Optimized 3D Drone Placement and Resource Allocation for LTE-Based M2M Communications

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***Abstract*—The deployment of drone-mounted communication systems has received increasing interest and attention recently as it allows significant improvement to the network access capacity and coverage. Many applications can benefit from such deployments in particular machine-to-machine (M2M) communications. In this study, we propose a technique for the rapid deployment of an LTE drone-mounted base station to serve a group of machine-type-communication devices (MTCDs) that are deployed in disaster situations or within remote applications. The objective is to maximize the number of served MTCDs while meeting their transmission delay requirements. This results in optimizing the 3D placement of the drone base station as well as the allocation of the available communication resources. We evaluated the proposed technique through several simulation experiments. The simulation results demonstrate significant improvement in the aggregate system throughput and the overall system deadline missing performance along with the increased number of served MTCDs compared to other drone placement approaches.**

Keywords—drone base station, LTE coverage, access network optimization, machine-to-machine communications

I. Introduction

Machine-to-Machine (M2M) communications are considered one of the main enablers of the Internet of Things (IoT) applications. In some situations, providing communication services to the IoT systems is challenging due to the unavailability of a regular communication infrastructure in the deployment area. For example, in monitoring applications, machine-type-communication devices (MTCDs) are generally deployed in areas such as deserts, forests, or even remote industrial operations, where it is hard to have access to the regular wireless communication infrastructure. In such applications, the data acquired by the MTCDs need to be timely transmitted elsewhere for further processing. In many circumstances, deploying terrestrial wireless communication base stations for the widely spread wireless network applications would not be a cost/time effective solution. The recent evolution of the unmanned aerial vehicle (UAV), or drone, technology and capabilities drew the researchers' attention to the possibility of having wireless communication services through these low-altitude platforms which could offer a reasonable solution for the aforementioned problem. Drones have recently received increasing attention in the literature for the use as base stations or communication relay nodes to enhance users' experience while using wireless networks. Some of these efforts addressed the issue of the optimal placement of the drones to serve a group of users or to respond to high traffic demands while considering specific quality of service (QoS) requirements such as the transmission power along with the maximum geographical coverage in both indoor and outdoor applications. Further studies were concerned about other important problems such as backhaul link connectivity, malfunctioned terrestrial base station offloading, beamwidth optimization, user association or clustering and data collection. In the previous studies, the optimization problems generally dealt with the system throughput, the data rate, the transmission power and the number of geographically covered users. However, the major challenges of the critical M2M communications such as the transmission deadline missing still require more attention. In addition, the studies in the literature established a static placement or constant trajectories for the drone base station deployment problems. Therefore, the dynamic placement of the drone deployments with respect to the traffic demands still needs to be addressed. The main objective of this study is to devise a dynamic 3D drone placement and resource allocation technique to provide LTE coverage to an MTCD deployment in communication-congested/damaged and/or distant areas using a drone-mounted aerial base station (ABS) with near-optimal radio resource scheduling under specific deployment conditions in the absence of terrestrial base stations. The goal is to ensure the deployment of the drone in such a way that maximizes the communication coverage while reducing the deadline missing of the involved M2M traffic. We, therefore, introduce a novel technique that utilizes the drone's mobility to ensure uninterrupted communication access for the MTCDs within the deployment and maintains the M2M communications QoS requirements. The proposed scheme dynamically improves the communication links for better channel conditions based on the near-optimal placement of the ABS deployment together with the proper scheduling of the communication resources. The rest of this paper is organized as follows. In Section II, we discuss the latest studies in the literature of using drones as communication providers. In Section III, the proposed system model and the problem formulation are presented. In Section IV, we describe the proposed technique and its associated algorithmic solution. The simulation results are presented and analyzed in Section V. Finally, the study is concluded in Section VI.

II. Related Work

In [1], multiple UAVs are used to provide wireless services for enhanced coverage and load balancing to handle high traffic requests over a certain geographical area. Drones in this study are used as middleware access points between the congested area and a ground base station where each drone is required to handle a specific number of users. In [2], public safety communication scenarios are considered where ABSs are used to respond quickly to natural disaster situations in which terrestrial base stations have been subjected to damage, so the effect of deploying UAVs as base stations in harsh environments on the total system throughput is evaluated. The ABS deployment for maximum coverage is also studied in [3] while considering QoS requirements through maintaining the channel capacity based on a prespecified threshold of the wireless links signal-to-noise ratio (SNR). The extended work in [4] uses disciplined convex programming tools to solve the drone 3D positioning problem with the minimum possible transmission power. Users' mobility is considered in [5] by

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using a reinforced learning technique that is based on a discounted reward method known as Q-learning. In this approach, the drone placement relies on the past experiences of the users' mobility, and this results in a dynamic network in response to users' position changes. Indoor applications are discussed in [6] and [7]. First, particle swarm optimization is used to optimally place the ABS to serve uniformly distributed users on each floor of a high-rise building in case of having an out-of-order terrestrial base station. Further, [7] introduces a gradient descent-based algorithm to find the optimal drone location when users are distributed in a symmetric manner along the entire building where the worst location is determined by the maximum path loss energy. Another proposed algorithm in [8] is concerned with finding the optimal 3D positioning to maintain the coverage for a specific group of users and reliable bandwidth allocation for the wireless backhaul link to maximize the summation of the users' logarithmic data rate. The study in [9] presents a hybrid network architecture by using an ABS flying in a circular motion around a ground base station's cell edge since users at the cell edges commonly suffer from poor communication coverage as compared to being close to the cell center. In [10], the study enables a wireless communication system for multi-users by ABS deployment using an adaptive beamwidth directional antenna. This is done by clustering the mobile users into cells that are served consecutively using a drone base station. In [11], multiple drones are used as ABSs to serve clusters of IoT users by optimizing the 3D ABSs placement, the resource allocation and the users' association for each drone. The main objective is to reduce the total IoT devices' transmission power and to maintain the data rate requirements in the uplink direction. The study in [12] proposes an algorithm that works on shortening the link between ground terminals and the UAV which results in increasing the overall system throughput. The proposed algorithm exploits drone's mobility in a circular trajectory to enhance the conditions of the communication channels over a constant period of time. Another study in [13] uses drone base stations and introduces a cluster-based resource allocation algorithm for M2M data collection applications. MTCDs are divided into QoS-based clusters. Each cluster head is responsible for gathering the devices' information to send it to the ABS. However, the diverse nature of the MTCDs and their associated QoS requirements challenge the clustering techniques in various applications. In [14], multiple ABSs are deployed to substitute for a malfunctioned ground base station. The study optimizes the drone placement problem with respect to the users' locations. Then the backhaul link is allocated, and the available resources are scheduled in accordance with the achievable data rate. To deal with the large dimensions of the modeled optimization problem, the variables are decoupled, and an iterative method is used to perform optimization over one type of the variables at a time. In these previous studies, the network communication technologies are not considered in the optimization problem formulation. The 3D placement problem is mainly modeled in terms of the geographical distances between drones and the associated users. Therefore, the proposed models in these studies are concerned with the geographical coverage of the drone base station which does not always guarantee the communication coverage. The optimal drone locations obtained in these studies are fixed or follow a predetermined trajectory according to the modeled deployment conditions and the solved optimization problems. Therefore, any change in the network traffic would not affect the drone placement and would adversely influence the overall system performance. Moreover, QoS demands are presented in the form of a threshold SNR or channel attenuation. The different delay requirements or the transmission deadlines, especially in M2M communications, are not taken into account in the aforementioned studies. Our work in this study differs from the previous efforts as follows. We propose a novel LTE-based technique that jointly optimizes the 3D dynamic placement of a drone base station and the resource allocation for an MTCD deployment over a large geographic area on the basis of the delay requirements of the involved MTCDs. As shown in Fig. 1, the drone keeps hovering in different positions over the deployment space to respond to the M2M strict data traffic demands. Therefore, the optimization problem in this study is solved along all the variable axes combined such as the drone placement and the resource scheduling to guarantee channels connectivity for optimal resource allocation to maintain the QoS requirements.

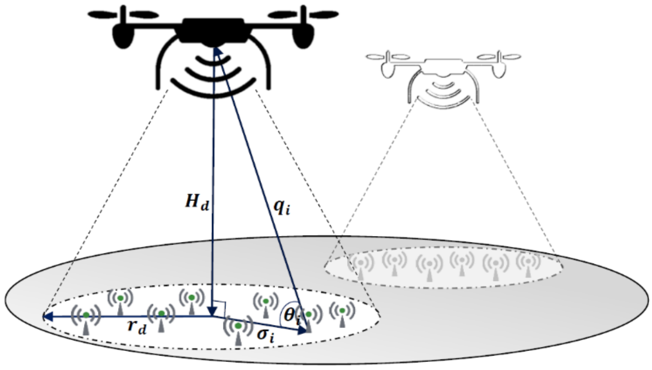

Fig. 1. Changing the drone's 3D positions in response to active MTCDs

III. System Model and Problem Formulation

This study considers a single drone base station dynamic deployment to serve a dense population of MTCDs that are distributed over a large geographic area. Initially, the free-space path loss model is calculated at the drone associated cell in accordance with [15]. The path loss equation in both line-of-sight (LoS) and non-line-of-sight (NLoS) links is given as

$$L_{LoS/NLos} = 20 \log\left(\frac{4\,\pi\, f_c q_i}{c}\right) + \varphi_{LoS/NLos}, \tag{1}$$

where φ_{LoS} and φ_{NLoS} are the averages of the additional losses of LoS and NLoS links respectively, q_i is the direct distance between an MTCD i and the drone that can be calculated as $q_i = \sqrt{{H_d}^2 + {\sigma_i}^2}$ where H_d is the drone altitude and σ_i is the ground distance between the drone perpendicular projection and an MTCD i as indicated in Fig. 1, f_c represents the carrier frequency and c is equal to the speed of light. The path loss equation is then estimated as

$$L_{i,d} = L_{LoS} P_{LoS} + L_{NLoS} P_{NLoS}, \tag{2}$$

where the probability of having NLoS links is given as $P_{NLoS} = 1 - P_{LoS}$ and the probability of having LoS links is represented in the form of a sigmoid function as follows

$$P_{LoS} = \frac{1}{1+a exp(-b(\theta_i - a))}, \tag{3}$$

where a and b are environment-dependent factors and $\theta_i = \frac{180}{\pi} \tan^{-1}\frac{H_d}{\sigma_i}$ represents the elevation angle as shown in Fig. 1. Consequently, the path loss model can be expressed as

$$L_{i,d} = \frac{\varphi_{LoS} - \varphi_{NLoS}}{1+a exp(-b(\theta_i - a))} + 10 \log(\sigma_i \sec\theta_i) + 20 \log\left(\frac{4\pi f_c}{c}\right) + \varphi_{NLoS}. \tag{4}$$

To calculate the maximum permissible coverage of the drone base station at which the communication channels between the MTCDs and the base station would not be lost or would violate a specific path loss threshold $L_{i,d}^{thr}$, the path loss model in (4) is solved to obtain the drone covered cell radius r_d with respect to θ_i at $L_{i,d}^{thr}$ in dB and then differentiated to calculate $\frac{\delta r_d}{\delta \theta_i}$. The resulting $\frac{\delta r_d}{\delta \theta_i}$ function is equated to zero as follows

$$\frac{\pi}{9\ln 10}\tan\theta_i^{max} + \frac{ab(\varphi_{LoS}-\varphi_{NLoS})exp\left(-b(\theta_i^{max}-a)\right)}{\left(1+aexp\left(-b(\theta_i^{max}-a)\right)\right)^2} = 0. \quad (5)$$

This determines the maximum allowable elevation angle θ_i^{max} that corresponds to the maximum achievable radius r_d of the drone supported cell at $L_{i,d}^{thr}$ in conjunction with the maximum allowable height H_d^{max}. Subsequently, the channel quality indicator (CQI) [16] that provides the information to decide on the modulation scheme is reported by the MTCDs based on the SNR value that is estimated using the path loss model in (4). If we multiply the reported spectral efficiency η_i by the physical resource block (PRB) bandwidth BW^{PRB} for the allocated PRBs within the LTE transmission time interval (TTI), the data rate R_i per TTI can then be calculated as

$$R_i = \eta_i BW^{PRB}\sum_{k=1}^{N_{RB}} I_{i,k}, \quad (6)$$

where BW^{PRB} is equal to 180 kHz [17], $I_{i,k}$ is a binary indicator for PRBs allocation and N_{RB} is the number of the available PRBs depending on the radio channel bandwidth. The buffer status report (BSR) sent by the served MTCDs to the drone base station shares the information regarding the amount of pending data in the uplink buffer of the MTCDs. From the CQI and the BSR, we calculate the total number of transmitted bits required by each MTCD to meet its delay requirements. The QoS class identifier (QCI) disseminates how data transmission is handled including the packet delay budget DB_i. To calculate the total time spent on transmitting each packet, the M/D/1 queue model is used to estimate the distribution of the queue waiting time [18] as follows

$$P[W_i \le t] = \left(1-\frac{\lambda_i}{R_i}\right)\sum_{\nu=0}^{z}\frac{\left(-\lambda_i(t-\nu T_i)\right)^{\nu}}{\nu!}\exp\left(\lambda_i(t-\nu T_i)\right), \quad (7)$$

where W_i is the waiting time of an MTCD i, λ_i denotes the average arrival rate of the MTCDs' data packets that is modeled as a Poisson process and z is an integer value such that $zT_i \le t \le (z+1)T_i$ where T_i is the deterministic service time. Since the total delay time of a transmission assignment can be estimated as $D_i = W_i + T_i$, the probability of transmission deadline missing occurrence is calculated as $P[D_i > DB_i] = 1 - P[D_i \le DB_i]$ where the waiting time distribution in terms of the transmission delay is given as

$$P[D_i \le DB_i] = \left(1-\frac{\lambda_i}{R_i}\right)\sum_{\nu=0}^{z}\frac{\left(-\lambda_i(DB_i-T_i-\nu T_i)\right)^{\nu}}{\nu!}\exp\left(\lambda_i(DB_i-T_i-\nu T_i)\right). \quad (8)$$

Since the proposed problem structure is to maximize the number of served users and to allocate the resources optimally in a way that minimizes the missed deadlines for each MTCD, the optimization problem can then be written as follows

$$\max_{x_d,y_d,H_d,I_{i,k}} \sum_{i=1}^{\mathbb{U}} u_i, \quad (9)$$

$$\textit{subject to} \quad H_d^{min} \le H_d \le H_d^{max}, \quad (9a)$$

$$P[D_i > DB_i] \le DM_i^{max}, \forall i \in u_s, \quad (9b)$$

$$\sum_{i=1}^{u_s} I_{i,k} \le 1, \forall k \in N_{RB}, \quad (9c)$$

$$x_d, y_d, H_d \in \mathbb{R}, \quad u_i \in \{0,1\}, I_{i,k} \in \{0,1\}, \forall i \in \mathbb{U}, k \in N_{RB}, \quad (9d)$$

where u_i is a binary index introduced to geographically indicate whether an MTCD i is covered by the ABS as mentioned in [3], [4] and calculated in (10), u_s is the subset representing the active MTCDs of the set $\mathbb{U}$ of the total deployed MTCDs, x_d and y_d are the ABS's 2D location coordinates, H_d^{min} is the lower bound of the drone's altitude and DM_i^{max} is the allowable probability of missing a deadline.

$$u_i = \begin{cases} 1, & \sigma_i \le r_d \\ 0, & \sigma_i > r_d \end{cases}, \quad (10)$$

where $\sigma_i = \sqrt{(x_i - x_d)^2 + (y_i - y_d)^2}$. We assume that an omnidirectional antenna is mounted on the drone, so the ground coverage can be modeled as a disk with a radius r_d where $r_d = H_d \cot\theta_i^{max}$. Hence, the optimization fitness function in (9) is modeled in terms of the drone placement in (10) and associated with the scheduling scheme through the constraints in (9b) and (9c).

IV. Proposed Algorithmic Solution

The Penalty Method [19] is used in the proposed algorithm to define multiple terms representing the constraints of (9) in a confined objective function. Then the derived objective function is solved by one of the unconstrained conventional meta-heuristic methods. The problem in (9) is reformulated as

$$\max_{x_d,y_d,H_d,I_{i,k}} f\left(x_d,y_d,H_d,I_{i,k}\right) = \sum_{i=1}^{\mathbb{U}} u_i - \sum_{i=1}^{u_s}\psi_i\, max(0, P[D_i > DB_i] - DM_i^{max})^2, \psi_i > 0, \quad (11)$$

where $f\left(x_d,y_d,H_d,I_{i,k}\right)$ is the unconstrained objective function and ψ_i is the penalty coefficient. The constraint penalty function will be zero if the solution satisfies the system limitations, so the penalty method allows the algorithm to converge to a near-optimal solution even if the solution is infeasible to some of the constraint functions such as the constraint in (9b). This scenario is applicable to our case due to the scarce radio resources compared to the large number of deployed MTCDs. We solve the resulting unconstrained mixed-integer nonlinear programming (MINLP) problem using the particle swarm optimization (PSO) algorithm [20]. Unlike other meta-heuristic approaches, this swarm intelligent model guarantees effective problem exploration and prompt convergence with minimum computational efforts for high dimensional spaces [21]. The algorithm updates each particle's position $\boldsymbol{P}_s$ that represents a row vector including the 3D drone placement and the PRBs scheduling scheme. This is done by updating its associated direction and speed $V_{s,n}$ which is calculated in the n-dimensional domain of (11) as

$$V_{s,n} = \mathrm{w}V_{s,n} + c_1 r_1\left(Pb_{s,n} - P_{s,n}\right) + c_2 r_2\left(Gb_n - P_{s,n}\right), \quad (12)$$

where c_1 and c_2 are the acceleration constants while r_1 and r_2 are uniformly distributed random variables and w is the inertia weight constant while Gb_n and $Pb_{s,n}$ are the global and personal best positions. The study in [21] introduces a discrete version of the PSO by introducing an adequate distance measure for the binary variables. The probability of changing a binary state is introduced to reformulate the velocity concept in the generic PSO. The proposed system structure combines the two velocity concepts to deal with the MINLP problem in (11). Moreover, this algorithmic solution integrates the unified

Algorithm 1: 3D drone placement and resource scheduling optimization

Input: $f(x_d, y_d, H_d, I_{i,k})$, ψ_i, H_d^{min}, H_d^{max}
Output: x_d, y_d, H_d, $I_{i,k}$

initialize a uniformly distributed swarm of size s within a finite span of the upper/lower bounds ub, lb of $\boldsymbol{P}_s$: $\boldsymbol{P}_s = [x_d\ y_d\ H_d\ I_{i,k}]$
set PSO parameters s, α, w, c_1, c_2, rg, $epochs$
$stagnation\ count = 0$, $rf = 0.05 \times epochs$ // refresh gap
compute $f(\boldsymbol{P}_s)$ // after mapping the relaxed $I_{i,k}$
determine Gb_n and local best $Lb_{s,n}$ in a ring rg
initialize $V_{s,n} = rand$
for $t \leftarrow epochs$
  if $counter > rf$, **then**
    if $stagnation\ count == 0$, **then**
      set $stagnation\ count$ and reset counter
      reinitialize $V_{s,n} = rand$
    else terminate, **end if**
  end if
  obtain new positions $P_{s,n}$: $P_{s,n} \in [ub, lb]$ and compute $f(\boldsymbol{P}_s)$
  determine updated Gb_n, $Lb_{s,n}$ and $Pb_{s,n}$
  calculate the updated w as per [22]
  update particles' velocities $V_{s,n}$
  normalize $V_{s,n}$, $\forall n > 3$ // for the discrete variables
  if $f(Gb_n^{t-1}) > f(Gb_n^t)$, **then**
    increment $counter$
  else reset $stagnation\ count$, $counter$, **end if**
end

model of PSO as suggested in [22] to allow the particles to learn from not only the personal and the global exemplars but the local exemplar as well to provide wide exploration to the search space. Hence, the particles' velocities are updated as

$$V_{s,n} = \alpha \times GV_n + r(1-\alpha)LV_{s,n}, \tag{13}$$

where α is a unification factor and r is a normally distributed random number while GV_n and $LV_{s,n}$ are the velocities of the global and local exemplars. A ring topology of size rg is used to specify the local neighbors of each particle. The potential solution is represented in the global best particle's position. Thus, the proposed framework is summarized in Algorithm 1.

V. Simulation Results

We modeled an LTE network with the configurations given in Table I which also shows the algorithm parameters. Throughout the simulation, the CQI index is updated regularly according to the calculated SNR value based on the current drone 3D position at each TTI. The communication channels are modeled and contaminated with additive white Gaussian noise considering a suburban environment. The Poisson traffic model is configured as per Table II which characterizes three different M2M applications. The results are presented along two different axes. First, we compare the proposed network performance to that of a deployed stationary ABS at the cell center at a height that allows the drone to geographically cover all the uniformly distributed MTCDs using the optimal locations obtained in [15]. The uplink scheduler used by this stationary base station is the delay-based scheduler proposed in [23]. The system evaluation metrics in this experiment include the deadline missing ratio and the cell aggregate throughput. Second, the proposed technique is compared against that in [3] in terms of the percentage of the geographically covered users with respect to the total number of deployed MTCDs. The values indicated in the results are the averages of 10 independent simulation runs. In Fig. 2, the overall system deadline missing ratio is illustrated. The figure shows that the proposed system outperforms the delay-based scheduler used on the stationary ABS. This is due to the fact that the drone's mobility enhances the channel conditions between the MTCDs and the ABS. The adaptive 3D placement in our technique assists the scheduler to meet the tight deadlines of the transmission assignments as the heuristic

TABLE I. NETWORK AND ALGORITHM PARAMETERS

Parameter	Value
Channel Bandwidth, Carrier Frequency f_c	3 MHz, 2 GHz
Number of PRBs and LTE Frames	15, 100
Number of Deployed MTCDs	100, 150, 200, 250, 300
Deployed MTCDs' Density	11 MTCDs/km^2
Environment Parameters a, b, φ_{LoS}, φ_{NLoS}	5.0188, 0.3511, 0.1, 21 [15]
Transmission and Noise Power	30, -70 dBm [3]
Deadline Missing Probability DM_i^{max}	10%
PSO Parameters s, α, w, c_1, c_2	50, 0.1, 0.729, 1.494, 1.494 [22]
rg, $epochs$	5, 250

TABLE II. TRAFFIC CONFIGURATIONS

Traffic Description	Alerts	Camera	Monitoring Sensor
Arrival Rate (pkt/s)	25	30	1
Packet Size (byte)	32	512	128
Profile Percentage %	20	20	60
Threshold Path Loss (dB)	95	98	100
Delay Budget (ms)	U(10,20)	U(125,250)	U(800,900)

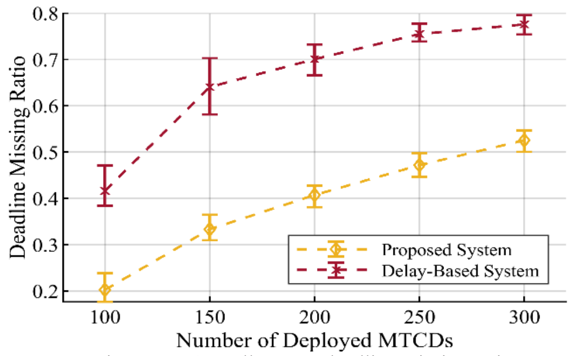

Fig. 2. Overall system deadline missing ratio

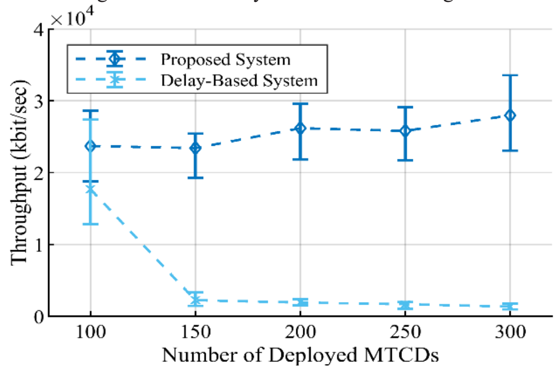

Fig. 3. System aggregate throughput

algorithm updates the drone's location with respect to the active MTCDs considering their delay requirements. The overall system throughput is also improved compared to the delay-based scheduler on the stationary ABS, as shown in Fig. 3. The aggregate throughput slightly changes or remains constant with the proposed technique. On the other hand, the overall system throughput decreases significantly with the static drone deployment. The reason is that the delay-based scheduler is typically concerned with serving the data traffic characterized by small-sized data packets with strict delay budgets such as alarms. Hence, the delay-tolerant large data packets of the camera traffic are congested in the transmission channels in case of using the delay-based static drone deployment as indicated in Fig. 5 which shows the aggregate throughput of the camera traffic profile. In both Fig. 4 and Fig. 5, the proposed technique succeeds in maintaining the QoS requirements for the different types of data traffic as it deals with the M2M demands dynamically by changing the penalty coefficient of the unconstrained objective function granting high priority to the alarm traffic. Fig. 6 shows the percentage of the covered devices relative to

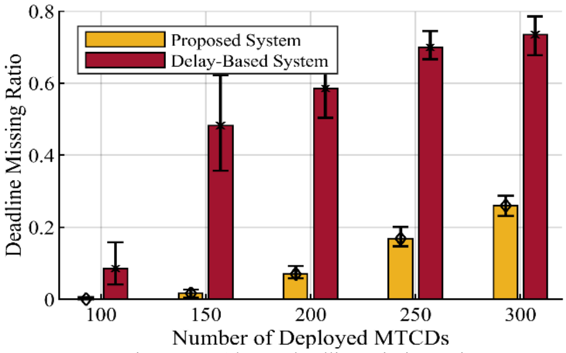

Fig. 4. Alarms deadline missing ratio

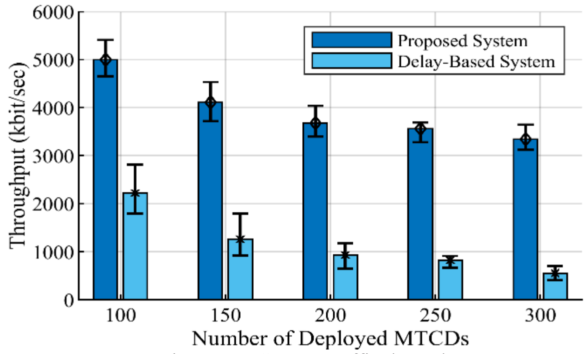

Fig. 5. Camera traffic throughput

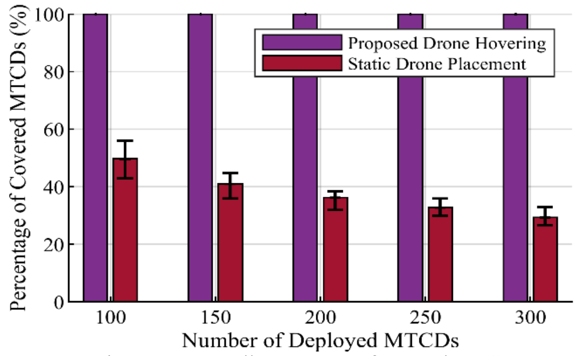

Fig. 6. Overall percentage of covered MTCDs

the total number of MTCDs. The maximum possible coverage is obtained in results by flying the drone over the deployment space while the optimal stationary location given in [3] has users' coverage not exceeding 50% of the deployed MTCDs.

VI. Conclusion

In this paper, we introduced a joint 3D placement and resource allocation technique for an LTE-based drone base station to serve a dense deployment of MTCDs. The drone's mobility is utilized to maximize the network coverage and to enhance the communication links. This optimizes the resource allocation and maintains the QoS requirements of different M2M traffic profiles. We formulated the optimization problem to obtain the instantaneous optimal drone's trajectory and network resources to handle the strict delay requirements of the MTCDs. The complete problem is solved using a PSO-based algorithm. Simulation results, in comparison to other placement and scheduling techniques, show the superiority of the proposed technique in covering a larger number of MTCDs with significantly better M2M QoS performance.

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