Application-Oriented On-Demand Data Collection in Sparse Underwater Acoustic Sensor Networks Using Mobile Elements

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***Abstract*—Underwater Wireless Sensor Network (UWSN) is a group of sensors and underwater vehicles, networked via acoustic links, which performs collaborative tasks and enables a wide range of aquatic applications. Due to hostile environment, resource constraints and peculiarities of the underlying physical layer technology, providing energy-efficient data collection in a sparse UWSN is a challenging problem. We consider mobility-assisted routing technique for enabling connectivity and improving the energy efficiency of sparse UWSN, considering it as a Delay/Disruption Tolerant Network (DTN) or Intermittently Connected Network (ICN). We use analytical models to investigate the performance of the data collection scheme. Based on the result that the DTN scheme improves energy efficiency and Packet Delivery Ratio (PDR) at the cost of increased message latency, we investigate techniques to improve its delay performance. The effects of using multiple mobile elements for data collection and activity-based priority-polling are investigated. In addition, the suitability of a hybrid architecture and hierarchical organization of mobile elements for supporting delay-sensitive applications in the mobility-assisted framework, is explored. The analytical results are validated through extensive simulations using NS-2 based Aqua-Sim simulator. The results show that our model for on-demand data collection can effectively capture the underwater acoustic network conditions and facilitate performance evaluation of event-driven data collection in sparse UWSNs prior to deployment. The improved DTN framework shows superior performance in terms of energy efficiency and successful data delivery over ad-hoc multi hop network, and in terms of message latency, fairness and buffer space requirement over simple polling-based DTN framework.**

Keywords–Underwater Sensor Networks; Delay Tolerant Network; Mobile Collector; Polling; Exhaustive Service; Fairness; Energy Efficiency; Hybrid Architecture.

I. INTRODUCTION

This paper extends our earlier work [1] presented at the Tenth International Conference on Wireless and Mobile Communication (ICWMC 2014), proposing two strategies for supporting delay-sensitive applications in mobility-assisted underwater data collection. Compared to the original paper, it contains more detailed analysis of the system model and introduces additional proposals for improving latency performance according to application requirements.

Underwater Wireless Sensor Networks (UWSNs) have emerged as powerful systems for providing autonomous support for several activities like oceanographic data collection, marine surveillance, disaster prediction, assisted navigation etc. As illustrated in Fig. 1, UWSN consists of a number of different types of sensor nodes and autonomous underwater vehicles (AUVs) used for collaborative monitoring tasks. Ordinary underwater (UW) sensor nodes deployed at different depths are used to sense the environment and generate data. UW sink nodes are responsible for collecting this data and forwarding it to the surface sink. Surface sinks are equipped with RF communication link with the on-shore control centre and other surface sinks, acoustic links with the underwater sensor nodes, and an optional fibre optic link with the UW sink. Since electromagnetic waves are heavily attenuated in the salty sea water and optical signals are affected by scattering, acoustic communication is the underlying physical layer technology used in UWSNs. Development of underwater acoustic communication systems for interesting practical applications are available in [2], [3], [4] and [5]. Features like high latency, low bandwidth, high error probability and 3-dimensional deployment make the UWSNs significantly different from terrestrial WSNs [6].

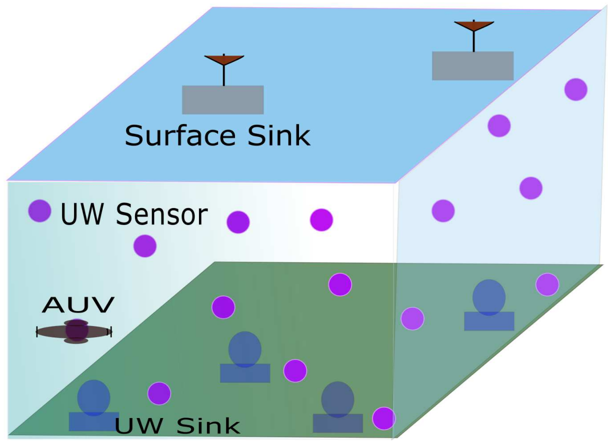

Figure 1. Underwater Sensor Network

The energy saving/efficiency is a critical issue for UWSN because of the high cost of deploying and/or re-deploying underwater equipment. Underwater sensors are expensive, mainly because of their more complex transceivers, and the ocean area that needs to be sensed is quite large.

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Hence, UWSN deployment can be much sparser compared with terrestrial WSNs. Due to sparse deployment, harsh environment, node mobility and resource limitations, the network can be easily partitioned and a contemporaneous path may not exist between any two nodes. This results in sparse UWSNs that need to be treated as Intermittently Connected Networks (ICN) or Delay / Disruption Tolerant Networks (DTN) [7]. At any given time, when no path exists between source and destination, network partition is said to occur. DTNs are characterised by frequent partitions and potentially long message delivery delays. Such networks may never have an end-to-end contemporaneous path and traditional routing protocols are not practical since packets will be dropped when no routes are available.

The primary objective of a DTN routing protocol is to obtain high message delivery ratios with satisfactory latency performance, while maintaining low overhead. The characteristics of DTN are quite different from that of Internet and hence new system architectures and routing protocols are required for DTNs. DTN routing protocols can be generally classified as *forwarding-based* and *replication-based*. *Forwarding-based* schemes keep one copy of a message in the network and tries to forward that copy towards the sink at the earliest possible forwarding opportunity. *Replication-based* approaches like multipath routing are resource-hungry and hence not suitable for resource-constrained underwater applications. *Forwarding-based* approaches are limited in their effectiveness due to instability (or even non-existence) of routes from any particular node to the destination. To combat intermittent connectivity in resource-constrained UWSNs, a natural solution is to extend the store-and-forward routing to store-carry-and-forward routing. Proactive mobility of special mobile nodes can be made use of, to improve message delivery ratio and to reduce energy consumption. Since the next hop may not be immediately available for the current node to forward data, it has to buffer the data until it detects a *contact* or forwarding opportunity.

The three main approaches reported in the literature for data collection in wireless sensor networks, in general, are [8]: (i) Base Station (BS) approach, which uses direct communication between the source and the sink; (ii) Ad hoc network, which uses a multi-hop path from the source to the sink; and (iii) Mobility assisted routing, which makes use of a mobile sink or mobile relays for data collection. The first approach provides fast delivery, but suffers from reduced life time of sensors due to increased requirement of communication energy when the source to sink distance is large. The ad hoc multi hop network provides medium delay with medium power requirement, but suffers from the 'hot spot' problem or the sink neighbourhood problem. In addition, an end-to-end contemporaneous path should exist for successful data collection, which is not always possible in the harsh marine environment in which UWSNs are deployed.

Mobility assisted routing approach supports the DTN concept of store-carry-and-forward and fills connectivity gaps in the network. Also, it reduces transmit power consumption and eliminates the relaying overhead. However, due to the limited travel speed of the mobile elements, data collection latency will be large, but such large latency may be acceptable in certain environmental sensing applications which are not time-critical. Typical example of such an application is the continuous monitoring and recording of the behaviour of underwater plates in tectonics, for later scientific analysis. Compared with periodic data collection in which the locations are given and fixed, event-driven data collection can shorten the response time, and can thereby support delay-sensitive applications. The arrival of events that require attention need not be deterministic and planned; instead, they can be online and stochastic. However, there exists no proper model for analyzing the performance of mobility-assisted event-driven data collection scheme in UWSNs. Investigation of event-driven on-demand data collection using energy-efficient mobility-assisted scheme in sparse UWSNs and enhancing it for supporting delay-sensitive applications like pollution monitoring and earthquake prediction, is the focus of this paper.

We start with a basic DTN framework for energy efficient data collection in sparse UWSNs using a single mobile sink; and then augment it with techniques to improve its data collection performance by: (i) introducing priority; (ii) employing multiple data collectors; (iii) deploying a hybrid architecture with both static and mobile sinks; and (iv) organizing the mobile collectors in a hierarchical structure. Analytical results for energy efficiency, packet delivery ratio (PDR), message latency, and sensor buffer occupancy are presented. The analytical results are validated using our own simulation model developed in Aqua-Sim [9], an NS-2 [10] based network simulator, developed by the University of Connecticut. The major contributions of this paper include: (i) Investigating an energy-efficient DTN framework for event-driven data collection in sparse UWSNs; (ii) Analyzing the performance metrics of the proposed framework; (iii) Proposing techniques to enhance the latency performance; and (iii) Developing the simulation model for validation of analytical results and further research. The rest of the paper is organized as follows. A brief review of the related work is given in Section II. The basic system model is presented in Section III and the expressions used for analytical results with this model are developed in Section IV. Techniques for delay performance enhancement of the basic model are discussed and analyzed in Section V. Section VI discusses the analytical and simulation results. The paper is concluded in Section VII.

II. Related Work

Several routing protocols have been developed for UWSNs, most of them suitable only for connected networks. A detailed review of different routing techniques for UWSNs is given in [11] and a comparative analysis of routing protocols is done in [12]. Vector Based Forwarding (VBF) [13] is a typical geographical routing protocol and Hop-by-hop Vector-based forwarding (HH-VBF) [14] is its more energy-efficient version, better suited for sparse networks. Both VBF and HH-VBF do not support mobility-assisted data collection and they require the network to be connected. Energy analysis of routing protocols for UWSNs is presented by Domingo [15] and by Zorzi et al. [16]. An approach for minimization of energy consumption in multi-hop UWSNs is proposed by Geethu et al. in [17]. Javaid et al. have proposed delay-sensitive routing schemes for UWSNs in [18] and chain based communication in cylindrical UWSNs in [19].

Recently, considerable effort has been devoted to developing architectures and routing algorithms for terrestrial

DTNs. Routing in DTNs is investigated by Jain et al. [20] and underwater DTN routing is discussed by Tolba et al. [21]. Adaptive data collection in sparse UWSNs using mobile elements is proposed by the authors in [22]. A message ferrying approach for data delivery in sparse mobile ad hoc networks is presented in [23]. Guo et al. have proposed an adaptive routing protocol for UWSNs, considering it as a DTN [24]. Shah et al. [8] have presented a three-tier architecture based on mobility to address the problem of energy efficient data collection in a terrestrial sensor network. The same architecture with an enhanced analytical model has been presented by Jain et al. [25]. An M/G/1 queueing model is used by He et al. [26] for mobility-assisted routing, proposed for reducing and balancing the energy consumption of sensor nodes. The use of controlled mobility for low energy embedded networks has been discussed by Arun et al. [27]. AUV-aided routing for UWSNs is discussed by Yoon et al. [28] and Hollinger et al. [29]. A mobile geocast routing protocol for efficient data collection from underwater sensor nodes is proposed by Chen et al. in [30]. Polling-based scheduling in body sensor networks has been discussed by Motoyama [31] and the usage of message ferries in ad hoc networks is considered by Kavitha et al. [32]. Delay and lifetime performance of mobility-assisted periodic data collection in sparse UWSNs is presented by the authors in [33].

Even though the development of routing protocols for dense/connected UWSNs and the adaptation of DTN approaches for terrestrial sensor networks has already been addressed thoroughly, the energy-efficient data collection in resource-constrained sparse UWSNs has not been adequately investigated. In addition, proper analytical models and simulation environment for the evaluation of all performance metrics and for the study of trade-offs in different data collection schemes are still lacking. Since field tests in the ocean bottom are costly and mostly infeasible prior to sensor deployment, realistic models will be extremely useful for designing application-oriented networks. Also, the reported DTN schemes in UWSNs are either resource-hungry or not suitable for on-demand data collection applications. Most of the mobility-assisted data collection schemes for sensor networks focus on the offline scenario, where the data collection is carried out in a periodic manner. A potential problem with this periodic data collection is that, certain sensor nodes may not have data to upload, and visiting them just to find that no data to collect is not efficient.

The adaptation of mobility-assisted schemes for event-driven on-demand data collection in UWSNs and the enhancement of DTN schemes for delay-sensitive applications are still unexplored. In this paper, we first propose an energy-efficient on-demand data collection scheme suitable for non-time-critical applications in UWSNs and then we augment it with techniques to support delay-sensitive applications.

III. SYSTEM MODEL

We consider large and sparse UWSNs with possibly disconnected components and with mobile elements used for data collection. Though both 3-dimensional and 2-dimensional deployments are possible, we limit our study to 2-dimensional network as shown in Fig. 2, with sensor nodes anchored to the ocean bottom. The static sensors monitor the underwater surroundings, generate data and store it in the sensor buffer. They have limited non-rechargeable battery power and they communicate using acoustic links. The underwater sink, acting like a base station (BS) is responsible for gathering the sensed data from the static sensors by employing mobile collectors (MCs) and forwarding the collected data to the surface sink. MCs are mobile entities with large processing and storage capacity, renewable power, and the ability to communicate with static sensors, underwater sink and other MCs (if any).

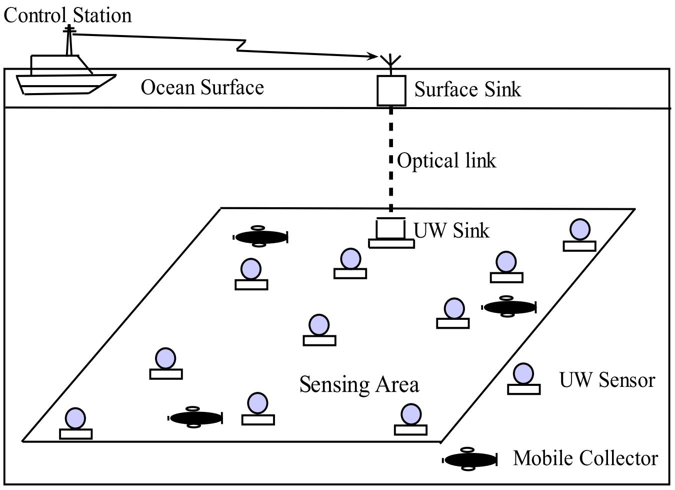

Figure 2. System Model : 2-D network with static sensors and MCs

When an event of interest occurs, the static sensors initiate data collection requests to the BS using direct or ad hoc multi-hop communication. The service request packet is assumed to be very short compared to data packets and the former will contain location information of the node, sensor buffer occupancy, priority of application, and any other relevant information like packet arrival rate or the delay-sensitivity of request. The BS will collect the requests and based on the system load and the delay constraints, it can decide the number of MCs needed and the sequence of visiting the nodes by each MC. Accordingly, BS will create one or more visit tables specifying the order of visiting the nodes and schedule the required number of MCs with a unique visit table assigned to each one of it. It maintains a service queue for the received data collection requests, and serve them with the first-come-first serve (FCFS) discipline. Serving a request means, the MC moves into the proximity of the corresponding sensor node and collects data from it.

As an MC moves in close proximity to (i.e., within transmission range of) a static sensor, the sensor's data is transferred to the MC and buffered there for further processing. We consider proactive controlled mobility of the MC, as the random mobility will fail to give latency bounds. Each MC will visit the sensor, collect the buffered data and proceed towards the next node in the visit table and this process is repeated. Sensors' bulk data communications are limited to transferring data to a nearby MC, so as to reduce energy consumption. Since the MCs are assumed to be resource-unconstrained and the BS (i.e., UW sink) is assumed to have a high speed link with the surface sink, we restrict our study to the collection of data from the static sensors deployed at the ocean bottom by the MC(s) travelling with a constant speed and pausing at the

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vicinity of sensors for data collection. The data is assumed to have been successfully delivered once it has been collected by the MCs.

IV. Analytical Study

In this section, we develop the necessary analytical expressions, the numerical results of which are compared with the simulation results in Section VI. All the features of acoustic channel, propagation and devices significantly affect the performance measures of the UWSN and hence the performance of data collection schemes.

A. Energy Efficiency

One important motivation for employing a mobile sink is that it increases the lifetime of the network by balancing the energy consumption of the sensor nodes. The energy consumption of the static nodes alone is considered, since the mobile node is assumed to be rechargeable or having much higher initial energy compared to the static sensors. The energy consumed by the static sensor nodes for sensing and processing is negligible compared with that for underwater acoustic data transmission, and hence we consider the energy consumption for data transmission only.

Underwater Channel: Propagation of sound underwater is at a very low speed of 1500 m/s and it occurs over multiple paths. Underwater acoustic communication channels are characterized by a path loss that depends not only on the distance between the source and the sink, but also on the signal frequency. Path loss is the sum of absorption loss (due to the transfer of acoustic energy in to heat) and spreading loss (due to the regular weakening of a sound signal as it moves outwards from the source). At shorter ranges, spreading loss plays a proportionally larger role compared with absorption loss. Spreading loss is frequency-independent, but depends on the geometry, where as the absorption loss increases with frequency.

The SNR of an emitted underwater signal at the receiver is expressed by the passive sonar equation as [34]

$$SNR = SL - TL - NL + DI \tag{1}$$

where SL is the source level, TL is the transmission loss, NL is the noise level, and DI is the directivity index. A micro pascal (μPa) is a measurement of pressure commonly applied to underwater sound. All quantities in (1) are in dB re μPa where the reference value 1 μPa corresponds to the intensity value of 0.67×10^{-18} W/m^2. Assuming a target SNR of 20 dB at the receiver, an ambient noise level of 70 dB (which is representative of underwater environments), and omnidirectional antennas for transmission and reception, we have the required source level SL = TL + 90 dB.

The transmission loss or the attenuation factor $A(l, f)$ of an underwater acoustic channel for a distance l and frequency f is given by (2) as [34]:

$$10\log A(l, f) = k.\ 10\log l + l.\ 10\log a(f) \tag{2}$$

where the first term is the spreading loss and the second term is the absorption loss. The spreading coefficient k = 1 for cylindrical spreading (shallow water scenario) and k = 2 for spherical case (deep water scenario). Thorp's formula [34] is used to express the absorption coefficient as:

$$10\log a(f) = \frac{0.11f^2}{1+f^2} + \frac{44f^2}{4100+f^2} + \frac{2.75f^2}{10^4} + 0.003 \tag{3}$$

The dependence of absorption loss on signal frequency implies the dependence of available acoustic bandwidth on communication distance. The resulting bandwidth limitation is a fundamental one due to the physics of acoustic propagation. Typical bandwidth of underwater channel is of the order of a few kilohertz at 10-100 km and 10 kilohertz at 1-10 km.

For a given target signal-to-noise ratio SNR_{tgt} at receiver, available bandwidth $B(l)$, and noise power spectral density $N(f)$, the required transmit power $P_t(l)$ can be expressed as a function of the transmitter-receiver distance l [16]. If P_r is the receive power, L is the packet size in bits, and α is the bandwidth efficiency of modulation, the energy consumption for the single hop data transfer of one packet becomes

$$E_{hop}(l) = \frac{P_r + P_t^{el}(l)L}{\alpha B(l)} \tag{4}$$

where $P_t^{el}(l)$ is the electrical power (in watts) corresponding to $P_t(l)$ in dB re μPa. Compared to P_r, P_t^{el} is very large and hence its contribution to the energy consumption of sensor nodes is significant. It is clear that the power consumption for data transfer over a single hop of length l increases with l, while the available bandwidth decreases with l. Hence, short range high bandwidth communication is to be adopted, whenever possible, to minimize energy consumption.

In order to investigate the superiority of the MC-based DTN model in conserving energy, let us compare the energy overhead associated with transferring one packet from the sensor to the BS using the ad hoc multi-hop approach and the *store-carry-and-forward* DTN approach. For this analysis purpose, we assume the network to be well connected so that ad hoc multi hop communication is possible from each sensor to the BS located at the centre. Also, for tractability of analysis, without losing generality, we assume the network layout to be circular. In order to quantify the potential savings in energy, we follow an approach similar to that of [27] with and without using a mobile node.

Assume N static sensor nodes with transmission range r are randomly and uniformly deployed over a circular area A of radius R with the sink located at the centre. We can calculate the minimum energy requirement of a node for transferring one packet generated by each node to the sink, using ad hoc multi-hop approach. Assuming ideal MAC such that no collisions occur, the packets originated by the nodes within a distance r from the sink need to be sent to the sink directly, whereas those generated by nodes at larger distances need to relayed by the inner nodes towards the sink.

If every static node located in the kth annulus of the circular area generates one packet, then the minimum number of transmissions due to packets originated from the kth annulus is $MinTx(k) = N\frac{A(k)}{A}k$, where $A(k)$ is the area of the k^{th} annulus and k = 1 for the innermost annulus. In the mobility-assisted data collection, irrespective of the position of the nodes, each static node transmits only the packets generated by it. Instead, in the case of multi-hop architecture, if every

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node generates 1 packet each, for a large value of N, on an average, the number of receptions and transmissions to be undertaken by a node in annulus k will be, respectively, $NodeRx(k) = \dfrac{A(k+1)}{A(k)} NodeTx(k+1)$ and $NodeTx(k) = 1 + \dfrac{A(k+1)}{A(k)} NodeTx(k+1)$, except for the outermost annulus $\left(k = \lceil \frac{R}{r} \rceil\right)$ where the corresponding values are 0 and 1.

The above analysis shows the increased relaying overhead of a sensor node with its proximity to the sink. If we define the *Energy Overhead Factor* (EOF) of a node as the ratio of the total number of transmissions from the node to the number of transmissions corresponding to the packets originated at that node, it is seen that all the sensor nodes have the same EOF (equal to 1 with an error-free channel) in MC-based scheme, while it is approximately equal to $NodeTx(k)$ in multihop network. High *Energy Overhead Factor* implies low energy efficiency.

A natural consequence of this unbalanced usage of stored battery power by the static sensor nodes in the adhoc multi hop network is the non uniformity in the residual energy of the sensor nodes after operation for a fixed amount of time. If E_i is the initial energy of a node, the maximum number of packet transmissions over a hop distance l that can be afforded by it before being completely drained off its energy will be $\dfrac{E_i}{E_{hop}(l)}$. Due to the absence of relaying overhead in MC-based architecture, the residual energy of all the nodes will be uniformly distributed in the network. At the same time, in the ad hoc multi hop network, due to the increased relaying overhead of the sensors with proximity to sink, residual energy of the 1-hop neighbours of the sink will be considerably small, compared to that of the nodes along the periphery of the network. This sink neighbourhood problem leads to premature death of the 1-hop neighbours of the sink, thus resulting in the disconnection of the sink from the rest of the network which means that the usefulness of the network is lost. Hence, in applications in which network lifetime is more important than message delay, mobility-assisted routing is the best option. In addition, in disconnected or partitioned networks in which both direct and ad-hoc multi hop communications are too costly in terms of energy consumption, the proposed mobility-assisted framework is the only option.

B. Data Collection Latency

Due to the mechanical movement of the MC to provide connectivity and facilitate data collection from the sensors located quite far apart, the latency of the sensed data in the mobility-assisted approach will be much larger compared to that in the other two approaches. In addition, since the sensed data is to be buffered till the next visit of the MC, buffer overflow and packet loss will occur if the sensor buffer space is not sufficient or if the inter-arrival time of the MC at a sensor is too high. Realistic estimation of these parameters using a proper analytical model is essential to assess the suitability of the proposed scheme for a particular application, based on the requirements of the application and the resource constraints of the network. A model matching the mobility-assisted on-demand data collection framework is a multiple-queue single-server queueing model or a *polling* model; a system of multiple queues accessed in cyclic or other specified sequence by a single server.

The traditional polling system consists of N infinite size queues and a single server that serves them one at a time [35]. The arrival process to queue i is assumed to be an independent Poisson process with rate λ_i. The customers arriving to queue i are assumed to have service time X_i, which is a random variable with first and second moments $E[X_i]$ and $E[X_i^2]$, respectively. After being served at queue i, the customer is assumed to leave the system. In the basic polling model, the server visits (or polls) the queues in a cyclic order and after completing a visit to queue i, it incurs a switch over period or *walk time*. The period during which the server continuously serves queue i is called the *service period* of queue i and the preceding period is called the *switch over* period of queue i. Mobile Collector and the static sensor buffers in our model correspond to the single server and queues of the polling model, respectively. Packets buffered in the sensor buffer, waiting for a transmission opportunity, are analogous to the customers waiting for service in the polling model. Travel time of the MC to move from one location to the next is modelled as the *walk time* and the sojourn time at each location to transfer data from the near by sensor's buffer to the MC is modelled as the *service time*.

According to the instant at which the MC leaves the sensor, different service policies are available, which prescribes how the packets (if any) from each sensor buffer will be collected. The important service policies applicable to on-demand data collection are: *Exhaustive*, *Gated* and *1-Limited*. In the *1-Limited* policy, at most one packet is collected from a sensor buffer at each visit. In the *Exhaustive* service, upon visiting a sensor, the MC collects all the packets until no more packets are available at that sensor buffer. In *gated* service, MC collects only those packets which are queued at its arrival instant. In other words, the packets that arrive during the course of the current data collection operation are not considered, where as under *Exhaustive* service policy, the MC collects the packets buffered so far plus the packets being generated when the already buffered packets are being transferred.

The inter-arrival times of service requests are assumed to be independent of MC travel time and data collection time. Assuming Poisson arrival of packets at rate λ_i at sensor buffer i, the traffic load at sensor i is defined by $\rho_i = \lambda_i \; E[X_i]$, $1 \leq i \leq N$, and the total offered load in the system is given by $\rho = \sum_{i=1}^{N} \rho_i$, where $E[X_i]$ is the mean packet transfer time. For system stability, ρ should be less than 1. If the mean of the total walk time is denoted by R, the mean cycle time of the MC is given by [35]

$$E[C] = \frac{R}{1-\rho} \tag{5}$$

For system stability, all packets that arrive during a cycle of the MC must be served during a cycle time. Hence, the mean service period for sensor buffer i during a cycle time will be

$$E[S_i] = E[X_i]\lambda_i E[C] = \frac{\rho_i R}{1-\rho} \tag{6}$$

and the mean number of packets collected from sensor buffer i in a polling cycle will be

$$E[\Phi_i] = \lambda_i E[C] \tag{7}$$

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Using (5) and (6), the average inter-arrival time of the MC at a sensor buffer can be evaluated as

$$E[I_i] = E[C] - E[S_i] = \frac{(1-\rho_i)R}{1-\rho} \quad (8)$$

We assume that the stability condition is achieved and the system is in steady state. The main performance measure in data collection is the mean waiting time of a packet in the sensor buffer, the exact analysis of which is difficult. Hence, we resort to the *pseudo-conservation law* based on the *stochastic decomposition* of unfinished work in an infinite-buffer polling system [35]. For analytical tractability, we assume a symmetric system with equal data generation rate λ and equal mean packet service time X at all sensors. Let the MC travel time between two consecutive locations be a random variable with mean and variance $E[Y]$ and Δ^2, respectively. Under the assumption of *exhaustive* service, The mean waiting time of the packet in the sensor buffer before the MC approaches it for data transfer can be obtained as [35]:

$$E[WQ]_{exh} = \frac{\Delta^2}{2E[Y]} + \frac{N\lambda E[X^2] + E[Y](N-\rho)}{2(1-\rho)} \quad (9)$$

With *gated* and *1-Limited* service policies, the expressions for mean waiting time become

$$E[WQ]_{gated} = \frac{\Delta^2}{2E[Y]} + \frac{N\lambda E[X^2] + E[Y](N+\rho)}{2(1-\rho)} \quad (10)$$

$$E[WQ]_{lim} = \frac{\Delta^2}{2E[Y]} + \frac{N\lambda E[X^2] + E[Y](N+\rho) + N\lambda\Delta^2}{2(1-\rho-N\lambda E[Y])} \quad (11)$$

At light loads (ρ approaching 0), the packet queueing delay is dominated by the travel time of the MC, and at heavy loads (ρ approaching 1) it is dominated by the sojourn time of the MC at the sensors. With *exhaustive* and *gated* service, ρ should be less than 1 to ensure stability of the system. For stable symmetric systems with a single MC and same parameters, the mean waiting time of the packets is smallest with *exhaustive* service policy and largest with *1-Limited*. Also, ensuring stability with *1-Limited* service requires the mean travel time of the MC to be smaller than the service time, which is not practically feasible. *Exhaustive* service policy is the optimal one as far as the average packet delay is concerned.

However, the effectiveness of data collection can not be quantified using the mean waiting time of packets alone. Another important parameter that matters, especially in delay-sensitive environments, is the fairness of data collection. Under the assumption of symmetric queues with equal data generation rates, the mean waiting time is independent of sensor location and packets generated by all sensors receive same treatment. Now, let us consider a situation in which the packet generation rates differ considerably among sensors, resulting in unequal loads offered by them. Let $\rho_i = \lambda_i E[X]$ be the load at sensor i. By following the approach used in [36], we observe that the dependence of mean waiting time at sensor i on the load offered by node i under the *exhaustive*, *gated* and *1-limited* service policies, can be expressed, respectively as

$$E[WQ_i]_{exh} \propto (1-\rho_i) \quad (12)$$

$$E[WQ_i]_{gated} \propto (1+\rho_i) \quad (13)$$

$$E[WQ_i]_{lim} \propto (1-\rho+\rho_i) \quad (14)$$

Equations (12), (13), and (14) reveal that the packets generated by different nodes are treated differently, based on the service policy. In *exhaustive* service, packets arriving to light-traffic sensors have longer average waiting time than those arriving to heavy traffic sensors. But in *gated* and *1-limited* service schemes, it is in the other way. The 1-limited service policy is usually considered to be a fair policy since only one packet is collected from each sensor in a cycle of the MC. *Exhaustive* service is less fair since one heavily loaded sensor can dominate the system, and will occupy the MC for a long time. This means that, although the average waiting time may be smaller for *exhaustive* service compared to the other two service policies, the maximal waiting time at the lightly loaded sensors may be larger. Hence, though *exhaustive* service gives optimum performance for delay-tolerant applications, it is not the optimum one for delay-sensitive applications. In delay-sensitive applications, if the packets are not collected before their deadline or expiry time, they will have to be discarded, thus reducing the number of packets receiving on-time service.

Computation of the average queueing delay of packets using (9) requires the knowledge of the mean and variance of MC travel time. To evaluate these parameters, we follow an approach similar to that in [26]. In our system model, the BS maintains a queue to store the received requests and serve them according to its service discipline, the simplest one being first-come-first-served (FCFS). We assume a square sensing field with static sensor nodes uniformly distributed in the network. The arrival of data collection requests to the BS is assumed to be a Poisson process and the communication is assumed to be loss-less. Due to the assumption of uniform distribution of node deployment, the locations of data collection requests can be treated as random points in the square sensing field, based on which the travel time of the MC between two consecutive locations can be evaluated. The probability density function of the distance between two arbitrary points in a unit square is given by

$$f_D(d) = \begin{cases} 2d(\pi - 4d + d^2) & 0 \le d \le 1 \\ 2d[2sin^{-1}(\frac{1}{d}) - 2sin^{-1}\sqrt{1-\frac{1}{d^2}} \\ \quad + 4\sqrt{d^2-1} - d^2 - 2] & 1 \le d \le \sqrt{2} \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

Using this, if the MC moves at a constant velocity V, the mean and variance of the MC travel time between two arbitrary points in a unit square area can be obtained as $0.4555/V$ and $3.95/V^2$, respectively.

Once the mean queueing delay of the message has been determined, the expected response time of the message, being the sum of its queueing delay in the sensor buffer plus service time by the MC (packet transmission time) can be obtained as

$$E[T] = E[WQ] + E[X] \quad (16)$$

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The sensor buffer occupancy of a tagged sensor will be maximum (equal to λ times the MC cycle time) when the MC approaches it for data collection and minimum (equal to zero for *exhaustive* service) when it leaves the sensor. The average sensor buffer occupancy

$$E[N_Q] = \lambda E[WQ] \tag{17}$$

and the number of messages in the system (in queue and in service)

$$E[N] = \lambda E[T] \tag{18}$$

The message latency and sensor buffer occupancy increase with the number of nodes N, packet arrival rate λ and the size of the deployment area, where as it decreases with the speed of the MC. However, the speed of the MC can not be increased beyond a limit (of the order of 20 m/s) due to practical limitations. Thus, the delay performance of the MC-based DTN scheme with a single mobile element is not at all comparable with that of ad hoc multihop network (of the order of several minutes for the former, while a few seconds for the latter). Correspondingly, the buffer requirement of static sensors is negligible in an ad hoc network, while it is considerably high in the MC-based scheme. Hence, the MC-based data collection approach, as such, is suitable only for delay-tolerant applications. Techniques to improve the delay performance so as to extend its suitability for delay-sensitive applications will be discussed in Section V.

C. Packet Delivery Ratio (PDR)

The Bulk Service Queueing model for mobility-assisted data collection as used by Jain et al. in [25] permits us to evaluate the success ratio of data collection. Here, the data generation and MC arrival processes are assumed to be renewal processes with average rates λ and μ respectively. It is also assumed that when an MC visits a sensor, no other sensor is near-by and contending for service. A maximum of K packets is transferred from the sensor to the MC in each visit. Data transmission does not incur any loss and the only loss (if any) is due to sensor buffer overflow.

Since a maximum of K packets are collected in one visit of the MC, the net service rate is $K\mu$. If the random variable Q represents the queue length at the MC arrival instant, the average of Q is used as a measure of the sensor buffer occupancy, which in turn, decides the Packet Delivery Ratio (PDR). As the service size is K packets, and if Q (queue length at MC arrival instant) is less than K then only Q packets are served, clearly

$$PDR_{MC} = \frac{\mu E\left[min(K, Q)\right]}{\lambda} \tag{19}$$

Assuming *exhaustive* service policy, all the data generated and buffered so far is transferred when the MC visits the sensor. Hence the amount of data in the sensor buffer when the MC approaches it, will be the minimum of : (i) the amount of data generated in one cycle time of the MC, and (ii) the sensor buffer size. For Poisson data generation, the amount of data generated in an interval depends only on the length of the interval and hence the expected sensor buffer length becomes

$$E[Q] = \frac{\lambda}{\mu} \tag{20}$$

For a fixed service size K, $E[Q]$ increases with λ and decreases with μ.

In a stable system, with the assumption of large K and infinite buffer space, and on substituting the value obtained from Eqn. (20) into (19), we get the Packet Delivery Ratio to be 1 with this model. If the sensor buffer space or the service size K is not sufficiently large to accommodate the incoming traffic without buffer overflow, packets will be dropped and PDR is reduced. Hence the sensor buffer size SB and service size K should be designed such that no packet is lost due to buffer overflow, for a given data generation rate λ and the MC arrival rate μ. However, sensor buffer size SB is limited by the size and hardware cost of the sensor memory.

Assuming ideal channel, no MC failures, and sufficiently large buffer space to avoid buffer overflow, the PDR will be theoretically 1 for delay-tolerant applications. But practically, there exists a probability that a node is not visited by the MC within a specified time period or deadline. In such situations, the significance of the data may be lost if the application is delay-sensitive, or the data itself may be lost due to buffer overflow. Since these two factors limit the PDR in MC-based data collection, care is to be taken to ensure that the sensors are equipped with sufficient buffer space as dictated by the load conditions, and the buffered packets are collected before their significance is lost, in delay-sensitive applications.

In the case of ad hoc multi hop network, the PDR is dependent on the node density, since a contemporaneous source-to-sink path should exist for successful packet delivery. To investigate the impact of node density on PDR, we assume the use of Vector-based Forwarding (VBF) as the routing protocol and follow the approach similar to the one used in [13] with appropriate modifications for 2-dimensional deployment. Assuming N nodes each with transmission range r, uniformly deployed in a square area of side A, the density d of nodes in the network = $\frac{N}{A^2}$. Now, if B represents the radius of the routing pipe in VBF, and P_l represents the loss probability of packets, it can be shown that the probability of successful delivery of a packet over h hops

$$PDR_{adhoc} = \left[1 - P_l^{\frac{1}{3}\pi B r^3 d^2}\right]^h \tag{21}$$

Equation (21) shows that, for a fixed packet loss probability P_l, probability of successful packet delivery increases with node density, width of routing pipe, and transmission range of sensor nodes in the ad hoc multi hop network that uses VBF. Increase in the width of routing pipe or the transmission range of sensor nodes will result in increased energy consumption, where as high node density is not feasible due to cost constraints and deployment restrictions. Thus, achieving a reasonably good delivery performance using ad hoc multi hop approach for event-driven data collection in sparse and energy-constrained environments is almost impossible. At the same time, probability of successful packet delivery is independent of node density in MC-based data collection, thus making it the better option for sparse and constrained networks, as far as successful data delivery is concerned.

V. Performance Enhancement

In this section, we investigate techniques to improve the delay and delivery performance of the basic DTN

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scheme with a single MC. Based on the study of latency performance in Section IV, we propose four techniques to reduce data collection latency and to enhance the support for delay-sensitive applications: (i) Use of multiple mobile collectors, (ii) Activity-based periodic polling, (iii) Hybrid architecture with both static and mobile sinks, and (iv) Hierarchical organization of mobile collectors. In the first technique, more than one mobile collectors are used, thus increasing the effective service rate, thereby reducing the message waiting time. In the second one, different priority is assigned to different nodes (based on data generation rate, traffic class, etc.), and the order and/or frequency of polling or visiting the static sensor nodes is modified to account for the differing activity conditions. The third technique uses a hybrid architecture of both ad-hoc multi-hop and mobility-assisted schemes, exploiting the advantages of both. In the fourth one, the MCs are organized in a hierarchical manner such that application-oriented differentiated packet delivery is made possible. We present these four techniques, as well as analytical expressions for the evaluation of their latency and delivery performance.

A. Multiple Mobile Collectors

In our basic polling model, there is only a single server, servicing a number of queues in a cyclic manner, which has been found to be unsuitable for delay-sensitive applications. When the input load is too high or the deadline requirements of the application are quite demanding, the BS may decide to schedule multiple MCs with different visit tables assigned to each. When the number of MCs is increased, the model is converted to a Multi Server Multi Queue (MSMQ) system or *multi server polling model*, the exact analysis of which is not available. Assuming independent MCs, symmetric Poisson-distributed data arrivals, independent and identically distributed *service times* and *walk times* and no server clustering, an approximate expression for the mean waiting time can be derived following the approach used in [37]. The total average amount of work arriving to the MSMQ per unit amount of time remains unchanged (= $N\lambda E[X]$) as in the single server system. At steady state, the MCs evenly share this load and if S is the number of MCs, the utilization factor of any one MC becomes

$$\rho_s = \frac{N\lambda E[X]}{S} \tag{22}$$

The time interval between two consecutive arrivals of any one MC at a tagged sensor buffer q can be evaluated as

$$E[C_q] = \frac{R}{S - N\lambda E[X]} \tag{23}$$

for $q = 1..N$.

Since stability is guaranteed by the finiteness of average cycle time, to ensure stability, the number of MCs

$$S > N\lambda E[X] \tag{24}$$

In other words, the packet arrival rate

$$\lambda < \frac{S}{NE[X]} \tag{25}$$

To get the mean message waiting time in the multiple MC case, the expression for mean waiting time in single MC case as given by (9) can be modified by substituting $E[X]/S$, $E[X^2]/S^2$, $E[W]/[S-(S-1)\rho]$, and $E[W^2]/[S-(S-1)\rho]^2$ in place of, respectively, $E[X]$, $E[X^2]$, $E[W]$, and $E[W^2]$. Thus, the mean waiting time in the multiple MC situation becomes

$$E[W_q] = \frac{E[W^2]}{2E[W][S-(S-1)\rho]} + \frac{N\left[\frac{\lambda E[X^2]}{S} + \frac{E[W](S-\lambda E[X])}{S-(S-1)\rho}\right]}{2(S - N\lambda E[X])} \tag{26}$$

Similar to the basic single MC network, here also, the expected waiting time of the packet in the sensor buffer and the average sensor buffer occupancy increase with the packet arrival rate λ, number of sensors N and the size of the deployment area and reduces with the speed of MCs. However, both performance metrics decrease with the number of MCs S, thus making the model better suited for heavy input load conditions, memory-limited sensors, and delay-sensitive applications. While the delay and delivery performance are improved by the use of multiple data collectors, energy consumption and network lifetime are not affected, since the number of transmissions and the range of transmission are not changed by the use of more number of MCs. Taking into account the higher cost of MCs compared to ordinary sensor nodes, minimum number of MCs that satisfy the application-specific latency constraints may be used.

B. Activity-based Priority Polling

In practical situations, all the sensor nodes may not be generating data at the same rate and hence our earlier assumption of symmetric queues may not be valid always. More packets will be generated in some areas having high activity that require immediate attention, while some other areas may be generating very few packets only. In such situations, it will not be efficient and fair to visit all the sensors in a cyclic manner. When the data generation rates among the static sensor nodes vary considerably, it will be better to visit the nodes with higher arrival rates more frequently, rather than following the cyclic order. In cyclic polling, the server visits the queues in the order $Q_1, Q_2, ..., Q_N, Q_1, Q_2, ..., Q_N, ...$ In *Periodic* polling, the server visits the queues in a fixed order specified by a *polling table* in which each queue occurs at least once [38].

Consider the single server polling model with the difference that the arrival rates at the queues are not equal, instead the packet arrival intensity at sensor i is λ_i, i = 1,...N. The offered load at sensor i is $\rho_i = \lambda_i E[X_i]$, where $E[X_i]$ is the mean service time at sensor i. The total offered load in the network $\rho = \sum_{i=1}^{N} \rho_i$. The MC visits the sensors according to a periodic - not necessarily cyclic - polling scheme. The approach followed in [38] can be used to minimize the workload in the system and to ensure *fairness* among the sensors by using optimum visit frequencies. For *exhaustive* service, assuming W_i to be the switch-over time from queue $i-1$ to queue i, the visit frequency at node i becomes

$$f_i^{exh} = \frac{\sqrt{\rho_i(1-\rho_i)/W_i}}{\sum_{j=1}^{N} \sqrt{\rho_j(1-\rho_j)/W_j}} \tag{27}$$

Now, all the nodes are not visited equally in a cycle, instead the nodes having more buffered data waiting for transmission

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(due to higher packet generation rate) will be visited more often than those with less buffered data. Assume that sensor i is visited n_i times in a cycle of the MC and these visits are spread as evenly as possible. Considering the interval between two successive MC visits to a node i as a sub cycle, the mean residual time of a sub cycle of i will be

$$ERSC_i \propto \frac{E[C]}{n_i} \tag{28}$$

where $E[C]$ is the mean time for one complete visit cycle of the MC according to the polling table. Now the mean waiting time at node i will be [38]:

$$(W_q)_i \propto (1 - \rho_i)\frac{E[C]}{n_i} \tag{29}$$

which shows that the sensor nodes with high data generation rates (having high values of ρ_i and n_i) get better treatment and majority of the generated packets get good treatment, in terms of waiting time and buffer requirement.

C. Hybrid Architecture

The scheme of employing a hybrid architecture of both ad hoc multi-hop and mobility-assisted data collection approaches is proposed here to provide application-oriented packet delivery. As illustrated in Fig. 3, there exist both static and mobile sinks in the network, the former one for collecting delay-sensitive critical data and the latter one for delay-tolerant bulk data. While setting up the network, the static sensors are organized in to a number of routing trees rooted at the static sink located at the centre of the deployment area. Mobile sink (MS) covers the entire network by following a trajectory suitable for periodic data collection, as shown in the diagram. It sojourns at predefined locations so as to collect buffered data from the near by sensors. The number of sojourn points and the transmission range of sensor nodes can be adjusted according to the node energy constraints and the message deadline requirements.

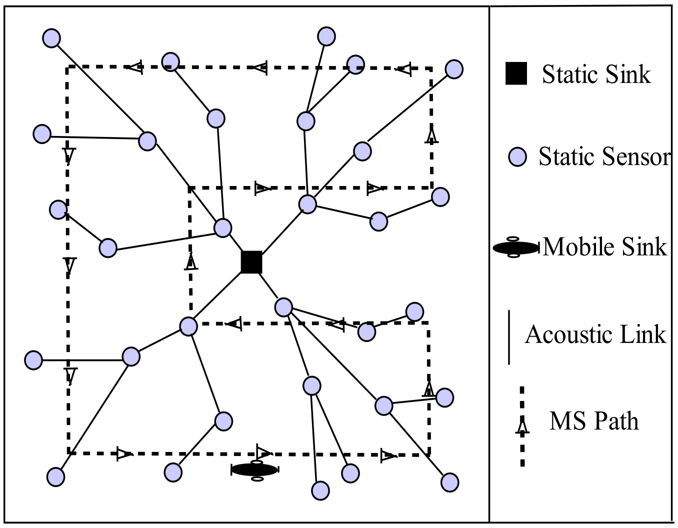

Figure 3. Hybrid architecture with static and mobile sinks

Each sensor node always keeps up to date information about its static path to the static sink. Any emergency information that requires immediate attention like disaster warning, hazard detection, etc., is transferred to the static sink using the ad hoc multi hop path, provided such an end-to-end contemporaneous path exists. If not, the sensor has to either transmit at a higher power level to improve connectivity at the expense of increased energy consumption. If that too fails, the node has to wait for the arrival of the MC. Because ad hoc multi-hop communication is used only for applications with tight deadline requirements, the sink neighbourhood or hot-spot problem is not expected to be as severe as in the pure ad hoc multi-hop approach. Hybrid architecture permits us to achieve trade-off between network lifetime and timeliness of data collection, though with increased complexity of keeping two data collection approaches in the same network.

The performance metrics like energy consumption, energy balancing, packet latency, and sensor buffer occupancy depend on the type of communication (ad hoc multi-hop or mobility-assisted), which in turn, depends on the nature of application: delay-sensitive or delay-tolerant. For delay-tolerant applications, mobility-assisted data collection with a single MC is made use of. The MC visits the sensors as discussed in the basic model in Section III for event-driven data collection or by following a trajectory as illustrated in Fig. 3, covering the entire deployment area in a cyclic fashion for periodic data collection. For symmetric queues, the delay performance of data collection can be evaluated using (9), (10), (16), and (17). For delay-sensitive applications, ad hoc multi-hop connection to the static sink is used, whose delay is negligible compared to MC-based approach, thus ensuring timely delivery of emergency data. However, for successful packet delivery, end-to-end connectivity is to be ensured, failing which packets will be dropped. We use VBF protocol [13] for multi hop routing. In VBF, the PDR is dependent on the density of nodes, width of routing pipe and transmission range of sensor nodes.

D. Hierarchical Architecture

This architecture is suitable for large networks with periodic and event-driven data collection, supporting both delay-tolerant and delay-sensitive applications. Unlike the hybrid architecture, there is no static sink here. The static nodes as well as the mobile collectors are organized into a number of tiers forming a hierarchical architecture. We have considered three tiers, which can be extended further according to the size of the network and the requirements of the application. As illustrated in Fig. 4, the entire network is organized into four non-overlapping clusters and three hierarchical tiers. All static sensor nodes have the basic responsibility of sensing the environment and buffering the sensed data. Additionally, they selectively forward delay-sensitive traffic to nodes that are more frequently visited by the MC.

The entire network area is divided into 16 equal square partitions (not shown in the diagram). During the set up phase of each round of data collection, Tier-3 nodes in each partition select one of them as a Tier-2 node based on residual energy; and Tier-2 nodes belonging to each cluster select one of them as a Tier-1 node based on proximity to the centre. Hence, there will be a maximum of 16 Tier-2 nodes and four Tier-1 nodes in the network under consideration. Tier-1 MC (MC1) cycles among the Tier-1 nodes alone, while the Tier-2 MC (MC2) cycles among the Tier-2 nodes. Tier-3 MC (MC3) follows a

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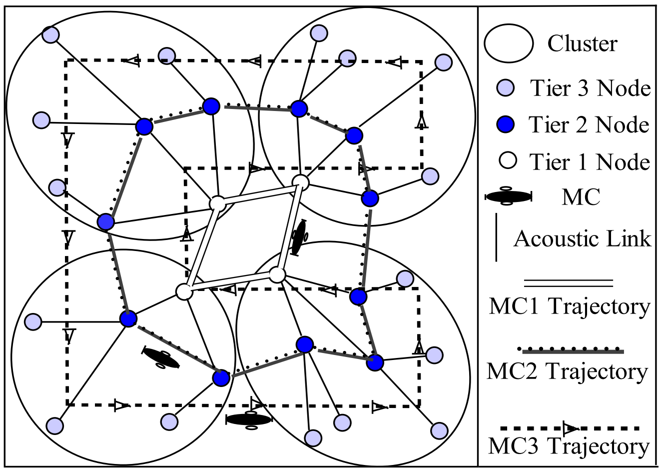

Figure 4. Hierarchical architecture

trajectory passing through the centres of all the 16 partitions, sojourning at the 16 locations for collecting delay-tolerant data (if any) from the Tier-3 nodes. Cycle time of the MC1 will be very small compared to its counterparts in other tiers. In other words, Tier-1 nodes are visited more often than Tier-2 nodes, while the latter is visited more often than Tier-3 nodes.

Based on the urgency of the sensed data, packets may be buffered at the originating node or forwarded to a node in the next tier. Upon receiving a packet, a Tier-3 node will check its delay-sensitivity. If it is delay-tolerant, it will be stored in the sensor buffer, to be collected by MC3. Otherwise, the packet will be forwarded to the respective Tier-2 node, where it will be buffered, to be collected by MC2. Tier-2 node will check whether the packet is time-critical and if so, it will be immediately forwarded to the Tier-1 node. Since the Tier-1 nodes are visited quite frequently, the latency performance will be good. Data is assumed to have been successfully delivered once it has been collected by any one MC.

For performance evaluation, we consider a square deployment area of size 2000m $\times$ 2000m and velocity of all the MCs to be 15 m/s. MC3 follows a trajectory as shown in Fig. 4 and for analytical tractability, trajectories of MC2 and MC1 are approximated by square paths of side 1000m and 500m, respectively, around the centre of the deployment area. Packet generation is assumed to be Poisson and symmetrical, with 10% of the generated packets being time-critical and 30% of the generated packets being delay-sensitive, but not time-critical. The maximum and average waiting times of each category of packets can be evaluated using (9) and (10). Unlike the hybrid architecture, here no multi-hop communication is used and hence PDR is independent of node density.

VI. Analytical And Simulation Results

Extensive simulations were done to validate our analytical results using the NS-2 based network simulator for underwater applications, Aqua-Sim. The unique characteristics of UWSNs like acoustic attenuation model, acoustic channel model, 3-dimensional deployment and very slow propagation make the existing terrestrial network simulators unsuitable for UWSN simulation study and resulted in the development of Aqua-Sim. Aqua-Sim is an event-driven, object-oriented simulator written in C++ with an OTCL (Object-oriented Tool Command Language) interpreter as the front-end. Following the object-oriented design style of NS-2, all UWSN entities are implemented as classes in C++. Several interesting works like [39] and [40] have already been implemented in this simulation system.

The codes simulating underwater sensor nodes, traffic, acoustic channels, MAC protocols, and a few routing protocols are already available in Aqua-Sim. We have incorporated in it, the DTN concepts of beaconing, *contact* discovery and *store-carry-and-forward* and the polling based (*exhaustive* service) data collection. Energy model with tunable transmit power and latency minimization techniques like the use of multiple mobile collectors, visit-frequency based priority polling, hybrid architecture with static and mobile sinks, and the hierarchical organization of sensors and mobile collectors were also implemented.

We have used the VBF routing protocol for implementing the multi hop network for comparison purpose and the MC-based DTN protocol developed by us in Aqua-Sim for the mobility-assisted short-range data collection purpose. We have employed the *Broadcast MAC* protocol with carrier sensing and collision avoidance, in which the MAC first senses the channel when a node has packet to send. If the channel is found to be free, the node broadcasts the packet, otherwise it backs off. If the number of back off exceeds a limit, the packet is discarded.

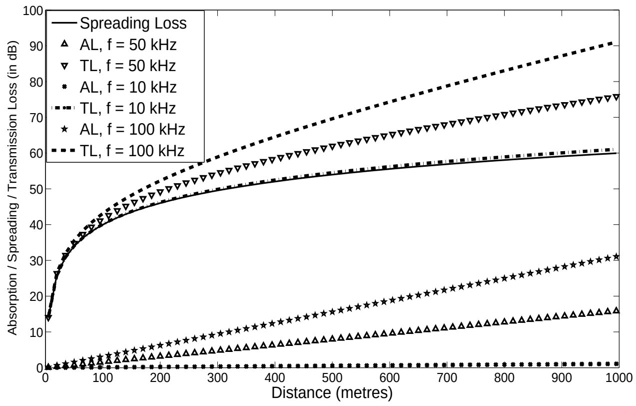

Figure 5. Transmission Losses in the deep water scenario (Analytical): AL - Absorption Loss, TL - Transmission Loss

Fig. 5 illustrates the impact of frequency of operation and distance between the sensor nodes on the total transmission loss in deep water, as expressed by (2). We have assumed a target SNR of 20 dB and noise level of 70 dB for this result. Transmission loss is the sum of spreading loss and absorption loss. Spreading loss is independent of frequency and its variation with distance is quadratic in deep water. Absorption loss increases with frequency and distance between nodes.

Higher transmission loss at larger source-to-sink distance leads to increased energy consumption as illustrated in Fig. 6 for the deep water scenario. Assuming tunable transmit power P_t, receive power P_r fixed at 0.075 W, and packet length L

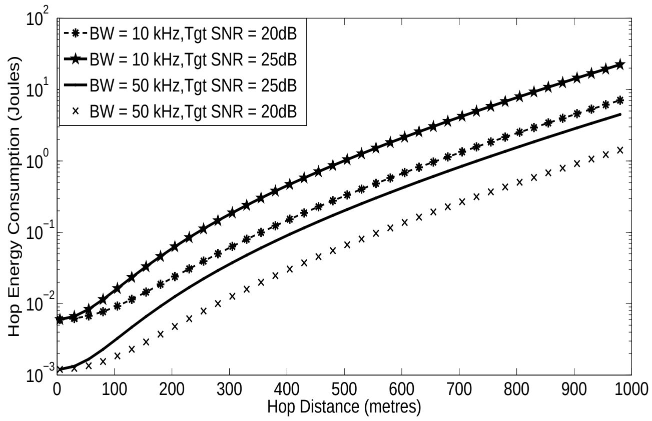

Figure 6. Hop Energy Consumption for varying hop length and bandwidth

fixed to 400 bits [9], the effect of hop length, target SNR, and channel bandwidth on per-hop energy consumption as expressed by (4) is plotted here. Decreasing the source to sink distance reduces the transmission loss and increasing the bandwidth reduces the time required for transmission. Both situations lead to reduced transmit energy consumption, thus validating the suitability of short range communication in energy-constrained environments.

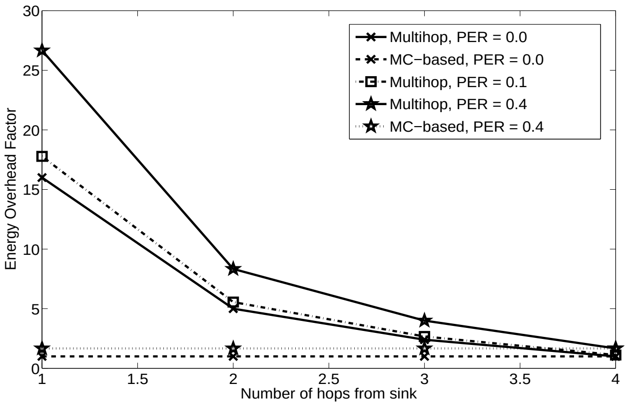

Figure 7. Transmit Energy Overhead of static sensor nodes with multi-hop and MC-based schemes for different PERs

Assuming static sensor nodes having transmission range 250m uniformly distributed in a circular area of radius 1000m, a comparison of the *Energy Overhead Factor* (defined in Section IV.A) in mobility-assisted and ad hoc multi-hop approaches is illustrated in Fig. 7. The variation of *EOF* of a node with its proximity to sink is also shown. As expected, nodes in the mobility-assisted approach have reduced and balanced overhead, irrespective of their location relative to the sink. At the same time, the relaying overhead of a sensor increases with its proximity to sink in the ad hoc multi hop network. The impact of packet error rate (PER) on the energy overhead due to non-ideal channel is also shown in this figure. Due to increased relaying overhead, the nodes nearer to the sink will deplete their battery power soon. If we define the lifetime of a network as the timespan till the first node dies due to energy depletion, it is evident that the use of mobile elements for data collection leads to enhanced lifetime of the network due to reduced and balanced energy consumption among the sensor nodes.

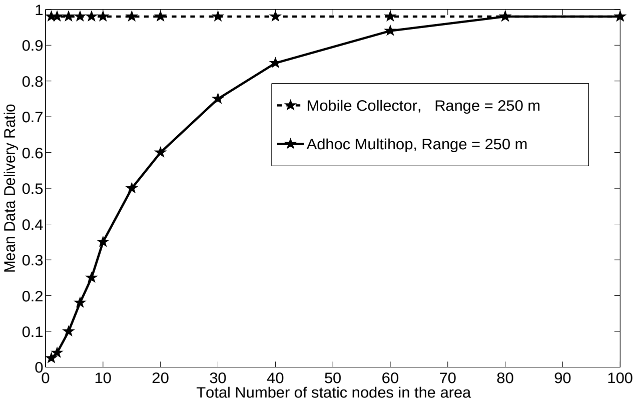

Figure 8. PDR with multi-hop and MC-based data collection (Delay-tolerant application)

The variation of PDR with node density is shown in Fig. 8. Assuming infinite buffer size and no communication errors, ideally the PDR should be 1 for the MC-based data collection scheme, irrespective of the number of nodes in the network. For ad hoc multi-hop network, as indicated by (21), delivery ratio is very small for low node density due to end-to-end connectivity issues. As the node density is increased, PDR increases initially and finally reaches a maximum value and then remains almost constant. For the MC-based scheme, delivery ratio is independent of node density. Hence, it is the ideal one for sparse and disconnected networks, provided the network lifetime and successful data delivery are of prime concern and the application is not time-critical. If the sensors are not equipped with sufficient buffer space to avoid buffer overflow at high loads, packets will be dropped and PDR reduced. Also, in delay-sensitive applications, if the packets are not received before the application-specified deadline, significance of the data will be lost, which is equivalent to loss of packets that leads to reduced PDR.

Assuming controlled motion of a single MC with speed 15 m/s for on-demand data collection in a square area of size 2000m $\times$ 2000m with 10 nodes randomly and uniformly distributed in this area, analytical results illustrating the variation of mean waiting time of a packet, mean cycle time of MC, mean travel time of the MC in a cycle, mean sojourn time of the MC in a cycle and the inter-visit time of the MC at a tagged sensor node were obtained for varying load conditions using our basic model and plotted in Fig. 9. The sensors are visited by the MC based on FCFS policy as indicated by the visit table assigned to it and the sensor buffers are serviced according to the *Exhaustive* service policy. As expected, the waiting time of packets, cycle time of the MC, sojourn time of the MC in a cycle, and the inter-visit time at a tagged node increase with the system load. However, the walk time of the MC is independent of the load. At light loads, the cycle time of the MC and the waiting time of the packets are dominated by the travel time of the MC, while at heavy loads, they are dominated by the sojourn time (pause time of the MC near

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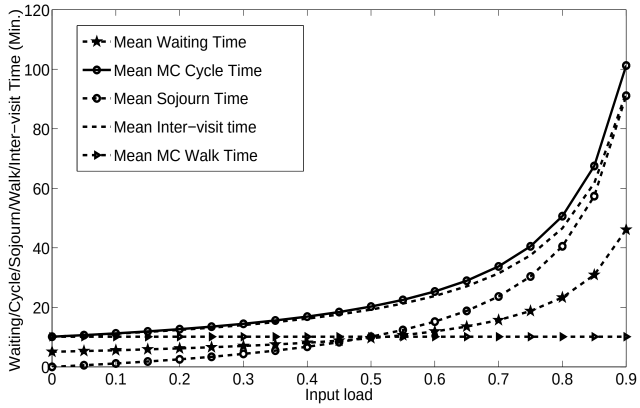

Figure 9. Mean packet waiting time / Cycle time /Data Transfer Time / Inter-visit Time with polling model (Analytical)

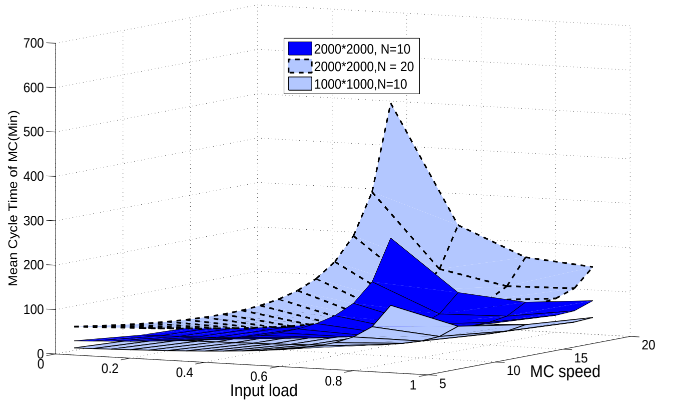

Figure 11. Mean Cycle time variation with load, speed and deployment area (Analytical)

the sensor for data transfer). When the system load approaches unity, stability is lost and the delay values grow exponentially. This situation should be avoided, otherwise delay will not be bounded and sensor buffers will overflow. The results also act as a guide to decide when to go for multiple mobile collectors for meeting the delay constraints specified by the application.

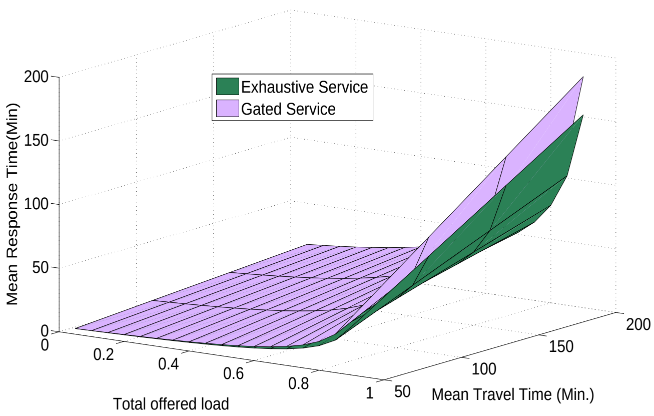

Figure 10. Mean Response Time with different service policies (Analytical)

The variation of mean response time of a packet, as evaluated using (16) for varying input load under the *exhaustive* and *gated* service policies, is illustrated in Fig. 10. Compared to *gated* service policy, *exhaustive* service policy results in smaller mean waiting time and response time, and hence more optimal. For a fixed input load, response time increases with the mean travel time of the MC. Hence, efficient MC scheduling policies can be employed to reduce the travel time and to improve the latency performance of data collection.

Assuming *exhaustive* service policy of the MC, the impact of factors like input load, MC speed, number of sensors and dimensions of the sensor deployment area on the average cycle time of the MC is illustrated in Fig. 11. As expected, the MC cycle time increases with the number of nodes and area of deployment, whereas it decreases with MC speed. The sensor buffer occupancy, shown in Fig. 12 also exhibits a similar behaviour. The buffer occupancy is zero when the MC leaves a sensor and maximum when the MC approaches it. If the sensor buffer space is not sufficiently high, packets will be lost due to buffer overflow, resulting in reduced PDR.

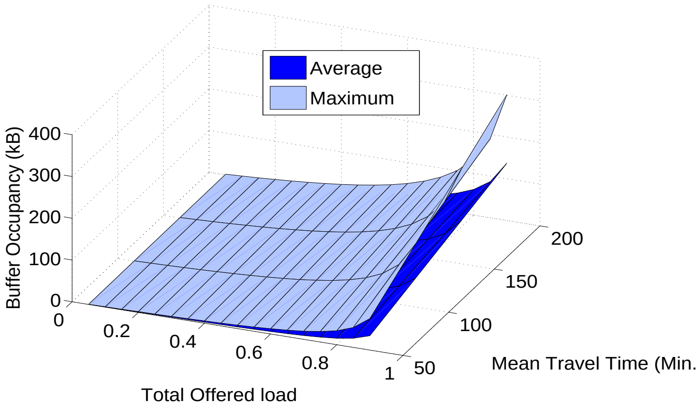

Figure 12. Variation of sensor buffer occupancy (Analytical)

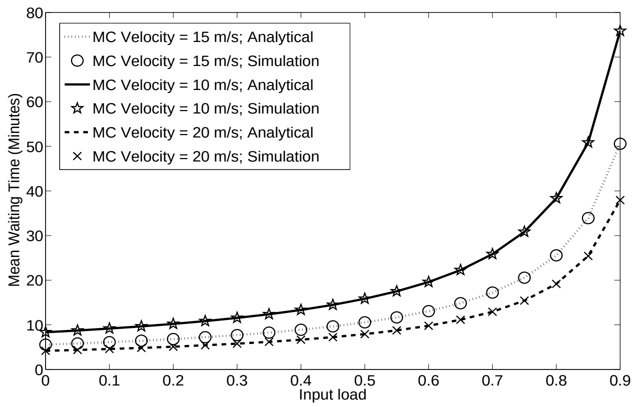

Figure 13. Waiting Time variation with load and MC speed

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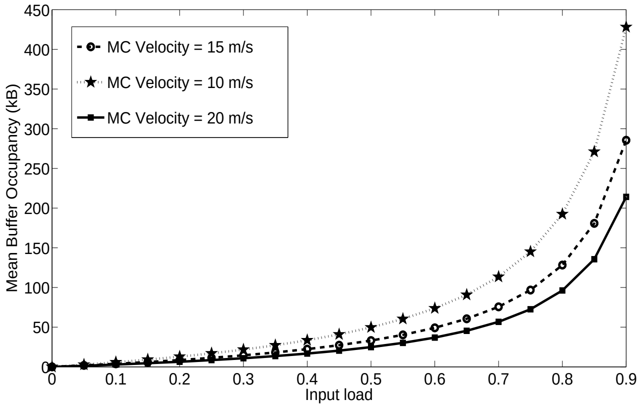

Figure 14. Variation of Mean Buffer Occupancy with speed of MC

Simulations were done with the same network conditions and fixing the packet size at 50 Bytes and data rate at 10 Kbps. The mean waiting time obtained for different values of data generation rate and different speeds of the single MC are plotted in Fig. 13. The sensors are equipped with sufficient buffer space so that packets are not lost due to buffer overflow. For a fixed number of nodes, deployment area, packet size, and MC speed, the variation in input load is effected by varying the packet generation rate. The mean waiting time increases with the input load and decreases with the speed of the MC. Analytical and simulation results show close agreement, validating the suitability of our model.

The analytical results showing the impact of input load and MC speed on the mean sensor buffer occupancy in the basic framework has been illustrated in Fig. 14. Similar to the waiting time of packets, the average number of packets in the sensor buffer awaiting their turn for transmission also increases with input load and decreases with MC speed. This result gives us an idea about how to decide the buffer size of the sensors, considering the load conditions and MC speed.

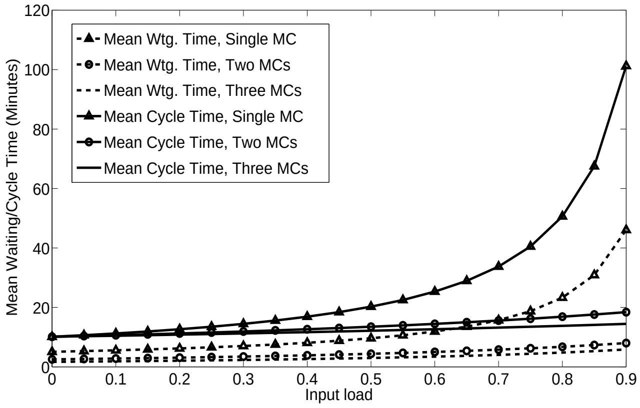

Figure 15. Delay Performance with Multiple MCs

Since it is not practical to have MC speeds above 20 m/s, use of multiple MCs is to be adopted for heavy traffic environments, delay-sensitive applications, and very limited sensor buffer situations. Keeping the same network conditions as used in our basic model, the results showing the impact of number of MCs on packet delay performance is plotted in Fig. 15. As expected, for a fixed number of MCs, the mean waiting time increases with input load. Also, for a fixed load and MC speed, as the number of MCs is increased, the queueing delay is decreased. The sensor buffer occupancy also shows the same behaviour, as illustrated in Fig. 16. Simulation results related to mean waiting time and sensor buffer occupancy have shown close agreement with the analytical ones.

However, the cost of MCs is much larger compared to that of ordinary sensor nodes and a large number of MCs will lead to interference problems and increased complexity of implementation. Hence, the optimum number of MCs may be selected based on the delay constraints of the application and the cost considerations of MC deployment. In the scenario we have considered, it is observed that the performance gain obtained by using 3 MCs over 2 MCs is much less compared to that obtained by using 2 MCs over a single one. The results act as a guide to decide the number of MCs, based on the application-specified delay constraints and sensor-specific buffer space constraints.

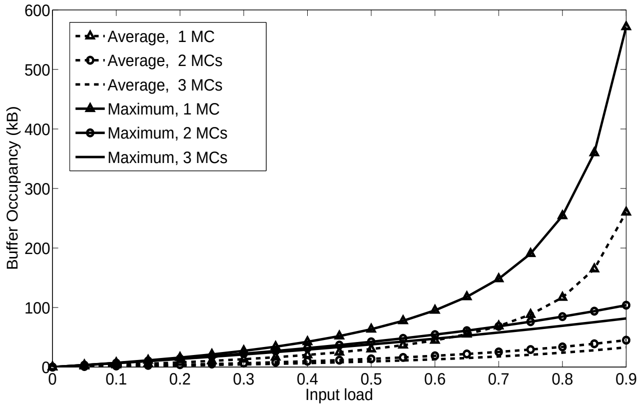

Figure 16. Sensor Buffer Occupancy with Multiple MCs

To demonstrate the improvement in delay performance due to activity-based priority polling, we have considered the same network conditions with 10 sensor nodes randomly and uniformly distributed in a square area of size $2000m \times 2000m$, generating packets (of size 50 bytes) at different rates, a single MC moving at 15 m/s, and the channel having a data rate 10 kbps. Table I gives the visit frequency and the mean waiting time for different packet arrival rates. Based on simulation for a fixed finite amount of time, the packets failing to get service due to the single MC not arriving within a fixed time interval is also noted.

With same packet size and data transmission rates, the nodes with high packet generation rate contribute more to the system load. In our activity-based priority polling scheme, nodes with higher load receive preferential treatment in terms of number of visits in a single cycle of the MC. The more the frequency of MC visits at a sensor node, the less the queueing delay of packets in the buffer and higher the chance of being collected before their application-specified deadline. In the scenario we have considered, node G generates 8 packets per minute, and these packets experience an average queueing

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TABLE I. MEAN MESSAGE WAITING TIME AND PDR AT DIFFERENT NODES

Node id	Arrival Rate (Pkts/min)	MC Visits	PDR (%)	Waiting Time (Minutes)
A	0.01	3	16.7	23
B	0.1	10	33.3	18.7
C	0.25	17	38.2	11.5
D	0.5	24	46.3	10.7
E	1.0	34	54.5	8.78
F	4.0	69	91.1	8.1
G	8.0	96	99.6	7.0
H	0.2	15	35.7	13.9
I	5.0	77	92.6	7.5
J	2.0	49	74.4	8.3

delay of 7 minutes. At the same time, node A generates only 0.01 packets per minute and they experience an average queueing delay of 23 minutes. Similarly, fixing the packet collection deadline at 7 minutes, very few (only 0.4 $\%$) packets generated by the highly active node G miss the deadline. Though the deadline miss ratio is high (83.3 $\%$) in the case of node A, A can naturally be assumed to be placed in a relatively inactive region of the network generating very few packets, the successful collection of which does not contribute considerably to the overall functioning of the network. Thus, the scheme provides support for delay-sensitive applications and differentiated packet delivery, by reducing the packet waiting time and deadline miss ratio in the areas of high event activity.

Due to unequal visit frequency at different nodes, each node receives its share of service from the MC proportional to its sensing activity or the load offered by it. In addition, by reducing the unnecessary travels of MC to the low data rate regions in the network, the overall system utilization is improved and the fraction of packets getting collected within the specified deadline is increased. However, this performance enhancement is at the cost of increased waiting time and deadline misses at the low load nodes. Thus, though the scheme ensures fairness by means of allocating service of MC proportional to the offered load, the scheme appears to be not fair in terms of the mean waiting time and deadline miss ratio at all nodes in the network.

The results demonstrating the impact of using a hybrid architecture for data collection in delay-sensitive applications are illustrated in Fig. 17. As expected, the PDR for delay-sensitive applications depends heavily on the node's end-to-end connectivity with the static sink, which in turn depends on the density of nodes in the area and the transmission range of nodes. As the network becomes sparse, connectivity gaps occur and sensors get isolated from sink, resulting in increased deadline miss ratio. The option available is to communicate at a higher transmit power for critical situations, of course at the expense of increased energy consumption. Thus, the results exhibit two trade offs: (i) between the probability of on-time service completion and cost of deploying large number of sensor nodes; and (ii) between the probability of on-time service completion and energy consumption due to higher transmission range. Delivery

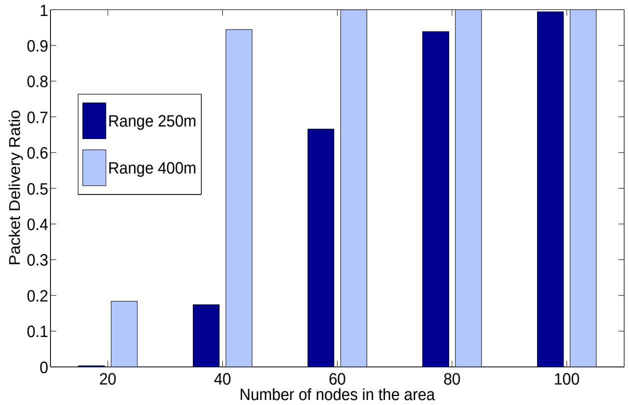

Figure 17. PDR for Delay-sensitive Applications using Hybrid Architecture

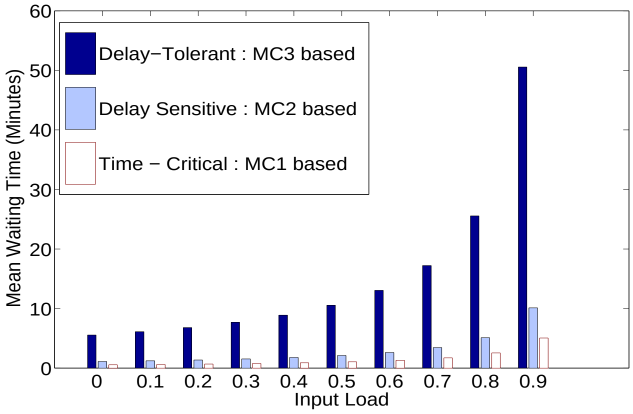

Figure 18. Delay performance using Hierarchical Architecture

performance for delay-tolerant applications are similar to that of the basic MC-based model. Latency performance is not shown, since the latency of delay-sensitive packets is negligible due to the use of ad hoc multi hop approach and that of delay-tolerant packets has already been discussed.

The latency performance of the architecture with hierarchical organization of sensor nodes and MCs is illustrated in Fig. 18. Packets belonging to different applications receive differential treatment in terms of average waiting time. Since good latency performance implies good delivery performance in MC-based delay-sensitive data collection, packet miss ratio will be minimum for all the three types of applications supported: Delay-tolerant, Delay-sensitive and Time-critical. Compared to the hybrid architecture, the advantage is the independence of delivery performance on node density. However, the scheme suffers from increased complexity of maintaining 3 MCs with hierarchical organization.

VII. Conclusion

Application-oriented event-driven data collection in sparse underwater acoustic sensor networks has been investigated in this paper. First, a mobility-assisted framework for energy-efficient on-demand data collection for delay-tolerant application has been proposed. Analytical models for performance metrics like energy efficiency, message latency, packet delivery ratio, and sensor buffer requirement have been evaluated. The basic mobility-assisted data collection framework for event-driven data collection has been found to exhibit superior performance over ad-hoc multi-hop network in terms of energy efficiency and packet delivery ratio at the cost of increased latency. Thus, it is more suited for sparse or disconnected networks and in situations where network lifetime is more important than message delay.

We have augmented the basic model with techniques for improving the latency performance so as to support delay-sensitive applications also. Techniques like multiple mobile collectors and activity-based priority polling have been found to improve the delay and delivery performance. Hybrid architecture with static and mobile sinks as well as the hierarchical architecture of mobile collectors have been proposed to support application-oriented differentiated packet delivery. The basic DTN framework for delay-tolerant applications and the enhanced models for delay-sensitive applications have been implemented in the NS-2 based network simulator, thus enhancing the scope for further research in this area. As a future work, we plan to extend this study to 3-dimensional networks and to investigate techniques for optimizing the network performance adaptively based on application requirements and network constraints.

References

[1] J. M Janardanan Kartha and L. Jacob, "On-demand data collection in sparse underwater acoustic sensor networks using mobile elements," in Proceedings of The Tenth International Conference on Wireless and Mobile Communications, ICWMC 2014, Seville, Spain, pp. 105–111.

[2] M. Ardid, J. A. Martínez-Mora, M. Bou-Cabo, G. Larosa, S. Adrián-Martínez, and C. D. Llorens, "Acoustic transmitters for underwater neutrino telescopes," Sensors, vol. 12, no. 4, 2012, pp. 4113–4132.

[3] S. Adrián-Martínez, M. Bou-Cabo, I. Felis, C. Llorens, J. Martínez-Mora, M. Saldaña, and M. Ardid, "Acoustic signal detection through the cross-correlation method in experiments with different signal to noise ratio and reverberation conditions," in Ad-hoc Networks and Wireless. Springer, 2014, pp. 66–79.

[4] Uwsn research lab, university of connecticut. [Online]. Available: http://uwsn.engr.uconn.edu/

[5] Woods hole oceanographic institution. [Online]. Available: http://www.whoi.edu/

[6] I. F. Akyildiz, D. Pompili, and T. Melodia, "Underwater acoustic sensor networks: research challenges," Ad hoc networks, vol. 3, no. 3, 2005, pp. 257–279.

[7] K. Fall, "A delay-tolerant network architecture for challenged internets," in Proceedings of the 2003 conference on Applications, technologies, architectures, and protocols for computer communications. ACM, 2003, pp. 27–34.

[8] R. C. Shah, S. Roy, S. Jain, and W. Brunette, "Data mules: Modeling and analysis of a three-tier architecture for sparse sensor networks," Ad Hoc Networks, vol. 1, no. 2, 2003, pp. 215–233.

[9] P. Xie, Z. Zhou, Z. Peng, H. Yan, T. Hu, J.-H. Cui, Z. Shi, Y. Fei, and S. Zhou, "Aqua-sim: an ns-2 based simulator for underwater sensor networks," in OCEANS 2009, MTS/IEEE Biloxi-Marine Technology for Our Future: Global and Local Challenges. IEEE, 2009, pp. 1–7.

[10] ns-2 network simulator. [Online]. Available: http://www.isi.edu/nsnam/ns, [last accessed : May 2015]

[11] M. Ayaz, I. Baig, A. Abdullah, and I. Faye, "A survey on routing techniques in underwater wireless sensor networks," Journal of Network and Computer Applications, vol. 34, no. 6, 2011, pp. 1908–1927.

[12] S. Ahmed, I. Khan, M. Rasheed, M. Ilahi, R. Khan, S. H. Bouk, and N. Javaid, "Comparative analysis of routing protocols for under water wireless sensor networks," arXiv preprint arXiv:1306.1148, 2013.

[13] P. Xie, J.-H. Cui, and L. Lao, "Vbf: vector-based forwarding protocol for underwater sensor networks," in NETWORKING 2006. Networking Technologies, Services, and Protocols; Performance of Computer and Communication Networks; Mobile and Wireless Communications Systems. Springer, 2006, pp. 1216–1221.

[14] X. Peng, Z. Zhong, N. Nicolas, C. Jun-Hong, and S. Zhijie, "Efficient vector-based forwarding for underwater sensor networks," EURASIP Journal on Wireless Communications and Networking, vol. 2010, 2010, pp. 1–13.

[15] M. C. Domingo and R. Prior, "Energy analysis of routing protocols for underwater wireless sensor networks," Computer Communications, vol. 31, no. 6, 2008, pp. 1227–1238.

[16] M. Zorzi, P. Casari, N. Baldo, and A. F. Harris, "Energy-efficient routing schemes for underwater acoustic networks," Selected Areas in Communications, IEEE Journal on, vol. 26, no. 9, 2008, pp. 1754–1766.

[17] K. S. Geethu and A. V. Babu, "Minimizing the total energy consumption in multi-hop uwasns," Wireless Personal Communications, 2015, pp. 1–17.

[18] N. Javaid, M. Jafri, S. Ahmed, M. Jamil, Z. Khan, U. Qasim, and S. Al-Saleh, "Delay-sensitive routing schemes for underwater acoustic sensor networks," International Journal of Distributed Sensor Networks, 2014.

[19] N. Javaid, M. R. Jafri, Z. A. Khan, N. Alrajeh, M. Imran, and A. Vasilakos, "Chain-based communication in cylindrical underwater wireless sensor networks," Sensors, vol. 15, no. 2, 2015, pp. 3625–3649.

[20] S. Jain, K. Fall, and R. Patra, Routing in a delay tolerant network. ACM, 2004, vol. 34, no. 4.

[21] S. Tolba, M. Hakami, A. Mihdhir, Y. Zhu, S. Le, and J. H. Cui, "Underwater delay tolerant routing in action," in Oceans, 2012. IEEE, 2012, pp. 1–6.

[22] M. J. Jalaja and L. Jacob, "Adaptive data collection in sparse underwater sensor networks using mobile elements," in Ad-hoc Networks and Wireless. Springer, 2014, pp. 57–65.

[23] W. Zhao, M. Ammar, and E. Zegura, "A message ferrying approach for data delivery in sparse mobile ad hoc networks," in Proceedings of the 5th ACM international symposium on Mobile ad hoc networking and computing. ACM, 2004, pp. 187–198.

[24] Z. Guo, G. Colombo, B. Wang, J.-H. Cui, D. Maggiorini, and G. P. Rossi, "Adaptive routing in underwater delay/disruption tolerant sensor networks," in Wireless on Demand Network Systems and Services, 2008. WONS 2008. Fifth Annual Conference on. IEEE, 2008, pp. 31–39.

[25] S. Jain, R. C. Shah, W. Brunette, G. Borriello, and S. Roy, "Exploiting mobility for energy efficient data collection in wireless sensor networks," Mobile Networks and Applications, vol. 11, no. 3, 2006, pp. 327–339.

[26] L. He, Y. Zhuang, J. Pan, and J. Xu, "Evaluating on-demand data collection with mobile elements in wireless sensor networks," in Vehicular technology conference Fall (VTC 2010-Fall), 2010 IEEE 72nd. IEEE, 2010, pp. 1–5.

[27] A. A. Somasundara, A. Kansal, D. D. Jea, D. Estrin, and M. B. Srivastava, "Controllably mobile infrastructure for low energy embedded networks," Mobile Computing, IEEE Transactions on, vol. 5, no. 8, 2006, pp. 958–973.

[28] S. Yoon, A. K. Azad, H. Oh, and S. Kim, "Aurp: An auv-aided underwater routing protocol for underwater acoustic sensor networks," Sensors, vol. 12, no. 2, 2012, pp. 1827–1845.

[29] G. A. Hollinger et al., "Underwater data collection using robotic sensor networks," Selected Areas in Communications, IEEE Journal on, vol. 30, no. 5, 2012, pp. 899–911.

[30] Y.-S. Chen and Y.-W. Lin, "Mobicast routing protocol for underwater sensor networks," Sensors Journal, IEEE, vol. 13, no. 2, 2013, pp. 737–749.

[31] S. Motoyama, "Flexible polling-based scheduling with qos capability for wireless body sensor network," in Local Computer Networks Workshops (LCN Workshops), 2012 IEEE 37th Conference on. IEEE, 2012, pp. 745–752.

2015, © Copyright by authors, Published under agreement with IARIA - www.iaria.org

[32] V. Kavitha and E. Altman, “Queuing in space: Design of message ferry routes in static ad hoc networks,” in Teletraffic Congress, 2009. ITC 21 2009. 21st International. IEEE, 2009, pp. 1–8.

[33] J. Janardanan Kartha and L. Jacob, “Delay and lifetime performance of underwater wireless sensor networks with mobile element based data collection,” International Journal of Distributed Sensor Networks, vol. 2015, 2015.

[34] R. J. Urick, “Principles of underwater sound,” McGraw-HiII, New York, London, 1983.

[35] H. Takagi, Stochastic analysis of computer and communication systems. Elsevier Science Inc., 1990.

[36] Y. Gong and R. De Koster, “A polling-based dynamic order picking system for online retailers,” IIE Transactions, vol. 40, no. 11, 2008, pp. 1070–1082.

[37] M. Ajmone Marsan, L. De Moraes, S. Donatelli, and F. Neri, “Cycles and waiting times in symmetric exhaustive and gated multiserver multiqueue systems,” in INFOCOM’92. Eleventh Annual Joint Conference of the IEEE Computer and Communications Societies. IEEE, 1992, pp. 2315–2324.

[38] O. J. Boxma, Analysis and optimization of polling systems. Centre for Mathematics and Computer Science, 1991.

[39] T. Hu and Y. Fei, “Qelar: a machine-learning-based adaptive routing protocol for energy-efficient and lifetime-extended underwater sensor networks,” Mobile Computing, IEEE Transactions on, vol. 9, no. 6, 2010, pp. 796–809.

[40] M. Xu, G. Liu, and J. Guan, “Towards a secure medium access control protocol for cluster-based underwater wireless sensor networks,” International Journal of Distributed Sensor Networks, vol. 2015, 2015.

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