grid $A$, mobile nodes which located in grid $A$ can select different waypoints located in different grids. Number of selected grids is referred to the degree of freedom of grid $A$. Average degree of freedom is obtained by taking average over number of grids of all grids.

**Average Social Degree.** This metric was proposed to capture social context points. For measuring the social degree, the entire simulation area is logically divided into number of equal grids (length and height of grids are set according to the simulation area). The social degree of a mobile node is difference between the total number of grids and the number of grids which mobile node was paused on them. It is normalized by the total number of grids. Average social degree is obtained by taking average over social degree of all nodes.

**Average Link Change Rate.** Link change rate is the number of link appearance and disappearance in unit time. This metric is an indicator of topology change [1].

**Average Inter Contact Time.** For two mobile nodes $i$ and $j$, at time $t_1$, inter contact time $(i,j)$ is the length of the longest time interval $[t_1,t_2]$ during which nodes are not in transmission range of each other. Moreover, these nodes are in transmission range of each other at $(t_1-\epsilon)$ and $(t_2+\epsilon)$ where $\epsilon > 0$. Formally,

$$ICT(i,j,t_1) = t_2 - t_1$$  \hspace{1cm} (1)

Average inter contact time is average over all pairs. Formally,

$$\frac{ICT}{P} = \frac{\sum_{t=0}^{T} \sum_{i=1}^{N} \sum_{j=i+1}^{N} ICT(i,j,t)}{P}$$  \hspace{1cm} (2)

Where $N$, $T$, $P$ are number of nodes, simulation time and number of $(i,j,t)$ with $ICT(i,j,t) \neq 0$ respectively.
IV. THE PROPOSED METHOD

Our proposed method is based on the fuzzy set theory. Given a set of patterns \( \{p_1, p_2, \ldots, p_n\} \), a fuzzy \( c \) partition of these patterns specifies the degree of membership of each pattern in each class. It is represented by \( c \times n \) Matrix \( U \), where \( u_{ik} \) for \( i = 1, \ldots, c \) and \( k = 1, \ldots, n \) is the degree of membership of \( p_k \) in class \( i \). The following property must be true for \( U \) to be a fuzzy \( c \) partition [11].

\[
\sum_{i=1}^{c} u_{ik} = 1, \quad 1 \leq k \leq n
\]

\[
\sum_{k=1}^{n} u_{ik} > 0, \quad 1 \leq i \leq c
\]

\[
u_{ik} \in [0, 1], \quad 1 \leq i \leq c, \quad 1 \leq k \leq n
\]

We used fuzzy set theory to assign mobility class membership to mobility traces which have been collected from real environments. Mobility class membership determines in what degree the real world mobility traces are similar to each mobility class.

Our proposed method is operated in two phases: training phase and test phase (Fig. 2).

The inputs of training phase are known mobility traces of which the user of the fuzzy mobility analyzer already knows the mobility class. The known mobility traces have been generated by mobility simulators. In the first stage, the mobility metric selection module, selects appropriate mobility metrics for representing the input mobility traces. Then, each mobility trace is viewed as a \( d \) dimensional mobility metrics vector. For fuzzy classification module, the fuzzy K-Nearest Neighbors (F-K-NN) method has been used [11]. In this method, \( k \) nearest neighbors to each unknown mobility trace are found. Then, the mobility class membership in each class is assigned according to the following equation.

\[
u_i(p) = \frac{\sum_{j=1}^{K} u_{ij}(1/ \| p - p_j \|^2/(m-1))}{\sum_{j=1}^{K} (1/ \| p - p_j \|^2/(m-1))}
\]

(4)

Where \( u_{ij} \) is the mobility class membership of the \( j \)th mobility metrics vector in the \( i \)th mobility class. The variable \( m \) determines the weight of distance in calculating membership.

In the results presented in section V, we used \( m = 2 \). In Fig. 3, a pseudo-code for F-K-NN is shown.

For distance metric, normalized Euclidean distance has been used. Given two \( d \) dimensional mobility metrics vectors \( x, y \), the normalized Euclidean distance is defined as:

\[
D(x, y) = \left( \sum_{i=1}^{d} \frac{| x_i - y_i |^2}{\sigma_i^2} \right)^{1/2}
\]

(5)

Where \( \sigma_i^2 \) is variance of the \( i \)th dimension.

Using this method, the degree of similarity between real mobility traces and mobility classes would be analyzed. The main goal of this phase is to determine the mobility class membership of an unknown mobility trace in each mobility class. Mobility class membership corresponds to the degree of similarity between real mobility traces and mobility classes. In the first stage, the preprocessing module removes environment noise from unknown mobility traces. Then, the mobility metric measurement module measures mobility metrics which were selected in the training phase. Next, each unknown mobility trace is represented with a \( d \) dimensional mobility metrics vector. Finally, the fuzzy classification module assigns the mobility class membership to the unknown mobility traces.

In this section, we present results obtained from evaluating well known mobility traces.

For training phase, we chose mobility traces which have been generated by mobility simulators. We used our previously developed mobility simulator called MobiSim [12] to generate mobility traces. MobiSim is an open source java based simulator which can generate mobility traces for various mobility scenarios.
models. Due to the variety of mobility models, we just selected some widely used mobility models as representatives of their mobility classes. We generated Random walk (RW), Random Waypoint (RWP), Random Direction (RD) and Levy walk as representatives of random models, Gauss-Markov from random variants models, Reference Point Group Model (RPGM) from group models, Manhattan from geographic models and Slaw from social models.

In all models, 20 nodes move in the area of 500m x 500m for a period of 10000 sec. The transmission range is assumed to be equal to 250m. For all models except Levy walk and Slaw, speed varies from 5 to 15 m/s. In Slaw and Levy walk, pause time and path length have levy distribution [3] and velocities are chosen according to the path length at each step. We chose one as a coefficient of pause time distribution in these models. For Levy walk, we chose the coefficient of path length distribution from 1 to 1.5.

In the training phase, 20 known mobility traces have been selected from each of RW, RWP, RD, Levy walk, Gauss-Markov, RPGM, Manhattan and SLAW models. Then, the selected mobility metrics are extracted for each known mobility trace. Next, mobility class memberships of the known mobility trace in random, random variants, group, geographic and social mobility classes are calculated.

For the test phase, we chose unknown mobility traces which have been collected from real environments. The first data set contains mobility traces of taxicabs in San Francisco, USA. It contains the GPS coordinates of approximately 500 taxis over 30 days in San Francisco Bay Area, USA. The average time interval between two records is less than 60 seconds [13]. We used linear interpolation to find positions at every 60 seconds. The second data set includes mobility traces of humans in five sites. These are two university campuses (NCSU and KAIST), New York City, Disney World (Orlando), and North Carolina state fair. The GPS receivers record the current positions at every 10 seconds into a daily track log. The data set contains positions at every 30 seconds by taking average over three samples [3]. The third data set contains a number of traces of Bluetooth sighting by groups of users carrying small devices (iMotes) for a number of days. Three iMote-based experiments were used. The first gathered data from eight researchers and interns working at Intel Research lab in Cambridge. The second obtained data from twelve doctoral students and faculty comprising a research group at the University of Cambridge Computer Lab. The third experiment was conducted during the IEEE INFOCOM 2005 conference in Miami where 41 iMotes were carried by attendees for 3 to 4 days[14].

In the test phase, each of the input mobility metric is extracted from the unknown mobility traces. Then, the unknown mobility trace is represented with a vector of mobility metrics. Next, F-K-NN is used to assign mobility class membership into unknown mobility traces.

Tables I to IV show the simulation results with different input mobility metrics and several real world scenarios. In these tables each row refers to the test trace and each column refers to the assigned mobility class membership. For example, the value of $ith$ row and $jth$ column indicates the mobility class membership of the $ith$ trace in the $jth$ class. We have tested this method with different values for $K$. All the following results were obtained by using 5 for $K$.

Tables I and II show the mobility class membership of cab tracker traces in each mobility class. In Table I, average degree of freedom and average spatial dependency have been selected as mobility metrics. As shown in Table I, cab tracker traces have the highest mobility degree in the geographic class.

The RW, RWP, RD, Levy walk, Gauss-Markov, Manhattan and Slaw models, have the lowest average degree of spatial dependency. In RW, RWP, RD, Levy walk, Gauss-Markov and Slaw, movement of each node is independent of its neighbors. Therefore, the degree of spatial dependency is low. In Manhattan, a node's movement is influenced by nodes behind it in the same lane. This implies that the Manhattan has a high spatial dependency. But due to lanes with opposite directions in this model, the positive degree of spatial dependency cancels with the negative degree of spatial dependency of a node with its neighbors in the opposite direction. As a result, Manhattan like random models have low values of spatial dependency. In RPGM the leaders of each group determine the movement pattern of group members. Therefore, RPGM has the highest degree of spatial dependency.

In Manhattan, the movement of mobile nodes is restricted to a predefined map. As a result, Manhattan has the lowest average degree of freedom. After Manhattan, Levy walk and Slaw have the lowest value. In these models, the lengths of flights which are lines between two consecutive waypoints, have a truncated power-law distribution. This causes most of the selected flight lengths fall into a limited range. Truncated flights imply geographic restrictions. Therefore, Levy walk and Slaw have low value for average degree of freedom. Since, in RW, RWP, RD, Gauss-Markov and RPGM models, mobile nodes move freely and without any restrictions, these models have high value for average degree of freedom.

In cab tracker traces the movement of each taxi is independent of its neighbors. Therefore the degree of spatial dependency is low. Since the movements of taxis are restricted

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Fig. 3. The pseudo-code for F-K-NN

```plaintext
Procedure F-K-NN( test mobility metrics vectors, training mobility metrics vectors, k)
    for each testing instance
    
        find the kth nearest instance of
        the training set according to a
        distance metric
        for each mobility class
        
            compute the mobility class
            membership according to mobility
            class membership of k nearest
            neighbors in that class

}
```
to the streets, these traces have low average degree of freedom. Therefore, geographic mobility class (Manhattan) has the most similarity to cab tracker traces where the average degree of spatial dependency and the average degree of freedom have been selected as mobility metrics (Table I).

In Table II, average degree of temporal dependency and average degree of spatial dependency have been selected as mobility metrics. As shown in Table II, cab tracker traces have the highest mobility degree in random and social mobility classes.

The RW, RWP, RD and RPGM models, have the lowest average mobility degree of temporal dependency. Because in these models the movement pattern of each node is independent of its previous movement. Manhattan and Gauss-Markov have medium values. In Manhattan, the velocity of a node is temporarily dependent on its previous velocity. But sudden stops due to pauses in the intersection of streets lead to reduction of temporal dependency. In Gauss-Markov, frequent changes of velocity and direction of mobile nodes at each time reduce the temporal dependency. Therefore, Manhattan and Gauss-Markov have medium values. Levy walk and Slaw have the highest value for temporal dependency. In these models a velocity is selected according to the flight length. Since flight length has a truncated power-law distribution in Slaw and Levy walk, most of the flights lengths have short length. Therefore, Slaw and Levy walk have the highest value of temporal dependency.

The taxi movement contains three consecutive phases. In the first phase, the taxi smoothly increases its speed to reach a desirable speed. After that, the taxi moves smoothly according to the desirable speed. In this phase, the taxi speed smoothly fluctuates around the desirable speed. In the third phase, it reduces its speed to zero before a full stop. This pattern of movement causes a high degree of temporal dependency in cab tracker traces. So, the cab tracker traces have the highest mobility degree in random (Levy walk) and social (Slaw) mobility models where spatial and temporal dependency have been selected as mobility metrics (Table I).

Table III shows the mobility class memberships of human mobility traces in each mobility class. In Table III, average social degree and average degree of temporal dependency have been selected as mobility metrics. As shown in Table III, human mobility traces have the highest mobility degree in random and social mobility classes.

Since the movement pattern of mobile nodes in Slaw is confined to 3 to 5 regions, this model has the highest average social degree. After Slaw, Levy walk, RD and Manhattan have the highest values. In RD, the mobile node pauses and changes its direction when it reaches to the simulation boundary. This implies that the simulation boundaries are social context points. In Manhattan, the mobile node pauses and changes its direction when it reaches the intersection of streets. Therefore, mobile nodes in Manhattan move in some specific regions. RW, RWP, Gauss-Markov and RPGM have the lowest value for social degree. This is due to the fact that in these models there aren’t any social context points.

The human mobility traces have high social degree due to existence of social context points. Since the current velocity is independent on the previous velocity, these traces have high average degree of temporal dependency. Therefore, human mobility traces have the highest mobility class membership in Levy walk and Slaw where the average social degree and the average degree of temporal dependency have been selected as mobility metrics (Table III).

Table IV shows the mobility class membership of iMote-based mobility traces in each mobility class. In Table IV, average link change rate and average inter contact time have been selected as mobility metrics. As shown in Table IV, iMote-based mobility traces have the highest mobility degree in social mobility class.

Lack of similarity between movement directions of neighboring nodes in RW, RWP, RD and Gauss-Markov causes links between neighboring nodes to change frequently. As a result, these models have the highest link change rate and the lowest inter contact time. Manhattan and RPGM have medium values for link change rate and inter contact time. In RPGM most of the time, nodes are close to each other and the link between each neighbor node would not be changed. In Manhattan, mobile nodes must consider the safety distance so the neighbor nodes have similar velocities and directions and the link between two neighbors node would not be changed. Since in Slaw and Levy walk models the velocity difference between neighboring nodes have the lowest value, Slaw and Levy walk have the lowest link change rate and the highest inter contact time.

The iMote-based mobility traces have the lowest link change rate and the highest inter contact time. Therefore, iMote-based mobility traces have the highest mobility degree in Slaw where the average link change rate and the average inter contact time have been selected as mobility metrics (Table IV).

In summary, we can conclude the following points:

1) Although in Levy walk each node selects mobility parameters such as pause time and path length randomly, this model is not similar to other random models such as RW, RWP and RD.
2) The Levy walk and Slaw models have the same mobility metrics. Because these models were proposed to emulate human walk and both of them have the same distributions for pause time and flight length. Also in both models the velocity is selected according to the flight length.
3) Real world mobility traces have temporal dependency, geographic restrictions and social context points.
4) Each mobility class captures some mobility characteristics of real world mobility traces.
5) Based on geographic restrictions, Manhattan is most similar to the real world mobility traces.
6) Based on temporal dependency, Levy walk and Slaw are most similar to the real world mobility traces.
7) Based on graph connectivity metrics, Levy walk and Slaw is most similar to the real world mobility traces.
8) Manhattan can emulate the movement pattern of mobile
nodes in streets, if temporal dependency is added to this model.

VI. CONCLUSION

In this paper, we introduced a new method for evaluating the mobility models based on mobility metrics. Moreover, we introduce some new mobility metrics. The proposed framework uses fuzzy set theory to assign mobility class membership into real world mobility traces. The mobility class membership can specify to what degree the real world mobility trace belongs to each mobility classes or mobility models. We tested this framework using some of well known mobility models. The results illustrated the effectiveness of the proposed framework.

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