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Energy-Efficient Discovery Strategies for WSNs with Mobile Elements

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List of Abbreviations

2BD	Dual Beacon Discovery
ARQ	Automatic Repeat reQuest
DIRL	Distributed Independent Reinforcement Learning
DTN	Delay Tolerant Network
EC	Erasure Coding
HDC	High Duty Cycle
LDC	Low Duty Cycle
LRB	Long Range Beacon
MANET	Mobile Ad hoc Network
MDC	Mobile Data Collector
ME	Mobile Element
MR	Mobile Relay

MS	Mobile Sink
MULE	Mobile Ubiquitous LAN Extensions
PILOT	Predefined, Intelligent, Lightweight tOpology managemenT
PTW	Pipelined Tone Wakeup
RADA	Resource Aware Data Accumulation
RFID	Radio Frequency IDentification
SMART	Scan-based Movement Assisted sensoR deploymenT
SRB	Short Range Beacon
STEM	Sparse Topology and Energy Management
SWIN	Shared Wireless Infostation Model
VLDC	Very Low Duty Cycle
WNs	Wireless Nodes
WSN	Wireless Sensor Network
WSN-MEs	Wireless Sensor Networks with Mobile Elements

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Vita and Publications

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Publications

- K. Kondepu, F. Restuccia, G. Anastasi, M. Conti, ”A Hybrid and Flexible Discovery Algorithm for Wireless Sensor Networks with Mobile Elements”, Proceedings of the IEEE International Symposium on Computers and Communications (ISCC 2012), Cappadocia, Turkey, July 1-4, 2012.

- F. Restuccia, K. Kondepu, G. Anastasi, M. Conti, ”Energy Efficiency in Wireless Sensor Networks with Mobile Elements”, Proceedings of the 2nd year workshop in the COST Action IC0804 on Energy Efficiency in Large Scale Distributed Systems, Published by IRIT July 2011. ISBN: 978-2-917490-18-1.

- K. Kondepu, G. Anastasi, M. Conti, ”Dual-Beacon Mobile-Node Discovery in Sparse Wireless Sensor Networks”, Proceedings of the IEEE International Symposium on Computers and Communications (ISCC 2011), Corfu, Greece, June 28 - July 1, 2011.

- K. Kondepu, ”A Hierarchical Discovery Scheme for WSNs with Mobile Elements ”, Ph.D Forum Proceedings of IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks, WoWMoM-2011, Lucca, Italy, June 20-24, 2011.

Other Publications

- K. Kondepu, Chiranjeev Kumar, ”An Effective Pointer-Based HLR Location Management Scheme for PCS Network”, Proceedings of IEEE COMSNETS, January 5-10, 2009, Bangalore, India.

- K. Kondepu, Chiranjeev Kumar, Rajeev Tripathi, ”Partially Overlapping Super Location Area (POSLA): An efficient Scheme for Location Management in PCS Networks”, VTC 2008 spring - 67th IEEE Vehicular Technology Conference, May 11-14, 2008, Singapore.

- Chiranjeev Kumar, K. Kondepu, Rajeev Tripathi, ”An Efficient Analytical Method for Location Management Strategy in Cellular Mobile Network”, Published in the Proc. of ICCST-2007 held at University of California, Berkeley, U.S.A, 24-26 October 2007, pp.374-379, (*Secured Best Paper Award*).

Abstract

Energy-Efficient Discovery Strategies for WSNs with Mobile Elements

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In sparse wireless sensor networks, data collection is carried out through specialized Mobile Elements (MEs) thatvisit sensor nodes, gather data, and transport them to the collection point. Since visit times are typically unpredictable, one of the main challenges in this kind of networks is the energy-efficient discovery of MEs by sensor nodes. This thesis focuses on adaptive discovery schemes, where the sensor node's duty cycle is adjusted over time according to the probability that the ME is nearby. Initially, a hierarchical approach is proposed based on two different Beacon messages emitted by the ME (Long Range Beacons and Short Range Beacons). Simulation results show that the proposed

scheme can provide a significant energy reduction with respect to a single Beacon, especially when the discovery phase is long. Later, two different adaptive discovery schemes are considered (a learning-based approach and a hierarchical approach). And their performance in different mobility scenarios is evaluated. Simulation results show that a learning-based approach is not suitable when the ME moves in an irregular pattern, and a hierarchical approach is not able to learn and exploit information about the specific mobility pattern of the ME. Finally, a hybrid discovery algorithm is proposed that combines a learning-based approach with a hierarchical approach. The proposed algorithm is very flexible as it can adapt to different mobility patterns of the MEs. The performance of the proposed approach has been evaluated through extensive simulation analysis and is compared with the existing adaptive algorithms, that only leverage either a learning-based approach or a hierarchical approach. The results show that the proposed hybrid discovery algorithm outperforms all other discovery schemes for all the considered scenarios.

Chapter 1

Introduction

A Wireless Sensor Network (WSN) typically consists of large number of sensor nodes densely deployed over a geographical area. Sensor nodes are small devices capable of sensing data from the surrounding environment, process them locally and/or transfer them to a data collection point (usually referred to as *sink node*) through multi-hop communication. However, many real-life monitoring applications do not require a fine-grained sensing. Examples of such applications include monitoring of weather conditions in large areas, air quality in urban environments, terrain conditions in precision agriculture, and so on. In all these cases, a sparse network can be used. In a sparse WSN, the distance between the neighboring nodes is (much) larger than the transmission range of each sensor node, and thus, multi-hop communication is not feasible. Data collection in sparse WSNs is accomplished through Mobile Elements (MEs), i.e., special mobile nodes that visit sensor nodes regularly, collect data and transport them to the sink node. MEs can also be used in dense sensor networks to allow a more uniform distribution of energy consumption among sensor nodes, thus increasing the network lifetime [1]. Depending on the application scenario, MEs can either be a part of the external environment (e.g., cars, buses, persons, animals), or be a part of the networking infrastructure (e.g., mobile robots). Also, MEs can have different mobility patterns, ranging from deterministic to completely random mobility [2, 3].

A detailed description of opportunities provided by sparse WSNs with MEs and challenges to be faced is reported in [3]. One of the main challenge is the timely and energy-efficient ME discovery. Unless the ME's mobility pattern is deterministic, arrival times are not exactly known to the sensor nodes. If the mobility pattern is somewhat predictable, the visit time can be estimated with some accuracy. Although the arrival time is predicted with some uncertainty, even under these circumstances the sensor node has to discover the presence of the ME in the area before exchanging data with it.

Ideally, the sensor node should be able to detect the presence of the ME every time it visits the sensor node to exploit *all contacts*, thus reducing delays and avoiding packet losses (e.g., due to data overflows at the sensor node's local buffer). In addition, the ME discovery should be *timely* - i.e., the ME should be detected as soon as it enters the communication range of the sensor node, so as to exploit the short time available for data exchange as much as possible. In practice, the discovery process is made difficult by sensor nodes energy constraints. Due to their limited energy resources, the sensor nodes cannot be always active, and usually operate on a duty cycle. Hence, a *discovery protocol* is used to detect the presence of the ME [3].

Discovery algorithms commonly used in WSNs with MEs are based on *periodic listening*. In this case, the ME regularly sends Beacon messages to announce its presence in the area, while sensor nodes wake up periodically for a short duration to check for possible advertisements from the ME. To ensure the timely discovery of (almost) all contacts, the Beacon period and the sensor node's duty cycle (i.e. the fraction of time during which the sensor node is active with respect to the total time) have to be properly defined. Specifically, a low duty cycle (i.e., a long inactivity period) reduces the energy consumption at the sensor node, thus increasing its lifetime. However, at the same time, it decreases the capability of detecting contacts. In general, using a fixed inactivity period usually results in a very inefficient scheme, especially when the total amount of time spent in the discovery state is large. Adaptive schemes that dynamically adjust the inactivity period of the sensor node, depending on the estimated probability that the ME is nearby, have thus been proposed [4, 5]. However, since the inactivity period is changed at the end of a predefined time slot, even after using an adaptive scheme, it may happen that the duty cycle is high but the ME is not nearby. Thus, a large amount of energy is wasted, especially if the time slot is large (for instance, it is 1 hour in [4] and 30s in [5]).

1.1 Thesis Contributions

Initially, a simple yet effective hierarchical approach has been proposed that leverages two different Beacon messages, namely a Long Range Beacon (*LRB*) and a Short Range Beacon (*SRB*), that are transmitted by the ME with different transmission ranges. LRBs announce the presence of the ME in the area, while SRBs inform the sensor node that the data exchange can actually take place. Sensor nodes can thus use a very low duty cycle for most of the time and increase it only upon receiving an LRB. Unlike other hierarchical discovery schemes in the literature [6, 7, 8, 9, 10], the proposed Dual Beacon Discovery (2BD) protocol does not require multiple radio technologies. Thus, it can be implemented on any sensor platform.

The 2BD protocol has been evaluated through simulation in a sparse WSN scenario. The obtained results show that 2BD can provide significant energy savings, when compared with the traditional approach based on a single Beacon, even when the discovery phase is short (e.g., 15s).

The proposed 2BD protocol can be used either as a standalone solution or in combination with adaptive discovery schemes (e.g., [3, 4, 11]), to further improve its *energy efficiency*. Hence, two adaptive discovery protocols are considered by taking different approaches for duty cycle adaptation. Resource-Aware Data Accumulation (RADA) [5, 11] leverages a learning-based approach, while proposed 2BD uses a hierarchical approach. The performance of the aforementioned protocols with that of the fixed schemes are compared through simulation analysis. However, simulation results show that a learning-based approach is not suitable when the ME moves in an irregular pattern and a hierarchical approach is not able to learn and exploit information about the specific mobility pattern of the ME.

Finally, a hybrid discovery protocol has been proposed, that combines both a learning-based approach and a hierarchical approach. Thus, the proposed protocol is very flexible and can adapt to every different mobility scenarios. The proposed protocol has been evaluated through simulation, and is compared with the existing adaptive discovery schemes. The simulation results show that the hybrid approach outperforms existing adaptive schemes, which only leverage either a learning-based approach or a hierarchical approach.

1.2 Thesis Organization

Chapter 2 provides a literature review along with some necessary background on topics that are related to this thesis. Chapter 3 describes 2BD scheme for sparse WSN with MEs, and it also presents performance analysis of two different adaptive discovery schemes along with their performances in a sparse network scenario. Chapter 4 provides the proposed hybrid discovery protocol. And finally, Chapter 5 concludes the thesis.

Chapter 2

State of the Art

Since sensor nodes are typically energy-constrained devices, a power management strategy is required to save energy and increase their life time. In the context of opportunistic networking, the objective of power management is to minimize energy consumption, while discovering contacts and transferring data. Ideally, the sensor node must sleep most of its time and wake-up only when the ME is nearby. An important aspect is related to the timely discovery of the ME by the sensor nodes. Energy-efficient discovery schemes are required to minimize energy consumption and to minimize the probability of missing contacts with MEs as low as possible. Even though MEs may appear less frequently, they have to be detected. The energy consumption during discovery can be reduced either by designing a general low-power protocols which detects MEs independent of its mobility pattern, or by optimizing the discovery protocol based on the knowledge available about the ME mobility.

The following sections describe the most significant schemes proposed in the literature for ME discovery and data transfer.

2.1 Wireless Sensor Networks

A WSN consists of large number of sensor nodes (e.g. motes, smart dust, etc) deployed over a geographical area. The power of WSN depends on sensor nodes that assemble and communicate between them. The most challenging issues in this area are identified as follows:

- Reducing the power consumed by the sensor nodes for extending the network lifetime.
- Implementing a simple and effective data collection protocol in the sensor network.

Sensor networks, similar to mobile ad-hoc networks, involve multi-hop communication. Many routing algorithms have also been proposed for mobile ad-hoc networks. But, these algorithms are not applicable to sensor networks due to several factors described in [12]. Some of these factors are:

- Sensor nodes are static, have energy constraints, and are highly vulnerable to failures.
- Sensor nodes use multi-cast communication, while ad-hoc networks use peer to peer communication.
- Sensor networks are usually larger than that of ad-hoc networks.
- Sensor networks have high density of sensor nodes when compared to ad-hoc networks.

In addition, sensor nodes have low data rate compare to mobile networks because sensor nodes have several constraints like- power, memory and processing, which prevents them from handling high data rate. When sensor nodes are deployed over a geographical area, they are able to sense the environmental data, process collected data locally and forward to the *sink node*. The sink nodes can be controlled remotely via Internet. Data is transferred from sensor nodes to the sink node through a multi-hop communication paradigm [13]. An example of a typical WSN architecture is depicted in Figure 2.1.

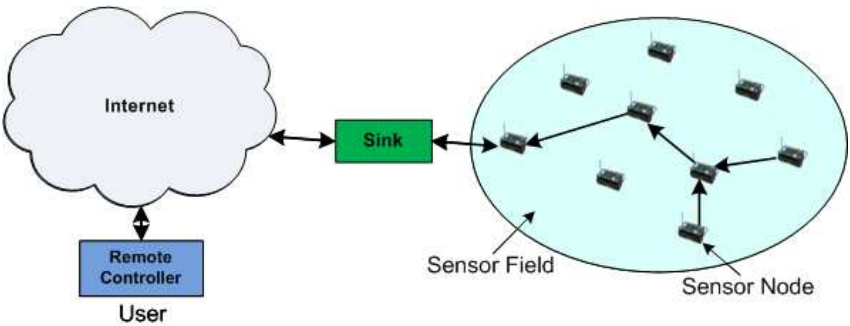

Figure 2.1: Wireless Sensor Network Architecture

In static WSNs, sensor nodes are densely deployed, and the data can be distributed using fixed routing or flooding as shown in Figure 2.1. Whereas in mobile WSN, dynamic routing is used. Challenges in mobile WSN include deployment, localization, self organization, navigation control, coverage, energy, maintenance and data processing. More recently, the use of mobility in Mobile Ad Hoc Network (MANETs) and Delay Tolerant Networks (DTNs) have received much attention [14, 15]. Subsequently, different approaches have also been adopted in WSNs [16]. MEs can be used to carry data between isolated parts of WSN. Several issues need to be addressed while introducing mobility in WSNs [17]. Among them, the following are considered to be the important issues:

- *Connectivity*: If sensor nodes are mobile, fewer sensor nodes are required, unlike in a dense WSN. MEs can be used to carry data between isolated parts of WSN and also to transfer data to sink or base station.

- *Energy Efficiency*: Sinks collect the data that are generated by sensor nodes. Generally, nodes close to the sink are more loaded than the others, so that they are subjected to rapid energy depletion, even when energy saving techniques are applied. By using MEs in network, sensor nodes can save the energy by directly communicating with ME instead of forwarding data to other sensor nodes like in multi-hop communication.

2.2 Wireless Sensor Networks with Mobile Elements

In recent years, different approaches have been proposed to exploit mobility in WSN. This section discusses specific features of Wireless Sensor Networks with Mobile Elements (WSN-MEs) by presenting possible architectures based on the role played by the MEs.

The basic elements in a WSN-MEs are described below:

Regular (sensor) nodes: Nodes that are source of information. Sensing is the main task of these sensor nodes, and also nodes can forward or relay the message in the network, depending on the specific application scenario.

Sinks (base stations): Nodes that are destination of information. They collect data sensed by sensor nodes either by visiting sensor nodes or through intermediate nodes. Energy consumption of individual sensor nodes is balanced, and overall energy consumption of all sensor nodes is minimized by introducing mobility in sink or base station.

Support nodes: Nodes that are neither source nor destination of information. These are special nodes to support network mobility and they act either as intermediate data collectors or as mobile gateways.

Depending on the mobility of the MEs, the network architecture of the WSN-MEs can be classified as *homogeneous* (network contains only regular nodes) or *non-homogeneous* (network contains special nodes).The network architecture of WSN-MEs is different from the traditional WSN because WSN-MEs can be sparse, where as traditional WSNs are mostly dense. Different types of MEs in WSN-MEs architecture are discussed below.

2.2.1 Mobile Elements

This section presents different kinds of MEs based on architectural aspects. They are presented in increasing level of mobility.

Relocatable nodes

Relocatable nodes are kind of mobile elements that forward data from source nodes to the sink while changing their location. Once they have moved to the new location, they usually remain stationary and then forward data to the base station using multi-hop communication. They change the topology of the network to maintain the network connectivity or coverage. A WSN-MEs architecture based on relocatable nodes is shown in Figure 2.2.

Relocatable nodes can be used to reconstruct the network

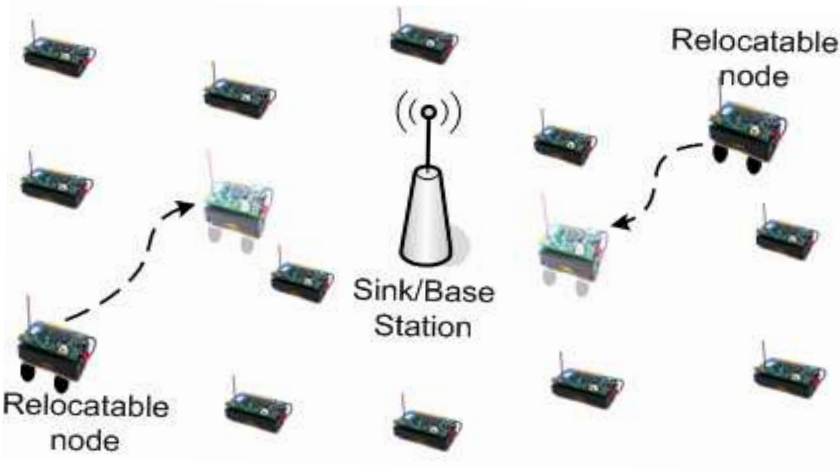

Figure 2.2: Architecture of WSN-MEs with relocatable nodes

connectivity whenever a link failure occurs in the network. A topology management system with relocatable nodes is proposed in [6]. In this case, special support nodes called PILOT (*Predefined, Intelligent, Lightweight tOpology managemenT*) can be used to maintain the link connectivity whenever link failure is predicted in the network. In detail, PILOT nodes move to locations where communication between nodes is not stable or failing, and acts as a bridge. Moreover, they actively change network topology to improve both communication reliability and energy efficiency. An algorithm for effective placement of relocatable nodes to achieve better network connectivity has been proposed in [18].

The problem of sensing coverage has been addressed in [19, 20]. In this case, the objective was to avoid the coverage holes and reduce communication costs by using relocatable nodes.

In a sensor network, coverage is an important factor taken into consideration while performing sensing tasks. MEs provide the required coverage. A set of distributed protocols have been designed in [20] to detect coverage holes. This is done by using Voronoi diagrams and iteratively moving MEs from densely deployed areas to sparsely deployed areas. Insights are also provided on how to choose protocols for different applications running under different conditions. Open issues related to the deployment scheme, sensing area, and sensitivity to communication range have also been discussed in [20].

In a WSN, sensing areas having no sensors deployed are referred to as *communication holes*. To reduce such holes, a SMART (*Scan-based Movement-Assisted sensoR deploymenT*) algorithm based on Hungarian method has been proposed in [19]. The proposed solution, also known as *seed planting method*, moves a sensor to each uncovered area to cover the hole(s). Simulation results show that a cost effective sensor deployment can be achieved by using this SMART algorithm.

In order to cover a small geographical area, many sensor networks deploy far more nodes than necessary. To cover the same area, few MEs may just be sufficient. Distributed schemes presented in [21] provide better coverage by using minimal communication and computation. For scalability and robustness distributed algorithms have been developed to physically react when event(s) occur in the network. The sensors are assumed to be in perfect position, and the navigation capability is presented to complement the simplicity of the designed algorithms. A class of motion controlled algorithms has been presented in [21] that trades off the memory and computation requirements with the positions of sensor nodes. These algorithms also represent trade-off between communication, computation and accuracy. Adopting these algorithms may lead to low power consumption in a system having limited number of sensor nodes.

To increase the lifetime of WSN with energy constrained nodes, [22] explores a novel approach based on linear programming. It solves the combined problem of determining the movement of the sink and the sojourn time taken to induce the maximum network lifetime. The objective function proposed in [22] maximizes the overall network lifetime, instead of minimizing the energy consumption at the nodes. Simulation results in [22] confirm the variation in the energy consumption of the nodes with the position of the sink node. Moreover, the nodes that are in close proximity to the sink get more drained than the other nodes.

Unlike unscalable stationary WSNs, WSNs with MEs can be deployed to monitor open (borderless) area, as they can self configure and relocate to the area of interest. A novel distributed algorithm Causataxis has been proposed in [23] that allow the MEs to relocate towards the region of interest and adjust its shape as the sensing environment changes. Causataxis adopts coordinated locomotion that has been inspired through growing and routing behaviors of a bio-system. A comparison between the Causataxis and the custom tuned swarm algorithm (uses virtual spring forces to relocate MEs based on local neighborhood information) had been done in [23]. The simulation results show that at the cost of slightly high communication overhead, Causataxis outperforms swarm algorithm in terms of sensing coverage, energy consumption, and noise tolerance.

Sensor deployment in any WSN is a critical issue as it affects the cost and the detection capability of any sensor network. Problems related to sensor placement and sensor dispatch have been addressed in [24]. Sensor placement deals with the technique for placing the sensors in the environment to achieve the maximum sensing coverage and network connectivity. Sensor dispatch deals with choosing a subset of sensors and delegating them with certain objective function to satisfy the properties of coverage and connectivity. Centralized and distributed energy efficient dispatch algorithms have been presented in [24]. In the centralized algorithm, the direction in which the sensor moves is based on the sensor placement, whereas in the distributed algorithm, the sensor moves in an autonomous manner. The proposed solution in [24] allows a sensing field to be in different shapes i.e., an arbitrary polygon with the possible existence of obstacles, and an arbitrary relationship of sensor's communication and sensing distances.

Depending on the location of the MEs in a WSN, the problem of coverage control has been addressed in [25]. The coverage problem has been treated as a local optimization problem, and for this, a distributed control and coordination algorithm with guaranteed convergence has been proposed. Experiments have been conducted by deploying Cyclops cameras (both indoor and outdoor) to validate the proposed algorithm.

Mobile Data Collectors

Mobile Data Collectors (MDCs) are special type of mobile elements that are responsible for gathering data from the sensor nodes. MDCs are not energy constrained and are powerful in terms of data storage and processing capabilities. MDCs can be either *Mobile Sinks* (MSs) or *Mobile Relays* (MRs), depending on the application scenario.

Mobile Sinks are mobile elements which collect data produced by sensor nodes that can also be used by them. In this case, MSs act as an end-point of data collection. A WSN-MEs based on mobile sinks is shown in Figure 2.3.

Mobile sinks can be used for data collection in urban scenario [26]. In this case, mobile phones or other popular devices carried by people act as MS to collect data using embedded sensors (e.g., Accelerometer, Microphone, Camera, Wi-Fi and so on), and send the collected data to remote servers which provide services to remote users. A similar approach is proposed in [27], where multiple MSs can be in contact with a single sensor node at the same time. A WSN with mobile sinks is considered in [28], where ordinary sensor nodes are stationary and densely deployed. In this case, mobile sinks collect data from each sensor node by using multi-hop communication paradigm.

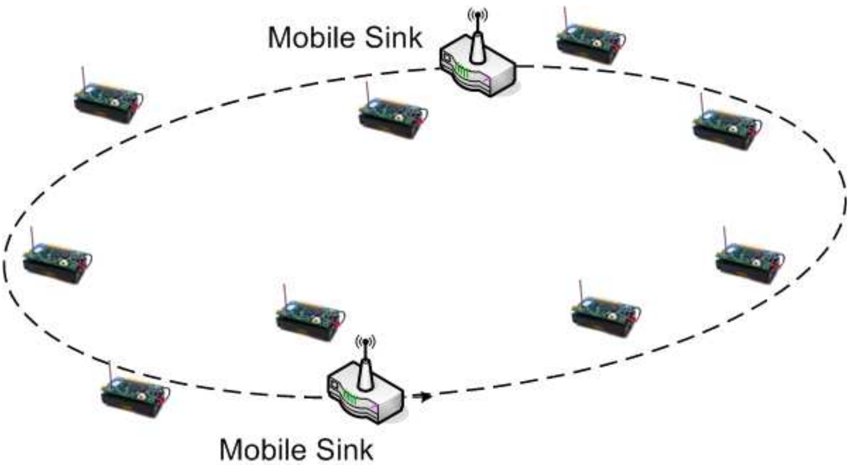

Figure 2.3: Architecture of WSN-ME with MDCs: Mobile Sinks

A different class of solutions have been proposed in [29, 30] for data collection in WSNs with mobile sinks by using analytical models. For example, in [29], the analytical models are flexible enough to support different mobility patterns of mobile sinks and data collection strategies.

A hierarchical structure for large-scale sensor networks using a clustering algorithm with mobile sinks has been proposed in [31]. In this algorithm, cluster heads are randomly selected in time-driven scenarios. A cluster head gathers data from the nodes, saves it in a buffer, and then transfers it to the mobile sink which is traversing in the communication range. In this case, the energy consumption is minimized because not all data from cluster heads require multi-hop relays to reach the sensor network. Slow movement of mobile sink leads to high latency in data collection and to address this problem, a rendezvous based data gathering scheme has been proposed in [32]. This scheme uses sub set of nodes known as rendezvous points which act a temporary static sink that collect data from other sensor nodes. The collected data is transfered to the mobile sink when it is found in the communication range. In this case, the mobile sink avoids traveling extensively to collect data from each sensor node, thereby saving energy and reducing data collection delay.

An integer based linear program approach along with a flow-based routing protocol has been proposed in [33] to increase the lifetime of WSN. As the position of the base stations are fixed before commencing the data collection (using multi-hop communication),the program minimizes the energy spent by a sensor node, This approach leads to an energy efficient usage of multiple mobile base stations.

A load balancing algorithm that finds the turning points in the path (linear/curve) of the mobile sink to prolong the network lifetime has been proposed in [34]. The mobile sink called *SenCar* initially moves in a linear path gathering the data from sensor nodes through multi-hop communication. To balance the traffic load a turning point is derived based on energy expenditure due to data collection. This energy efficient data gathering scheme significantly prolongs network life time. A data collection algorithm based on sink mobility with predefined path is also proposed in [35].

Mobile Relays are special mobile elements that are capable of moving all over the network to collect data from the sensor nodes. The collected data is then delivered to the sink or base station [36]. MRs work as relay nodes,so they are neither the source nor the destination of information. A WSN-MEs based on mobile relays is shown in Figure 2.4.

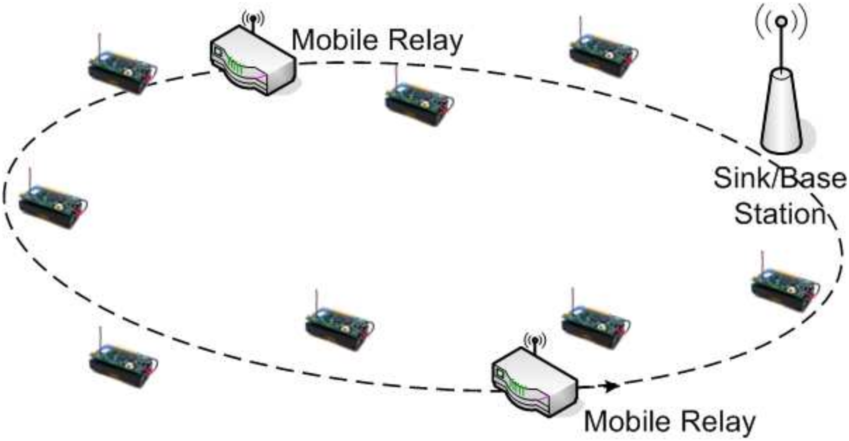

Figure 2.4: Architecture of WSN-ME with MDCs: Mobile Relays

Many different proposals have been addressed by using MRs in the context of opportunistic networks. Among them, the well known message ferrying approach has been proposed in [14]. Message ferries offer a service to relay messages in a sparse mobile ad-hoc network. Message ferries move around in the network area and collect data from the source nodes, then they carry the stored data and forward them towards the destination node. Hence, message ferries can be seen as a moving communication infrastructure that enables data transfer in sparse wireless networks.

Similar approaches have also been proposed in the data-MULE system [37, 38]. The data-MULE system consists of a three-tier architecture described below:

- The top tier consists of a set of Access Points (APs) which receive data from the middle tier. These devices can be set up at convenient locations where network connectivity and power are set.

- The middle tier is composed of mobile relays called Mobile Ubiquitous LAN Extensions (MULEs). For example, MULEs can be vehicles, people, or animals too. MULEs move around in the area covered by the sensors to collect the data and deliver them to AP, when they are within communication range. In addition, MULEs can communicate to each other to improve the system performance.

- The bottom tier is occupied by randomly distributed sensor nodes. These are used to sense data from the surrounding environment and send them directly to MULEs passing by.

A scheme that takes advantage of a mobile cluster head and hierarchical topology of clustering to maximize the life time of a sensor network has been proposed in [39]. Sensor nodes which transmit the collected data to the base station consume more energy compared to other sensor nodes not involved in this activity. This leads to an unequal energy distribution of residual energy in the network. Some energy rich nodes, named as cluster heads, when moved in a controlled fashion and placed in event occurring areas can collect and relay the same data to the base station, thereby reducing the transmission energy of the sensor nodes present in the critical areas. This scheme increases the overall lifetime of the network.

Mechanisms that use mobile relays to prolong network lifetime have been proposed in [40]. The proposed mechanisms consider that the MEs can inherit the sensing and the relaying responsibilities of a bottleneck nodes. When a ME moves to the location of the bottleneck node and performs the tasks on its behalf, the bottleneck node can go to sleep and save energy. This prolongs the life time of the bottleneck node, thereby improving the lifetime of the network.

Mobile Peers

Mobile peers are different from MDCs that are ordinary mobile nodes (i.e, sinks or mobile relays) in WSN-MEs. In this case, the sink can also be mobile. The data carried by the mobile peers (i.e., its own data and data collected from the other peers, while moving in the network area) is transferred, once it reaches the area covered by the base station or access point. Figure 2.5 shows a WSN-MEs architecture based on mobile peers.

In [41, 42], people act as mobile peers to collect data opportunistically from other portable devices or from the surrounding environment. In this case, sensor nodes are not used mainly for monitoring the environment , but to distinguish people in terms of both interactions and control information. A similar approach has been proposed in [43], where cyclists collect the data from the surrounding environment and transfer it to a remote server to evaluate the cyclist performance and the cyclist environment (e.g., sound level, carbon dioxide level, number of cars on that route, etc), which further provides information to remote users.

Zebranet [44] and SWIM (*Shared Wireless Infostation Model*) [45] projects focus on wildlife monitoring applications by using mobile peers. Sensor nodes are attached to zebras in the Zebranet project, or whales in SWIM system, so that they exchange the gathered information during encounters (more about Zebranet is briefly described in Section 2.4).

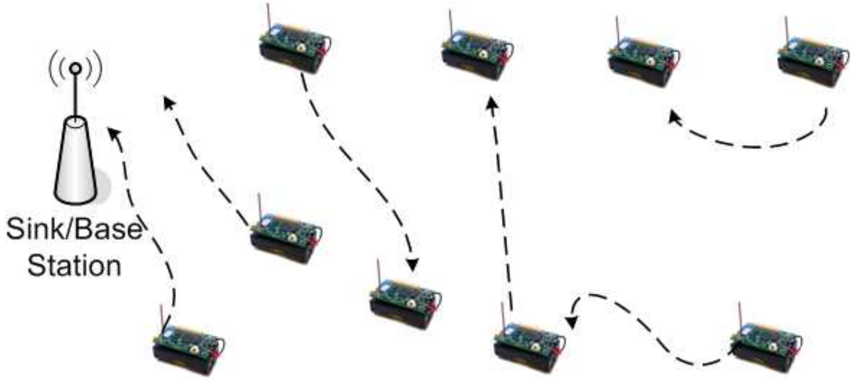

Figure 2.5: Architecture of WSN-MEs with Mobile peers

2.3 Energy-Efficient Data collection in WSN-MEs

Figure 2.6 shows the reference scenario for the data collection in WSN-MEs. The amount of time spent by the sensor node in the discovery state until the ME has not yet entered into the contact area is called *waiting time*. As ME arrivals are generally unpredictable, the sensor node initially performs a discovery phase for the timely detection of the ME. If the ME is not detected by the sensor node immediately, it should wait for a certain amount of time, called *discovery time*. Upon successfully detecting the ME, the sensor node switches from the discovery state to the data transfer state, and starts transmitting data to the ME. If the discovery phase takes more time, the sensor node cannot exploit the whole available *contact time* for data transfer. The portion of the contact time which can be actually used for subsequent data transfer is called *residual contact time*. However, the sensor node may still remain awake even after the ME is not reachable.

Based on above discussion, two main phases of data collection are described below:

- *Discovery* is the first step for collecting data in WSN with MEs. As the presence of ME in the contact area is generally unknown to sensor nodes, the goal of discovery protocol is to detect contacts as soon as they occur, and at the same time consume less energy. In other words, discovery should try to maximize the number of detected contacts, and also the residual contact time, while minimizing the energy consumption. Discovery protocols are described in Section 2.3.1.

- *Data transfer* takes place immediately after discovery. The goal of data transfer protocol is to get the most out of the residual contact time to maximize the throughput (in terms of messages successfully transferred per contact) while minimizing the energy consumption. Data transfer protocols are described in Section 2.3.2.

In WSN-MEs the communication between sensor nodes and MEs is opportunistic, i.e., data is exchanged only both are in the communication range of each other. In principle, a sensor node can continue to remain in its sleep mode and wake up only for data transfer.In practice, unless the ME's motion is deterministic, the sensor node cannot know in advance when the ME will enter into its communication range. Hence, a *discovery protocol* is necessary for detecting the presence of the ME [3].

2.3.1 Energy-Efficient Discovery Approaches

This section describes the main approaches to energy-efficient discovery in WSNs with MEs. As shown in Figure 2.7, discovery strategies can be broadly classified into three differ-

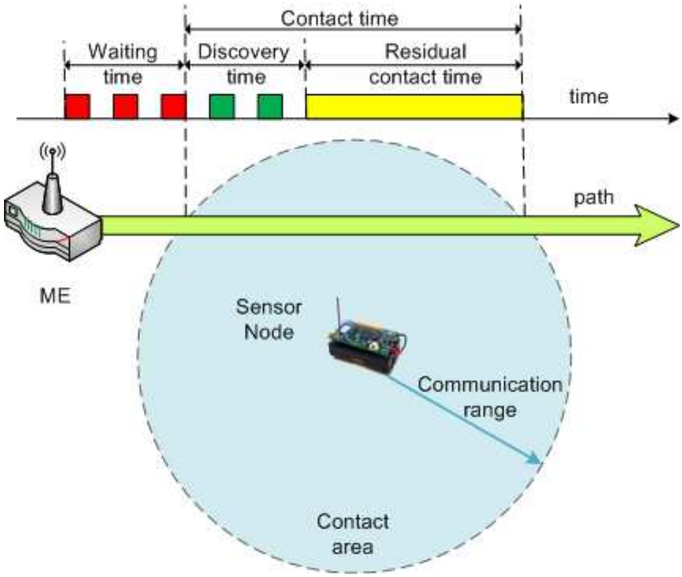

Figure 2.6: Reference scenario for data collection in WSN-MEs

ent categories, namely *scheduled rendezvous*, *on demand*, and *asynchronous* schemes.

In *scheduled rendezvous* schemes, the sensor node and the ME agree on the specific time instant at which the ME will visit the sensor node. Therefore, the sensor node can wake up at that specific time instant, thus minimizing its energy consumption. Of course, this scheme requires that (**i**) clocks of the sensor node and ME are synchronized, and (**ii**) ME follows a very strict schedule, so that the sensor node can know in advance when it will enter its transmission range. For instance, in [46], MEs are assumed to be on board of public transportation shuttles, which visit sensor nodes according to a tight schedule. Due to the aforementioned limitations, scheduled rendezvous schemes have limited applications in practical scenarios.

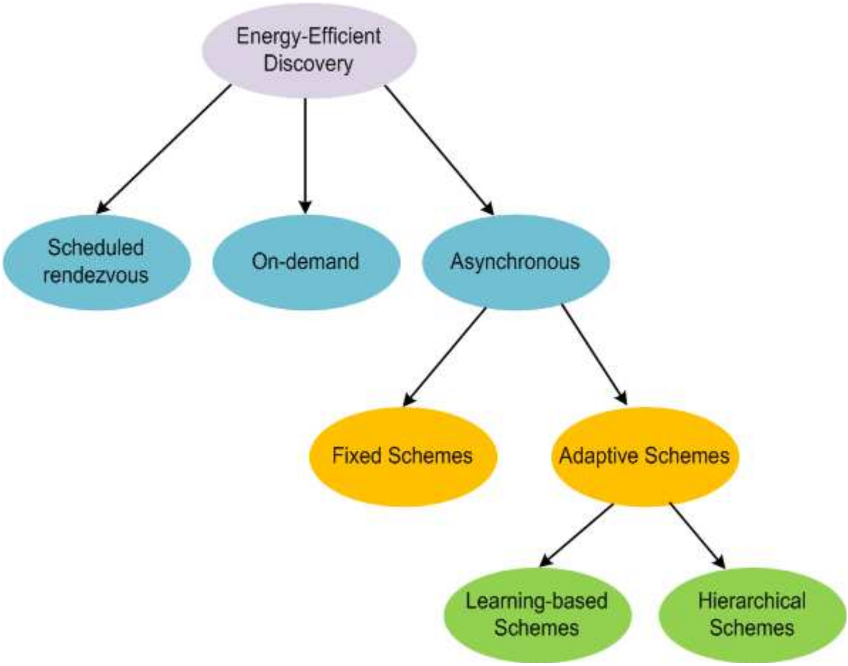

Figure 2.7: Classification of energy-efficient discovery strategies

In *On-demand* schemes, the sensor node is completely passive and is woken up by an action initiated by the ME. For instance, a radio-triggered activation approach, similar to that used in Radio Frequency Identification (RFID) systems, is proposed in [47, 48]. The ME sends a wakeup message (or signal) that contains enough energy to trigger the activation of the static sensor node. The energy provided by the wakeup message is used by the sensor node to generate an interrupt, which in turn enables the radio transceiver. In practice, on demand schemes are often implemented by means of two different radios (or radio channels) [7, 49], i.e., a low-power control radio for sending wakeup signals, and a high-power data radio for communication.

On-demand schemes are appealing in the context of sparse WSNs because they are able to significantly reduce the energy consumption of sensor nodes. An additional feature of on-demand schemes allow a very timely detection of the ME. However, they have some major disadvantages. For instance, both the radio-triggered activation approach (e.g., radio trigger emitters) and multiple radios approach (e.g., low-power control radios) have a very short coverage range. In addition, these schemes require special hardware support, which is not available on currently off-the-shelf commercial platforms.

Asynchronous schemes allow the sensor node to detect the ME and communicate with it, without any pre-programmed rendezvous or explicit activation message. Asynchronous discovery schemes for WSN-MEs are typically implemented in the form of *periodic listening*. As shown in the Figure 2.8, the ME periodically sends beacon messages to announce its presence in the surrounding area. The duration of a beacon message is given by T_D, and the time between subsequent beacon messages is T_B. On the other side, sensor nodes wake up periodically to listen for possible beacons from the ME by using a duty cycle δ, defined by the active time T_{ON} and the sleep time T_{OFF}, i.e., $\delta = T_{ON}/(T_{ON} + T_{OFF})$. The active time of the sensor node is set to $T_{ON} \geq T_B + T_D$, so that a complete beacon can be received while in the active time. As soon as a sensor node receives a beacon message, it realizes that the ME is within its transmission range and communication is thus feasible.

Asynchronous periodic-listening schemes can be further categorized as fixed and adaptive schemes. In *fixed periodic listening* [1, 2, 37, 50, 51], the discovery protocol parameters used by the sensor node (i.e., duty cycle) and ME (i.e., beacon emission rate) are constant over time. Using a fixed approach results in a simple but inefficient scheme, especially when the sensor nodes spend a long time in the discovery state. Conversely, in *adaptive periodic listening* [4, 5, 9, 11, 52], one or both of the aforementioned parameters are varied over time based on the probability that the ME is nearby. Adaptive periodic-listening schemes proposed so far differ in the parameter that is varied over time (beacon emission rate or duty cycle), and specific approaches (e.g., learning-based or hierarchical) are used to decide on when to vary it.

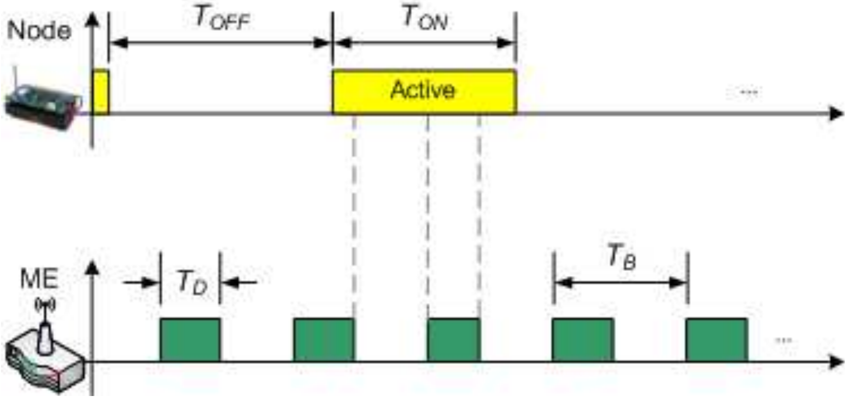

Figure 2.8: Periodic Discovery Process

Learning-based schemes [4, 5, 11] try to predict the next MEs visit time based on the past history. In [4], time is divided in hours, and for each hour, the probability to come in contact with a ME is estimated using a reinforcement learning algorithm. The beacon emission rate is then adjusted on hourly basis, depending on the estimated contact probability and the available energy. A similar approach is also used in [11, 52], where time is divided into time slots of shorter duration (i.e., 100s) and a more complex approach based on Q-learning is used to estimate the contact probability. Learning-based schemes are very well-suited when the ME's motion has some regularity, that can be learned and exploited to predict the next arrival time with a certain accuracy. However, they are unsuitable when the ME moves in an irregular pattern [53].

Hierarchical schemes have been proposed in [8, 10] to address the problem of device discovery in mobile opportunistic networks using handheld devices, equipped with two or more radios with different transmission range, bit rate and energy consumption (e.g., a Mote radio and a Wi–Fi interface). In [8], when a connection with a nearby device is desired, the lower-level radio channel is used to discover, configure, and activate the higher-level radio subsystem. Data exchange only occurs through the higher-level radio. For instance, a mobile device can receive the Wi–Fi configuration parameters from a nearby Wi–Fi Access Point through the Mote radio. This information in turn is used to activate and configure its Wi–Fi interface on the mobile device. In [10], sensor nodes can work in different operation modes with different power consumptions. They remain in the lower power mode for most of the time and switch to higher power modes only when the ME is nearby.

Hierarchical discovery in sensor networks with MEs (possibly) is addressed in [9], where the *network interrupt* approach is proposed. Sensor nodes are assumed to be equipped with two different radios, i.e., a primary high-power radio (usually in sleep mode) and a control low-power radio (always powered on). A node can activate the primary radio of nearby node at any time by just sending a beacon over the low-power radio. *Sparse Topology and Energy Management* (STEM) [6] and *Pipelined Tone Wakeup* (PTW) [54] also use two different radio channels for wakeup signal and data packet transmissions respectively. While these proposals have some similarities with 2BD protocol (proposed in the next chapter), the following differences exist:

- 2BD addresses a different scenario, i.e., WSNs instead of opportunistic networks of handheld devices.

- 2BD does not require multiple radio technologies, that are unavailable in current sensor platforms.

- 2BD uses long-range communication for discovery and short-range communication for data exchange, while other hierarchical schemes use vice versa.

An additional feature of 2BD relies on a single radio for both discovery and data exchange. Furthermore, 2BD can be implemented on all currently available sensor platforms.

2.3.2 Data Transfer Approaches

Figure 2.9 shows the state diagram of the sensor node. As ME arrivals are generally unpredictable, the sensor node initially performs a discovery phase for the timely detection of the ME. After successful detection of the ME, the sensor node switches from discovery state to data transfer state and starts transmitting data to the ME. At the end of transfer phase, the sensor node may switch to the discovery state again in order to detect the next ME passage. However, with the availability of knowledge (even partial) about ME mobility, the sensor node can exploit this knowledge and go to sleep state for some time, to further reduce its energy consumption. Otherwise, when no knowledge on the ME mobility pattern is available, the sensor node directly enters the discovery state. In [2], a power management framework has been proposed to exploit the knowledge about the ME mobility pattern in terms of energy efficiency and delivery performance. But, the proposed approach mainly targets opportunistic networks.

Many approaches have also been proposed for WSNs and

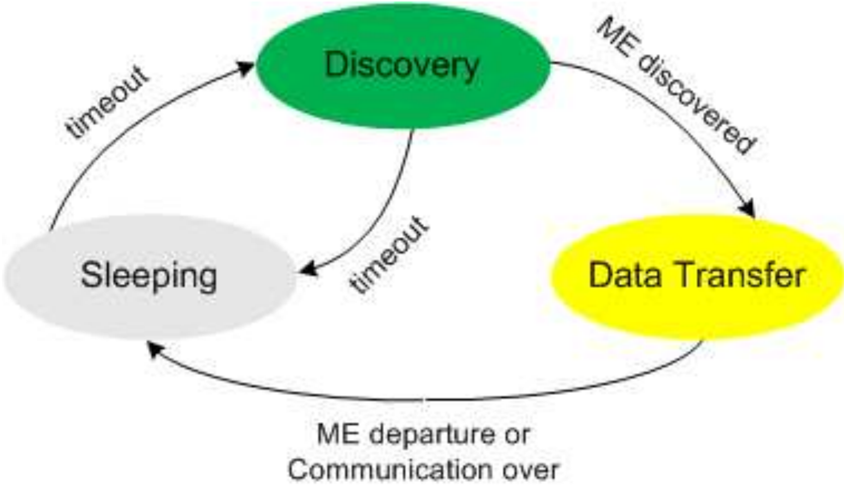

Figure 2.9: State diagram for the sensor node during data collection

many papers focus on the mobility of the ME [55, 56]. Some works also address the problem of energy efficient data collection from sensor node's perspective. For instance, [57] considers a periodic wakeup for discovery followed by stop-and-wait protocol for data transfer. A stop-and-wait protocol for data transfer is also used in [1], where the ME is assumed to be controllable. A different approach is investigated in [46], assuming that the ME's mobility is completely predictable. A window-based *Automatic Repeat reQuest* (ARQ) scheme has been proposed in [58]. A scenario is considered, wherein sensor nodes have a limited number of messages to transfer during each contact and uses a realistic message loss model derived from the real measurements [59]. In [58], an analytical approach is used to show, how a window size larger than one message may significantly improve the number of successfully transfered messages, while minimizing the energy consumption of the sensor node. However, the approach in [58] does not consider the effect of the ME discovery on the subsequent data transfer phase at all.

A performance evaluation of data collection jointly considering both discovery and data transfer is presented in [37, 60, 61, 62]. In [37], a periodic wakeup scheme has been adopted for the discovery and, the mobility pattern of the ME follows a Poisson distribution. In [60, 61, 62], a periodic wakeup scheme for discovery, and a window-based ARQ with a selective retransmission for reliable data transfer has been considered. In addition, they considered different parameters (e.g., the duty-cycle) and performance metrics (e.g., the contact miss rate and the residual contact time) to investigate performance of both the discovery phase and the data transfer phase.

An alternative approach to data transfer based on Erasure Coding (EC) has been proposed in [63]. EC scheme does not require selective retransmissions. In this context, collected data are split into a number of blocks, which also include additional redundant information, so that the original data can be recovered even though a part of the encoded data is lost. In [27] an hybrid adaptive data transfer protocol has been proposed that combines EC approach with an ARQ scheme for reliable data delivery by considering multiple MEs in a sparse WSN scenario. Simulation analysis in [27] shows that the hybrid adaptive protocol guarantees better performance compared to a pure ARQ scheme based on acknowledgments and selective retransmissions, even when there are many MEs simultaneously in contact with the sensor node. In addition, [64] considers an urban sensing scenario performing experiments with a real testbed for reliable and efficient data transfer. In this case, sensor nodes are sparsely deployed in an urban sensing area to collect the environmental data, and MEs are used to collect data sensed by sensor nodes opportunistically. Even with the limited storage and processing capabilities that are commercially available in the present sensor platforms, the experimental results in [64] shows that the hybrid approach is feasible with high probability of data transfer.

To this end, the data transfer phase depends on the adopted communication paradigm. An ME moves faster when there are no nodes in the communication range. When buffer has limited data, the sensor node transmits it in a fraction of time. If the buffer is empty or if the ME is not reachable, then the sensor node simply goes to sleep state. However, the sensor node generally cannot know when the ME leaves the communication area. In practice, the sensor node assumes that the ME left the communication area, when it misses N_{ack} consecutive acknowledgments (ACKs). At the same time, the ME assumes that the data transfer phase is over, when it does not receive any message within a predefined timeout.

2.4 Typical Applications of WSN

WSNs have potential applications in both, civil and military areas, ranging from monitoring (e.g., biomedical health, power and inventory location, indoor or outdoor environment, agriculture, etc.) [65, 66, 67, 68] to target tracking (e.g., objects, animals, humans, vehicles, etc.) [69, 70]. Many sensor network applications have been discussed in [12, 13]. Some typical WSN applications are described below:

Environmental Monitoring

Sensor networks have been used for environmental monitoring (like forest, ocean, terrains, etc.) and disaster management (like wildfire, etc.). For both the applications, large number of sensor nodes can be deployed in the area of interest. The WSNs process the data acquired from multiple sensors to monitor event in that particular location. Macroscope of Redwood [71] is one such project were the redwood trees are monitored to understand their habitat by observing- air temperature, humidity and solar radiation.

Highway Traffic Monitoring

Monitoring and surveillance is of vital importance for transport sector. Traffic congestion is a big problem for both, developing and developed countries as poor traffic management can incur big loss to the country's economy. Traffic pulse technology [72] is one such system developed with WSNs. The system has stationary Wireless Nodes (WNs) nodes that- collects data from the sensor network, processes them, stores them in the database, and then forwards it to applications which generate real time information. Some of the parameters collected are lane occupancy, lane by lane travel speeds, temperature, pollution levels, etc. The above parameters are collected every 60 seconds and sent to the data center over a WN.

Medical Application

Tiny wearable wireless medical sensor prototypes like pulse oximeter, electrocardiogram (EKG) have been developed by Harvard University that monitors patient's vital data like- heart rate, oxygen saturation, EKG, etc. and they are relayed to hand-held devices using wireless platform [73]. The information collected through the sensor nodes can be easily integrated with patient's record and provide emergency medical care for the elderly and disabled patients when required. Moreover, the collected information can also be used for real time analysis by correlating it with the existing data to provide vital emergency service to patients and staff that take care of them.

Wildlife Monitoring

Wildlife monitoring through WSNs has played a vital role in preserving the animals in their natural habitat. Low cost and high coverage area makes WSN an interesting option for tracking animals. Animals prefer certain habitat based on their needs and this result in varying population densities among different species for the same habitat [74]. Hence, there is a need to understand the movement of the animals in order to protect them. Zebranet system [44] is a WSN solution to track animal migration. Sensor nodes (containing GPS unit, micro controller, off-chip memory and microphone) are attached to each peer (zebra) that not only generates its own data, but also carries and forwards all data received from other peers (zebra) with which it has come in contact. The peers finally upload the collected data when they are close to the base station. A mechanism is provided to flush data which has already been transferred to the base station from the network, as it is no longer required.

Military Application

Ad-hoc WSNs have been developed in counter sniper application(e.g., PinPtr) for accurate detection and location of shooters in an urban environment [69]. The shockwaves from the shot and its position is computed by the dense deployment of sensors. Even after multiple sensor failures due to shock, the remaining sensors in the dense network still provide good coverage and accuracy. The performance of these sensor-based counter sniper systems have been tested with field trials in real training facilities and it is on par with the existing centralized system. With better power handling mechanisms, miniaturization of hardware and packaging (basically to withstand rugged weather conditions), these systems have the capability to be deployed in real hostile situations.

2.5 Summary

This chapter described the background and the literature review on various topics associated with the work presented in the thesis. Different types of architectures in WSN with MEs have been discussed. Moreover, a detailed classification of discovery approaches available till date has been discussed and is compared with the proposed work. Apart from typical applications of WSN, a brief background on data transfer schemes have also been mentioned.

Chapter 3

Dual Beacon Discovery Protocol

This chapter addresses the problem of ME discovery by using a hierarchical scheme. Here, 2BD protocol is proposed, which takes a simple hierarchical approach based on two different duty-cycle values.

3.1 System Overview

The reference scenario is depicted as shown in Figure 3.1. A single ME is considered in a sparse network scenario, wherein at any given time, the ME can communicate with at most one sensor node. The data transfer (communication) can take place only during a *contact*, i.e., when the sensor node and the ME are in the transmission range of each other. The area within the communication range of the static node is referred to as *contact area*, and the overall time spent by the ME inside the contact area is called *contact time*. Obviously, the contact time depends on the path followed by the ME and its speed.

Since the ME's motion cannot be controlled, its arrival time cannot be predicted by the sensor node. Therefore, the sensor node performs a discovery phase for the timely detection of the ME. Upon detecting the presence of the ME, the sensor node can switch from the discovery state to the data transfer state and start exchanging data with it. Since the discovery phase takes some time, the actual time available for data communication is (significantly) shorter than the nominal contact time. This time interval is referred to as the *residual contact time*. At the end of the data transfer phase, the sensor node can switch to the discovery state once again to detect the next contact. However, if (even partial) information about ME mobility are available, the sensor node can exploit these information and go to sleep for some time, thus saving energy.

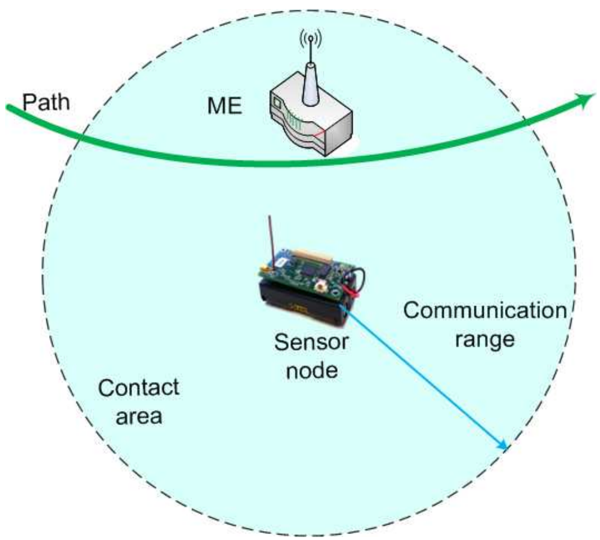

Figure 3.1: Reference scenario.

3.2 Dual-Beacon Discovery Protocol

Before introducing the 2BD protocol, it may be worthwhile describing briefly the discovery protocol based on a single Beacon, that is commonly used in WSNs with MEs. As shown in Figure 3.2, to announce its presence in the area, the ME emits Beacon messages of fixed duration T_{BD} at regular time intervals T_{BI}. On the other side, the sensor operates on a duty cycle and wakes up periodically to listen for possible Beacons. Upon receiving a Beacon, it realizes that the ME is within the contact area and the data transfer phase can thus take place. To allow a correct behavior, the sensor node's active period T_{ON} must be sufficiently long to ensure the complete reception of a Beacon message, i..e, the following relationship must hold: $T_{ON} \geq T_{BI} + T_{BD}$.

In this discovery protocol, both active and inactive periods are fixed and consequently the duty cycle used in the discovery phase, defined as $\delta = T_{ON}/(T_{ON} + T_{OFF})$ is also fixed. For better energy efficiency, the inactivity period (and hence the duty cycle) should be adjusted dynamically during the discovery phase, based on the probability that the ME is close to the contact area. To implement this ideal strategy in a real environment, the 2BD protocol takes a simple hierarchical approach based on two different duty-cycle values[1]. The sensor node typically operates with a *low duty cycle* δ_L to save energy, and switches to a *high duty cycle* δ_H only when the ME is supposed to be close to the contact area. Information about the ME's location are made available to sensor nodes by the ME itself through two different Beacon messages, namely *Short Range Beacons* (SRBs) and *Long Range Beacons* (LRBs).

[1] In principle, the protocol could be extended easily to the case of multiple duty-cycle values.

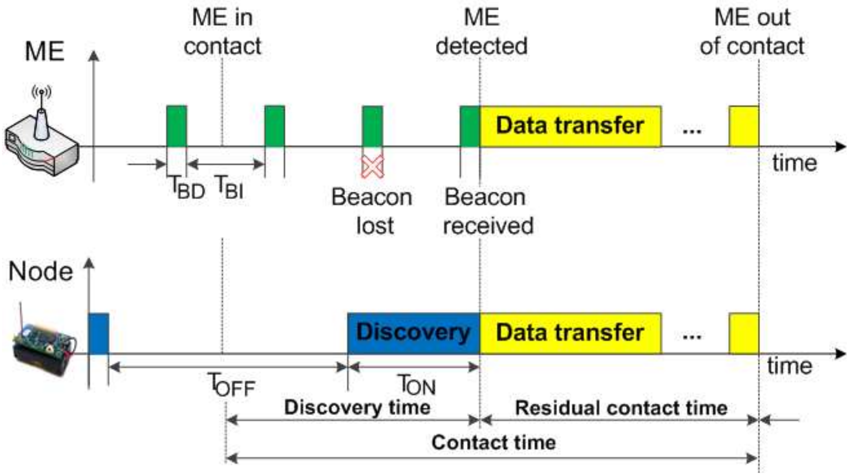

Figure 3.2: Traditional discovery protocol.

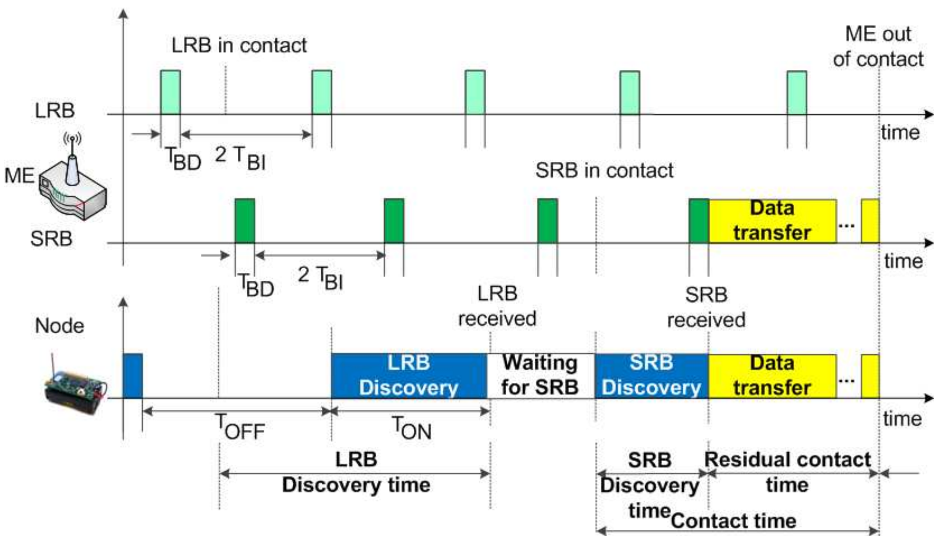

Figure 3.3: 2BD discovery protocol.

SRBs and LRBs are periodically emitted by the ME in an interleaved fashion as shown in Figure 3.3. For both the emission period is equal to $2 \cdot T_{BI}$, so that the overall Beacon period is still T_{BI}, similar to the traditional approach. However, the two Beacon types are associated with different transmission ranges, and thus convey different information. SRBs are transmitted with the same transmission-power level used for data transfer phase, and thus they experience a transmission range *r* (referred to as *communication range*). Therefore, they are aimed at informing the sensor node that the ME is within the contact area and data transfer, can thus take place. Instead, LRBs are sent with more transmission power, and hence they have a transmission range *R* larger than the communication range *r* (*R* is referred to as the *discovery range*).

During the discovery phase, a sensor node operates with a duty cycle δ_L and wakes up periodically for possible Beacons from the ME. Upon receiving an LRB, the sensor nodes increases the duty cycle to δ_H and waits for an SRB. As soon as an SRB is received (irrespective of the current duty cycle), the sensor node switches to 100% duty cycle and starts the data transfer phase. To avoid energy wastage after receiving an LRB, the duty cycle is reset to the low value δ_L if a subsequent SRB is not received within a pre-defined timeout.

3.3 Simulation Setup

An *ad hoc* event-driven simulator was implemented to evaluate the performance of the 2BD protocol, and was compared it with the traditional discovery protocol based on fixed duty cycle. The sparse scenario depicted in Figure 3.1 considers one sensor node and a single ME. For the sake of simplicity, and without losing in generality, the ME is assumed to move with a constant speed v, along a straight line at a fixed distance D from the sensor node. Under this hypothesis, the duration of the (nominal) contact time depends only on the ME's speed. To evaluate the performance of the two considered discovery protocols, the following indexes are measured:

- *Contact Miss Ratio*, defined as the fraction of potential contacts that are not detected by the sensor node.
- *Residual Contact Ratio*, defined as the ratio between the average residual contact time and the nominal contact time.
- *Energy per Contact*, defined as the average energy consumed by the sensor node per detected contact.

The Energy per contact is derived as the ratio between the total energy consumed by the sensor node in the discovery state and the number of detected contacts. With the single-Beacon protocol, the total energy consumption is given by

$$E_1 = T_{disc} \cdot \delta \cdot P_{rx} \tag{3.1}$$

where T_{disc} is the total time spent by the sensor node in the discovery state, δ is the duty cycle used for discovery, and P_{rx} is the power consumption in the receive mode. Similarly, while using the 2BD protocol, the energy consumption can be expressed as

$$E_2 = [T_{LR} \cdot \delta_L + T_{SR} \cdot \delta_H] \cdot P_{rx} \tag{3.2}$$

where T_{LR} (T_{SR}) is the total time spent waiting for an LRB (SRB) and, thus, using the low (high) duty cycle δ_L (δ_H). Finally, to measure energy savings obtained by 2BD, with respect to the single-Beacon approach, the following index is used

$$S = \frac{E_1 - E_2}{E_1} \tag{3.3}$$

where E_1 and E_2 are defined as above.

The Contact Miss Ratio and Residual Contact Ratio measure the performance of the discovery protocol, while the Energy per Contact indicates its energy efficiency. Ideally, *all contacts* (i.e., the Contact Miss Ratio should be zero) must be detected within acceptable Residual Contact Ratio to transfer all data available at the sensor node to the ME (with the minimum energy expenditure). In practice, depending on the specific application, missing a limited number of contacts is permissible. The acceptable Residual Contact Ratio depends on several factors, e.g., data acquisition rate, average inter-contact time, quality of communication channel, etc. The following case-study application must discover at least 90% of contacts (i.e., Contact Miss Ratio $<$ 10%) with a Residual Contact Ratio higher than 40%.

Unless specified, the experiments use the parameter values shown in Table 3.1. Transmission and reception power consumption are those of the ChipCon CC2420 transceiver [75], assuming a supply voltage of 3 Volts. The communication range of both the sensor node and the ME is assumed to be constant and is equal to 50m. Two additional values for *r* (i.e., 25m and 75m)[2] are considered, to evaluate the impact

[2] All these value are consistent with the transmission and reception power consumptions indicated in Table 3.1. Please consider

of the communication range on the performance of the 2BD protocol. The ME can vary dynamically its transmission-power level so as to transmit SRBs and LRBs with transmission ranges *r* and *R*, respectively. We do not make any specific assumption about the antenna used by sensor nodes. Therefore, we assume an ideal disc model for communication, i.e., the transmission range of sensor nodes is constant and equal for all sensor nodes. In addition, packets transmitted by a sensor node are received by corresponding nodes only if the distance between nodeTo derive confidence intervals, the replication method with 90% confidence level was used. In all experiments, ten replicas were performed, each consisting of at least 10,000 ME passages (i.e., potential contacts).

3.4 Simulation Results

To compare the performance of 2BD with that of the single-Beacon protocol, several experiments were performed under different operating conditions. For each experiment, the maximum duty cycle that must be used with the single-Beacon approach was determined to meet the application requirements (i.e., Contact Miss Ratio <10% and Residual Contact Ratio >40%). Then, an investigation was carried out on how much gain can be achieved in terms of energy efficiency and/or performance using the 2BD protocol instead of the single-Beacon protocol.

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that, for a given transmission power, the communication range can be different depending on environmental conditions.

Table 3.1: SIMULATION PARAMETERS.

Parameter	**Value**
Beacon period (T_{BI})	100 ms
Beacon duration (T_{BD}, all)	10 ms
ME Speed (v)	40 Km/h
Distance from the sensor node (D)	15 m
Discovery range (R)	100m, 200m
Communication range (r)	50 m
Nominal contact time	8.6 s
High Duty Cycle(δ_H, 2BD)	3%
Transmission power (P_{tx}) at 0 dBm	52.2 mW
Reception power (P_{rx})	56.4 mW

3.4.1 Impact of the Discovery Range

Figure 3.4 and Figure 3.5 show the Contact Miss Ratio and Residual Contact Ratio as functions of the duty cycle used by the sensor node. For the 2BD protocol, the duty cycle shown on the x-axis is the low duty cycle δ_L (the high duty cycle is always set to 3%). In this specific scenario, where the communication range r is equal to 50m, a duty cycle of 1.3% is needed to meet the application requirements when using the single-Beacon protocol. Instead, with 2BD the same requirements can be achieved with a low duty cycle δ_L equal to 0.8% if R=100m, and 0.5% if R=200m.

From the results in Figure 3.4 it is not yet clear whether or not this also results in a better energy efficiency, as in 2BD, the low duty cycle phase is followed by an high duty cycle phase. To make the comparison fair, the total energy con-

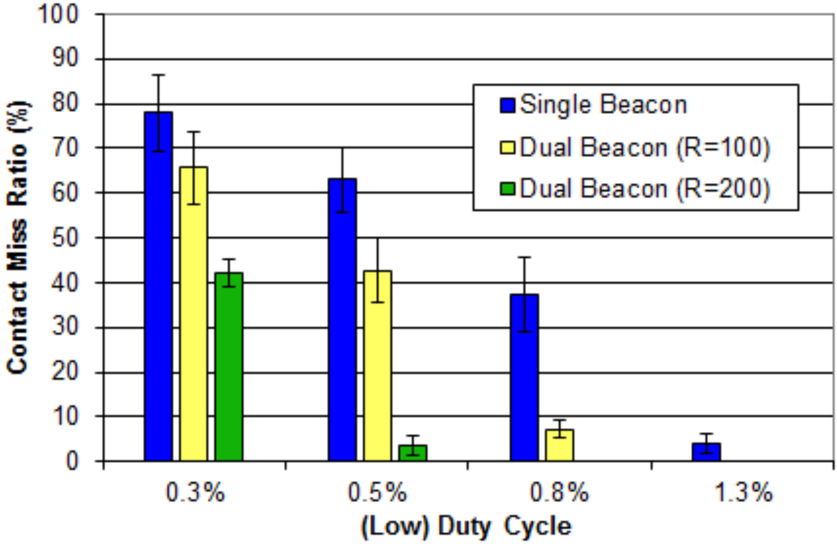

Figure 3.4: Contact Miss Ratio (r=50m).

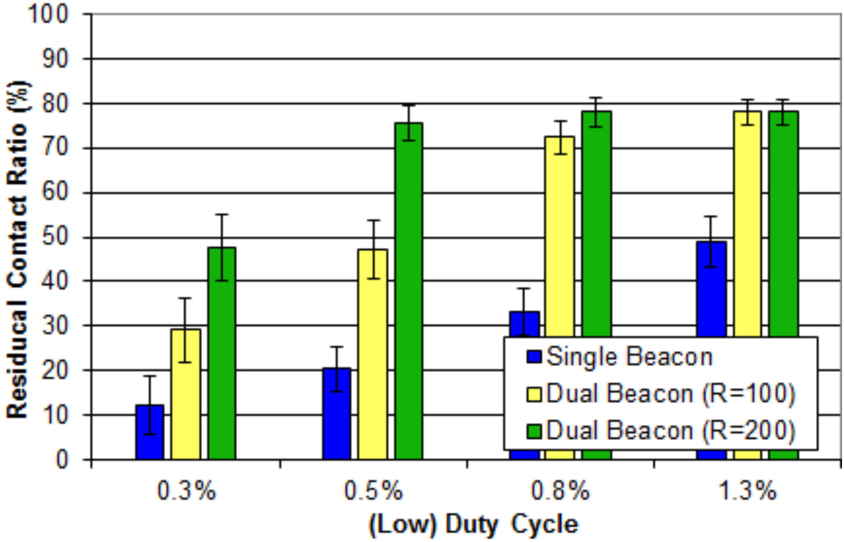

Figure 3.5: Residual Contact Ratio (r=50m).

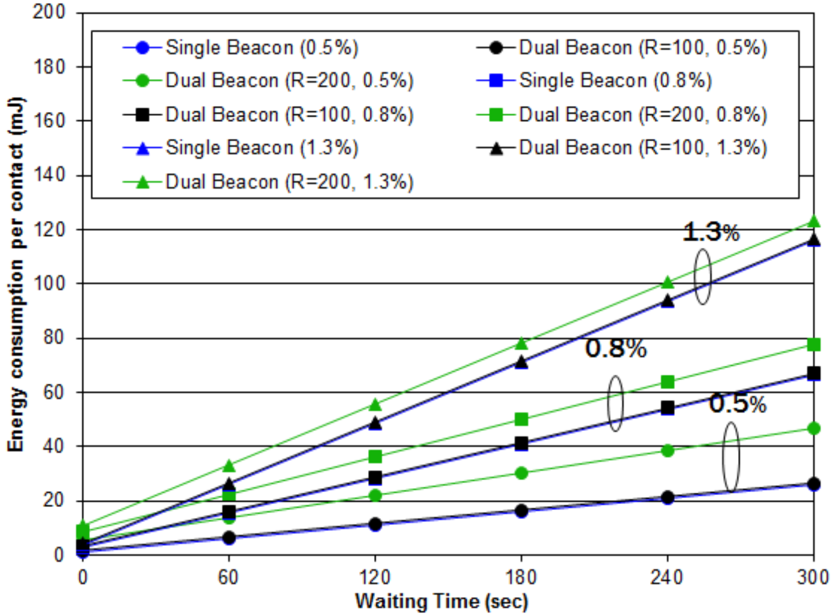

Figure 3.6: Average energy consumption per contact.

sumed by the two protocols is compared during the overall discovery phase. Such a comparison is shown in Figure 3.6 which shows the average total energy consumed per detected contact as a function of the *waiting time*, i.e., the time interval from when the sensor node enters the discovery state to when the ME enters the communication range of the sensor node. It may be worthwhile recalling here that the communication range r is assumed equal for both the protocols (and thus, the waiting time is equal for both the protocols). As expected, the energy per contact increases with the waiting time. In addition, for a given waiting time, the energy per contact consumed with 2BD is slightly higher than that consumed with the single-Beacon protocol using a duty cycle $\delta = \delta_L$. This is due to the additional energy consumed during the high duty cycle phase, i.e., while waiting

Table 3.2: ENERGY SAVINGS WITH DUAL BEACON (r=50m).

Waiting Time (s)	**R=100m** δ_L=0.8%	**R=200m** δ_L=0.5%
15	22.2%	22.2%
30	33.3%	33.3%
60	38.5%	46.2%
120	40.8%	55.1%
180	42.2%	57.7%
240	42.6%	58.5%
300	43.1%	59.5%

for SRBs. However, since this phase is typically much shorter than the total discovery phase, and 2BD is able to satisfy the application requirements with a low duty cycle δ_L significantly smaller than δ, the results in Figure 3.6 clearly show that the 2BD can provide relevant energy savings with respect to the single-Beacon approach. Table 3.2 shows the relative energy savings S provided by 2BD for different waiting times. As expected, energy savings become more and more relevant as the waiting time increases. However, even for short waiting times (e.g., 15s), the energy reduction provided by 2BD is more than 20%. Finally, it is to be emphasized that the 2BD protocol not only reduces the energy consumption, but it also provides a better performance in terms of Residual Contact Ratio (highlighted in Figure 3.5).

3.4.2 Impact of the Communication Range

In the previous section, the communication range was assumed to be 50m, and correspondingly, the nominal contact

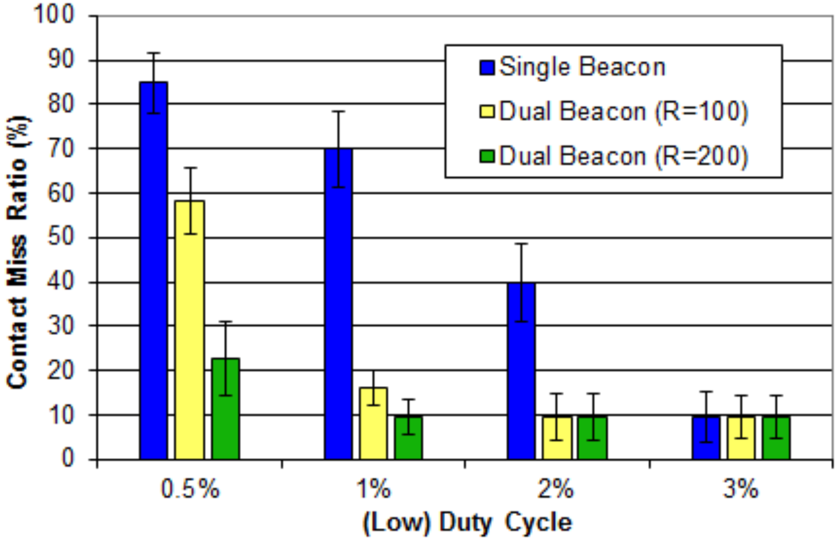

Figure 3.7: Contact Miss Ratio (r=25m).

time was 8.6s. In this section, the impact of the communication range (i.e., the contact time) on the performance of 2BD has been investigated. To this end, two additional values for r, i.e., r=25m and r=75m (the corresponding contact times are 3.6s and 13.2s, respectively) are considered. The obtained results are discussed below.

When the communication range is small, i.e., r=25m, the contact time is short (3.6s), and thus the probability to miss contacts is high, especially if the sensor node's duty cycle is low. As shown in Figure 3.7 and Figure 3.8, with the single-Beacon approach, the minimum duty cycle that allows detecting at least 90% of contacts (with a Residual Contact Ratio $>$ 40%) is 3%. Whereas, using 2BD, the same requirements can be satisfied with a significantly smaller (low) duty cycle, i.e., δ_L=2% if R=100m, and δ_L=1% if R=200m (the high duty cycle is always set to 3%). Energy savings provided by

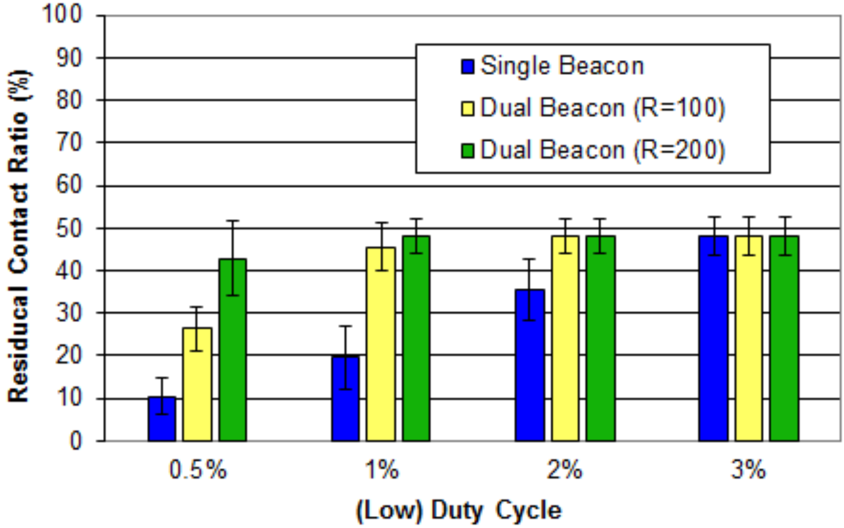

Figure 3.8: Residual Contact Ratio (r=25m).

2BD with respect to the single-Beacon approach for different waiting time are shown in Table 3.3. The trend is very similar to the one observed in the previous scenario (i.e., when r=50m).

Finally, to analyze the case in which the communication range is relatively large i.e., 75m, and hence the nominal contact time is long enough (13.2s) to allow the detection of almost all contacts, even with a low duty cycle. From Figure 3.9 and Figure 3.10, with the single-Beacon approach, the application requirements can be satisfied with a 0.9% duty cycle. However, even in this less-critical scenario, 2BD is able to provide a significant improvement in terms of energy efficiency as the same application requirements can be met with δ_L=0.7% if R=100m, and δ_L=0.5% if R=200m. The resulting energy savings for different waiting times are shown in Table 3.4. Since the scenario is now less critical for discovery, energy savings achieved by 2BD are generally smaller than

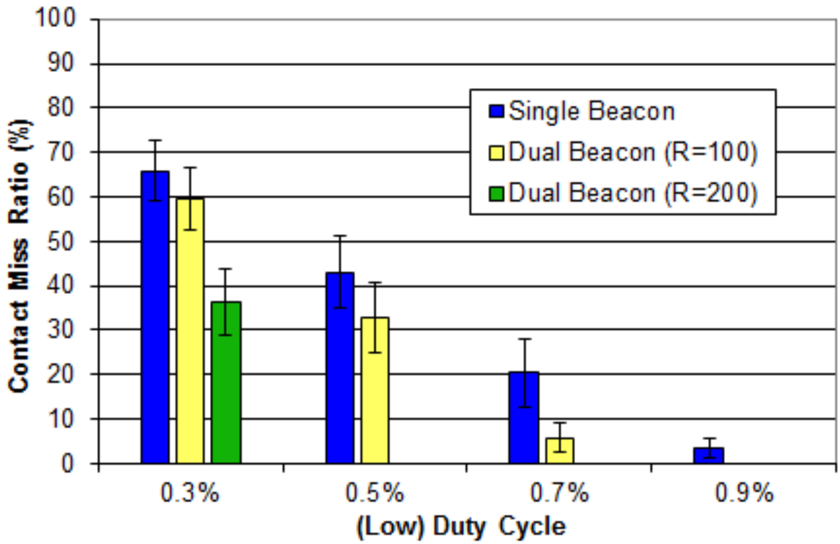

Figure 3.9: Contact Miss Ratio (r=75m).

previous scenarios. However, the results in Table 3.4 show that with 2BD, it is possible to achieve significant energy reductions even in this scenario.

3.5 Resource-Aware Data Accumulation

RADA [11] is an adaptive discovery protocol that tries to learn the mobility pattern of the ME using Q-Learning, a form of reinforcement learning that does not require a model of the environment. In fact, it follows the *Distributed Independent Reinforcement Learning* (DIRL) approach [76] and relies on following elements:

- A state representation consisting of both system and application variables.

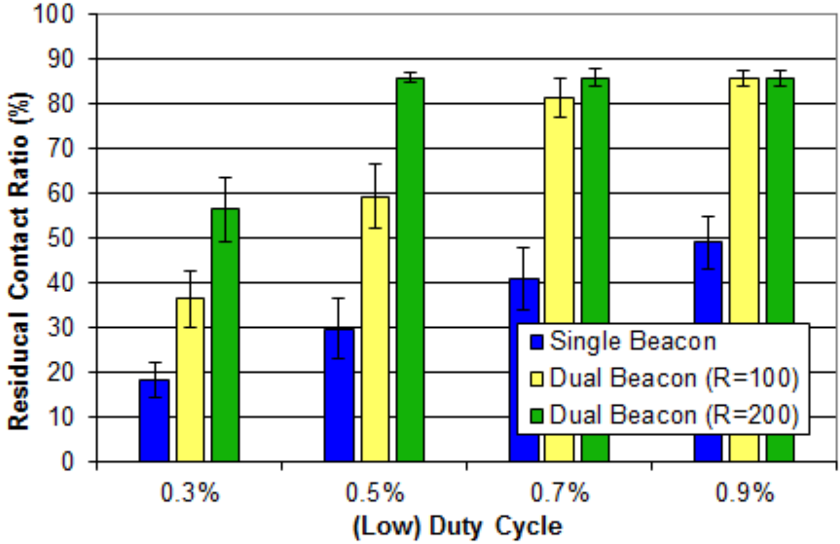

Figure 3.10: Residual Contact Ratio (r=75m).

Table 3.3: ENERGY SAVINGS WITH DUAL BEACON (r=25m).

Waiting Time (s)	R=100m δ_L=2%	R=200m δ_L=1%
15	21.0%	26.3%
30	26.7%	40.0%
60	29.6%	51.9%
120	31.7%	58.4%
180	32.4%	60.8%
240	32.8%	62.6%
300	33.1%	63.2%

Table 3.4: ENERGY SAVINGS WITH DUAL BEACON (r=75m).

Waiting Time (s)	R=100m δ_L=0.7%	R=200m δ_L=0.5%
15	14.3%	0.1%
30	20.0%	10.0%
60	26.3%	26.3%
120	26.5%	35.3%
180	28.0%	30.8%
240	30.3%	39.4%
300	30.9%	40.7%

- A set of tasks (i.e., duty cycles) that can be executed by the sensor node.
- A reward function r associated with each task.
- A utility function Q(s, τ) for performing the task τ in a state s.

The objective of the system is to maximize the long-term utility that can be achieved by executing different tasks. In this system the state s corresponds to the inter-contact time as observed by the sensor node. That is, the time elapsed from the beginning of a contact to the beginning of the subsequent one. The reward function r provides the *immediate reward* achieved by executing a task. It is positive if a success has been obtained, negative otherwise. Instead, the utility function gives the *long-term utility* of performing a task. **Q** is an utility look-up table, whose generic element Q(s, τ) provides the utility of performing task τ in the state s. It is defined as the expected value of the sum of the immediate reward r, and the discounted utility of the resulting state s'

after executing task τ, i.e.

$$Q(s, \tau) = E[\rho + \gamma \cdot e(s')|s, \tau] \tag{3.4}$$

where $e(s') = max_\tau\ Q(s', \tau)$ over all tasks τ. The above expected value is conditioned to state s and task τ. Since Q-Learning is done online, Equation 3.4 cannot be applied directly as the stored utility values might not have converged to their final values. In practice, Q-Learning is used with incremental updates as given by the following equation:

$$Q(s, \tau) = (1 - \alpha) \cdot Q(s, \tau) + \alpha \cdot [r + \gamma \cdot e(s')] \tag{3.5}$$

In Equation 3.5, α is a learning-rate[3] parameter between 0 and 1, that controls the rate at which a sensor node tries to learn by giving more (α close to 1) or less (α close to 0) weight to the previously learned utility value. Furthermore, γ is a discount-factor, also between 0 and 1; the higher the value, the greater the sensor node relies on future reward, rather than on immediate reward. Time is divided into time domains (of fixed duration T_D) and the utility function is updated periodically at the end of each time domain. Then, based on the learned utility, the task that maximizes the long-term utility is selected for execution in the immediate future.

RADA algorithm uses an *exploitation* and *exploration* phase. During the exploitation phase, the next task is selected according to the learned utility (as described above), while in the exploration phase it is picked up *randomly* from the set of available tasks. The exploration phase is accessed at the end of the time domain, with a probability ϵ evolving dynamically as below

[3]Preliminary simulations were run for different values of learning-rate (α), and the best performance was found when α is equal to 0.5.

$$\epsilon = \epsilon_{min} + max\left\{0, \frac{(\epsilon_{max} - \epsilon_{min}) \cdot (c_{max} - c)}{c_{max}}\right\} \quad (3.6)$$

where $\epsilon_{min}(\epsilon_{max})$ is the minimum (maximum) exploration probability, while c and c_{max} denote the number of contacts detected by the sensor node when Equation 3.6 is evaluated, and the maximum number of detected contacts to be considered for calculating ϵ.

The utility function explained through Equation 3.4 and Equation 3.5 takes into account both the immediate reward r coming from executing task t in state s, as well as the long-term utility resulting after executing task t. At each step, RADA selects the best task according to the learned utility i.e., the task that maximizes the long-term utility. Specifically, time is divided into time domains of fixed duration (100s). At the end of each time domain, RADA observes the current state s and selects the task to be executed in the next time domain. Although the definition of tasks are strictly related to the specific application scenario, the following tasks (i.e., duty cycles) have been defined in [5, 11]. In order to make the derivation of tasks more general, the actual duty cycles are defined on the basis of a maximum allowed duty cycle δ_{max}.

- *High Duty Cycle* (HDC): The sensor node operates with a high duty cycle equal to δ_{max}. This task should be selected whenever there is a high probability of the ME being nearby.

- *Low Duty Cycle* (LDC): The sensor node operates with a low duty cycle equal to $0.5 \cdot \delta_{max}$. This task should be selected whenever there is a low probability of the ME being nearby.

- *Very Low Duty Cycle* (VLDC): The sensor node operates with a very low duty cycle, equal to $0.1 \cdot \delta_{max}$. This task should be selected whenever there is a very low probability of the ME being nearby.

RADA executes different tasks according to the algorithm illustrated in Figure 3.11. Initially, all Q-values are set to zero. The *exploration* and *exploitation* strategy for selecting the task in each time domain is carried out according to Equation 3.6. After the execution of the selected task t, DIRL observes the new obtained state s' and compares it with all existing states based on a Hamming distance. If any existing state s'' has a Hamming distance of s' lower than the predefined threshold θ, then s' is set to s''. Otherwise, a new state is created and added to the existing set. Finally, DIRL computes the reward r (explained below) for the task t (executed while in the state s) and updates the Q-values accordingly.

Different mobility patterns require different state definitions to suitably characterize the environment for reinforcement learning. Different mobility patterns are described in section 3.6. Basic state variables can simply be represented as i_{ct} (the inter-contact time as observed by a sensor node), i_r (a boolean value denoting if an ME is discovered or not), and t_{od}(time-of-day value corresponding to the specific time at which the state is evaluated). These variables can be customized to learn any specific scenario. For additional learning, number of state variables can be increased, but this would lead to higher storage and computational requirements of the sensor node, and hence would affect the overall performance.

In RADA, the tasks are scheduled based on the learned probability that the ME is in contact for a specific amount of time to be discovered. The efficiency of data collection is termed high when this is achieved with low energy consumption. For all the tasks scheduled by a sensor node, RAD-

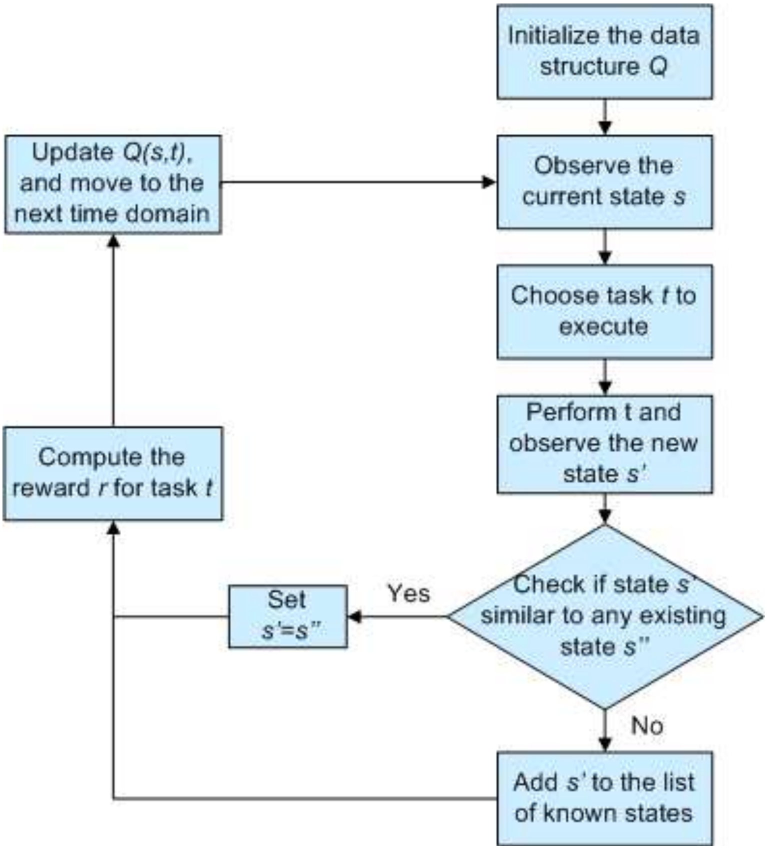

Figure 3.11: Distributed Independent Reinforcement Learning Algorithm.

A learns this probability through a local reward function defined as

$$r = (n_c \cdot e_p - 1) \cdot e_s \tag{3.7}$$

where n_c denotes the number of contacts detected while executing the task, e_p is the expected price of the task for each contact, and e_s the energy spent. Thus, for each task, the reward is positive if the ME is successfully detected or negative (equal to minus e_s) if it is not.

3.6 Performance Evaluation

This section evaluates the performance of both the adaptive discovery protocols, 2BD (see section 3.2) and RADA (see section 3.5). For the sake of comparison, this analysis also considers the following two non-adaptive schemes:

- *Fixed*. In this scheme, the duty cycle is fixed over time and is equal to the average duty cycle used by RADA. Operationally, for each mobility scenario, RADA was run first and then the duty cycle of *Fixed* was set accordingly.
- *Fixed-HD*. The duty cycle is fixed and is equal to 3%.

The OMNeT++ simulation tool was used to implement all the considered discovery schemes. A sparse network scenario was analyzed with just one sensor node and a single ME. For the sake of simplicity, the ME is assumed to move with a constant speed *v* along a straight line at a fixed distance *D* from the sensor node. Under this assumption, the nominal contact time depends only on the ME's speed.

To evaluate the performance of the considered discovery schemes, the following performance indexes are measured:

- *Discovery Ratio*, defined as the ratio between the number of contacts successfully detected by the sensor node, and the total number of potential contacts.
- *Residual Contact Ratio*, defined as the ratio between the average residual contact time and the total contact time.
- *Activity Ratio*, defined as the ratio between the active time and the total time spent during the discovery phase.
- *Energy per Contact*, defined as the average energy consumed by sensor nodes in the discovery phase per detected contact.

The Discovery Ratio provides a measure of the *effectiveness* of a discovery scheme. However, the Discovery Ratio alone is not enough to characterize the effectiveness of the different discovery schemes. In fact, the Residual Contact Ratio gives the amount of the contact time that can be actually exploited by the data transfer phase. Ideally, these indexes should be close to 100%. Conversely, the Activity Ratio gives the fraction of time during which the sensor node is active in the discovery phase, and hence it indirectly measures the *energy efficiency* of a discovery scheme. Ideally, this index should be as low as possible.

This analysis considers the following three ME mobility patterns, resulting in a corresponding number of mobility scenarios with an increasing uncertainty about the ME's arrival time at the sensor node:

- *Deterministic*: ME arrivals are periodic. The value of the inter-contact time is fixed and is equal to 30 min

(1800s).

- *Gaussian*: ME arrivals are regular. The inter-contact time is a random variable, distributed according to a normal distribution with the mean equal to 30 min and the standard deviation equal to 1 min.

- *Random*: ME arrivals are completely random. The inter-contact time is a random variable with a uniform distribution between [0, 30] min.

In all experiments, fifteen independent replications were performed, each consisting of at least 1000 ME passages, and derived confidence intervals at a level of 90%. The sensor node was equipped with a Chipcon CC2420 radio transceiver [75]. The channel quality is modeled using the well-known disk model, i.e., packet loss is assumed to be 0% when the sensor-ME distance is lower than the transmission range, and 100% otherwise. All other simulation parameters are summarized in Table 3.5.

Figure 3.12 shows the Discovery Ratio of the considered discovery schemes for different mobility scenarios. As expected, Fixed-HD always provides a highest Discovery Ratio. However, 2BD has a Discovery Ratio very close to that of the Fixed-HD in all the considered scenarios. RADA performs very well in the deterministic scenario, while its performance decreases when the uncertainty in the ME's arrival time increases. In the random scenario, RADA exhibits poor performance in terms of Discovery Ratio because more than 60% of potential contacts are missed. This happens because when ME arrivals are random, there is no regular pattern that can be learned and exploited. In the random scenario, even the Fixed scheme performs better than RADA (it may be worthwhile to note that the Fixed has the same average duty cycle of RADA). Figure 3.13 shows the Residual Con-

Table 3.5: SIMULATION PARAMETERS.

Parameter	**Value**
Beacon period (T_{BI})	100 ms
Beacon duration (T_{BD}, all)	10 ms
ME Speed (v)	40 Km/h
Distance from the sensor node (D)	15 m
Communication range (r)	50 m
Nominal contact time	8.6 s
Discovery range (R, 2BD)	200m
High Duty Cycle(δ_H, 2BD)	3%
Maximum duty-cycle (δ_{max}, RADA)	3%
State distance threshold (θ, RADA)	1.0
Time Domain (TD)	100 s
α, γ (RADA)	0.5
ϵ_{min}, ϵ_{max} (RADA)	0.5
c_{max} (RADA)	100

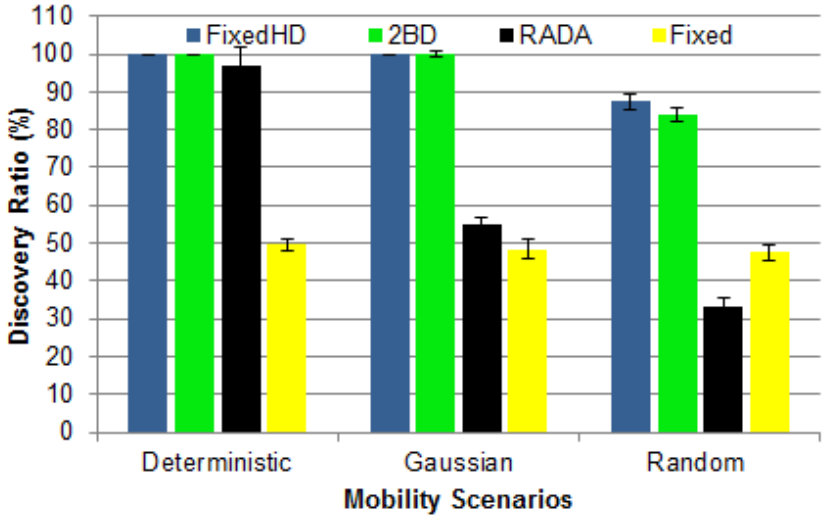

Figure 3.12: Discovery Ratio.

tact Ratio of different discovery schemes in different mobility scenarios. In deteministic scenario, both 2BD and RADA provide a Residual Contact Ratio, which are very close to the value obtianed by the Fixed-HD. However, all the discovery schemes performance decrease when the uncertainty in the ME's arrival time increases.

Figure 3.14 shows the Activity Ratio of various discovery schemes for different mobility scenarios. As expected, Fixed-HD has the highest energy consumption, while RADA and Fixed have the same Activity Ratio. 2BD has the lowest Activity ratio in all the considered scenarios. Hence, one can draw the conclusion that among all the considered scenarios, the 2BD is the most efficient discovery protocol. It allows saving a significant amount of energy when compared to non-adaptive schemes. RADA performs well when the ME mobility pattern is very regular. However, its performance tends to decrease when the uncertainty in the arrival process

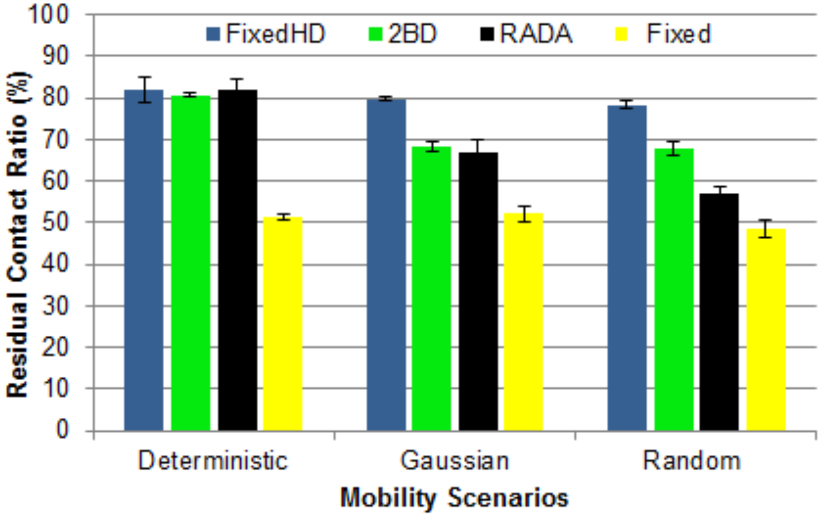

Figure 3.13: Residual Contact Ratio.

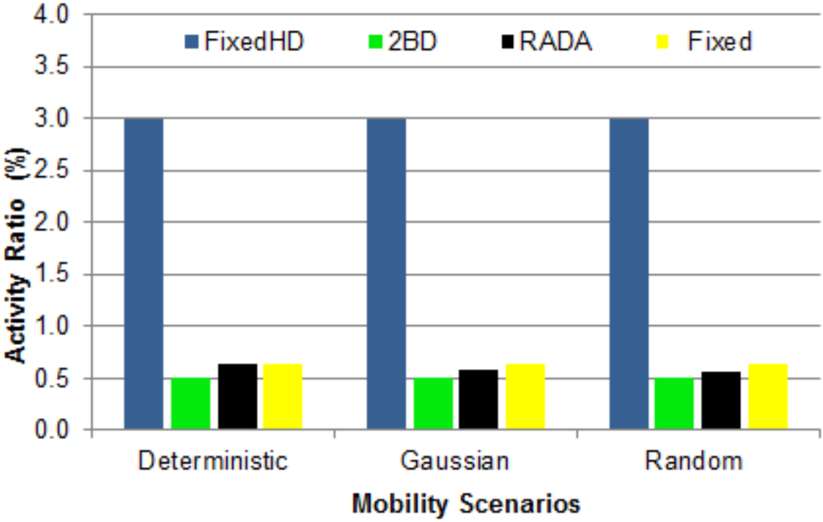

Figure 3.14: Activity Ratio.

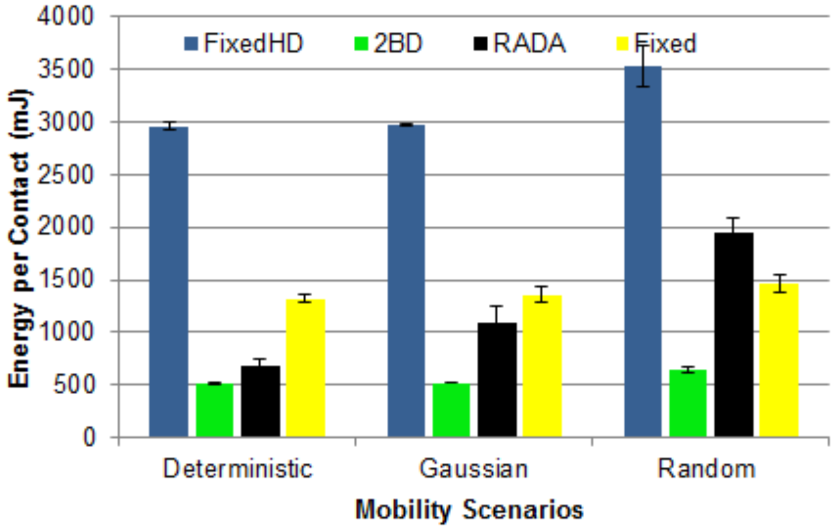

Figure 3.15: Energy per Contact.

increases. This behavior is better emphasized in terms of Energy per Contact, as shown in Figure 3.15

3.7 Summary

This chapter presented a hierarchical discovery scheme based on two different Beacon messages for energy efficient and timely discovery in sensor networks with MEs. It has been shown that using a traditional approach for discovery, based on periodic Beacon emission by the ME and periodic listening by the sensor with fixed duty cycle, may be inefficient, especially when the discovery phase is long. The performance of the 2BD protocol has been analyzed through simulation in a sparse network scenario. The obtained results show that the proposed approach, though being simple, can provide a significant energy reduction with respect to the traditional single-Beacon approach. Even when MEs arrival times can be predicted with some accuracy, and the time spent in the discovery state is short (e.g., 15s), the proposed approach can provide an energy saving by more than 20%. In addition, two different adaptive discovery protocols RADA and 2BD were also evaluated. Their performance have also been compared with that of non-adaptive schemes commonly used in practice. Simulation results have showed that the 2BD outperforms all other discovery schemes. However, it is unable to predict the ME's arrival time. RADA performs well when the ME mobility pattern is very regular, while its performance tends to decrease when the uncertainty in the MEs arrival process increases.

Chapter 4

A Hybrid Discovery Protocol

Chapter 3 addressed the problem of mobile node discovery in sparse sensor networks, where data collection is carried out through MEs. Performance of adaptive schemes and non-adaptive schemes have also been compared. This chapter shows how to combine the proposed hierarchical approach with a learning-based approach.

4.1 Hybrid Discovery Algorithm

The Hybrid discovery algorithm combines a learning-based approach with a hierarchical approach. Specifically, it tries to learn the mobility pattern of the ME and predicts its next arrival time, on the basis of the past history, using *Q-Learning* [77], i.e., a form of reinforcement learning that does not require a model of the environment. The duty cycle of the sensor node is then adjusted according to this prediction. Hence, the sensor node is in sleep mode most of the time, and activates only when the ME is about to arrive. Since the prediction may not be accurate, the Hybrid algorithm exploits an additional hierarchical approach to increase its *energy efficiency*. The sensor node initially activates with a *low duty cycle* and switches to a *high duty cycle* only when the ME is nearby, as described in Section 3.2.

The prediction algorithm is based on Q-Learning, specifically like RADA [11], which follows the DIRL approach (as described in Section 3.5), and relies on following elements:

- A state representation consisting of both system and application variables.
- A set of tasks (i.e. duty cycles) that can be executed by the sensor node.
- A reward function ρ associated with each task.
- A utility function $\mathbf{Q}$.

As any other learning algorithm, Hybrid also includes an *exploitation* and *exploration* phase. During the exploitation phase, the next task is selected according to the learned utility (as described in Section 3.5), while in the exploration phase it is picked up *randomly* from the set of available tasks.

Although the definition of tasks is strictly related to the specific application, the following tasks (i.e., duty cycles) are defined in Hybrid:

- *Sleep Mode (SLP)*: The sensor node keeps the radio in sleep mode. Based on the learned utility, this task is selected whenever the ME is not expected to arrive.
- *Low Duty Cycle (LDC)*: The sensor node operates with a *low duty cycle* δ_L. Based on the learned utility, this

task is selected when the ME is expected to arrive in the next time domain.

- *High Duty Cycle (HDC)*: The sensor node operates with a *high duty cycle* δ_H. Unlike the other tasks, HDC is not selected on the basis of learned utilities. Instead, it is chosen whenever a LRB is received from the ME starting the activation phase.

Algorithm 1 shows the actions performed by the sensor node. Initially, the algorithm initializes the look-up table $\mathbf{Q}$ and the set Λ of tasks that can be selected during the exploration phase (i.e., SLP, LDC, HDC). Boolean variable *LRB-rcvd* (*SRB-rcvd*) is initialized to *False*. *LRB-rcvd* (*SRB-rcvd*) will be set when a LRB (SRB) is received respectively, thus starting the activation (communication) phase. A node that has received a LRB may experience either a *contact* (if it receives a SRB) or a *false activation* (if it fails to receive a subsequent SRB). To avoid energy wastage due to false activations, a timer is used. The timeout value T_{out} is set according to the worst case, i.e., when the distance between the sensor node and the ME is zero. Finally, an initial task is randomly selected from set Λ.

At each step, the algorithm executes the previously selected task, until one of the following events occur:

(i) LRB reception;

(ii) SRB reception;

(iii) Timeout expiration;

(iv) End of the communication phase, and

(v) End of current time domain.

Algorithm 1 Hybrid algorithm

```
init
    s = 0; Q(0, τ) for all τ;
    Λ = {SLP, LDC, HDC};
    LRB-rcvd = False; SRB-rcvd= False;
    T_out = (R + r)/v;
    Select an initial task τ from Λ randomly;
end init
loop
    execute τ;
    wait (event);
    switch (event) {
    case (LRB reception):
        LRB-rcvd =True;
        τ = HDC; start timer (T_out);
    case (timeout):
        LRB-rcvd = False;
        τ = LDC;
    case (SRB reception):
        SRB-rcvd=True; stop timer;
        Start communication phase;
    case (end of communication):
        SRB-rcvd = False;
        LRB-rcvd = False;
        τ = LDC;
    case (end of time domain):
        if SRB-rcvd = False {
            if (LRB-rcvd = True) τ = HDC;
            else {
                Calculate new state s';
                if ∃ s'' : s' ≈ s'' then s' = s''
                else add s' to the list of known states;
                Calculate reward for task τ in state s;
                Update Q(s, τ);
                choose a new task τ to execute
            // through exploration (with prob. ϵ ) or exploitation
            } // end else
        } // end if
    } // end switch
end loop
```

Upon receiving a LRB (case **i**) the sensor node sets the *LRB-rcvd* flag and selects the HDC task. Finally, the false activation timer is started. If the timer expires without receiving any SRB (case **ii**), the sensor node selects the LDC as the next task and resets the *LRB-rcvd* variable. Instead, if a SRB is received before the timeout expiration (case **iii**), the sensor node sets the *SRB-rcvd* flag, stops the false activation timer, and enters the communication phase. At the end of the communication phase (case **iv**), both of the *LRB-rcvd* and *SRB-rcvd* variables are reset. Finally, at the end of the time domain (case **iv**), if the communication phase is in progress (i.e., a SRB has been received), no action is performed. If a LRB has been received (i.e., the sensor node is inside the activation phase), HDC is maintained as the next task. Otherwise, the new resulting state s' (i.e., inter-contact time) is measured. If s' is similar to a state s'' previously stored in the Q structure (i.e., the Hamming distance between s' and s'' is less than a pre-defined threshold [76]), s' is assimilated to s''. Otherwise, s' is added to the list of known states. Finally, the reward for task τ corresponding to state s is calculated, and $Q(s, \tau)$ is updated accordingly.

Specifically, the reward for any task is calculated as $\rho = (n_c \cdot p_m \cdot e_p - 1) \cdot e_s$, where n_c, p_m and e_p denote the number of contacts detected in the last time domain (i.e., 0 or 1), the price multiplier for the executed task, and the expected price. The negative part of the reward represents the cost for executing the task. This cost is proportional to the time e_s, during which the sensor node was active during the last time domain (e.g., $e_s = \delta_L \cdot T_D \cdot P_{RX} + (1 - \delta_L) \cdot T_D \cdot P_{SL}$ for the LDC task). The reason behind using a price multiplier and an expected price is to allow a symmetric evaluation of the reward function. Thus, for each task, the reward is positive if the ME is successfully detected. If the ME is not detected, the reward is negative (equal to minus e_s). The price multiplier

Table 4.1: REWARD FUNCTION'S PARAMETERS

LRB	**SRB**	n_c	**Price Multiplier (p_m)**	e_p
NO	NO	0	-1	100
NO	YES	1	1	100
YES	YES	1	2	100
YES	NO	0	-2	100

p_m for task τ is calculated as shown in Table 4.1.

4.2 Simulation Environment

The OMNET++ simulation tool [78] was used to evaluate the performance of the proposed Hybrid discovery protocol. The single ME is assumed to move with a constant speed v along a straight line at a fixed distance D from the sensor node. In a sparse scenario, assuming the distance between neighboring sensor nodes is very large (i.e., larger than the discovery range R), one can concentrate on a single sensor node. However, in the last part of the analysis, a scenario where there are multiple sensor nodes and the distance between them is not necessarily so large (see Section 4.3.1) has also been considered.The following performance indexes are measured during analysis:

- *Discovery Ratio*, defined as the ratio between the number of contacts successfully detected by the sensor node and the total number of potential contacts.

- *Residual Contact Ratio*, defined as the ratio between the average residual contact time and the total contact time
- *Activity Ratio*, defined as the ratio between the active time (i.e. the radio is on) and the total time spent during the discovery phase.
- *Energy per Contact*, defined as the average energy consumed by sensor nodes in the discovery phase per detected contact.

The Discovery Ratio and Residual Contact Ratio provide a measure of the *effectiveness* of a discovery scheme. Ideally, these indexes should be (close to) 100%. The Activity Ratio and the Energy per Contact measure the *energy efficiency* of the discovery scheme. Ideally, these indexes should be as low as possible.

To evaluate the performance of the Hybrid protocol, it was compared with the following adaptive solutions that exploit either a learning-based approach or a hierarchical approach.

- RADA. This protocol relies on the same prediction algorithm used in Hybrid. However, it does not exploit the hierarchical mechanism based on LRBs and SRBs. Sensor nodes are typically in sleep mode and get activated only when the ME is expected to arrive.
- 2BD. This protocol uses a hierarchical approach based on LRBs and SRBs, but it is not able to predict the ME's arrival time. Sensor nodes are always in LDC and switch to HDC upon receiving an LRB.

For completeness, a fixed scheme is considered (referred to as *Fixed*), where the duty cycle is constant over time and is equal to HDC. Table 4.2 shows the duty cycle values used by different protocols. To make the comparison fair, the same values of HDC and LDC were considered for various algorithms. Also, the same set of duty cycles were used for Hybrid and RADA (HDC, LDC, SLP).

Table 4.2: DUTY CYCLE VALUES

Algorithm	**HDC**	**LDC**	**SLP**
HYBRID	3%	0.5%	0%
RADA	3%	0.5%	0%
2BD	3%	0.5%	-
Fixed	3%	-	-

In all experiments, fifteen independent replications were performed, each consisting of 1000 visits of the ME, and derived confidence intervals with a level of 90%. Since the discovery process is of main interest, the channel quality was modeled using the disk model, i.e., packet loss is assumed to be 0% when the distance between sensor node and ME is lower than the communication range r, and 100% otherwise. Unless stated, all the other simulation parameters are as shown in Table 4.3. The learning parameters are set as in [11], while the power consumption values have been derived from the datasheet of Chipcon CC2420 radio transceiver [75].

4.3 Simulation Results

4.3.1 Impact of the ME mobility pattern

The analysis assumes that the ME visits the sensor node at regular times, on average every T_{TOUR} (inter-arrival time).

Table 4.3: SIMULATION PARAMETERS.

Parameter	**Value**
LRB/SRB period ($2T_{BI}$, Hybrid and 2BD)	200 ms
Beacon period (T_{BI}, RADA and Fixed)	100 ms
Beacon duration (T_{BD}, all)	1 ms
ME Speed (v)	40 Km/h
Distance from the sensor node (D)	15 m
Communication range (r)	50 m
Nominal contact time	8.6 s
Discovery range (R, Hybrid and 2BD)	200m
Power Consumption in Receive Mode (P_{RX})	56.4 mW
Power Consumption in Sleep Mode (P_{SL})	0.6 μW
Time Domain (TD)	100 s
α (Hybrid and RADA)	0.5
γ (Hybrid and RADA)	0.5
ϵ_{max} (Hybrid and RADA)	0.5
ϵ_{min} (Hybrid and RADA)	0.05
c_{max} (Hybrid and RADA)	100

The following four different ME mobility patterns are considered, resulting in a corresponding number of scenarios with increasing randomness in the inter-arrival time.

- *Deterministic*: ME arrivals are periodic. The inter-arrival time is fixed and is equal to 30 min (1800s).
- *Gaussian-1*: The inter-arrival time is a random variable, distributed according to a normal distribution with the mean equal to 30 min and the standard deviation equal to 1 min .
- *Gaussian-10*: Same as *Gaussian-1*, but with the standard deviation equal 10 min.
- *Uniform*: The inter-arrival time is uniformly distributed between [0, 30] min.

Figures 4.1– 4.4 show the impact of the ME's mobility pattern on different discovery schemes in terms of Discovery Ratio, Residual Contact Ratio, Activity Ratio, and Energy per Contact respectively. When the mobility pattern is deterministic, all schemes exhibit a Discovery Ratio close to 100%. As expected, Fixed always provides a highest Residual Contact Ratio. However, all the adaptive schemes have a Residual Contact Ratio close to that of the Fixed in the deteministic scenario. In any case, Hybrid has a Residual Contact Ratio higher than other adaptive schemes when the uncertainty in the inter-arrival time increase. However, the Activity Ratio of Hybrid is significantly lower than that of the other schemes, resulting in a lower energy consumed per detected contact. When the randomness of the inter-arrival time increases, the Activity Ratio of all the adaptive schemes is approximately the same (i.e., around 0.5%), i.e., the sensor node is in LDC for most of the time. However, Hybrid outperforms both 2BD and RADA in terms of percentage

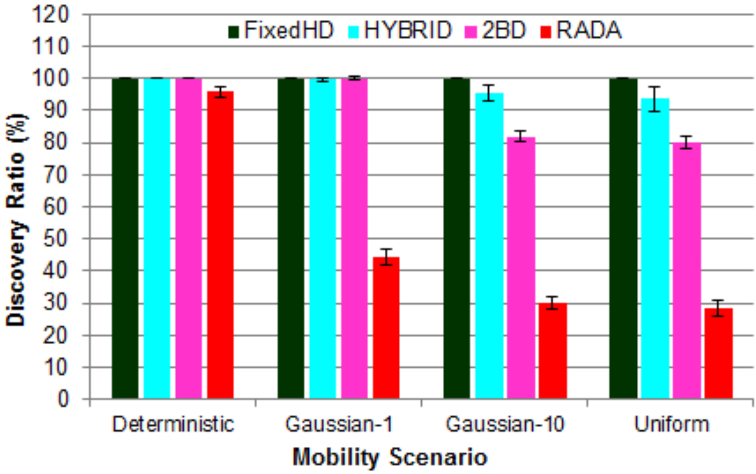

Figure 4.1: Impact of the mobility pattern in terms of discovery ratio

of detected contacts. Hence, it experiences a lower Energy per Contact. Specifically, Hybrid provides a Discovery Ratio very close to that of Fixed in all the considered mobility scenarios, with an Activity Ratio of about 1/6 (in the worst case), thus achieving a huge reduction in energy consumption. Henceforth, only the *Gaussian-1* scenario will be considered.

4.3.2 Impact of inter-arrival time

In Figure 4.4 the Energy per Contact has been calculated assuming an inter-arrival time of 30 minutes (i.e., 1800s). Obviously, the energy consumption is strongly influenced by this value. To investigate the impact of the inter-arrival time on the average energy consumption per contact, different values for this parameter were considered (while leaving all the other parameters unchanged). The obtained results, in

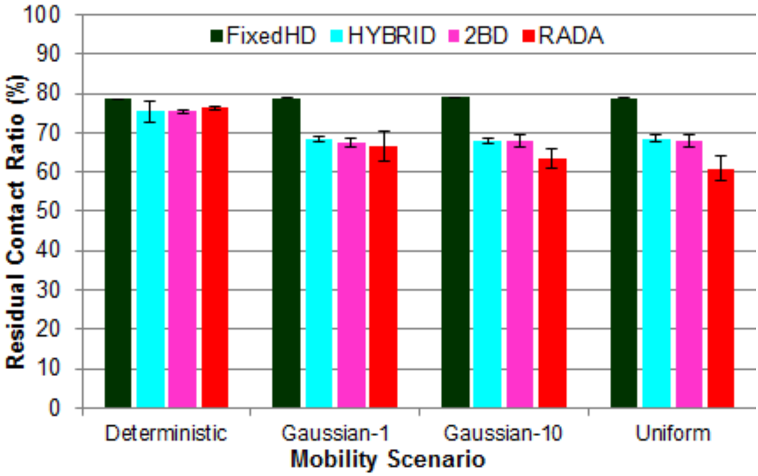

Figure 4.2: Impact of the mobility pattern in terms of residual contact ratio

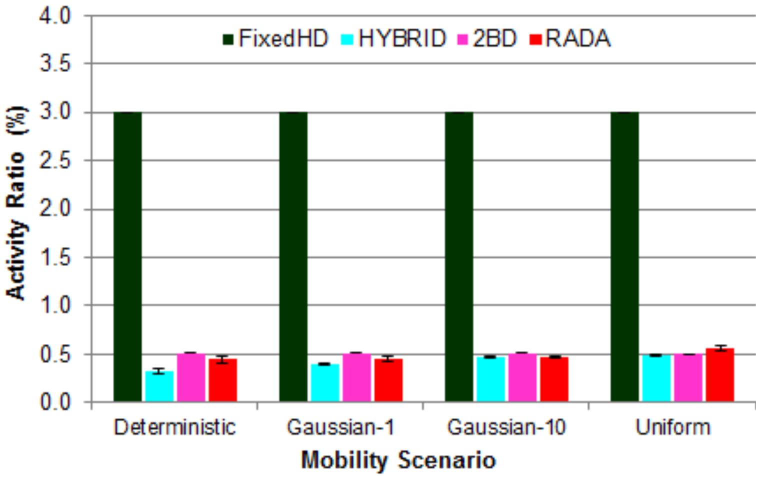

Figure 4.3: Impact of the mobility pattern in terms of activity ratio

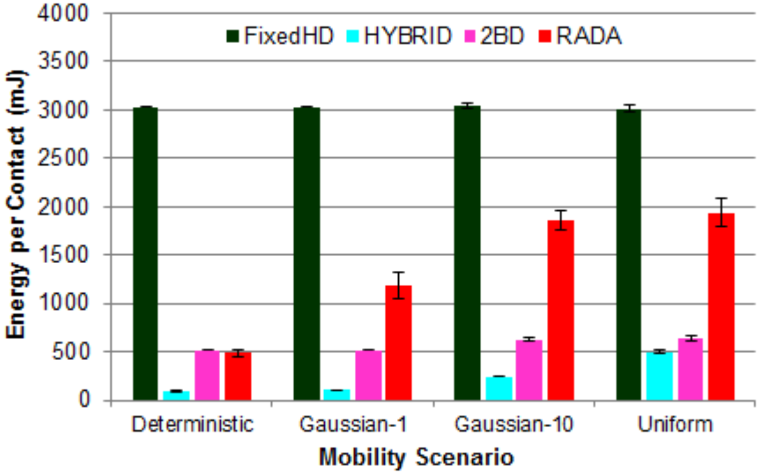

Figure 4.4: Impact of the mobility pattern in terms of energy per contact

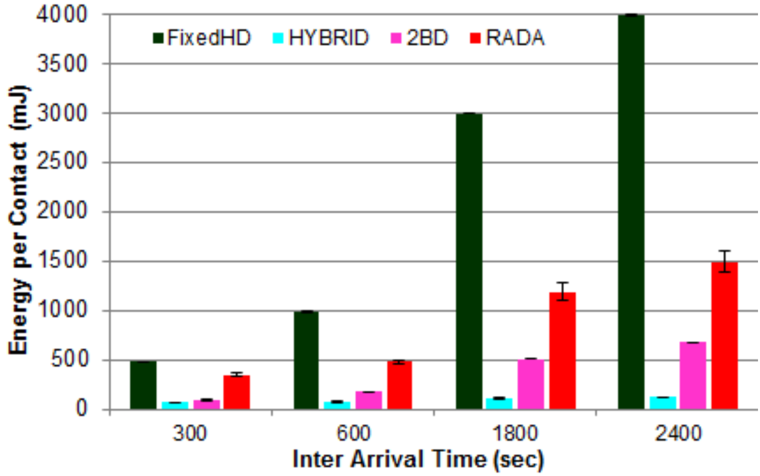

Figure 4.5: Impact of inter-arrival time in terms of energy per contact

terms of Energy per Contact, are summarized in Figure 4.5. As expected, the difference in the energy consumption of the Hybrid scheme with respect to the other schemes increases with the inter-arrival time. This is because the higher the inter-arrival time, the longer will be the time the sensor node spends in the discovery phase. Table 4.5 shows the energy savings provided by Hybrid with respect to 2BD and RADA, that emphasizes the benefits of using the proposed approach.

4.3.3 Impact of the contact duration

Another important issue to be investigated is the impact of contact duration on different schemes. In the considered scenario, the (nominal) contact duration only depends on the ME's speed. Therefore, six different values for v, (i.e., 2, 4, 6, 20, 40, 60 km/h) are considered. The obtained results are summarized in Figures 4.6– 4.11. As show in Figures 4.6–4.7, at lower speeds (i.e., 2, 4, and 6 km/h), all the considered schemes obtained a discovery ratio and a residual contact ratio close to 100%. In terms of Activity Ratio (see Figure 4.11), all the adaptive schemes exhibit the same performance and their Activity Ratio is not significantly influenced by the ME's speed. This is because all discovery schemes tend to be in LDC for most of the time. In terms of Discovery Ratio (see Figure 4.9), the performance of all schemes decreases as the speed increases because the nominal contact time reduces and there is less time available for discovery. However, Hybrid exhibits the highest delivery ratio among the adaptive schemes at all speeds, which results in a lower energy spent per contact. As expected, Residual Contact Ratio (see Figure 4.10) decreases significantly with increase in ME's speed in all considered mobility scenarios. In fact, all the adaptive schemes can use a large share of the contact duration when the speed is 20 km/h. However, Hybrid has the

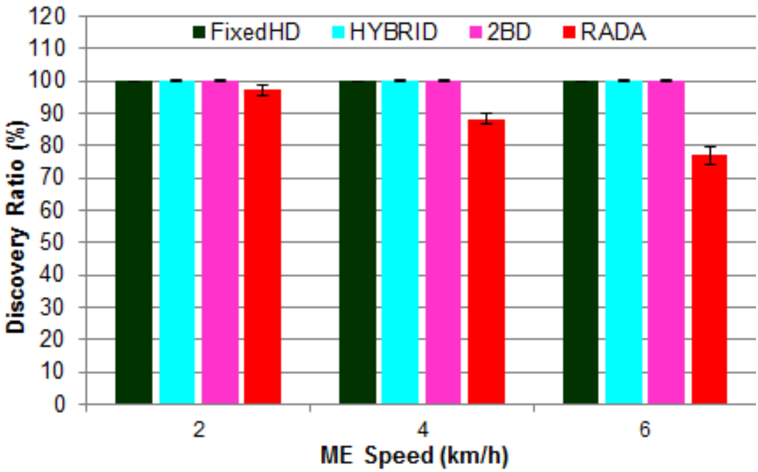

Figure 4.6: Impact of the ME's speed (lower) in terms of discovery ratio.

highest Residual Contact Ratio, and is able to exploit around 60% of the contact duration even when the speed is 60 km/h.

4.3.4 Impact of the Discovery Range

Both 2BD and Hybrid use a hierarchical mechanism based on LRBs and SRBs; LRBs are transmitted with a transmission range R, larger than the transmission range used for SRBs. It is thus extremely important to evaluate the impact of the R parameter on their performance. To this end, three different values for R (i.e., 150m, 200m, 250m) are considered. The obtained results are shown in Figures 4.12– 4.14. Fixed and RADA are not influenced by this parameter as they use a single beacon type. They have been included in the plots just for comparison. From the results obtained, it clearly emerges that increasing R increases the probability of detecting a po-

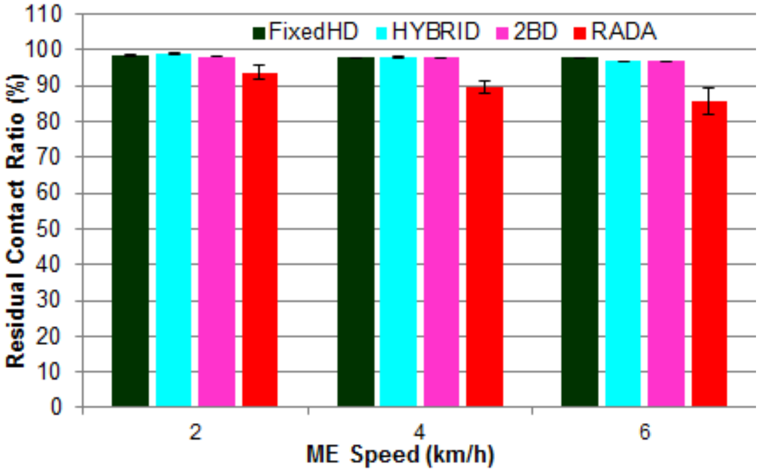

Figure 4.7: Impact of the ME's speed (lower) in terms of residual contact ratio.

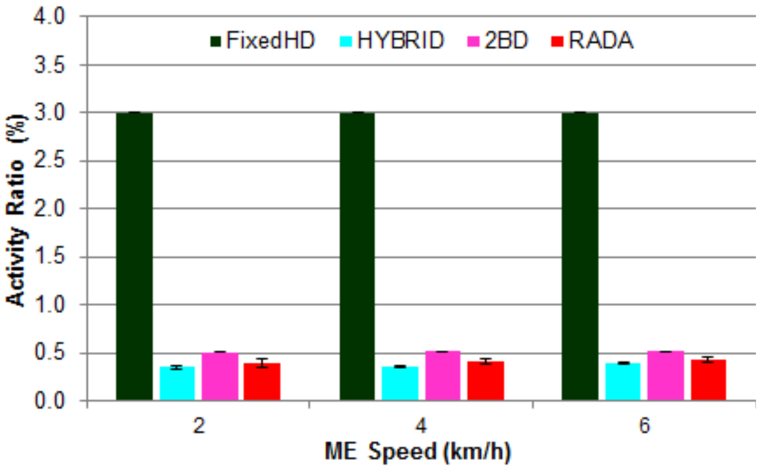

Figure 4.8: Impact of the ME's speed (lower) in terms of activity ratio.

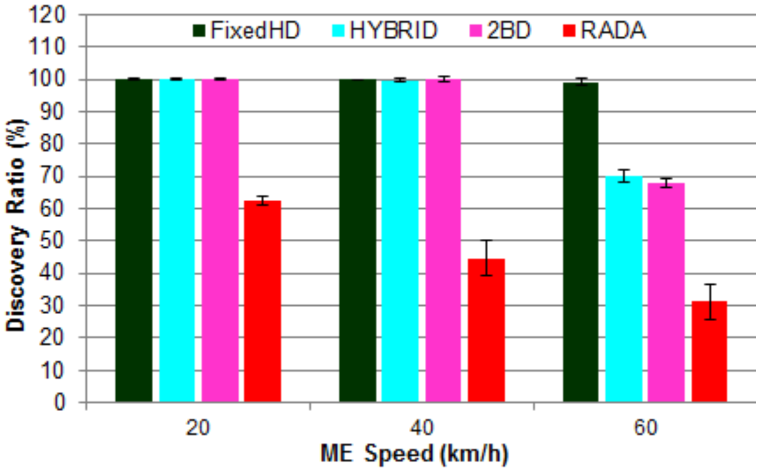

Figure 4.9: Impact of the ME's speed in terms of discovery ratio.

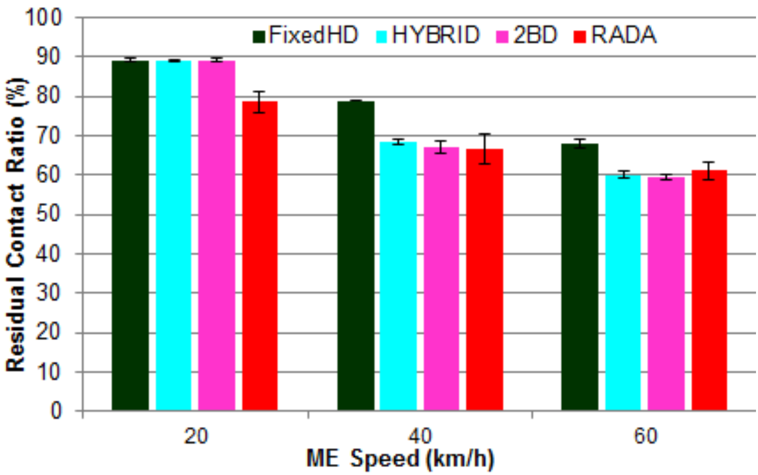

Figure 4.10: Impact of the ME's speed in terms of residual contact ratio.

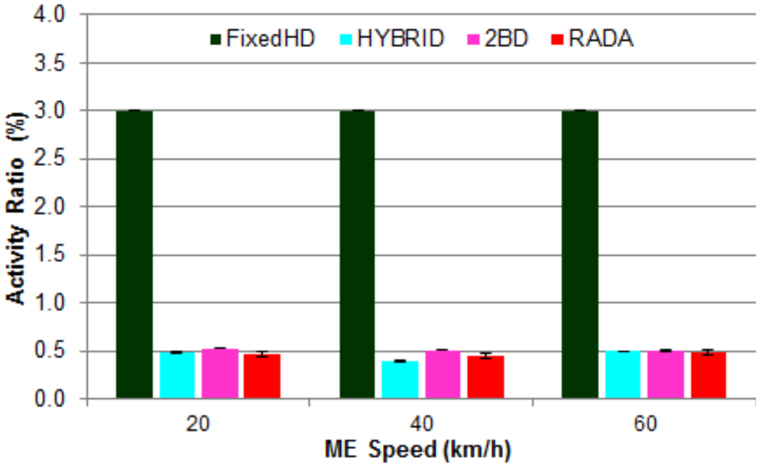

Figure 4.11: Impact of the ME's speed in terms of activity ratio.

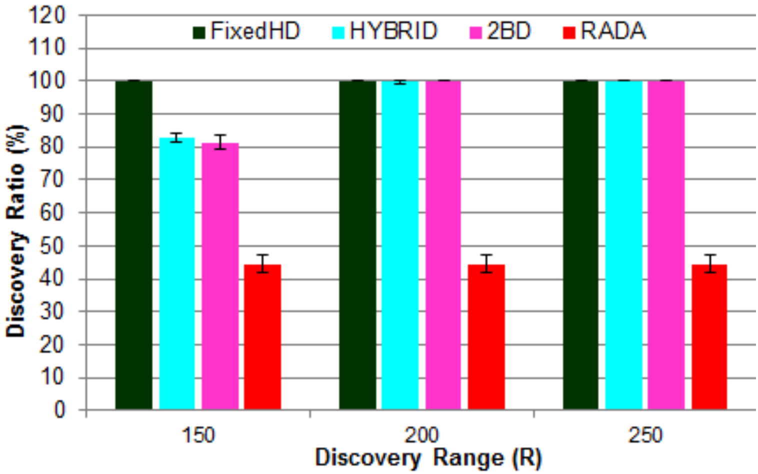

Figure 4.12: Impact of the Discovery Range in terms of discovery ratio.

tential contact. In addition, it also provides a better performance in terms of Residual Contact Ratio, as highlighted in Figure 4.13. However, after a given value (i.e., 200m in the considered scenario), a further increase in the R value does not provide any significant advantage in terms of Discovery Ratio. But it increases the energy consumption (see Figure 4.16).

This behavior is better emphasized by the Activity Ratio, which tends to increase with R. This is because the sensor node remains in HDC for a time proportional to R. Eventually, the Hybrid marginally outperforms 2BD for all the considered R values, especially in terms of Activity Ratio. This is because Hybrid can also exploit the prediction algorithm which puts the radio in sleep mode (selecting the SLP task) when there is a low probability to receive a LRB (based on the learning utility).

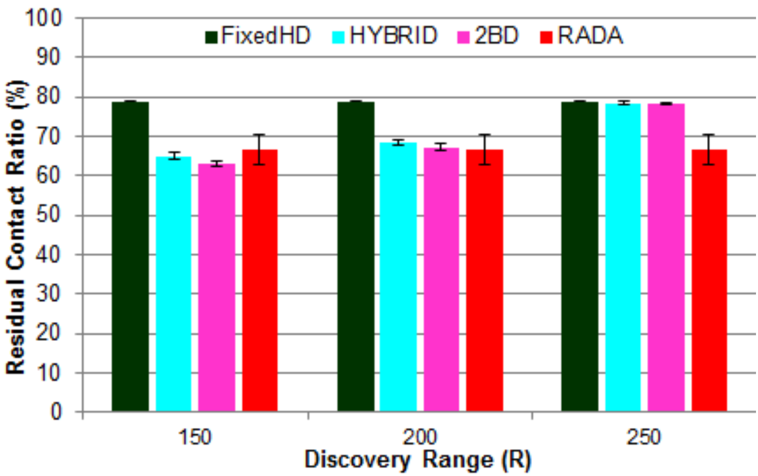

Figure 4.13: Impact of the Discovery Range in terms of residual contact ratio.

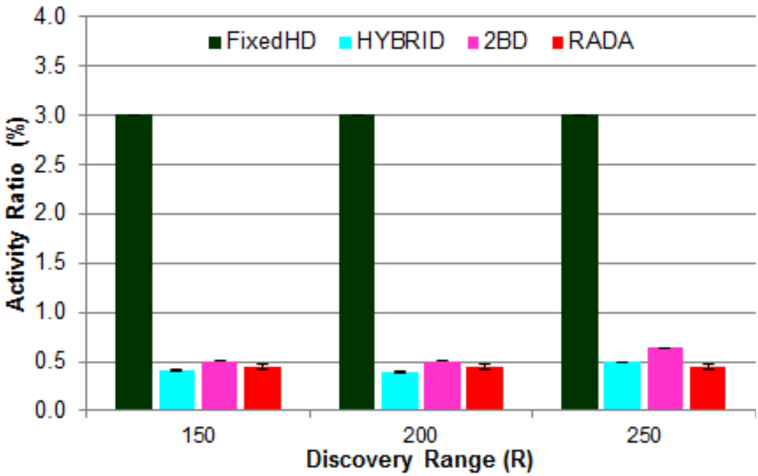

Figure 4.14: Impact of the Discovery Range in terms of activity ratio.

4.3.5 Impact of false activations

So far the performance of the various discovery schemes have been analyzed by assuming a sparse scenario and focusing on a single sensor node. To extend the analysis, in this section, a scenario with multiple sensor nodes is considered, where the distance between them is not necessarily larger than R. In such a scenario, the hierarchical mechanism (based on LRBs and SRBs) used by Hybrid and 2BD may cause *false activations*. A false activation occurs, whenever a sensor node receives a LRB (and switches to high duty cycle). But it will never receive a SRB because it is located outside the ME's communication range (see Figure 4.15). Obviously, false activations result in energy wastage, and the fraction of sensor nodes that experience a false activation increases with the discovery range R. In the following, the impact of false activations are analyzed based on the total energy consumed by a sensor node per detected contact. Assuming that the

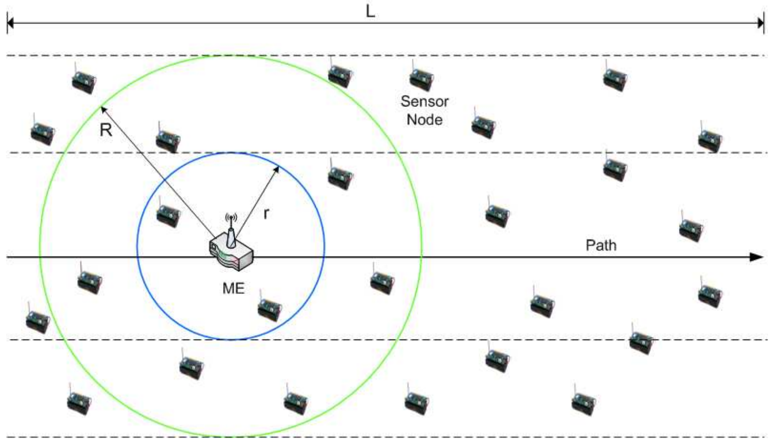

Figure 4.15: A network scenario where false activations can occur.

sensor nodes are uniformly distributed with density d over a rectangular area of size $2R \cdot L$. When the ME crosses this area (see Figure 4.15), the number of nodes that can experience a contact (i.e., can receive a SRB) at each ME's passage is $2r \cdot L \cdot d$, while the number of nodes that can experience a false activation is $2 \cdot (R - r) \cdot L \cdot d$. Hence, the average number of false activations per (potentially) detected contact is

$$F(R) = \frac{2 \cdot (R - r) \cdot L \cdot d}{2r \cdot L \cdot d} = \frac{R}{r} - 1 \tag{4.1}$$

Since sensor nodes remain active for at most a timeout period T_{out} after receiving a LRB (see Section 4.1), the energy consumed by a single sensor node due to a false activation is

$$E^1_{FA} = T_{out} \cdot [\delta_H \cdot P_{RX} + (1 - \delta_H) \cdot P_{SL}] \tag{4.2}$$

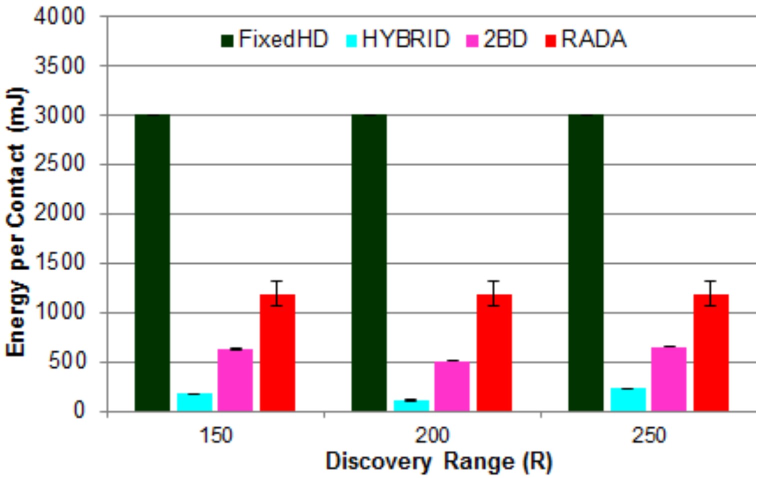

Figure 4.16: Impact of the Discovery Range on energy per contact in sparse scenario.

where δ_H denotes the high duty cycle and P_{RX} (P_{SL}) is the power consumed by sensor nodes in receive (sleep) mode. Hence, the average total energy consumed due to false activations per detected contact is given by

$$E_{FA} = (\frac{R}{r} - 1) \cdot T_{out} \cdot [\delta_H \cdot P_{RX} + (1 - \delta_H) \cdot P_{SL}] \qquad (4.3)$$

Equation 4.3 shows that the wasted energy increases linearly with the discovery range R. For the set of considered values, the energy increases from 30.45 mJ (when R=150m) to 45.68 mJ (when R=250m). To evaluate the impact of false activations, some simulations assuming the scenario in Figure 4.15 were run (simulation parameters are given in Section 4.3.4). It can be found that, when there is a single sensor node, the average energy (per contact) consumed by sensor nodes located *inside* the communication range of the ME is very sim-

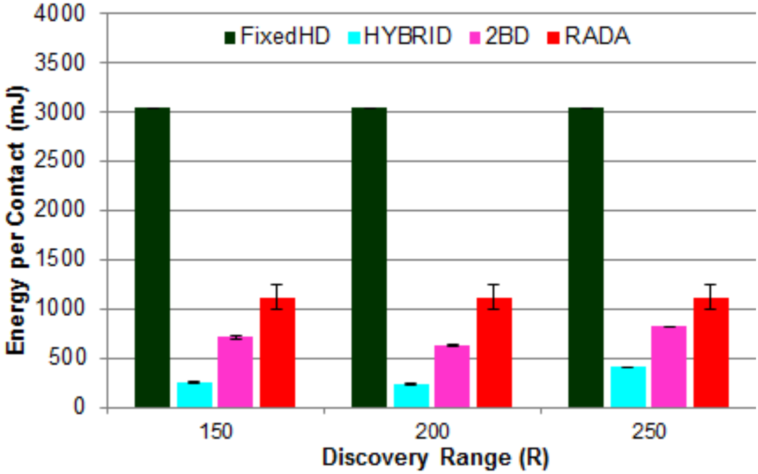

Figure 4.17: Impact of the Discovery Range on energy per contact in a scenario where false activations can occur.

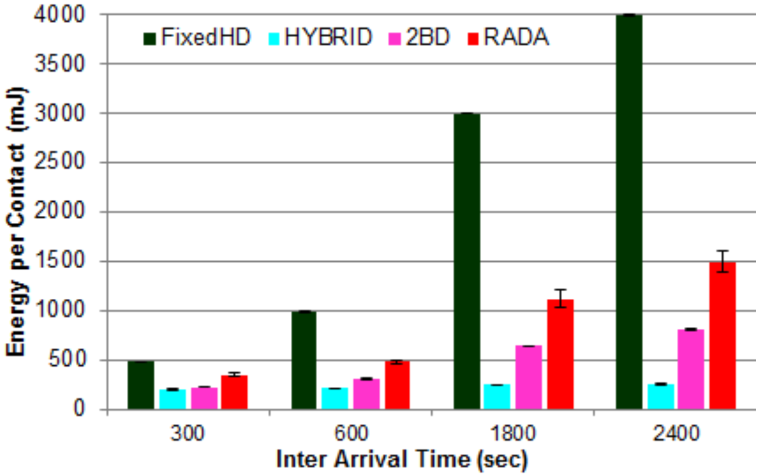

Figure 4.18: Impact of inter-arrival time on energy per contact in a scenario where false activations can occur.

Table 4.4: ENERGY SAVINGS PROVIDED BY HYBRID IN SCENARIOS WITH/WITHOUT FALSE ACTIVATIONS FOR DIFFERENT DISCOVERY RANGES.

Discovery Range (m)	**False Activations?**	**2BD**	**RADA**
150	NO	72.7%	85.6%
	YES	64.3%	78.7%
200	NO	79.1%	91.0%
	YES	62.4%	80.6%
250	NO	64.4%	81.7%
	YES	50.5%	66.0%

ilar to that measured in Section 4.3.4 (see Figure 4.16). This is because sensor nodes inside the communication range are deployed in such a way that the average distance from the ME's paths is still the same. The average total energy consumption (per detected contact) including the energy consumed due to false activations by sensor nodes, located *outside* the communication range is shown in Figure 4.17. The simulation results confirm the previous analysis (i.e., Equation 4.3). Even though the energy consumption increases in the considered scenario, Hybrid still outperforms the other adaptive schemes. Table 4.4 emphasizes this conclusion by showing the energy savings provided by Hybrid with respect to 2BD and RADA in scenarios with/without false activations for different values of the Discovery Range. Figure 4.18 shows the impact of false activation as a function of inter-arrival times. Energy saving provided by Hybrid with respect to 2BD and RADA in scenarios with/without false activations, for different inter-arrival times are show in Table 4.5.

Table 4.5: ENERGY SAVINGS PROVIDED BY HYBRID IN SCENARIOS WITH/WITHOUT FALSE ACTIVATIONS FOR DIFFERENT INTER-ARRIVAL TIMES.

Inter-Arrival Time (s)	**False Activations?**	**2BD**	**RADA**
300	NO	27.9%	81.5%
	YES	13.5%	42.3%
600	NO	59.2%	85.2%
	YES	31.8%	56.6%
1800	NO	79.1%	91.0%
	YES	62.2%	78.2%
2400	NO	82.6%	92.1%
	YES	68.5%	82.9%

4.4 Summary

This chapter proposed a hybrid discovery algorithm for energy-efficient node discovery in WSN using MEs. The algorithm combines a learning-based approach with a hierarchical approach using Long Range Beacons and Short Range Beacons. The performance of the hybrid scheme has been investigated through simulation, and it has also been compared with existing adaptive algorithms that leverages either a learning-based or a hierarchical approach. The simulation results have shown that, the proposed algorithm can adapt to different mobility patterns of the ME, thanks to its hybrid nature. In comparison with other existing adaptive discovery algorithm, it allows a very large energy saving, especially when sensor nodes spend a long time in the discovery phase.

Chapter 5

Conclusions

This thesis has addressed different adaptive discovery schemes for WSN-MEs. A hierarchical discovery scheme has been proposed, based on two different Beacon messages, for energy efficiency and timely discovery in sensor networks with MEs. Also, it has been shown that the traditional approach for discovery (i.e., based on periodic Beacon emission by the ME and periodic listening by the sensor with fixed duty cycle) may be inefficient, especially if the discovery phase is long. The performance of the 2BD protocol through simulation in a sparse network scenario has been analyzed. The obtained results show that the proposed approach, even if simple, can provide a significant energy reduction with respect to the traditional single-Beacon approach. Even when MEs arrival times can be predicted with some accuracy and the time spent in the discovery state is short (e.g., 30s), the proposed approach can provide an energy saving up to 40%.

In addition, two different adaptive discovery protocols, RADA (i.e., which leverages a learning-based approach) and 2BD (i.e., which uses a hierarchical approach) were evaluated through simulation. Their performance was compared with that of non-adaptive schemes commonly used in practice. Simulation results have shown that 2BD outperforms all other discovery schemes in all the considered scenarios, providing significant energy savings. Moreover, simulation showed that RADA performs well when the ME mobility pattern is very regular, while its performance tends to decrease as the uncertainty in the MEs arrival process increases.

Finally, a hybrid discovery algorithm that combines a learning-based approach with a hierarchical scheme has been proposed. The performance of hybrid scheme has been investigated through simulation, and it has also been compared with existing adaptive algorithms that only leverage either a learning-based approach or a hierarchical approach. Simulation results have shown that the proposed algorithm can adapt to different mobility patterns of the ME, thanks mainly to its hybrid nature. In comparison with other existing adaptive discovery algorithm, it allows a very large energy saving, especially when sensor nodes spend a long time in the discovery phase.

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