Tracking Pedestrians and Emergent Events in Disaster Areas

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***Abstract*—Most of the existing research on emergency evacuation strategies focus on city evacuation planning that highly depends on the use of vehicles or evacuation from buildings. However, for large areas with limited use of vehicles such as theme parks, evacuation of pedestrians and emergent events must be tracked for safety reasons. As hazards may cause certain damages to services, networks with disaster resilience are needed to achieve mission-critical operations such as search and rescue. In this paper, we develop a method for tracking pedestrians and emergent events during disasters by opportunistic ad hoc communication. In our network model, smart-phones of pedestrians store and carry messages to a limited number of mobile sinks. Mobile sinks are responsible for communicating with smart-phones and reaching the emergent events effectively. Since the positioning of the mobile sinks has a direct impact to the network performance, we propose *physical force based* (PF), *grid allocation based* (GA) and *road allocation based* (RA) approaches for sink placement and mobility. The proposed approaches are analyzed through extensive network simulations using real theme park maps and a human mobility model for disaster scenarios. The simulation results show that the proposed approaches achieve significantly better network coverage and higher rescue success without producing increased communication overhead compared to two random mobile sink movement models.**

***Index Terms*—Opportunistic communication, mobile sink, disaster resilience, evacuation, mobility management.**

I. Introduction

Internet has been used worldwide, offering various services which made daily lives of people easier in many ways. However, it is not a reliable communication source during disaster times as accessing the Internet services requires certain infrastructure, which may be damaged due to occurrence of hazards. While relying only on the Internet may cause people suffer in natural or man-made disasters, researchers nowadays focus on the networks resilient to disasters. These networks are supposed to provide and maintain acceptable levels of quality of service during disaster times, as well as accidents or faults in infrastructure in ordinary times.

As the increase in the likelihood of the more intense hazards is expected due to climate change [1], disaster resilience in networks is becoming an increasingly popular research area. Many studies nowadays focus on communication problems in cities damaged by disasters such as earthquakes or floods. These problems also apply to large areas in which the vehicle use is limited such as theme parks and campus environments. Furthermore, the operators of these environments have challenges of evacuating pedestrians, rescuing injured people, and providing them access to ambulances or transportation services. We study the use of disaster resilient networks as a solution to communication and the safe evacuation problems in large and crowded disaster areas. Places which restrain people from using transportation vehicles such as airports, city parks (e.g., Central Park in New York city), shopping malls, fairs, and festival areas are considered in this context.

In this study, we focus on the application scenario of theme parks which are large and crowded entertainment areas due to several reasons. Large-scale theme parks have substantial economic contributions to their regions. While overall popularity of theme parks increases every year, global success of the growing industry is severely affected by disasters such as Hurricane Irene [2]. A natural or man-made disaster in a theme park may cause damages to regions such as Central Florida as theme parks with highest yearly attendances and also being known as home to natural disasters such as hurricanes, floods and tornadoes.

We model the theme park environment as follows. We first model the area of a theme park and define it as a combination of roads, obstacles and lands. Real theme park maps are extracted for synthetic generation of the theme park models. As the people in theme parks are the main actors, we consider them as part of

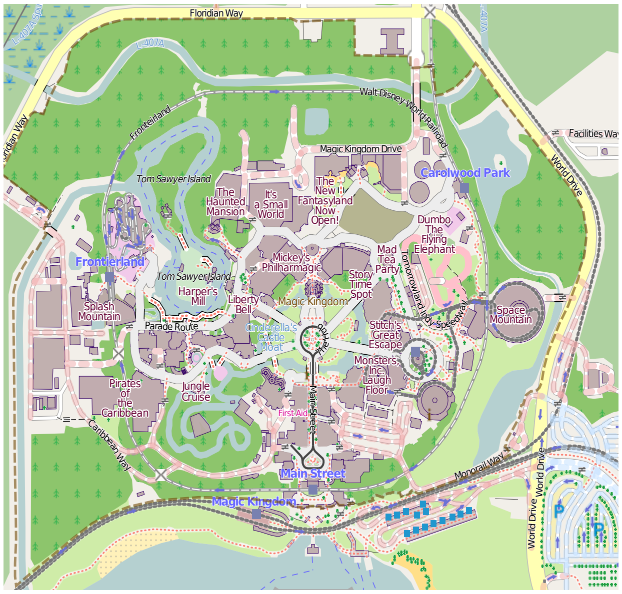

Fig. 1. The map of the Magic Kingdom park (extracted from OSM).

the environment. Modeling the mobility of pedestrian crowds is necessary for modeling these environments. Therefore, we use a realistic human mobility model for simulating the movements of the pedestrians in disaster areas [3]. With this mobility model, we are able to simulate the mobility of people in theme parks who aim to escape from the disaster area to the exit gates by walk in order to reach ambulances or transportation services. Moreover, we model the crowd dynamics and social interactions of the pedestrians during the evacuation by the social force model [4].

In this paper, we use our pedestrian mobility model in [3], [5] as basis for simulating the movement of pedestrians in theme park during their evacuation. We propose new algorithms for initial sink placement and sink mobility. We comprehensively analyze the proposed tracking evacuation approach which is first proposed in [6]. Extensive experiments are conducted for five sink mobility approaches to observe the results with various parameter values in in-depth analysis of the network performance.

Handling emergent events is one of the major challenges in theme park environments due to inevitable problems that can occur due to hazards. Therefore, in addition to the technological security measures, theme park administrators also deploy a large number of security employees, for some parks more than a thousand, walking on foot or riding bicycles [7]. We believe that using automated networked systems and mobile sinks can help reducing infrastructure requirements by large team of security personnel.

As a disaster response strategy, we propose using a networked system which includes mobile sensor nodes and a limited number of mobile sinks as described in Section II. Mobile phones carried by pedestrians can be leveraged as sensor devices which communicate with each other and with mobile sinks. Mobile sinks monitor the evacuation process by patrolling in the disaster area, collecting data from the sensor nodes. They also have the goal of reaching to people who need to be rescued. Mobile sinks can be autonomous robots (e.g., search and rescue robots [8]) or security personnel which patrol by walk or by electronic transportation vehicles such as Segway Patroller [9] with a tablet computer attached on it. Sensor nodes create messages when they witness people who need immediate help. They are responsible for storing and carrying the messages, sharing the messages with each other, and delivering to the mobile sinks via hop-by-hop wireless communication.

We consider such formation of WSNs with mobile sinks as a replacement to cellular networks for providing communication in extreme conditions. The use of mobile sinks enables adaptability of the approach to various environments (e.g., festivals, public parks) where pre-installed infrastructure may or may not exist. In the case of popular theme parks such as Disney World, certain infrastructure such as video cameras can be leveraged in some scenarios when the pre-installed system continue operating during the disaster. Most of the existing studies related to evacuation and disaster management tackle the problems of optimizing evacuation times (e.g., avoiding bottlenecks, finding exit points) or assisting people for their safe evacuation and directing them in indoor [10] or outdoor environments [11], [12]. The output of these solutions include improved evacuation times. Our approach, on the other hand, focuses on tracking the people's locations during their evacuation (without any interference to their behavior). While our approach does not aim for shorter evacuation times, it is helpful for finding and reaching out to the people who may be in emergency situations.

Our approach differs from the existing ones that depend on usage of UAVs (e.g., quadcopters). While drone operations can be helpful in such scenarios, they require certain infrastructure and control of operations. Moreover, they have various constraints including weather conditions, vision-based limitations (resolution, coverage of large area, darkness, etc.), and limited lifetime of the batteries. Considering the disaster scenarios, especially in regions such as Central Florida, adaptability to weather conditions such as having strong winds is a major drawback of such systems. Moreover, the infrastructure requirements for communication during operations are similar to the requirements of Internet services. On the other hand, these approaches can be beneficiary in certain scenarios and the two strategies can work together by eliminating each other's limitations.

Sensor devices are carried by ordinary theme park visitors whose only goal at the time of a disaster would be safely escaping from the . While we do not assume any control over the visitors, we focus on the effective placement and mo environment bility of mobile sinks in the area to gather more data from sensor nodes to find pedestrians in need of help in shorter amount of times. For efficient tracking of the pedestrians and emergent events during the evacuation, we propose three heuristic approaches in Section III, namely, *physical force based* (PF), *grid allocation based* (GA) and *road allocation based* (RA) approaches for mobile sink placement and mobility. PF is inspired by the natural gravitation, in a way that sensor nodes attract mobile sinks, while mobile sinks have negative impacts on each other. In GA, each sink allocates a number of grids as its own operation region. Grids are created on top of the roads in the processed theme park model. Lastly, in RA, each sink allocates one or multiple roads close to each other and operates on top of the allocated roads. After allocation of grids or roads, mobile sinks patrol in their allocated regions by a random movement model. The performances of the proposed approaches are evaluated in Section IV with extensive network and human mobility simulations and compared with two random mobility models for mobile sinks. We summarize the related work in Section V and finally conclude in Section VI.

II. Theme park and network model

In this section, we describe modeling of the theme park environment and the proposed network model respectively.

A. Theme park model

Real theme park maps are used to model the theme park environment for disaster scenarios. After automated processing of the map, the model defines a theme park as combination of *roads*, *obstacles* and *lands*. The roads are defined as pedestrian ways containing waypoints. The waypoints are the movement points of the pedestrians. The roads direct the pedestrians to the target locations in the map. Moreover, the mobile sinks travel on top of the roads for patrolling or reaching the regions of the emergent events. The gates are considered as the target locations and they are placed close to the borders of the park. The gates connect the theme park with the outside world and facilities such as transportation vehicles (e.g., ambulances, buses).

The obstacles are categorized into two types. Attractions in a theme park contain man-made buildings and other structures such as roller-coasters, fences, or walls. During evacuation from the disaster area, these structures may prevent free movement of the pedestrians. They are considered in the model as man-made obstacles. Moreover, there may be natural obstacles such as lakes, trees, river and so on. We include both types of obstacles in the theme park model, such that none of the pedestrians or mobile sinks is able to pass through them. The lands are the regions having no obstacle or road. Pedestrians can choose to pass through the lands in certain times such as when they do not have the option to travel on the roads (e.g., road is closed due to occurrence of hazard) or when the lands provide obvious shortcuts.

While the model of the theme park can be created synthetically (e.g., during design stage of a theme park) or using real maps, we use OpenStreetMap (OSM) [13] for existing theme parks and extract their maps. These maps containing the OSM data are parsed to generate the roads, the obstacles, the lands, and the gates. The user-tagged waypoints are collected from the OSM data. The processing also involves connecting the consecutive waypoints to create the roads. The roads have width values according to their OSM types (footway, path, and pedestrian way).

Fig. 1 shows a real map of Magic Kingdom park in Disney World in Orlando. This map is processed to find the waypoints, the roads, the gates, and the obstacles. The generation of the theme park models are achieved for various parks such as the parks of Disney World and Universal Studios computationally using the OSM data. It is also possible to create a non-existing theme park in design stage manually and create the theme park model in the same fashion.

In the pedestrian mobility model, theme park pedestrians aim to evacuate theme park by following waypoints on the roads and reaching the gate points. The micro-mobility decisions include selecting waypoints in their visibility or preferring to choose to walk on the land if some roads are unavailable due to disaster. The social interactions between the pedestrians cause slow-downs or delays in the movements of the crowds. The social force model equations that are used for modeling the social interactions (micro-mobility) and the macro-mobility of the pedestrians are briefly described in Appendix.

B. Network model

We propose a network model with sensor nodes and mobile sinks for the purpose of efficient tracking of the pedestrians and the emergent events during the disasters.

In the rest of this section, we define the roles of the sensor nodes, mobile sinks and the routing protocol respectively.

1) Sensor nodes: Sensor nodes represent mobile devices carried by theme park visitors. The sensing of an emergent event can be automatically done by the devices (e.g., by sensing sounds) or messages can be explicitly created by the users' input to their smartphones. Marking the location of a person in need of help is an example of an emergent event. Whenever such event is sensed, a message including location and the sensing time is stored in buffer of the sensor node. The sensor node then carries the data and sends the messages on its buffer to other sensor nodes or to a mobile sink through wireless communication. Sensor nodes are assumed to have limited capacities in terms of energy, storage, and transmission power.

2) Mobile sinks: Mobile sink nodes represent either mobile autonomous robots or security personnel carrying mobile devices. A security personnel can use an electronic transportation device if available with a tablet computer attached to it. The mobile sinks patrol in the theme park and collect data from the sensor nodes. When they receive a message with a new unknown emergent event, they move to the region of the event. Mobile sink nodes are more powerful devices with enhanced computation and communication capabilities, storage and energy resources, while they exist in limited numbers.

They need to communicate during their operation for collaborative handling of the event region by sharing the workload. For instance, individual mobile sinks can be assigned for patrolling in their local areas while together they cover the whole region. Furthermore, during an emergent event, one mobile sink can be assigned for a rescue task while the others continue their ordinary operation.

3) Routing Protocol: The message delivery to mobile sinks is done via hop-by-hop wireless transmissions. The epidemic routing protocol [14] is used with minor modifications regarding to the purpose of our model. Epidemic routing is a commonly used protocol for opportunistic social networks and it is mainly developed for mobile wireless networks considering missions such as disaster recovery or military deployment. Epidemic routing provides a benchmark as it produces optimum packet delivery ratio and message delay.

In epidemic routing, whenever a pair of nodes are within the transmission range of each other, they create a new session in which one of them acts as the initiator and the other acts as replier. The session consists of three phases. In the first phase, the initiator initiates a session by sending a summary vector of *Message IDs* located in its buffer. In the second phase, the replier compares its own vector and the received (initiator's) vector, then requests messages by sending the difference vector, which is the vector of *Message IDs* of the message that do not exist in its buffer. In the third phase, initiator sends the messages missing in replier's buffer and finally closes the session.

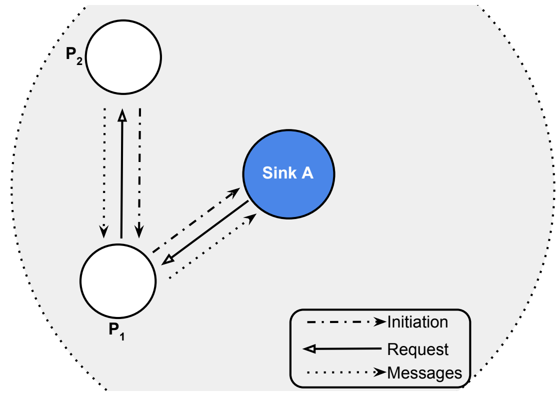

Fig. 2. Opportunistic message transfers between $Sink\ A$ and sensor nodes P_1 and P_2.

Fig. 2 illustrates two different sessions and the type of message transmissions during opportunistic communication between the two sensor nodes P_1, P_2 and the mobile sink, $Sink\ A$. In this figure, the two sensor nodes are placed inside the transmission range of the mobile sink. However, at this time only one sensor node has an open session with the mobile sink. Concurrently, P_1 and P_2 has a session in which P_1 requests messages. Therefore, the sensor node P_2 acts as the initiator and P_1 acts as the replier.

In the second session, $Sink\ A$ acts as the replier and P_1 acts as the initiator. In the epidemic routing protocol, there are three types of transmissions between the initiator and the replier, which we call *initiation*, *request*, and *messages* respectively. *Initiation* contains the summary vector of *Message IDs* which are located in the initiator's buffer. *Request* contains the difference vector and in the last transmission (*Messages*), initiator sends the messages requested by the replier.

In our model, sensors act as either initiator or replier while mobile sinks always act as repliers, since their responsibility is to gather data from sensors. Moreover, after a pair of sensor nodes successfully finish a session, they wait for a specific time period before initiating a new session. This duration can be specified empirically and according to the density of the sensor nodes and their speeds at that time. For instance, if sensors stuck and wait in a road for long time due to high crowd densities, the time period can be adjusted to prevent unnecessary communication overhead which leads to energy consumption.

III. Sink Placement and Mobility

In this section, we propose an initial placement strategy and three heuristic approaches for mobile sink mobility.

A. Initial placement

Let us start this section by describing the initial placement process of the mobile sinks. The process starts with the creation of a grid layout on the theme park model. The grids are specified with relatively small sizes (e.g., 50x50m) in comparison to relatively larger disaster area (e.g., 1000x1000m). The small-sized grids are located only on top of the roads. In other words, obstacles and lands are excluded during the process of grid creation as we assume that the mobile sinks do not have the ability to patrol on top of the obstacles or lands. Grid creation process starts with the generation of 2D quasi-random points. Number of the generated points is equal to the number of mobile sinks. This generation is repeated iteratively (N times) and at each iteration, the sum of pairwise distances between the quasi-random points are computed. We keep the set of quasi-random points with the highest distance sum. Since this computation is handled offline before the start of the operation of mobile sinks, it does not cost an overhead to the system. Therefore, the iteration can be repeated many times in order to have the best result. The time complexity of the initial placement algorithm depends on the random point generation technique and the number of iterations.

The best set of quasi-random points are marked as the *base points*. For each grid, the closest base point is selected and the grid is marked with the index of this base point. Fig. 3 illustrates creation of the grids in a simple case, where the grids are uniformly assigned to 4 base points. The creation of grids and the assignment is the base for initial mobile sink distribution. As shown in the figure, each mobile sink is placed on a random place, which is one of the points in the grids with corresponding indices (e.g., grids with indices 1, 2, 3, or 4) . The main purpose is to distribute the sinks in a way that they share the workload of the entire disaster area while they are all located on top of the roads to start their patrolling duty.

The pseudocode for the initial placement of mobile sinks is given in Algorithm 1. First, the quasi-random points are iteratively generated (lines [4-20]). Later, grids are assigned to the base point indices, such that each grid is assigned to a base point index bp. At the end, each base point index bp has a set of grids $GridSet(bp)$ (lines [21-29]). D_{ij} is the distance between the current grid g_i and current base point p_j ($p_j \in B$). T corresponds to the number of grids. After the assignment is finished, each mobile sink m_i is placed on top of a waypoint which is selected randomly among all waypoints contained by the particular grid set (lines [30-37]).

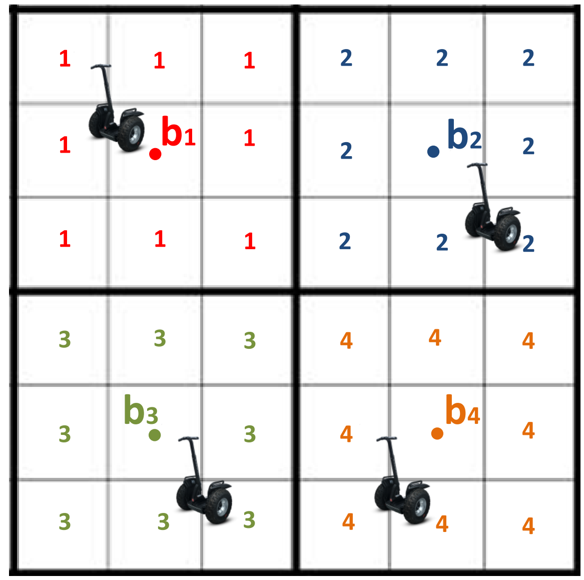

Fig. 3. Grid allocation based placement of 4 mobile sinks.

The initial placement procedure is conducted only once before the mobile sinks start their operation. The initial placement can be used as a common procedure for various mobile sink mobility models. On the other hand, the movement decisions of the mobile sinks during their operation varies according to choice of the mobility model.

B. Sink mobility

Let us now describe the mobility models for the mobile sinks.

1) Physical force based sink mobility (PF): In PF, the main goal of the sink mobility is tracking and following people along during the evacuation process. Inspired by Newton's law of universal gravitation, each pedestrian assumed to have a unit mass which attracts the mobile sinks, while distances cause less attractions. A mobile sink that detected a group of people tends to follow the group as long as it does not encounter another larger group or other mobile sinks on the way.

The mobile sinks also have masses larger than the unit mass and the mobile sink masses cause inverse forces in the opposite direction. The sink mass is equal to the division of the number of pedestrians by the number

Algorithm 1 Initial placement of mobile sinks

$B := \{\}$ ▷ Set of base points
$G := \{g_1, g_2, ..., g_T\}$ ▷ Set of grids
$M := \{m_1, m_2, .., m_K\}$ ▷ Set of mobile sinks
$MinSum \leftarrow \infty$
for $i := 1$ to N **do**
  $Q := \{p_1, p_2, ..., p_K\}$ ▷ Set of quasi-random points
  $Sum \leftarrow 0$
  for $j := 1$ to K **do**
    for $k := 1$ to K **do**
      if $j \neq k$ **then**
        $D \leftarrow Distance(p_j, p_k)$
        $Sum \leftarrow Sum + D$
      end if
    end for
  end for
  if $MinSum > Sum$ **then**
    $MinSum \leftarrow Sum$
    $B \leftarrow Q$
  end if
end for
for $i := 1$ to T **do**
  $MinDist \leftarrow \infty$
  for $j := 1$ to K **do**
    if $D_{ij} < MinDist$ **then**
      $bp \leftarrow p_j$ ▷ Base point index
      $MinDist := D_{ij}$
    end if
  end for
  $GridSet(bp) \leftarrow GridSet(bp) \cup \{g_i\}$
end for
$W \leftarrow \{\}$
for $i := 1$ to K **do**
  for each $g \in GridSet(p_i)$ **do**
    $W \leftarrow W \cup WaypointSet(g)$
  end for
  Select a random $w \in W$
  $InitialPosition(m_i) \leftarrow w$
end for

of mobile sinks. Each mobile sink computes a physical force vector based on the positions of people and the other mobile sinks and moves along the direction of the physical force vector. The mobile sinks' inverse forces ("pushing" effect) on each other prevents them covering the same areas by getting very close to each other and creating inefficiency by sharing the workload in terms of coverage of the whole region.

Fig. 4 illustrates the movement direction of the $Sink\ A$ after encountering with pedestrians P_1 and P_2 with unit masses and $Sink\ B$ with a higher mass producing the strongest physical force among the three forces $\vec{F_1}$, $\vec{F_2}$ and $\vec{F_B}$. In this case, $Sink\ A$ moves in the direction of the vector $\vec{V_A}$, which is the sum of the three physical force vectors.

Having n pedestrians and m mobile sinks with masses 1 and M respectively, the physical force movement vector $\vec{V_a}$ on the $Sink\ A$ is calculated as follows:

$$\vec{V_a} = \alpha \cdot \left(\sum_{i=1}^{n} \vec{F_i} - \sum_{j=1}^{m} \vec{F'}_j \right) \ s.t.\ \ j \neq a \tag{1}$$

where

$$\left| \vec{F_i} \right| = G \cdot \frac{M \cdot 1}{d^2}, \tag{2}$$

$$\left| \vec{F'}_j \right| = \lambda \cdot G \cdot \frac{M \cdot M}{d^2}. \tag{3}$$

λ is an empirical constant value, which defines the impact of the sink mass $M = \frac{n}{m}$ and the gravity constant G. α is the constant which adjusts the magnitude of the sum vector $\vec{V_a}$. The value of n changes during the operation according to the number of people in the environment at that time. Overall complexity of the computation for each mobile sink is $O(n + m)$.

For simplicity and applicability in real scenarios, mobile sinks can be considered having only local knowledge based on their visible areas. In other words, computation by each sink can be done based on only the pedestrians and the mobile sinks in its visible area. By this approach most of the masses (e.g., pedestrians) which have longer distances (d) are ignored. However, we can assume them having negligible forces due to their distance.

2) Grid allocation based sink mobility (GA): In this approach, each mobile sink allocates a set of grids according to the grid indices which were found in the initial grid creation phase. Basically, the grids in Fig. 3 are used for allocation in a way that each sink is responsible for the grids with a particular number. For instance the grids which are marked as 1 are assigned to the first mobile sink, while the grids with mark 2 are assigned to the second sink, and so on. During the operation, each sink patrols in its allocated grids. The sink chooses a random waypoint as the next destination point among the waypoints which are placed on top of the set of the allocated grids. After reaching to the next destination, the sink decides another next destination and updates in the same fashion. This mobility model aims to divide the workload of the disaster area evenly on the patrolling

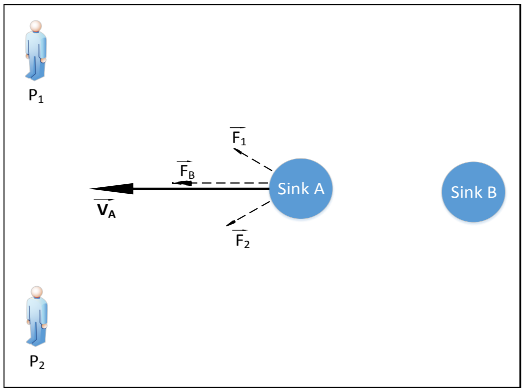

Fig. 4. The physical forces and movement vector of $Sink\ A$ along with pedestrians P_1, P_2 and $Sink\ B$.

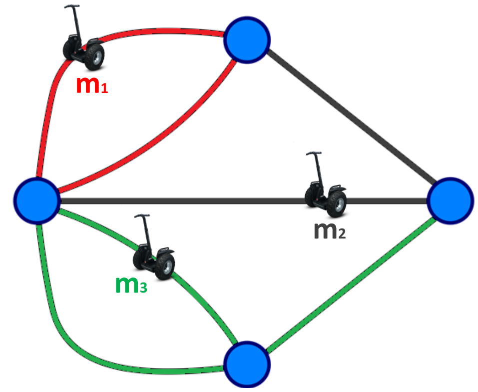

Fig. 5. Road allocation to 3 mobile sinks $M := \{m_1, m_2, m_3\}$.

mobile sinks, while they are not intercepting on each other's region.

Algorithm 2 Sink mobility with Grid Allocation

1: $M \leftarrow \{m_1, m_2, ..., m_M\}$ ▷ Set of mobile sinks
2: **for** $i := 1$ to M **do**
3: $\quad CurrentPosition(m_i) \leftarrow InitialPosition(m_i)$
4: **end for**
5: **for** $t := 0$ to T **do**
6: $\quad$ **for** $i := 1$ to M **do**
7: $\quad\quad$ **if** $NextDestination(m_i) = CurrentPosition(m_i)$ **then**
8: $\quad\quad\quad N := SizeOf(GridSet(p_i))$
9: $\quad\quad\quad$ **for** $j := 1$ to N **do**
10: $\quad\quad\quad\quad W := \{\}$
11: $\quad\quad\quad\quad$ **for** each $g \in GridSet(p_i)$ **do**
12: $\quad\quad\quad\quad\quad W \leftarrow W \cup WaypointSet(g)$
13: $\quad\quad\quad\quad$ **end for**
14: $\quad\quad\quad\quad$ Select a random $w \in W$
15: $\quad\quad\quad\quad NextDestination(m_i) \leftarrow w$
16: $\quad\quad\quad$ **end for**
17: $\quad\quad$ **else**
18: $\quad\quad\quad$ Move towards $NextDestination(m_i)$
19: $\quad\quad$ **end if**
20: $\quad$ **end for**
21: **end for**

Algorithm 2 includes the pseudocode for the sink mobility with GA. After the initial placement, the current positions are set as the initials (lines [2-4]). Throughout the operation of the mobile sinks (from start time $t := 0$ to end time $t := T$), the movement decisions are made in discrete time intervals. Whenever the mobile sink reaches a next destination, it updates its next destination with a random waypoint selected in the waypoint set of the particular base point index $WaypointSet(p_i)$ (lines [5-16]). If the mobile sink has not reached its next destination, it continues its movement towards $NextDestination(m_i)$ (lines [17-19]).

While this procedure handles the patrolling duty of the mobile sinks, the mobile sink will move towards an event in the case of emergency. At the time of an emergency event, $NextDestination(m_i)$ of the mobile sink is set as the location of the event, which is received from the sensor nodes.

3) Road allocation based sink mobility (RA): In the road allocation based sink mobility (RA) approach, each sink allocates one or multiple roads and patrols only these roads during its operation. The allocation is based on the grids and the waypoints on each road. Multiple grid indices may contain waypoints on the same road. In this case, the number of waypoints that corresponds to each grid index is calculated and compared. The best grid index with most number of waypoints marks the road with its index, which will be then used for allocation by the mobile sinks. The main purpose of using grids for road allocation is the aim of allocating the closer roads by the same sink instead of the sink having roads in different regions. Initial placement of RA is different than the previous two approaches, because after sinks finish allocating the roads, each sink chooses a random waypoint among the waypoints on its allocated roads. During the operation, mobile sinks iteratively decide their new destinations by randomly choosing random waypoints on their allocated roads whenever they reach a destination.

Fig. 5 illustrates the simple allocation of the roads to the mobile sinks m_1, m_2, m_3 in the road network. Each road is assigned to a mobile sink while a mobile sink may allocate multiple roads. The RA approach guarantees for mobile sinks to operate in separate regions from each other such that at any given time of the operation, multiple mobile sinks cannot be patrolling on the same roads. RA can be seen as an alternative way of balancing the workload of the disaster area among the mobile sinks.

Initial placement of RA is implemented by Algorithm 3. In this algorithm, each road is assigned to a base point index, bp, according to the number of waypoints included by the grids with particular base point indices. The corresponding road is assigned to a bp with most number of waypoints (lines [4-19]). Later, each mobile sink is placed on top of a waypoint. The waypoint is selected randomly among all waypoints of the set of roads of each base point index (line[20-27]). This algorithm is for initial computation which can be done offline. Therefore, it does not create an overhead for computation to the mobile sinks. The time complexity is $O(KMG)$, where K is the number of roads, M is the number of mobile sinks, and G is the number of grids created.

Algorithm 3 Initial placement of Road Allocation

1: $R \leftarrow \{r_1, r_2, ..., r_K\}$ ▷ Set of roads
2: $B \leftarrow \{b_1, b_2, ..., b_M\}$ ▷ Set of base points
3: $M \leftarrow \{m_1, m_2, ..., m_M\}$ ▷ Set of mobile sinks
4: **for** $i := 0$ to K **do**
5:     $MaxSize \leftarrow 0$
6:     $bp \leftarrow null$ ▷ Selected base point index
7:     **for** $j := 0$ to M **do**
8:         $W := \{\}$
9:         **for** each $g \in GridSet(b_j)$ **do**
10:             $W \leftarrow W \cup WaypointSet(g)$
11:         **end for**
12:         $W \leftarrow W \cap WaypointSet(r_i)$
13:         **if** $W \neq \{\}$ and $SizeOf(W) > MaxSize$ **then**
14:             $MaxSize \leftarrow SizeOf(W)$
15:             $bp = j$
16:         **end if**
17:     **end for**
18:     $RoadSet(bp) \leftarrow RoadSet(bp) \cup r_i$
19: **end for**
20: $W \leftarrow \{\}$
21: **for** $i := 1$ to M **do**
22:     **for** each $r \in RoadSet(b_i)$ **do**
23:         $W \leftarrow W \cup WaypointSet(r)$
24:     **end for**
25:     Select a random $w \in W$
26:     $InitialPosition(m_i) \leftarrow w$
27: **end for**

While the initial placement of RA is different than the initial placement of GA, mobility decisions of RA during the operation follow a similar pattern with GA. The only difference between them is that with GA a mobile sink updates the next destination by selecting a random waypoint among all waypoints in the corresponding grid set. In RA, however, the random waypoint is selected among the waypoints in the road set. For some cases such as a case where most people stuck in a particular region, RA and GA may produce unbalanced workloads on the mobile sinks, as some of the mobile sinks do not encounter many sensor nodes. PF, however, overcomes this extreme case as people's locations attract mobile sinks.

Considering various environments and conditions arise during different types of disasters (e.g., flood, typhoon, earthquake), safe evacuation of people is a challenging and complex problem where providing an optimum solution is not feasible. However, we believe that the three heuristic approaches motivate the use of sink mobility in different environments (e.g., theme parks, city squares, festivals).

IV. Simulation Study

A. Simulation environment

We analyze the proposed network model and the sink mobility models PF, GA, and RA through simulations of the opportunistic network with mobile sinks. The simulation experiments are conducted for the Magic Kingdom park. We include two sink mobility models for comparisons, which are called "random target location" (RTL) and "random waypoint distribution" (RWD) models. In RTL, each mobile sink chooses any random target location on the map, then sets the closest waypoint to the target location as the sink's next destination. In RWD, each mobile sink chooses a waypoint randomly among all waypoints and sets it as the next destination. RWD favors the popular roads because popular roads tend to include more waypoints than other roads.

Various metrics can be used for evaluating the effect of the mobility models and the network performance. These metrics can be classified into two types: *Link-based* and *network coverage* metrics. Link-based metrics include intercontact times, recontact rate, minimum hop counts, message delays, and number of transmissions. Network coverage metrics include number of detected sensors, rescue success ratio, and average distance to detected event. We include performance results related to intercontact times, recontact rate, number of detected sensors, number of transmissions and rescue success ratio.

We evaluate the success of the opportunistic network with 1-10 mobile sinks and transmission ranges of 10, 20, 50 and 100m. Evaluation of each setting is based on 50 simulation runs. Each simulation run generates at

TABLE I
SIMULATION PARAMETERS

simulation time	2000 s
sampling time	2.0 s
disaster area size (≈)	800x800 m
number of sensor nodes	200
sensing range	20 m
sensor message storage capacity	100
transmission probability	0.9
grid width/height	50 m
number of effected people	20
rescue failure time	600 s
sink relative mass constant(λ)	0.5
physical force impact factor α	20.0
sink max speed	1 m/s
pedestrian max speed	1 m/s
pedestrian visibility	50 m

TABLE II
HUMAN MOBILITY PARAMETERS

number of pedestrians	1000
min speed	0.5m/s
max speed	2.5m/s
number of red-zones	20
red-zone active time	500s
red-zone radius	50m
random move distance	10m
visibility	50m
SFM - interaction strength (A)	0.11 $\pm$ 0.06
SFM - interaction range (B)	0.84 $\pm$ 0.63
SFM - relaxation time (τ)	0.5s
SFM - λ	0.1

least about 2000 message transmissions among sensor nodes or from sensor nodes to mobile sinks, while the number of transmissions to mobile sinks varies by the sink mobility model and parameters such as the number of mobile sinks. All nodes in the network communicate with the epidemic routing protocol [14]. We assume that after two sensor nodes close a session, they wait for a cut off time empirically set as 1 min before opening a new session.

Table I includes the list of the simulation parameters. Parameters related to the human mobility and the social force model can be found in Table II. Detailed information regarding the social force model can be found in Appendix. Disasters tend to have effects on the random locations of the area during the simulation time. In this simulation study, instead of creating artificial disaster zones, we marked the pedestrians which are effected due to the effects of disasters.

B. Performance results

1) Intercontact times: Intercontact time is defined as the duration between two consecutive encounters of a mobile sink with a sensor node. Intercontact times metric is commonly used for evaluating the performance of mobile opportunistic social networks. We analyze intercontact times of PF, GA, RA, RTL and RWD with 5 mobile sinks placed in the disaster area with 25m transmission range. The performance results of intercontact times with confidence bounds are shown in Fig. 6. The results reveal that among the five mobility approaches, PF and GA are the ones which produce shorter intercontact times while RWD produces the longest intercontact times meaning

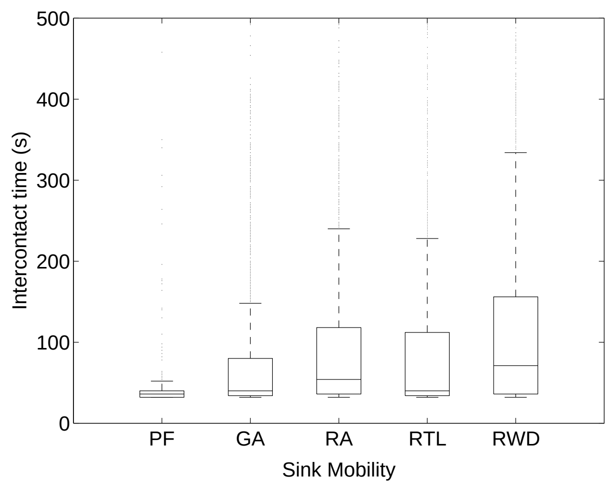

Fig. 6. Intercontact times of PF, GA, RA, RTL and RWD with confidence bounds.

the worst performance. Longer intercontact times cause mobile sinks to delay communicating with a previously contacted sensor node. Moreover, the intercontact times of PF seem consistent, so that it is easy for the mobile sinks to estimate the next contact time with a previously contacted sensor node. In particular, consistency in the intercontact times would allow us to find efficient methods for transmission scheduling.

A comparison of the intercontact times of the mobility approaches provided by various numbers of mobile sinks can be seen in Fig. 7. For PF, we observe that the number of mobile sinks does not have a significant impact on the intercontact times as the results stay in a constant level from 1 sink up to 10 sinks. Moreover, PF provides the best results for various numbers of mobile sinks. RWD and RTL also do not have significant decays in the intercontact times with the increasing number of mobile

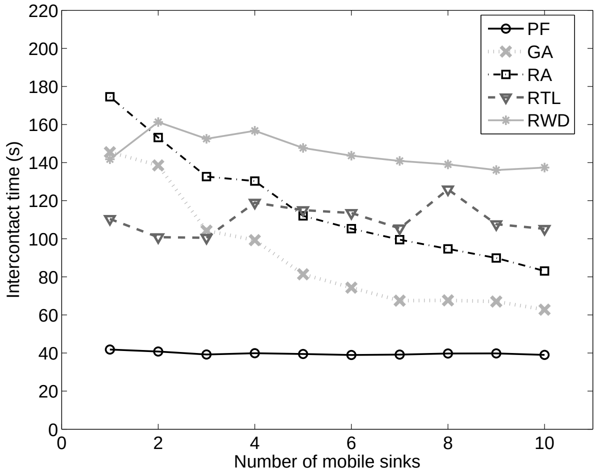

Fig. 7. Intercontact times of PF, GA, RA, RTL and RWD with 1 to 10 mobile sinks.

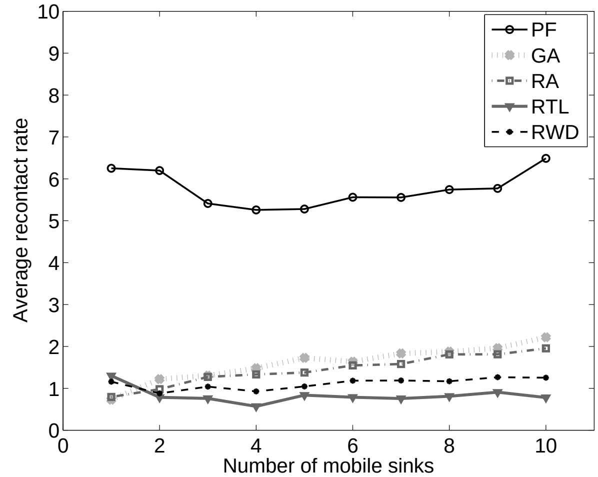

Fig. 9. Recontact rates of PF, GA, RA, RTL and RWD with 1 to 10 sinks.

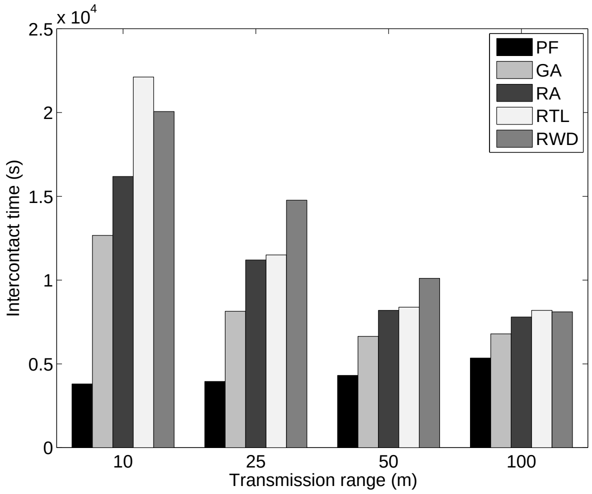

Fig. 8. Intercontact times of PF, GA, RA, RTL and RWD for 10m, 25m, 50m and 100m transmission ranges.

sinks. On the other hand, the intercontact times of the GA and RA approaches become shorter as higher number of sinks operate. Considering the fact that in the case of more mobile sinks, each sink is assigned to a smaller number of grids or roads. Therefore, their chances of encountering the same sensor nodes increase.

In Fig. 8, we observe that for all transmission ranges (10m, 25m, 50m and 100m), PF, GA and RA provide shorter intercontact times compared to RTL and RWD. As expected, with longer transmission ranges, intercontact times decrease for GA, RA, RTL and RWD. Moreover, the effects of mobile sink positioning approaches are more significant for lower transmission ranges.

2) Recontact rates: While intercontact times metric provides insight into the performance of the network, the intercontact times results do not involve the case which a mobile sink communicates with a sensor node only once during the entire simulation time. Therefore, we analyze the recontact count for each pair of mobile sink and sensor node, which is the number of contacts of the mobile sink and the sensor node after their first encounter. Recontact rate of a mobile sink is its averaged recontact count considering all the sensor nodes that communicated with the mobile sink. Fig. 9 shows the results of average recontact rates with settings ranging from 1 to 10 mobile sinks. The PF approach is the clear winner with an average rate of more than 5.0 due to sinks' behavior of following contacted sensor nodes and sticking with them as much as possible. The decrease in the rates for 3 sinks is caused by the masses of the mobile sinks which restrict them from staying close to each other. For the single mobile sink setting, we observe that recontact rates of GA, RA, RTL and RWD are very low without any significant difference between them. On the other hand, the rate difference becomes significant for multiple sinks. Among these four approaches, GA is the best one reaching the rate of more than 2.0, while RA reaches the rate of approximately 2.0. On the other hand, the rates of RTL and RWD do not significantly increase with the addition of more mobile sink nodes in the network.

As it can be seen on Fig. 10, PF produces the best outcome in terms of the recontact rates for 10m, 25m, 50m and 100m transmission ranges. On the other hand, RTL has the worst performance, producing less than half of the recontact rates of PF for all transmission ranges. Moreover, longer transmission ranges provide higher recontact rates for all mobile sink positioning

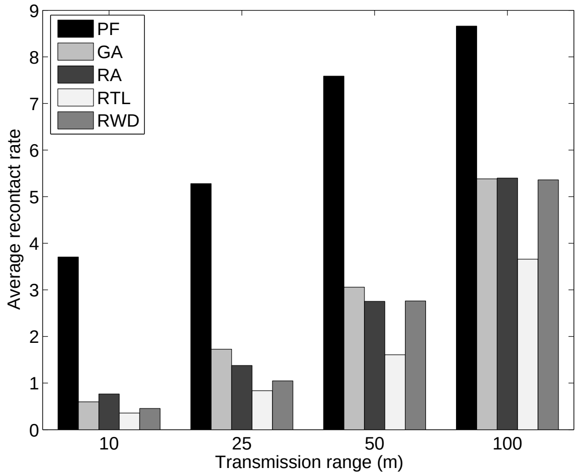

Fig. 10. Recontact rates of PF, GA, RA, RTL and RWD for 10m, 25m, 50m and 100m transmission ranges.

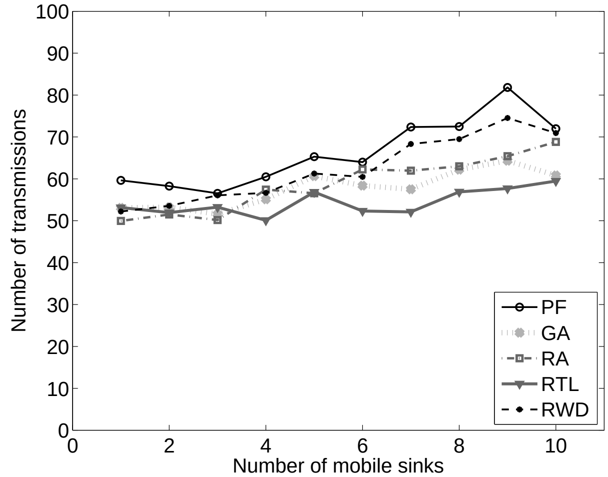

Fig. 12. Average number of transmissions of PF, GA, RA, RTL and RWD with 1 to 10 mobile sinks.

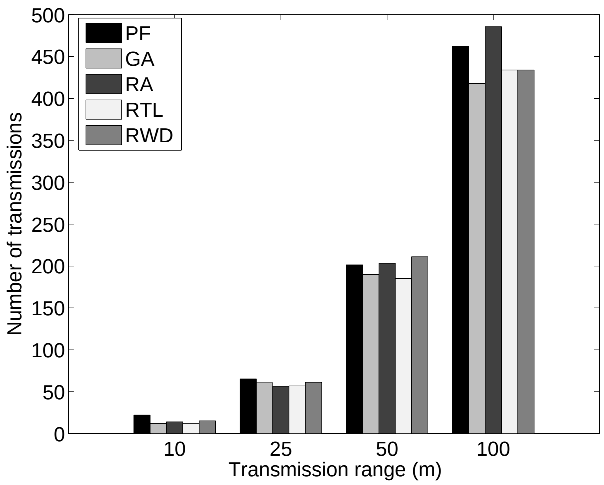

Fig. 11. Average number of transmissions of PF, GA, RA, RTL and RWD for 10m, 25m, 50m and 100m transmission ranges.

strategies.

Considering intercontact times and recontact rates for analyzing the tracking success of the mobile sinks, we observe that PF is the best strategy. Compared to RTL and RWD, GA and RA are better tracking strategies since they produce shorter intercontact times and higher recontact rates.

3) Number of transmissions: The number of transmissions metric represents the wireless communication overhead which leads to the energy consumption of the sensor nodes and the mobile sink nodes. We consider the average number of wireless transmissions of all nodes in the network including the transmissions in successful or failed sessions. Fig. 11 shows the results of the approaches with 5 mobile sinks for transmission ranges of 10m, 25m, 50m and 100m. First of all, we observe that increase in transmission range dramatically increases the number of transmissions. This is an expected result and it is caused by the exponential increase in the number of neighbors of a sensor node. In the case of having limited energy resources, a more effective routing protocol may provide better energy preservation for sensor nodes with high transmission ranges. Secondly, the use of PF results more wireless transmissions while the difference is not very significant. This is an expected side effect of the PF strategy since mobile sinks are able to communicate with sensor nodes multiple times and in shorter time periods. Nonetheless, sinks are in limited number and the number of transmissions among sinks and sensor nodes is significantly fewer than the number of transmissions among sensor node pairs. Furthermore, sinks are assumed to have more resources in terms of energy and storage while sensor nodes which are neighbors of the sinks may consume more energy resources.

As an expected outcome of having more mobile sinks, the number of transmissions increase from 1 mobile sink to 10 mobile sinks as shown in Fig. 12. However, the increase is not dramatic. From 1 sink to 10 sinks, it is less than 20% for RA, about 15% for PF and less than 15% for the other three approaches. Considering the successful network coverage provided by having multiple mobile sinks, the increase in the number of transmissions is acceptable.

4) Number of detected sensors: We use the total number of detected sensors metric in our analysis to have better insight into the network's coverage performance. We mean that a sensor is detected when there is a direct communication of the sensor with any mobile sink.

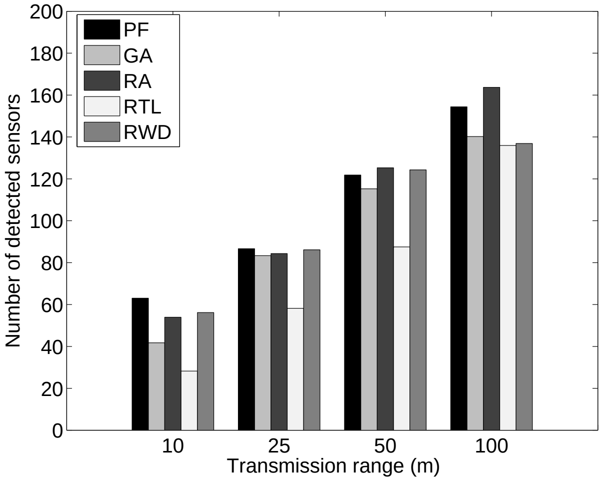

Fig. 13. Number of detected sensors of PF, GA, RA, RTL and RWD for 10m, 25m, 50m and 100m transmission ranges.

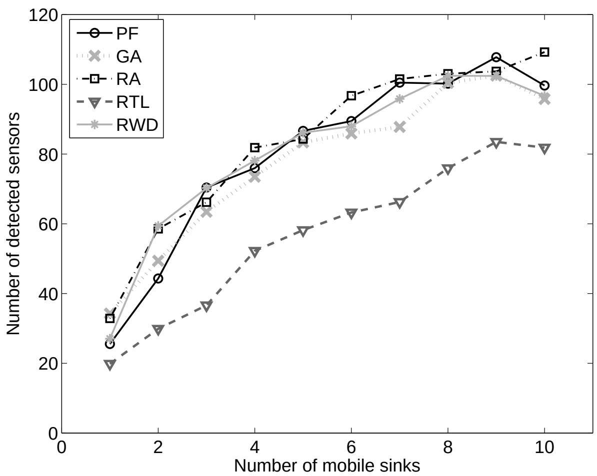

Fig. 14. Number of detected sensor nodes of PF, GA, RA, RTL and RWD with 1 to 10 mobile sinks.

Fig. 13 reveals the results of the approaches with 10m, 25m, 50m and 100m transmission range values with 5 mobile sinks. Among all the approaches, RA and PF are overall the best ones reaching up to more than 80% of the 200 sensor nodes. RWD also provides a reasonably good coverage of sensor nodes since the mobile sinks mostly choose the popular locations where sensor nodes are also most likely present. With higher transmission ranges, the coverage performance is better for all the approaches. Having 50m or 100m transmission ranges, RA provides the best network coverage such that most sensor nodes encounter with at least one mobile sink along their way.

Fig. 14 shows the total number of detected sensors of the strategies from 1 to 10 mobile sinks. First, we observe that the number of detected sensors are higher for RA and PF compared to the other three approaches. RTL provides the worst performance, having less number of sensor nodes detected for all cases. Moreover, the increase in the number of mobile sinks brings an increase in the number of detected sensor nodes. In comparison to the single mobile sink setting, the number of detected sensors becomes more than 3 times higher for 10 mobile sinks. Hence, one can say that the network coverage is highly dependent on the number of mobile sinks.

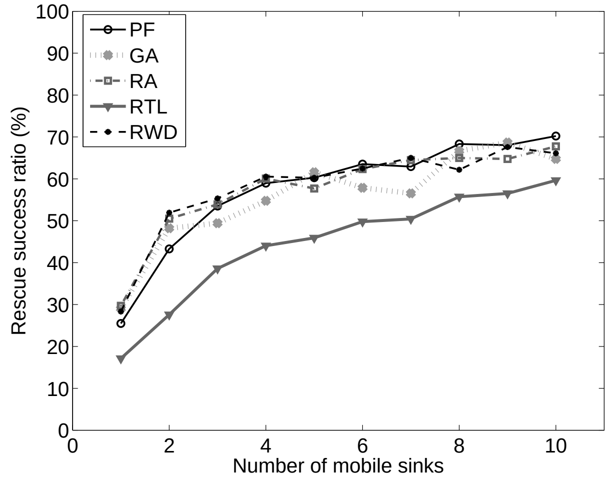

Fig. 15. Rescue success rates of PF, GA, RA, RTL and RWD with 1 to 10 mobile sinks.

5) Rescue success ratio: We mark pedestrians “to be rescued” in the following cases. When a red-zone (effect of the disaster) occurs in a certain region, the people who are located in that region are marked to be rescued. For each experiment, 20 red-zones, as circular areas with 50m radius, are created at random times with an active time of 500s (see Table II. The locations of the red-zones are randomly selected on the map.

Considering the mobile sinks with capability of acting to the emergent events, they should be able to reach the areas where pedestrians in need of help exist. Moreover, the time it takes to reach an emergent event must be short. Thus, for evaluating the rescue success, we calculate the sum of the message delay and the travel time of the mobile sink after it receives the message.

We assume a rescue time of 10 minutes, which includes the message delay and the travel time. Fig. 15 shows the success ratio results of the approaches with 25m transmission range. This figure also reveals the effect of having multiple mobile sinks to rescue success ratios. With 10 mobile sinks, PF reaches more than 70% of the emergent events in less than 10 minutes. For RTL, success ratio increases from 10% to 60% from 1 to 10 mobile sinks while for the other approaches it increases approximately from 30% to 70%.

By analyzing the results of the simulation experiments, we observe that our proposed approaches overall perform better compared to RTL and RWD. PF produces better recontact rates and intercontact times, since the method is designed in a way that when a mobile sink encounters a large group of people, it follows the group during their evacuation therefore creating and therefore contacting the same nodes throughout this period. However, this creates more transmissions as can be seen in the results. GA and RA on the other hand, provides a trade off between recontacts and number of transmissions. Moreover, PF, GA and RA provides better coverage (detected sensors) since they are all distribute the mobile sinks in the area and ensure they do not intersect in the same areas. On the other hand, RWD and RTL do not provide collaborative coverage which creates certain inefficiencies. In this sense, RTL provides the worst performance since the even the targets are placed in different places of the map, the pedestrian roads the mobile sinks move along are the same in many cases.

Overall, the network simulations provide promising results in terms of metrics such as intercontact times, rescue success ratios, number of detected sensor nodes, and average recontact rates. The performance results show that the proposed network model and the approaches can be very useful as a disaster response strategy in environments with limited vehicle use such as theme parks. As an interesting finding of the simulation study, we first observe that having multiple sinks clearly produces better network performance. Moreover, we observe that with the use of 200 sensor nodes, which corresponds to only 2% of the 10,000 pedestrians, the mobile sinks can achieve 70% rescue success. Furthermore, higher rescue success ratios can be achieved with vehicles having higher speeds. Finally, for PF, GA, and RA mobile sink mobility approaches, we find that fewer than or equal to 7 mobile sinks are sufficient enough to track most of the pedestrians during their evacuation.

V. Related Work

We previously studied the use of WSNs with mobile sinks in theme parks for the purpose of event coverage [15], [16]. In these studies, we focused on the use of mobile sinks for security in theme parks in ordinary scenario of theme park operation. Events are classified as emergency situations such as health issues or pickpocketing which may happen anytime during the daily activities. In this paper, on the other hand, we focus on the communication of sensor nodes and mobile sinks in disaster times and mission-critical operation of search and rescue.

There are many research studies for solving the emergency evacuation problem in city environments such as downtown areas and evacuation of buildings during disasters. Hadzic et al. [17] propose techniques for evacuation guidance in real time for pedestrians during emergency. This study focuses on evacuation from buildings during a fire. Similarly, Barnes et al. [18] propose an algorithm for directing people to exits through arbitrarily complex building layouts for emergency situations such as fires. A simulation-based system for evacuation is proposed by Zou et al. [19] and six different evacuation plans for evacuation of Ocean City are simulated. Park et al. [20] propose a rule based approach to model spontaneous evacuation behavior considering a terrorist attack scenario in a complex metropolitan area. Chen and Zhan [21] compare the simultaneous and staged evacuation strategy in which vehicles are organized to evacuate according to the different sequences of the zones in the disaster area. They use an agent-based approach to model and simulate the evacuation of the vehicles. Chen et al. [22] propose a framework for estimation of pedestrian evacuation times as well as distribution (load balancing) of pedestrian loads into the exit gates. Kwon and Pitt [23] apply a dynamic traffic assignment model, “Dynasmart-P” to the evacuation problem for traffic in downtown Minneapolis, Minnesota. While the aforementioned studies focus on the metropolitan areas which involves various services and the use of vehicles or building evacuations,we focus on the evacuation of pedestrians from a relatively smaller outdoor disaster areas. Gelenbe and Wu [24] survey the research related to WSNs and communications for enhancing emergency evacuation and Ibrahim et al. [25] reviews the intelligent evacuation management systems which cover the aspects of guiding people, evacuaton modeling, monitoring, and disaster prediction.

There exist studies related to modeling pedestrian mobility. Shiwakoti et al. [26] focus on the use of biological entities such as ants for empirical study to pedestrian crowds to enhance safety of pedestrians in emergency conditions. Helbing et al. simulate the mobility of pedestrian crowds for the ordinary scenario and the evacuation situations in [4]. Georgoudas et al. [27] propose an anticipative system to avoid congestions at the exit points during the evacuation of the pedestrians.

Fujihara and Miwa [28] investigate the effects of opportunistic communications in evacuation times for disaster scenarios. El-Sergany et al. [29] propose a model for evacuation planning and disaster management in flood disaster scenarios. Iizuka et al. [12] propose the use of mobile devices of evacuees to form an ad hoc network and find the evacuation routes accordingly and avoid congestions. Vukadinovic et al. [30], [31] study the mobility of theme park visitors based on GPS traces and analyze impacts of the human mobility on wireless ad hoc networking. Kamiyama et al. [32] considers the evacuation problem in network consisting of a directed graphs with capacities and transit times on their arcs. Helgason et al. [33] investigate the effects of the human mobility on the wireless communication performance of ad hoc and delay tolerant networks. Khan et al. [34] propose an approach where some sensor nodes in the sensor networks temporarily act as mobile sinks in order to achieve connectivity of WSNs during catastrophic events. Qing-Shan and Ying [35] formulate the problem of outdoor evacuation as a scheduling problem in queuing network and considers human guidance and the probability of crowd panics. Tseng et al. [36] develop a navigation algorithm based on WSNs to safely guide people to a building exit and help them avoid hazardous areas. Clementi et al. [37] propose using mobile ad hoc networks for data flooding where nodes move independently at random and exchanges data when they are in each other's transmission range. They show that node mobility enhances the speed of information spreading even for sparse and disconnected networks. Rozner et al. [38] study the joint optimization of opportunistic routes with a model-driven optimization approach and achieve better performances compared to shortest-path routing and opportunistic routing protocols such as the conflict-graph (CG) model. Our model is unique and different than the existing studies of opportunistic networks in terms of having multiple mobile sinks and pedestrians with smartphones. In this case, performance of the opportunistic network highly depends on the positioning of the mobile sinks and the pedestrian mobility.

The use of mobile sinks in sensor networks have various advantages such as prolonging network lifetime, while it brings challenges such as finding efficient strategies of mobile sink movement and routing towards mobile sinks. Khan et al. [39] survey various data collection approaches that exploit sink mobility. They classify these approaches in three categories: path constrained, path unconstrained, and controlled sink mobility-based schemes. Han et al. [40] propose a routing topology for WSNs with multiple mobile sinks, while Liu et al. [41] proposed a topology control algorithm considering the mobile nodes in underwater WSNs. Vecchio and López-Valcarce [42] propose a greedy approach for controlling the mobile nodes in WSNs. Boloni et al. [43] demonstrate an agent-based coalition formation approach including multiple mobile agents and simulate the New Orleans environment for the hurricane Katrina aftermath.

There are many studies aiming to provide solution to the disaster management problem. Winter et al. [11] study the evacuation problem in disaster areas and propose the use of a mobile service "Get-Me-Out-Of-Here" (GOH) running on smartphones. Benefits of communication among people are observed for the evacuation scenarios in which individuals have only the local knowledge of the environment. Uddin et al. [44] propose an agent-based mobility model of people with different roles such as rescue workers and volunteers as well as vehicles such as police patrol cars and ambulances. They also propose the intercontact routing [45] for disruption-tolerant disaster response networks to reduce the resource overhead. Gao et al. [46] list the characteristics of disruption-tolerant networks as low node density, unpredictable mobility and lack of global knowledge and they aim to optimize data access by the cooperative caching mechanism.

Ayday and Fekri [47] focus on the security problem of delay tolerant networks, which are commonly used for disaster response, and they propose a trust mechanism to efficiently detect malicious nodes in the networks. Drugan et al. [48] investigate clustering of dynamic networks with the help of community detection mechanisms for mission-critical application domains such as rescue and emergency services. Palmer et al. [49] develop the "RAVEN" framework for collaborative data collection by using smartphones during a disaster. Another data collection system is proposed by Fujiwara et al. [50]. Their system involves the use of sensor networks and an access network for detecting damages in a disaster and sending the data to an emergency control center. Tuna et al. [51] propose a system for automatically deploying a WSN using multiple robots for the purpose of human existence detection in disaster environments. Their approach involves simultaneous deployment of the sensor nodes during the exploration of an unknown area and WSN-based communication. Our study differs from these disaster management studies as we propose using mobile sinks which can follow a determined route while there exists an uncertainty in the movement decisions of the pedestrians.

VI. Conclusion

In this paper, we propose a network model which involves the use of smartphones and mobile sinks for tracking pedestrians during evacuation from disasters. We consider the use of multiple mobile sinks and propose three sink placement and mobility approaches, namely, *physical force based* (PF), *grid allocation based* (GA) and *road allocation based* (RA) movement strategies.

The performances of the proposed network model and these approaches are evaluated in comparison to two random sink mobility models through extensive network and mobility simulations for the theme park scenario. We observe that our approaches produce better results in terms of the network coverage and the rescue success, while they do not bring extra communication overhead to the network. Moreover, it is shown that having multiple mobile sinks in the network has significant advantages over having a single mobile sink.

We find that our network model with multiple mobile sinks can be useful as part of emergency evacuation planning in large and crowded areas with limited vehicle use. While we focus on the theme parks, the techniques developed in this paper can be adapted to various similar environments such as university campuses, large-scale shopping malls, festival areas, airports and so on.

APPENDIX

We describe the mobility behavior of the pedestrians as follows. The pedestrians have local knowledge of the map and the knowledge of the location of the exit gate that they first entered through. The local knowledge is defined by the maximum visibility parameter which shows the visible distance for each visitor and possible obstacles. This parameter represents the radius of the circular visible area. We do not assume any communication among pedestrians and no external broadcasting system for raising the awareness.

Initially, the pedestrians are randomly distributed to the waypoints. They try to reach the target point by moving among the waypoints and mark the visited waypoints along their way. The next destination is selected among visible and unmarked waypoints according to their distances and directions from the current position of the pedestrians. If there is no candidate among waypoints for the next destination, the new destination is set by exploration with a random direction. All of the above steps describe the global movement from the initial point to the target point and they are defined as the macro-mobility behavior.

We consider micro-mobility of a pedestrian between any two consecutive waypoints. We use the social force model (SFM) [4] and model the social forces on the pedestrians according to their social interactions with the environment. By this model, the pedestrians adapt their speed and direction of the movement from a waypoint to another. In SFM, the sum of the social forces is given by

$$f_\alpha(t) = \frac{1}{\tau_\alpha}(v_\alpha^0 e_\alpha^0 - v_\alpha) + \sum_{\beta(\neq\alpha)} f_{\alpha\beta}(t) + \sum_i f_{\alpha i}(t), \quad (4)$$

for a pedestrian α where τ_α denotes the relaxation time, $v_\alpha^0 e_\alpha^0$ is the desired velocity, and the sums correspond to the social forces by the other pedestrians (β) and the obstacles (i) respectively. The acceleration is then given by $f_\alpha(t)$ and the individual fluctuations. Assuming $f_{\alpha\beta}(t) = f(d_{\alpha\beta}(t))$, circular specification is given by

$$f(d_{\alpha\beta}) = A_\alpha e^{-d_{\alpha\beta}/B_\alpha} \frac{d_{\alpha\beta}}{\|d_{\alpha\beta}\|}, \quad (5)$$

where A_α, B_α denote the interaction strength and the interaction range respectively.

For the elliptical specification of the model, the circular specification formula is expressed as a gradient of an exponential decaying potential $V_{\alpha\beta}$, where elliptical interaction force via the potential is $V_{\alpha\beta}(b_{\alpha\beta}) = ABe^{-b_{\alpha\beta}/B}$. In this equation, $b_{\alpha\beta}$ is the semi-minor axis of the elliptical equipotential lines and given by

$$2b_{\alpha\beta} = \sqrt{(\|d_{\alpha\beta}\| + \|d_{\alpha\beta} - y_{\alpha\beta}\|)^2 - \|y_{\alpha\beta}\|^2}, \quad (6)$$

where $y_{\alpha\beta} = (v_\beta - v_\alpha)\Delta t$ and $\Delta t = 0.5s$.

$$f_{\alpha\beta} = -\nabla_{d_{\alpha\beta}} V_{\alpha\beta}(b_{\alpha\beta}) = -\frac{dV_{\alpha\beta}(b_{\alpha\beta})}{db_{\alpha\beta}} \nabla_{d_{\alpha\beta}} b_{\alpha\beta}(d_{\alpha\beta}) \quad (7)$$

Equation 4 gives the repulsive force and $\nabla_{d_{\alpha\beta}}$ denotes the gradient with respect to distance between α and β. Using chain rule, this leads to

$$f_{\alpha\beta(d_{\alpha\beta})} = A_\alpha e^{-b_{\alpha\beta}/B} \cdot \frac{\|d_{\alpha\beta}\| + \|d_{\alpha\beta} - y_{\alpha\beta}\|}{2b_{\alpha\beta}} \cdot \frac{1}{2}\left(\frac{d_{\alpha\beta}}{\|d_{\alpha\beta}\|} + \frac{d_{\alpha\beta} - y_{\alpha\beta}}{\|d_{\alpha\beta} - y_{\alpha\beta}\|}\right). \quad (8)$$

Considering the angular dependence between two encountered pedestrians, with an angle of $\varphi_{\alpha\beta}$, the angular-dependent pre-factor $w(\varphi_{\alpha\beta})$ is given by the below equations

$$\cos(\varphi_{\alpha\beta}) = \frac{v_\alpha}{||v_\alpha||} \cdot \frac{-d_{\alpha\beta}}{||d_{\alpha\beta}||} \quad (9)$$

$$w(\varphi_{\alpha\beta}(t)) = \left((1-\lambda_\alpha)\frac{1+\cos(\varphi_{\alpha\beta})}{2} + \lambda_\alpha\right), \quad (10)$$

where the parameter λ_α with $0 \leq \lambda_\alpha \leq 1$ is found by evolutionary optimization as $\lambda_\alpha \approx 0.1$. The fitness of the social force model increases with the addition of the angular dependence formulation to the model.

As a consequence of SFM, the time it takes for the pedestrian to move to a destination point varies. The main impact of this model is that the usage of the same roads by the pedestrians causes an increase in the social interactions. This increase slows down the flow of the pedestrians along the roads. Since the theme parks are crowded areas with limited vehicle use, SFM is the best-fit model to represent the crowd dynamics during the evacuation of the pedestrians in theme parks. For more detailed information related to the pedestrian mobility, we refer the readers to our previous work in [3].

References

[1] S. Hallegatte, "Trends in hazards and the role of climate change," in *Natural Disasters and Climate Change*, 2014, pp. 77–97.

[2] "Theme index: Global attractions attendance report," Themed Entertainment Association (TEA), Tech. Rep., 2013.

[3] G. Solmaz and D. Turgut, "Pedestrian mobility in theme park disasters," *IEEE Communications Magazine*, vol. 53, no. 7, pp. 172–177, July 2015.

[4] D. Helbing and A. Johansson, "Pedestrian, crowd and evacuation dynamics," *Encyclopedia of Complexity and Systems Science*, vol. 16, no. 4, pp. 6476–6495, 2010.

[5] G. Solmaz and D. Turgut, "Theme park mobility in disaster scenarios," in *Proc. of IEEE GLOBECOM'13*, December 2013, pp. 399–404.

[6] G. Solmaz and D. Turgut, "Tracking evacuation of pedestrians during disasters," in *Proc. of IEEE GLOBECOM'15*, December 2015.

[7] "Report on safety," Walt Disney Resorts and Parks, Tech. Rep., January 2008. [Online]. Available: http://thewaltdisneycompany.com/about-disney/security

[8] P. Manns, K. Daun, J. Schubert, A. Stumpf, and O. von Stryk, "Towards highly reliable autonomy for urban search and rescue robots," *RoboCup 2014: Robot World Cup XVIII*, vol. 8992, p. 118, 2015.

[9] "SEGWAY," http://www.segway.com.

[10] L.-W. Chen, J.-J. Chung, and J.-X. Liu, "GoFAST: a group-based emergency guiding system with dedicated path planning for mobile users using smartphones," in *Proc. of IEEE MASS'15*, 2015, pp. 467–468.

[11] S. Winter, K.-F. Richter, M. Shi, and H.-S. Gan, "Get me out of here: collaborative evacuation based on local knowledge," in *Proc. of the ACM SIGSPATIAL'11 International Workshop on Computational Transportation Science*, November 2011, pp. 35–42.

[12] Y. Iizuka, K. Yoshida, and K. Iizuka, "An effective disaster evacuation assist system utilized by an ad-hoc network," in *HCI International 2011 Posters Extended Abstracts*, ser. Communications in Computer and Information Science, 2011, vol. 174, pp. 31–35.

[13] H. M. and P. Weber, "OpenStreetMap: User-generated street maps." *Pervasive Computing*, vol. 7, no. 4, pp. 12–18, December 2008.

[14] A. Vahdat and D. Becker, "Epidemic routing for partially connected ad hoc networks," Technical Report CS-200006, Duke University, Tech. Rep., 2000.

[15] G. Solmaz and D. Turgut, "Optimizing event coverage in theme parks," *Wireless Networks (WINET) Journal*, vol. 20, no. 6, pp. 1445–1459, August 2014.

[16] G. Solmaz, K. Akkaya, and D. Turgut, "Communication-constrained p-center problem for event coverage in theme parks," in *Proc. of IEEE GLOBECOM'14*, December 2014, p. 40864091.

[17] T. Hadzic, K. N. Brown, and C. J. Sreenan, "Real-time pedestrian evacuation planning during emergency," in *Tools with Artificial Intelligence (ICTAI), 2011 23rd IEEE International Conference on*, 2011, pp. 597–604.

[18] M. Barnes, H. Leather, and D. Arvind, "Emergency evacuation using wireless sensor networks," in *Local Computer Networks, 2007. LCN 2007. 32nd IEEE Conference on*, 2007, pp. 851–857.

[19] N. Zou, S.-T. Yeh, G.-L. Chang, A. Marquess, and M. Zezeski, "Simulation-based emergency evacuation system for Ocean City, Maryland, during hurricanes," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1922, no. 1, pp. 138–148, 2005.

[20] Y. S. Park, E. Manli, M. Hope, V. Sokolov, and H. Ley, "Fuzzy rule-based approach for evacuation trip demand modeling," in *Transportation Research Board 89th Annual Meeting*, no. 10-2635, 2010.

[21] X. Chen and F. B. Zhan, "Agent-based modelling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies," *Journal of the Operational Research Society*, vol. 59, pp. 25 – 33, 2008.

[22] L.-W. Chen, J.-H. Cheng, and Y.-C. Tseng, "Optimal path planning with spatial-temporal mobility modeling for individual-based emergency guiding," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 45, no. 12, pp. 1491–1501, 2015.

[23] E. Kwon and S. Pitt, "Evaluation of emergency evacuation strategies for downtown event traffic using a dynamic network model," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1922, pp. 149–155, 2005.

[24] E. Gelenbe and F.-J. Wu, "Large scale simulation for human evacuation and rescue," *Computers & Mathematics with Applications*, vol. 64, no. 12, pp. 3869–3880, 2012.

[25] A. M. Ibrahim, I. Venkat, K. Subramanian, A. T. Khader, and P. D. Wilde, "Intelligent evacuation management systems: A review," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 7, no. 3, p. 36, 2016.

[26] N. Shiwakoti, M. Sarvi, G. Rose, and M. Burd, "Enhancing the safety of pedestrians during emergency egress," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2137, no. 1, pp. 31–37, 2009.

[27] I. G. Georgoudas, G. C. Sirakoulis, and I. T. Andreadis, "An anticipative crowd management system preventing clogging in exits during pedestrian evacuation processes," *Systems Journal, IEEE*, vol. 5, no. 1, pp. 129–141, 2011.

[28] A. Fujihara and H. Miwa, "Real-time disaster evacuation guidance using opportunistic communications," in *Proc. of the IEEE/IPSJ SAINT'12*, July 2012, pp. 326–331.

[29] A. T. El-Sergany and S. Alam, "Trip distribution model for flood disaster evacuation operation," *ITE Journal*, vol. 82, pp. 42–47, October 2012.

[30] V. Vukadinovic, F. Dreier, and S. Mangold, "Impact of human mobility on wireless ad hoc networking in entertainment parks," *Ad Hoc Networks*, vol. 12, pp. 17–34, 2014.

[31] V. Vukadinovic, F. Dreier, and S. Mangold, "A simple framework to simulate the mobility and activity of theme park visitors," in *Proc. of the WSC*, December 2011, pp. 3248–3260.

[32] N. Kamiyama, N. Katoh, and A. Takizawa, "An efficient algorithm for the evacuation problem in a certain class of a network with uniform path-lengths (algorithmic aspects in information and management)," *Lecture notes in computer science*, vol. 4508, pp. 178–190, 2008.

[33] Ó. Helgason, S. T. Kouyoumdjieva, and G. Karlsson, "Opportunistic communication and human mobility," *IEEE Transactions on Mobile Computing*, vol. 13, no. 7, pp. 1597–1610, 2014.

[34] S. A. Khan, L. Bölöni, and D. Turgut, "Bridge protection algorithms–a technique for fault-tolerance in sensor networks," *Ad Hoc Networks*, vol. 24, pp. 186–199, 2015.

[35] J. Qing-Shan and G. Ying, "Event-based evacuation in outdoor environment," in *Proc. of the CCDC'12*, 2012, pp. 33–38.
[36] Y.-C. Tseng, M.-S. Pan, and Y.-Y. Tsai, "Wireless sensor networks for emergency navigation," *Computer*, vol. 39, no. 7, pp. 55–62, 2006.
[37] A. Clementi, F. Pasquale, and R. Silvestri, "Opportunistic MANETs: mobility can make up for low transmission power," *IEEE/ACM Transactions on Networking*, vol. 21, no. 2, pp. 610–620, 2013.
[38] E. Rozner, M. K. Han, L. Qiu, and Y. Zhang, "Model-driven optimization of opportunistic routing," *IEEE/ACM Transactions on Networking*, vol. 21, no. 2, pp. 594–609, 2013.
[39] A. W. Khan, A. H. Abdullah, M. H. Anisi, and J. I. Bangash, "A comprehensive study of data collection schemes using mobile sinks in wireless sensor networks," *Sensors*, vol. 14, no. 2, pp. 2510–2548, 2014.
[40] S.-W. Han, I.-S. Jeong, and S.-H. Kang, "Low latency and energy efficient routing tree for wireless sensor networks with multiple mobile sinks," *Journal of Network and Computer Applications*, vol. 36, no. 1, pp. 156–166, 2013.
[41] L. Liu, R. Wang, and F. Xiao, "Topology control algorithm for underwater wireless sensor networks using gps-free mobile sensor nodes," *Journal of Network and Computer Applications*, vol. 35, no. 6, pp. 1953–1963, 2012.
[42] M. Vecchio and R. López-Valcarce, "Improving area coverage of wireless sensor networks via controllable mobile nodes: A greedy approach," *Journal of Network and Computer Applications*, vol. 48, pp. 1–13, 2015.
[43] L. Boloni, M. A. Khan, and D. Turgut, "Agent-based coalition formation in disaster response applications," in *Distributed Intelligent Systems: Collective Intelligence and Its Applications, 2006. DIS 2006. IEEE Workshop on*. IEEE, 2006, pp. 259–264.
[44] M. Uddin, D. Nicol, T. Abdelzaher, and R. Kravets, "A post-disaster mobility model for delay tolerant networking," in *Proc. of the WSC'09*, December 2009, pp. 2785 –2796.
[45] M. Uddin, H. Ahmadi, T. Abdelzaher, and R. Kravets, "Intercontact routing for energy constrained disaster response networks," *IEEE Transactions on Mobile Computing*, vol. 12, no. 10, pp. 1986–1998, Oct 2013.
[46] W. Gao, G. Cao, A. Iyengar, and M. Srivatsa, "Cooperative caching for efficient data access in disruption tolerant networks," *IEEE Transactions on Mobile Computing*, vol. 13, no. 3, pp. 611–625, 2014.
[47] E. Ayday and F. Fekri, "An iterative algorithm for trust management and adversary detection for delay-tolerant networks," *IEEE Transactions on Mobile Computing*, vol. 11, no. 9, pp. 1514–1531, 2012.
[48] O. V. Drugan, T. Plagemann, and E. Munthe-Kaas, "Detecting communities in sparse manets," *IEEE/ACM Transactions on Networking*, vol. 19, no. 5, pp. 1434–1447, 2011.
[49] N. Palmer, R. Kemp, T. Kielmann, and H. Bal, "Raven: Using smartphones for collaborative disaster data collection," *Proceedings of ISCRAM*, 2012.
[50] T. Fujiwara, H. Makie, and T. Watanabe, "A framework for data collection system with sensor networks in disaster circumstances," in *Proc. of IEEE International Workshop on Wireless Ad-Hoc Networks*, 2004, pp. 94–98.
[51] G. Tuna, V. C. Gungor, and K. Gulez, "An autonomous wireless sensor network deployment system using mobile robots for human existence detection in case of disasters," *Ad Hoc Networks*, vol. 13, pp. 54–68, 2014.

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