Mobility-Based Communication in Wireless Sensor Networks

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ABSTRACT

Wireless sensor networks are proposed to deliver in situ observations at low cost over long periods of time. Among numerous challenges faced while designing WSNs and protocols, maintaining connectivity and maximizing the network lifetime stand out as critical considerations. Mobile platforms equipped with communication devices can be leveraged to overcome these two problems. In this article existing proposals that use mobility in WSNs are summarized. Furthermore, a new approach to compute mobile platform trajectories is introduced. These solutions are also compared considering various metrics and design goals.

INTRODUCTION

Wireless sensor networks (WSNs) have been proposed as powerful means for in situ observation of events and environments over long periods of time [1]. A large number of small and simple sensor devices communicate over short-range wireless interfaces to deliver observations over multiple hops to central locations called sinks. With these properties, WSNs are considered for several critical application scenarios including battlefield surveillance, habitat monitoring, traffic monitoring, and security applications. Sensor nodes, and hence these applications, are subject to constraints such as limited processing, storage, communication capabilities, and limited power supplies.

Among numerous challenges faced while designing WSNs and protocols, *maintaining connectivity* and *maximizing the network lifetime* stand out as critical considerations. The connectivity condition is generally met by deploying a sufficient number of sensors, or using specialized nodes with long-range communication capabilities to maintain a connected graph. The second consideration, network lifetime, is directly related to how long the power sources in sensor nodes will last. The network lifetime can be increased through energy conserving methods such as using energy-efficient protocols and algorithms, and battery replenishment techniques.

The mobile devices can also be used as an orthogonal method to address the connectivity and lifetime problems in WSNs. In many deployment scenarios, mobile platforms are already available in the deployment area, such as soldiers in battlefield surveillance applications, animals in habitat monitoring applications, and buses in a traffic monitoring application. In other scenarios mobile devices can be incorporated into the design of the WSN architecture, such as airborne and ground-based vehicles. With communication devices on mobile platforms, the connectivity and energy efficiency (hence, network lifetime) problems can be addressed as follows:

- Connectivity: Mobile platforms can be used to carry information between isolated parts of WSNs.
- Energy efficiency: Information carried in mobile devices can reduce the energy consumption of sensor nodes by reducing multihop communication.

In this article an overview of proposals that utilize mobile communication devices in WSNs is presented, and two new approaches are introduced. The classification of mobile-device-based solutions is followed by a description of selected proposals available in the literature. Then we propose a new solution suite to calculate paths for mobile devices that collect information from sensors, based on knowledge of geographical data generation rates. Then the properties of existing and proposed solutions are compared qualitatively. Finally, we conclude this article with brief comments on future research directions on mobile devices in WSNs.

MOBILITY IN WSNS

A number of approaches exploiting mobility for data collection in WSNs have been proposed in recent years. These approaches can be categorized with respect to the properties of sink mobility as well as the wireless communication methods for data transfer:

- Mobile base station (MBS)-based solutions: An MBS is a mobile sink that changes its position during operation time. Data generated by sensors are relayed to MBS without long term buffering.
- Mobile data collector (MDC)-based solutions: An MDC is a mobile sink that visits sensors. Data are buffered at source sensors until the MDC visits the sensors and downloads the information over a single-hop wireless transmission.

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- Rendezvous-based solutions: Rendezvous-based solutions are hybrid solutions where sensor data is sent to rendezvous points close to the path of mobile devices. Data are buffered at rendezvous points until they are downloaded by mobile devices.

MBS-Based Approaches

In WSNs, stationary sinks constitute central locations where the communication activities are concentrated. This high level of concentration causes depletion of energy supplies of sensors in the vicinity of the sink, leading to disconnection of the sink from the network. The primary objective of MBS-based solutions is to move the sink in the network to distribute energy consumption evenly. Algorithms developed for MBS deployment target calculation of trajectories of MBSs.

Base Station Relocation — The base station relocation method proposed in [2] aims to change MBS locations along the periphery of the sensing field such that the energy consumption of individual sensors is balanced and overall energy consumption of all sensors is minimized. For this purpose, time is divided into rounds during which MBSs are stationary. At the end of every round, MBS locations are recomputed using inductive logic programming (ILP) methods minimizing an objective function. The two objective functions explored in [2] are total energy consumption of all sensors and maximum energy consumption of any sensor node in the next round. Based on the simulation results, it is observed that the first objective function results in more data collected throughout the network lifetime. On the other hand, the second objective function yields a longer network lifetime, which is defined as the time until the first node dies.

Joint Mobility and Routing — Motivated by uneven energy consumption in WSNs with stationary sinks, the load balanced data transmission in WSNs has been investigated in [3]. In this work the authors develop an analytical model that describes the communication load distribution in a WSN. It is shown that the network lifetime can be improved even when an optimally placed fixed sink is replaced by a randomly moving MBS. It is further shown that the optimum movement strategy for an MBS is to follow the periphery when the deployment area is circular. This result also agrees with the MBS relocation strategy presented in [2]. Finally, a heuristic solution for joint mobility and routing is presented: MBS moves on a circular trajectory inside the deployment region. Nodes inside this trajectory send their messages to MBS on shortest paths to reduce the energy consumption in central parts of the network. Nodes outside the MBS trajectory use paths composed of circular arcs followed by straight lines directed toward the trajectory center to reach the MBS. This strategy utilizes the residual energy in outer nodes otherwise not used. Analytical and simulation results show significant network lifetime improvements.

Move and Sojourn — Network lifetime elongation using MBSs has also been investigated in [4]. The proposed framework considers placement of sensors on grids. MBSs are also constrained to reside at one of the grid points where sensor nodes are placed. Delays associated with MBS movements are also assumed to be negligible. With these constraints, the problem formulation is also applicable to cases where sensors assume sink functionality in turns. The problem of determining the sojourn times of MBS sites is solved using linear programming (LP) methods. The LP solution maximizes network lifetime subject to balanced energy consumption constraints. It is shown through simulations that the use of MBSs increases network lifetime when compared to stationary sinks. Furthermore, it is also observed that lifetime maximizing solutions are achieved by nonuniform sojourn time distributions among grid points depending on the shape of the deployment area.

MDC-Based Solutions

Sparse WSNs are used to collect data at distant points in large areas. Observation of traffic density in a big city is such an application: Sensors are placed on roads to observe vehicles. As the number of cars along a road segment is highly correlated, a small number of sensors is sufficient for data collection. Such sparse deployment scenarios suffer from connectivity problems. Utilizing many relay nodes or using long-range communication interfaces to maintain connectivity can be very expensive for sufficiently large areas. A potential solution is to use MDCs that gather buffered information from sensors by visiting them individually. Existing MDC-based proposals can be classified according to the mobility patterns of the MDCs [5]:

- Random mobility: MDCs move in random patterns as proposed in [6].
- Predictable mobility: An MDC's movement pattern is known, as presented in [7].
- Controlled mobility: An MDC's movement is actively controlled in real time, as proposed in [8].

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Data Mules — The MDC concept has been first introduced in [6], where MDCs are referred as Data Mules. In this proposal, data generated by sparsely located sensors are buffered at sensors. MDCs move randomly and collect data opportunistically from sensors in their direct communication range. Collected data are then carried to a wireless access point. The performance of Data Mules proposal is evaluated using a Markov model based on a two-dimensional random walk mode for Mules, and the effect of buffer sizes, number of access points, and number of Mules on data loss rate is investigated. As the trajectory of MDCs in [6] is random, message transfer delay is not upper bounded.

Predictable Data Collection — In the predictable data collection proposal presented in [7], data is collected from sensors by vehicles that pass near sensors. Sensors are assumed to know the trajectory of MDCs (e.g., buses in a campus environment), which is leveraged to predict when data transfer will take place. Based on the predicted data transfer times, sensors sleep

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until the time of data transfer to save energy. In [7] a queuing model is introduced to accurately model the data collection process. Using this queuing system model, the success rate of data collection and power consumption are analyzed. It is observed that exploiting predictable MDCs can help save energy in WSNs.

Mobile Element Scheduling — In WSNs sensors may generate data at different rates. This behavior is more pronounced when data collection is performed as events occur or when the sampling rates are determined according to rate of change of the observed phenomenon. Data loss in a sensor node occurs if the content of data buffer is not transferred to MDCs before the buffer is completely full. In the mobile element scheduling (MES) proposal [8], an MDC called a mobile element (ME) is scheduled in real time to visit sensors such that no sensor buffer overflow occurs. The MES problem is proved to be NP-complete, and a heuristic solution called Earliest Deadline First (EDF) and its two variants are presented in [8]. With the EDF solution, the next node to be visited by an ME is chosen as the one that has the earliest buffer overflow deadline. EDF leads to high data loss rates as the nodes with consecutive deadlines may be located far from each other. To solve this problem, a variant of EDF called the Minimum Weight Sum First (MWSF) algorithm is proposed that considers buffer overflow deadlines as well as distances between nodes in determining the visiting schedule. Even though the MWSF solution considers both deadlines as well as distances, back-and-forth movements between far away nodes are not avoided completely.

Rendezvous-Based Solutions

When WSNs are composed of isolated network partitions, data generated in a partition can be accumulated at designated sensors. These designated nodes buffer collected data until they are relayed to an MDC. A similar method can also be used in connected networks to reduce the communication load (and energy consumption). Solutions that propose collection of data from designated sensor nodes by a mobile device constitute the class of rendezvous-based solutions. These carry properties of both MDC as well as MBS-based solutions: As in MBS-based solutions, data is relayed over multiple hops before being delivered to the mobile device. Furthermore, generated data is buffered for a relatively long period before it is relayed, as in MDC-based solutions. Hence, rendezvous-based solutions can be classified as a hybrid class between MDC- and MBS-based solutions.

Relayed Data Collection — An autonomous mobile router (MDC)-based solution is proposed in [5] to collect data from sensors. MDC traverses a linear path and transfers data from sensors when it enters their transmission range. Remaining nodes relay their data to the nodes closest to the MDC path via multihop transmission. Through a tree building initialization phase, all nodes determine if they can directly communicate with the MDC or not. If a node discovers that the MDC never enters its transmission range, it determines the node to which to relay its data such that the message traverses the shortest path before being buffered at an intermediate node. In [5] adaptive algorithms to adjust the speed of MDCs are proposed as well. These adaptive algorithms cause an MDC to slow down or stop when there are nodes in the transmission range to increase the amount of transferred data. An MDC moves faster when there is no node in range. The algorithm provides best effort service, and does not guarantee lossless data transfer. The relayed data collection approach is extended to utilize multiple MDCs in [9] to provide scalability of deployment area. Multiple MDCs with parallel linear paths are considered, and a load balancing algorithm is introduced to distribute the work among MDCs.

A New Approach to Optimization of MDC Trajectory

In some sparse WSNs, data generation rates of sensors can be estimated accurately. As an example, in traffic monitoring applications, data generation rates of sensors on road segments can be estimated based on the time of day and the location of the road in the city. The MES problem introduced in [8] can be used to determine the movement of MEs in real time. However, in addition to avoiding data loss, it is also important to minimize the ME speed. Furthermore, when the ME speed is below the minimum required level, data loss rates due to buffer overflow should be minimized as well. In this section we introduce an offline heuristic called the Partitioning Based Scheduling (PBS) algorithm that computes periodic paths of an ME to avoid sensor data loss at low ME speeds. We also present the Multihop Route to Mobile Element (MRME) algorithm that extends PBS to deliver urgent messages to MEs within specific delay bounds.

The PBS Algorithm

The PBS algorithm computes ME trajectories based on knowledge of the data generation rate of sensors and their locations. Every sensor node n_a is associated with a buffer overflow time o_a. The basic idea behind PBS is to create a path such that two consecutive visits to n_a are at most o_a apart. To achieve this, the PBS algorithm calculates the ME trajectory in two phases. In the *partitioning phase* nodes are grouped in such a way that nodes in a group have similar buffer overflow times and are closely located. In the *scheduling phase* the trajectories inside groups are computed, and then concatenated to form a complete trajectory. The minimum speed of ME is computed based on the complete trajectory length. The solution guarantees that no buffer overflow occurs if an ME traverses the path at the computed minimum speed.

The partitioning of nodes into groups is accomplished with a two-step process. In the first step, all nodes are grouped into bins B_i, $1 \le i \le M$, such that the minimum overflow time o^*_{i+1} in B_{i+1} is twice the minimum overflow time o^*_i in

B_i. Although every bin B_i has nodes with different overflow times, we assign the minimum overflow time o_i^* to all nodes in that bin. Consequently, we can treat all nodes in the same bin equally without violating the overflow conditions. In the second step, nodes in a bin B_i are partitioned into 2^{i-1} sub-bins B_i^j, $1 \le j \le 2^{i-1}$, using a 2d tree algorithm such that nodes in the same sub-bin are located close to each other.

The generation of visiting schedules is also accomplished in a two-step process. In the first step paths that traverse each node in a sub-bin once are calculated for each sub-bin individually. The sub-bin paths are calculated using a solution to the Traveling Salesman Problem (TSP). In the second step these partial paths are concatenated in such a way that the nodes are visited at appropriate frequencies. Note that a bin B_{i+1} is partitioned into twice as many sub-bins as B_i. However, a sub-bin of B_{i+1} needs to be visited only half as frequently as a sub-bin of B_i. Hence, we form cycles by concatenating paths from one sub-bin B_i^j from every bin B_i. Assuming M bins, 2^{M-1} cycles are created, which are concatenated to form a super-cycle. In every super-cycle nodes of B_1 are visited 2^{M-1} times, and nodes of B_M are visited only once. Finally, a minimum speed is calculated by dividing the super-cycle length by the minimum overflow time o_1^* of bin B_1, which ensures that there is no buffer overflow if the ME travels at that minimum speed.

Let us consider a case where the sensor overflow times are distributed over a narrow range $[o_{\min}, o_{\max}]$ such that $o_{\max} < 2 \cdot o_{\min}$. This suggests that all nodes must be treated more or less identically. A main concern is that the first step of the partitioning phase of PBS assigns all nodes to B_1 and calculates a single TSP path for the entire network, which is not efficient. This problem can be solved by increasing the number of sub-bins calculated by the second step of PBS. If we wish to partition that single bin into 2^{M-1} sub-bins, a dummy overflow time

$$o'_{\min} = \frac{o_{\min}}{2^{M-1}}$$

can be introduced for a nonexisting node. In that case, $M - 1$ empty bins, $B_1, \ldots, B_{M-1}$, and a nonempty bin B_M are created. The second step of PBS then partitions B_M into 2^{M-1} sub-bins. The super-cycle is then simply the concatenation of TSP paths of B_M^j, $j = 1, \ldots, 2^{M-1}$.

Figure 1 demonstrates a simple example of the PBS algorithm. Partitioning with respect to buffer overflow times results in bins $B_1 = \{n_1, n_2, n_3\}$ and $B_2 = \{n_4, n_5, n_6, n_7\}$ for the sample network. Then B_2 is partitioned into two with respect to sensor locations resulting in $B_2^1 = \{n_4, n_5\}$ and $B_2^2 = \{n_6, n_7\}$. Nodes in B_1 are visited every cycle, and nodes in B_2 are visited every other cycle. Let us assume B_{21} is visited every even cycle, and B_2^2 every odd cycle. In the example of Fig. 1, two cycles of ME visits are formed by the PBS algorithm. The first cycle consists of the nodes in B_1^1 and B_2^1 with visit order of n_1, n_2, n_3, n_4, n_5, and back to n_1. The second cycle consists of the nodes in B_1^1 and B_2^2 with the order of n_1, n_2, n_3, n_6, n_7, and again back to n_1.

The performance of PBS is evaluated through simulations where region-dependent event occurrence rates are simulated assuming that events are concentrated at locations called *eyes*. The nodes in the eye centers have the highest data generation rates, which drop radially outward. The three scenarios A, B, and C correspond to sensor fields with one, four, and nine eyes, respectively. Scenario D corresponds to uniformly distributed data generation rates over the sensor network. In Fig. 2 the data loss rate of PBS and MWSF are shown for these four scenarios for varying ME speeds. It can be observed that the minimum required ME speed is consistently lower for PBS solutions than the MWSF solutions. Furthermore, the data loss rates are significantly smaller for PBS when the ME is constrained to move at slower speeds. The detailed description of the PBS algorithm and detailed simulation results can be found in [10].

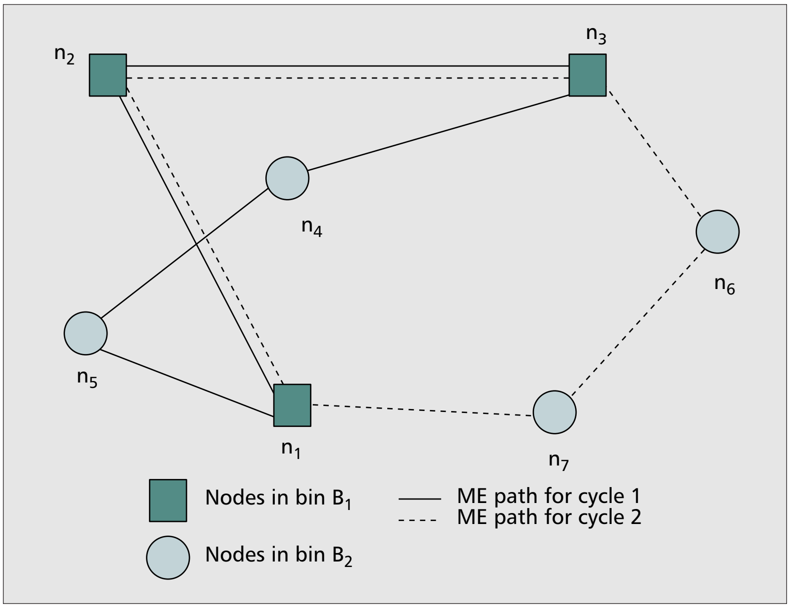
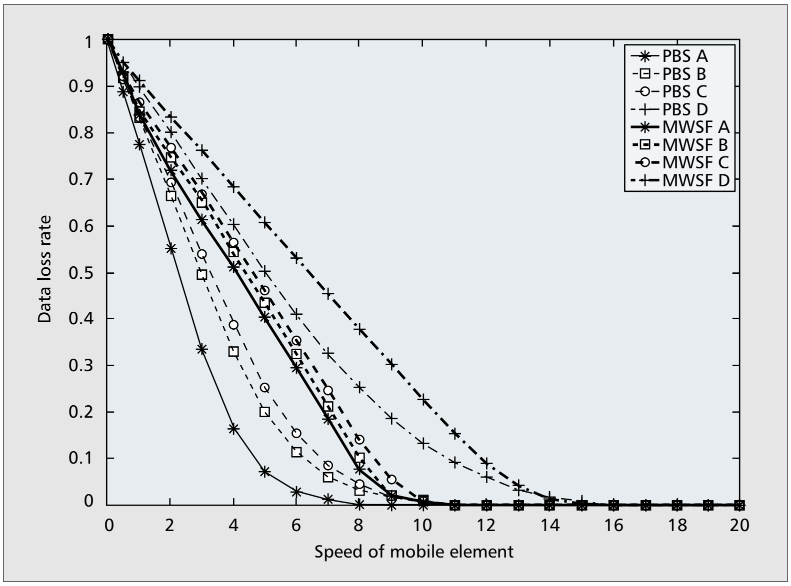


Figure 1. *A sample network deployment and the ME path generated by the PBS algorithm. The overflow times for the nodes are as follows: $o_1 = o_2 = o_3 = 4$ time units; $o_4 = o_5 = o_6 = o_7 = 8$ time units.*

The MRME Algorithm

Being an MDC-based scheme, the primary objective of the PBS algorithm is to ensure that the data is collected before sensor buffer overflows occur. It is also possible that sensors generate urgent messages that must be delivered to MEs within given delay bounds in addition to regularly generated data. As an example, sensors in the traffic observation scenario may also detect accidents in addition to regular data collected. The accident information is an Urgent Message (UM) that must be delivered to an ME in Δ amount of time. We introduce the MRME algorithm to satisfy the timely delivery requirements of infrequently generated urgent messages in addition to regularly generated and buffered observations.

The basic idea of the MRME solution is to relay UMs to other sensors that are guaranteed to be visited in $\Delta - T_{tx}$ amount of time, where T_{tx} is the time spent to relay information from its source to the sensor where it will be picked up. If a sensor n_a has an overflow time $o_a \le \Delta$, the



■ **Figure 2.** *Performance evaluation of PBS and MWSF algorithms on topologies A, B, C, and D with respect to data loss rate.*

UM is guaranteed to be delivered to the ME by its deadline. If $o_a > \Delta$, three possibilities exist to guarantee on time delivery of the UM. The first option is to reduce the overflow time of n_a artificially such that the new overflow time $o_a^{new} = \Delta$. The second option is to find another sensor n_b with overflow time $o_b < \Delta - T_{tx}$, where T_{tx} is the data relay time between n_a and n_b. The third option is to use a combination of the former two: find another sensor n_b and update its overflow time as $o_b^{new} = \Delta - T_{tx}$.

The MRME algorithm is a turn-based heuristic search algorithm. In the initialization phase, nodes that have overflow times less than Δ are marked as covered. In every turn nodes are inspected to determine overflow time reduction possibilities and how many additional nodes can consequently use that node to relay their UMs. For this purpose, a gain value is computed for all nodes, which is a function of the reduction of overflow time and the additional nodes that use the node as rendezvous points. In each round the gain function $Gain(i,d)$ is computed for each node n_i and d number of hops, $d = 1, \ldots, D$, as follows:

$$Gain(i,d) = \sum_{n_j \in C(n_i,d)} \frac{o_j - \Delta}{\Delta} - \alpha \cdot \frac{o_i - (\Delta - d \cdot t_{tr})}{(\Delta - d \cdot t_{tr})}, \quad (1)$$

where $C(n_i,d)$ is the d-hop neighbors of the inspected node n_i, D is the maximum number of hops to be considered, and t_{tr} is the maximum time a packet needs to be relayed one hop. In Eq. 1 the first term in the summation corresponds to the total gain of the neighbors by using n_i as a relay point for their UMs rather than reducing their overflow time to Δ, and the second term is the loss of n_i due to potential reduction of its overflow time, weighed with a positive value α. The optimal α parameter is dependent on the system parameters and is found to be around unity in most simulated scenarios.

In every round the node n_i^* that yields the largest gain $Gain(n_i^*,d^*)$ is selected, and its overflow time is updated as $o_i' = \Delta - d^* \cdot t_{tr}$. After this update, n_{i^*} and its d^*-hop neighbors $n_j \in C(n_{i^*},d^*)$ are marked as covered, as well. The overflow time reduction process is repeated until all nodes are covered. Then, the PBS algorithm is run with the updated overflow times and a lossless schedule is calculated. Note that MRME is guaranteed to compute a feasible ME trajectory, possibly at a higher minimum ME speed, even if a node does not have any neighbors to relay its UMs since the overflow time of such nodes is reduced to Δ to guarantee timely UM delivery.

Figure 3 demonstrates an example of UM-related overflow time update. Let n_i have the lowest overflow time O_i. In Figs. 3a and 3b the overflow time of n_i is decreased to relay UMs of its one- and two-hop neighbors, respectively, assuming that $t_{tr} = 10$. As delivering UMs over two hops takes more time, o_i must be reduced more in the latter case, which would increase the loss of n_i. However, the potential gain is that more node overflow times remain unchanged for one-hop neighbor coverage. If $D = 2$, $Gain(n_i,1)$ and $Gain(n_i,2)$ are computed for all nodes in the network according to Eq. 1, and the node/hop number pair that gives the highest gain is selected to increase the number of covered nodes.

The performance of the MRME algorithm is evaluated through simulations. In Fig. 4 the UM loss rate is depicted for varying ME speeds in scenario D for MRME, PBS, and MWSF. As depicted in this figure, MRME guarantees lossless delivery of UMs for much smaller speeds than PBS and MWSF while providing guaranteed collection of regularly generated data at the same time. Details of the MRME algorithm and extensive simulation results can be found in [11].

Comparison of Mobility-Based Communication Proposals

Among the three classes of mobility-based proposals, the MBS-based solutions aim to prolong the WSN lifetime by breaking the correlation of data paths over deployment time. As messages are relayed over multiple wireless hops, the message latency is as small as in fixed sink scenarios. Multihop communication also results in no long-term buffering of information and the highest energy consumption in the sensor nodes since sensors relay third party messages to the sinks. Mobility of the mobile platforms is controlled by the algorithms. Possible application scenarios for *base station rrelocation* and *move and sojourn* proposals include sensor networks for battlefield surveillance with ground-based vehicles, and for *joint mobility and routing*, similar surveillance scenarios with UAVs as sinks. Among the three representatives of this class, the performance of the base station relocation, and joint mobility and routing proposals have no dependence on MBS speed, while the move and sojourn proposal requires almost instantaneous mobility of the MBS.

On the other hand, MDC-based solutions do not allow multihop communication and require MDCs to pick up data from their source sensors

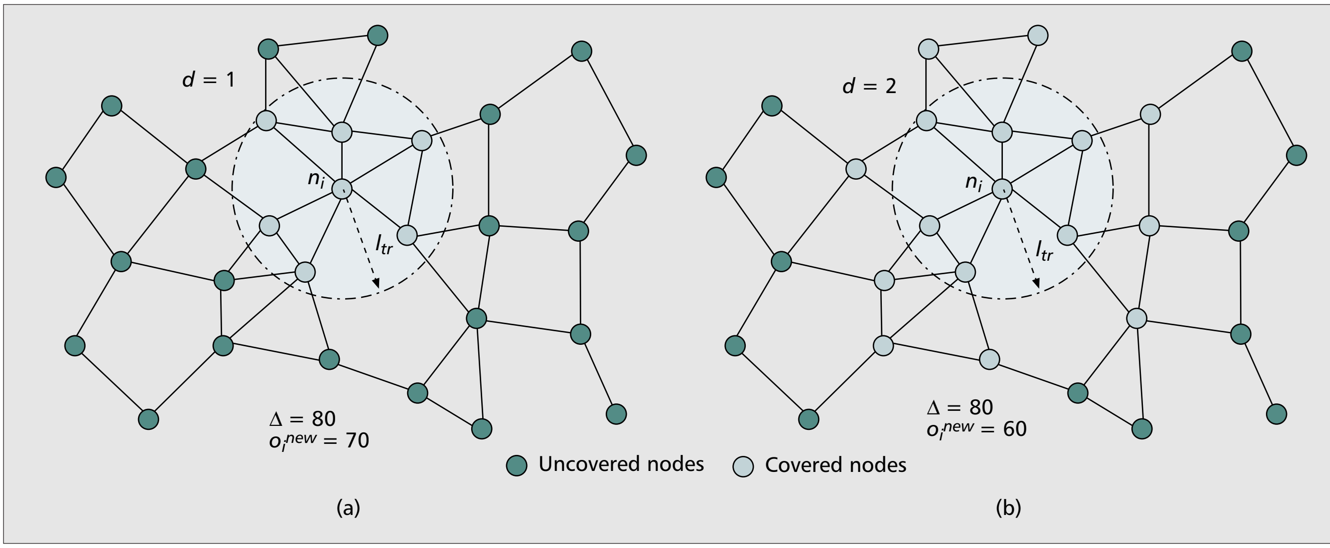


Figure 3. *Reduction in overflow time to cover a) one-hop; b) two-hop neighbors in MRME. Here we use* covered nodes *to refer to the nodes whose UMs can be collected by an MDC before Δ.* o_i^{new} *denotes the new overflow time of* n_i *according to the MRMEalgorithm* (t_{tr} *= 10).*

directly. Solutions in this class are appropriate for sparsely deployed sensor networks and where sensor node lifetime is the primary concern. Furthermore, collected information must be insensitive to delays since they are buffered for a long time before being delivered to MDCs. Since no third party information is relayed, sensors use the least amount of energy, but also require the largest buffer sizes to hold data until delivery. Applications of these solutions include environmental monitoring for data mules, non-urgent traffic and parking information dissemination for predictable data collection, large volume data applications where real-time status information is available at low cost for MES, and traffic monitoring applications with fixed sparse sensors for PBS. The energy savings in sensor nodes are countered with the highest level of platform mobility: MDCs must move relatively fast to ensure that no data is lost due to buffer overflow. While data mules and predictable data collection leverage the mobile platforms that already exist in the environment, MES and PBS control the movement of MDCs. Among the existing proposals, PBS controls the movement of MDCs most efficiently, yielding the lowest MDC speed among the solutions in this class.

The rendezvous-based solutions show properties of both MBS- and MDC-based solutions. The information is collected at specific nodes, and delivered to the mobile devices when they approach the rendezvous points. Hence, both multihop communication as well as long-term buffering is used while relaying information to mobile devices. This approach results in medium message delays and medium levels of data collector mobility. Relayed data collection is the leading example of rendezvous-based solutions, which can be used directly on fixed bus routes. The MRME solution, on the other hand, uses MDC-based PBS solutions to relay regularly generated data and the rendezvous-based principles only to relay urgent messages. Therefore, it requires much higher mobile device speed.

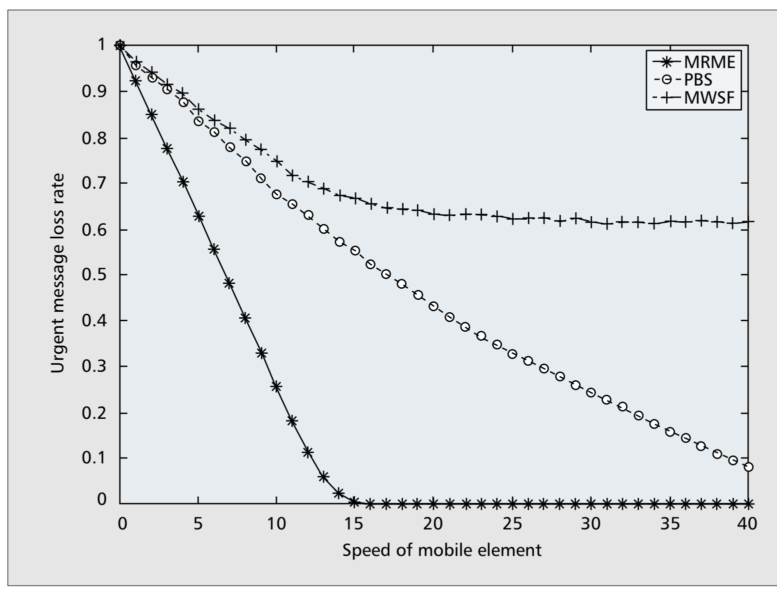


Figure 4. *Comparison of urgent message loss rate of MRME, PBS, and MWSF algorithms on scenario D.*

MRME can be used for collecting traffic information from medium-density fixed sensors that occasionally report (more urgent) small accidents and traffic jams. The properties of all mobility-based communication proposals are summarized in Table 1.

Conclusions and Future Research Directions

In this article mobility-based communication proposals for WSNs are discussed. Mobility-based communication can prolong the lifetime of WSNs and increase the connectivity of sensor nodes and clusters. We also introduce a new approach to compute the mobile device trajectories in sparse WSNs where data generation rates

Class	Algorithm	Multihop commun.	Long-term buffering	Mobility	Message latency	Algorithm execution	Platform mobility	Energy consumption
MBS	Base Station Relocation	Yes	No	Controlled	Low	Online	Low	High
	Joint Mobility and Routing	Yes	No	Controlled	Low	Offline	Low	High
	Move and Sojourn	Yes	No	Controlled	Low	Offline	Very High	High
MDC	Data Mules	No	Yes	Random	High	Offline	High	Low
	Predictable Data Collection	No	Yes	Predictable	High	Offline	High	Low
	MES	No	Yes	Controlled	Medium	Online	High	Low
	PBS	No	Yes	Controlled	Medium	Offline	Medium	Low
Rendezvous	Relayed Data Collection	Yes	Yes	Controlled	Medium	Online	Medium	Medium
	MRME	Yes	Yes	Controlled	Medium	Offline	High	Low

Table 1. *Comparison of mobility-based communication proposals.*

of sensors are known. Among the open research problems, real-time solutions that result in low mobile device speeds and cooperation between multiple mobile devices stand out as challenges that have significant impact. The adaptation of proposed solutions to WSNs with dynamic requirements should also be investigated as near-term research directions.

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