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Sujet

Dépendabilité de Services dans les Réseaux de Capteurs sans Fil : Gestion d'énergie

Soutenue en publique, le 20/03/2019, devant le jury composé de :

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PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA
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THESIS

Submitted for the degree of **Doctor of Philosophy**

In : **Computer Science**

By : **Lyes Khelladi**

Title

Dependability of Services in Wireless Sensor Networks : Energy management

Defended publicly, on Marsh 20^{th} 2019, with a jury composed of :

Mahfoud Benchaiba	Professor (U.S.T.H.B)	President
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Résumé

Dans cette thèse, nous abordons la problématique de *gestion efficace d'énergie* comme étant le défi principal à surmonter, en vue d'assurer la *dépendabilité* de services dans les réseaux de capteurs sans fil. En effet, la garantie de dépendabilité est compliquée par la rareté de la ressource énergétique qui favorise les défaillances fréquentes de nœuds, à cause de l'épuisement de leur batteries. Surmonter ce défi nécessite l'utilisation de mécanismes de gestion efficace d'énergie qui permettent une consommation optimisée de la ressource énergétique disponible, ainsi que son renouvellement continue. Dans cette optique, notre étude aborde deux aspects fondamentaux liés à la gestion d'énergie dans les réseaux de capteurs sans fil.

Le premier aspect concerne les méthodes de conservation d'énergie visant à minimiser l'énergie consommée par les services réseau, afin de prolonger leur durée de vie. Nous nous focalisons sur le service de routage, pour lequel nous nous efforçons de garantir l'efficacité énergétique, en tenant compte des scénarios de déploiements denses. Pour cela, un nouveau protocole de routage est proposé, en se basant sur le schéma de "Directed Diffusion". Notre protocole comporte deux techniques principales pour la conservation de l'énergie. Premièrement, un mécanisme de contrôle de topologie (PATC) est utilisé pour réduire la connectivité élevée du réseau, en supprimant les liens de transmission redondants, tout en conservant des routes efficaces en consommation d'énergie. Deuxièmement, une métrique de consommation d'énergie est introduite afin de permettre l'utilisation des routes avec une consommation d'énergie minimale. Les expériences de simulation ont montré que le protocole de routage proposé surpasse Directed Diffusion en terme d'efficacité énergétique.

Le deuxième aspect de gestion d'énergie est lié aux stratégies de rechargement des noeuds. Nous adoptons un modèle basé sur un chargeur mobile qui parcourt le réseau et recharge les nœuds capteurs se trouvant à sa proximité, en utilisant une technologie de Transfert d'Energie sans Fil (TEF). Avec ce modèle, les stratégies existantes de rechargement à la demande ne peuvent charger qu'un seul nœud à la fois, ce qui limite leur performance dans les réseaux à grande échelle. Pour pallier à cette insuffisance, nous proposons une nouvelle approche de rechargement qui exploite les avancées récentes dans le domaine du TEF simultané vers plusieurs nœuds. Notre stratégie vise à maximiser les opportunités de rechargement simultané, via une planification appropriée du chemin utilisé dans le tour de chargement, en plus d'un mécanisme de déclenchement de chargement basé sur un seuil minimal d'énergie au niveau des nœuds. Constatant que la solution au problème de planification du chemin est NP-dure, le modèle initialement établit a été reformulé en tant que problème de partitionnement en clique, et une solution heuristique à faible

complexité a été dérivée. Les performances de notre stratégie de rechargement ont été comparées avec des solutions de la littérature. Les résultats numériques démontrent l'efficacité de la stratégie de rechargement proposée dans l'amélioration de la dépendabilité du réseau via la réduction du taux de défaillance de nœuds, ainsi que l'optimisation de l'énergie consommée par le chargeur mobile.

Abstract

In this thesis, we address the problem of *efficient energy management* as a primary challenge to ensure *dependable services* in wireless sensor networks. Indeed, achieving dependability is particularly challenging because of the scarce energy resource that penalizes service availability, due to frequent node's battery depletion. Overcoming this challenge requires the use of efficient energy management mechanisms that allow an optimized consumption of the available energy resource, as well as its continuous renewal. With this perspective, our study discusses two fundamental aspects of energy management in wireless sensor networks.

The first aspect deals with *energy conservation* methods aiming to minimize the energy consumed by the network services, in order to prolong their lifetime. We focus on the *routing* service, for which we endeavor to guarantee energy efficiency considering *dense deployment* scenarios. To this end, a new routing protocol is proposed, based on the scheme of Directed Diffusion. Our protocol features two main techniques for energy conservation. Firstly, a power-aware topology control (PATC) mechanism is used to reduce the high network connectivity by discarding redundant transmission links, while maintaining energy-efficient routes. Secondly, an energy-consumption metric is introduced, allowing the use of the route that offers the minimum energy expenditure. The simulation experiments showed that the proposed routing protocol outperforms Directed Diffusion in terms of energy efficiency.

The second aspect of energy management is related to *harvesting strategies.* We adopt a harvesting model with a *mobile charger* that roves the network and charges the nearby nodes remotely, using a *Wireless Power Transfer (WPT)* technology. With this model, existing *on-demand* charging strategies can only charge a single node at once, which limits their scalability in large-scale networks. To solve this problem, we propose a new charging approach that exploits recent advances in the area of multi-node simultaneous WPT. Our strategy aims to maximize the opportunities for multi-node simultaneous charging through an appropriate path planning for the charging tour, in addition to a Threshold-based Tour Launching mechanism (TTL). Noticing the NP-hardness of the path planning problem, the original model has been reformulated as a clique partitioning problem, and lightweight heuristic

solution has been derived. The performance of our charging strategy has been compared to relevant strategies through extensive simulation experiments. Numerical results demonstrate the effectiveness of the proposed harvesting strategy in improving the network dependability by reducing the rate of node failures, as well as by optimizing the energy consumed by the mobile charger.

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I would like to convey my warm thanks to my family for all their love and encouragement. This Thesis is dedicated to my parents who raised me with a love of science and supported me in all my pursuits. Also, I would like to thank my brothers Rafik and Fouad. Last but not least, I would like to thank my encouraging, and patient wife Karima, whose faithful support during this long Ph.D journey is so appreciated.

[1] Project#AL16MO03: "*Distributed Protocols for Environmental Energy Harvesting Enabled Wireless Large-Scale Sensor Networks: Towards Exploiting Renewable Energy*"

Contents

Chapter 1

Introduction

1.1 Problem statement

For more than a decade, wireless sensor networks have been increasingly deployed to continually narrow the gap between the physical world and cyberspace. A wireless sensor network (WSN) is composed of a large number of sensor nodes that operate in an auto-organized and unattended manner. Typically, sensor nodes are tiny, low-cost and battery-operated devices whose sensing capabilities enable them to gather real-time data on surrounding environment. Gathered data is reported to the end-user via short-range multi-hop wireless communication. This interesting operational model helped in seamless integration of sensor networks in our everyday environment. Also, it empowered applications in plethora of emerging domains like Internet of Things (IoT), smart cities, industrial monitoring, etc. While the initial view of the community was that sensor networks will play a complementary role that enhances the quality of these applications, recent research results have encouraged practitioners to envision an increased reliance on sensor networks. However, to achieve this potential, a dependable design of WSNs' services has to be guaranteed.

In general, dependability relates to the property that indicates the ability of a system to deliver specified services to the user. This property can be defined in terms of different attributes including availability, reliability, safety, confidentiality, integrity and maintainability. Indeed, it is expected that a dependable system will be operational when needed (availability), and will keep operating correctly while being used (reliability). Moreover, some applications require the system to prevent unauthorized disclosure (confidentiality) or modification of information (integrity), or to ensure that the operations are not dangerous (safety)[Lap92, ATS06].

Achieving dependability in wireless sensor network is challenging, because of the energy scarceness entailed by the limited battery capacity of sensor nodes. These nodes are forced to operate for a finite duration, only as long as the battery lasts.

Finite node lifetime implies finite lifetime of the applications since in most scenarios, replacing the exhausted batteries may be hard and cost-prohibitive, with the large number of nodes in the network. Battery replacement may be even impossible if the sensor network is deployed in hostile or impractical environment. On the other hand, the sensor network lifetime should be long enough to fulfill the application requirements. In many cases, a lifetime in the order of several years may be required. Consequently, it is vital to deal with the frequent nodes failures caused by battery exhaustion, via sustainable and efficient management of the energy resource, to prevent the degradation of sensor network dependability in terms of availability and reliability.

1.2 Contributions

In this thesis, the issue of energy management is addressed from two distinct but complementary perspectives, namely: *energy conservation* and *energy harvesting*. The goal of energy conservation techniques consists in minimizing the energy consumed by the network services. Nevertheless, and despite of their significant role in prolonging the network lifetime, these techniques are unable, alone, to guarantee a sustainable operating due to the finite energy budget. Therefore, the field of energy harvesting is investigated with the objective to devise an efficient recharging scheme that allows continuous renewal of the energy resource, and guarantees perpetual network availability and reliability.

The first part of our work is dedicated to the problem of energy conservation in wireless sensor networks. After identifying the related challenges in different layers of the networking stack, we focus on routing protocols as a fundamental communication service that highly impacts the energy efficiency of the whole network. Particularly, we emphasize a major challenge that complicates the design of energy-efficient routing, which is the *high nodes density*. This challenge is being continuously raised by the emergent applications of sensor networks in the area of Internet of Things (IoT).

In this context, we propose a new routing protocol that is built on the well-known scheme of Directed Diffusion [IGE+03]. The latter has been recognized as a promising routing solution for emergent IoT applications of sensor networks, thanks to its data-centric paradigm. However, Directed Diffusion encompasses multiple functions that strongly penalize its performance in dense networks.

To deal with Directed Diffusion's shortcomings, our new protocol features two mechanisms for energy conservation. Firstly, a power-aware topology control (PATC) technique is employed to mitigates the performance degradation of routing in dense application scenarios. This is achieved by identifying and discarding the transmission links that are "redundant" in terms of energy dissipation, while maintaining energy efficient routes between the sink and sensor nodes. Secondly, a new energy consumption metric is adopted for route selection. This metric benefits from the power awareness feature in the topology control phase to estimate the energy expenditure of each discovered path, which enables the selection of the route with minimum energy consumption.

In the second part of this thesis, we tackle the problem of energy harvesting in wireless sensor networks. Sensor nodes can recharge their batteries by harvesting multiple forms of ambient energy such as solar, vibrational or wind energy. However, the major drawback in using such solutions is the high uncertainty associated with the power source. Indeed, the availability of environmental energy usually shows an erratic behaviour, since it depends on external parameters like the weather and the day conditions. To ensure a more reliable and deterministic energy provision, we adopt a concept based on wireless power transfer, in which a mobile vehicle brings clean electrical energy that is efficiently generated elsewhere and charges the sensor nodes wirelessly. In the following, we summarize our contributions to this area of research:

- Firstly, we provide a comprehensive and up-to-date survey on wireless charging strategies in sensor networks. The reviewed solutions are categorized based on different criteria like charger's nature (static or mobile), charger scheduling type (offline or on-demand), etc. In addition, the fundamental ideas of these solutions are explained and compared in terms of strengths and weaknesses. To the best of our knowledge, none of the existing surveys on wireless charging strategies has been devoted to the specific context of wireless sensor networks.

- The state of the art study revealed that all existing on-demand mobile charging solutions are limited to charge a single node at a time. This induces low performance of the mobile charger and makes the charging operation hard to scale up. Inspired by the interesting results of Kurs et al [KMS10] on simultaneous power transfer, we investigate the use of simultaneous charging in on-demand strategies, to improve the charger performance in large-scale networks.

- We propose a novel charger scheduling concept relying on *threshold-based tour launching* (TTL). Contrary to existing schemes that focus on shortening the charging time, we show that it is possible to delay the charging of requesting nodes, to maximize the benefit from multi-node simultaneous charging.

- To demonstrate the benefit of the TTL mechanism for the dependability of the network operations, a new metric called *cumulated failure time* is defined. The latter is shown to be more relevant than the *charging delay* metric that is traditionally adopted by existing solutions.

- At the tour planning level of the proposed strategy, a new modeling approach is used. It leverages simultaneous energy transfer to multiple nodes, with the aim of maximizing the number of nodes that are charged at each stop. Giving the NP-hardness of the problem formulation, we approximate it to a clique partitioning problem, and a simple heuristic is proposed. The resulting charging algorithm is shown to have a cubic time complexity in the number of nodes, with a good approximation ratio.

1.3 Organization

The remainder of this thesis is organized as follows. The second chapter discusses the challenge of energy conservation in wireless sensor networks. Also, it summarizes the main techniques employed in the literature to achieve energy efficiency in different layers of the network protocol stack. In the third chapter, we describe in detail our approach to guarantee an improved energy conservation at the routing service, considering dense deployment scenarios. The fourth chapter introduces the concept of energy harvesting through wireless power transfer, and reviews the enabling technologies. We compare the characteristics of these technologies with the objective to identify which ones are suitable for the context of wireless sensor networks. The fifth chapter surveys exisiting research efforts on wireless charging strategies in sensor networks. The state-of-the-art solutions are summarized and their advantages and weaknesses are highlighted. The sixth chapter presents our novel on-demand multi-node wireless charging strategy. We provide a detailed description of the solution's building blocks and we analyse their computation complexity. In addition, we present a thorough simulation study, evaluating the proposed techniques against the previous solutions. Finally, the thesis is ended with a conclusion summarizing the main ideas of our work and presenting possible extensions and future research directions.

1.4 List of publications

- **Journals:**
  - Lyes Khelladi, Djamel Djenouri, Michele Rossi, and Nadjib Badache. Efficient on-demand multi-node charging techniques for wireless sensor networks. *Computer Communications*, 101:44 – 56, 2017.
- **International conferences**
  - L. Khelladi, D. Djenouri, N. Lasla, N. Badache, and A. Bouabdallah. MSR: Minimum-stop recharging scheme for wireless rechargeable sensor networks. *In 2014 IEEE 11th Intl Conf on Ubiquitous Intelligence and Computing*, pages 378–383, Dec 2014.
  - L. Khelladi and N. Badache. Revisiting Directed Diffusion in the era of IoT-WSNs: Power control for adaptation to high density. *In 2017 8th International Conference on Information, Intelligence, Systems Applications (IISA)*, pages 1–6, Aug 2017.

Chapter 2

Energy conservation in WSNs

2.1 Introduction

The last years have witnessed the emergence of many technologies like Internet of Things (IoT), smart cities and smart grids, which stimulate the deployment of autonomous, self-configuring and large-scale wireless sensor networks (WSNs). However, a successful deployment of WSNs necessitates the design of energy-efficient operations in order to deal with the critical issue of *energy scarceness*. Indeed, sensor nodes are powered by a small battery with limited capacity. In addition, it could be inconvenient or impossible to replace batteries, since nodes may be deployed in a hostile or impractical environment. On the other hand, WSN's lifetime should be long enough to fulfill the application requirement. In most cases, a lifetime in the order of several years is required. Therefore, the primary design objective in WSNs is to integrate energy conservation mechanisms throughout all networking layers, so that the lifetime will be extended to the duration required by the application.

In this chapter, we will review the main mechanisms that have been developed to minimize energy consumption of sensor network protocols. The surveyed mechanisms are categorized with respect to their operational layer in the networking stack. Due to the important role of these enabling mechanisms, we mainly focus on stressing their design principles and features, instead of exhaustively surveying the related frameworks and networking protocols.

The remainder of this chapter is organized as follows. The second section introduces the basic concepts related to sensor network architecture and the energy efficiency design goal. In section 2.3, we study the existing energy conservation mechanisms in sensor network by classifying them into three categories. Section 2.4 summarizes the lessons learned from our study and highlights some open directions. Finally, section 2.5 concludes the chapter.

2.2 Basic concepts

Before studying energy conservation techniques in WSNs, we introduce the general network model and sensor nodes architecture that we will refer to in our study. This helps to identify the node and network components that are responsible for high energy dissipation. The identified components are targeted by the surveyed mechanisms for aggressive optimization, in order to ensure energy efficiency. In addition, this section shows the relationship between energy conservation and network lifetime, explaining the different metrics used to measure energy efficiency.

2.2.1 Network and node architectures

The architecture of a typical wireless sensor network (WSN) is depicted in Figure 2.1. It consists of one or multiples *sinks* (or base stations), and a *large* number of sensor nodes deployed over a wide geographic area, called *sensing field*. Sensor nodes continuously monitor physical parameters in the sensing field. Monitored parameters vary according to the WSN's applications. For example, in precision irrigation sensor networks, the network monitors the soil moisture in order to optimize the water used in irrigation by targeting dry parcels only. Sensory Data is transferred from sensor nodes to the sink using multi-hop communication protocols [AY05, SS15].

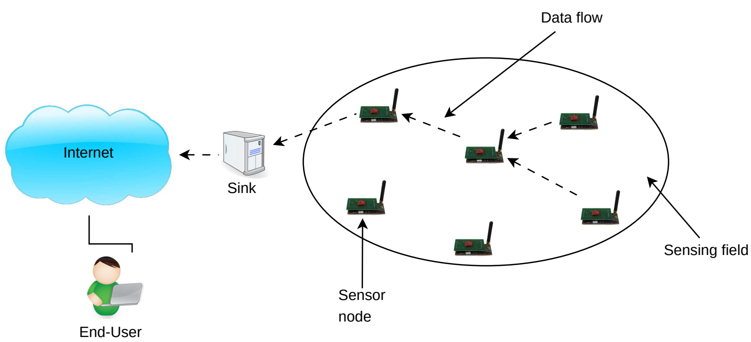


Figure 2.1: Sensor network architecture.

The protocol stack used by the sink and all sensor nodes is depicted in Figure 2.2. It consists of 5 layers and 3 vertical planes [ASSC02]. The physical layer addresses the need of simple but robust modulation, transmission, and receiving techniques. Since the environment is noisy and sensor nodes can be mobile, the data link layer, via its medium access control (MAC) protocol, must guarantee the node's access to transmission channels with minimum collision between neighbors' transmissions. The network layer takes care of routing the data supplied by the upper layer. The transport layer helps to maintain the flow of data if the sensor networks application requires it. Depending on the sensing tasks, different types of application software can be built and used on the application layer. The task and mobility management planes monitor movement and task distribution among nodes. Finally , the power management plane manages how a sensor node uses its onboard energy. It encompasses the energy conservation and harvesting techniques allowing a maximum extension of the overall network lifetime. Optimizing this plane represents the main topic addressed in this chapter, and throughout all our thesis.

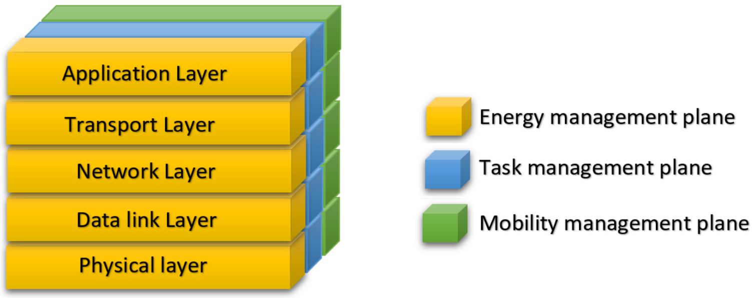


Figure 2.2: WSN protocol stack.

Concerning the architecture of each sensor node, it is composed of four subsystems, as illustrated in Figure 2.3.

- *Sensing unit:* includes one or more sensors along with associated Analog to Digital Converters (ADCs). An ADC converts the analog signal produced by sensors, based on observed events, into digital data that is fed into the computing unit.
- *Computing unit:* integrates a processing module (generally a micro-controller) and a small storage memory. Their missions is to manage the local procedures that enable cooperation with other nodes, in order to carry out the network's sensing application.
- *Communication unit:* responsible for connecting the node to the network by enabling communication with neighboring nodes through wireless medium.
- *Power unit:* usually consists of a small battery that supplies electric power to the three other modules.

In addition to the four units, a sensor node may contain additional subunits that are necessary for specific applications. For example, nodes may use a location finding *system* to determine their positions or a *mobilizer* to change their antennas orientation.

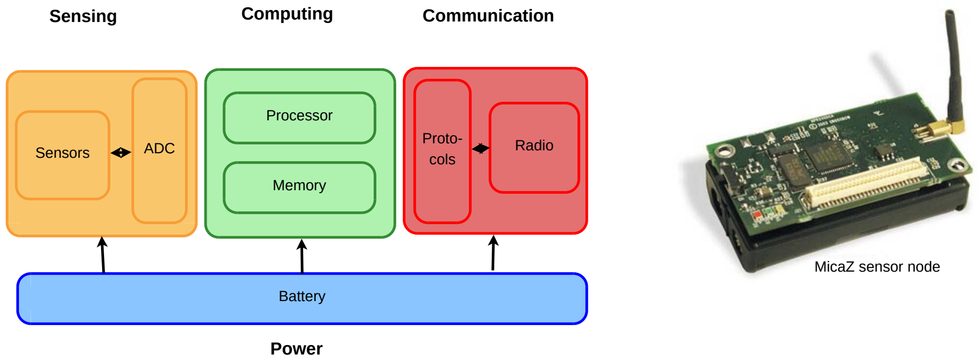


Figure 2.3: Sensor node architecture.

2.2.2 Energy efficiency and network lifetime

The energy efficiency of sensor networks can be evaluated at the individual node level or at the entire network level. At the node level, the energy efficiency is reflected by the node's power dissipation per unit of time. Power dissipation differs among nodes, according to several factors like the employed hardware components, the node's position and role within the network, etc. For example, it has been shown in [RSPS02] that the power characteristics of the two sensor nodes Rockwell's WINS and MEDUSA II differ significantly because of the adopted hardware architecture. However, there exist some principles that generally hold for every sensor node, independently from the aforementioned factors. These principles represent the key rules to achieve energy efficiency at the node's level, and can be summarized in the following points:

- The communication unit has an energy consumption much higher than the computing unit. Indeed, it has been demonstrated in [PK00] that the energy cost of transmitting 1Kb over a distance of 100 meters can serve to efficiently execute 3 million instructions. Therefore, it is recommended to process data locally in order to reduce traffic volume and optimize energy consumption.

- The radio's energy consumption is of the same order of magnitude in the reception and idle modes. Thus, keeping the transceiver idle results in useless energy dissipation. The radio should be completely shut off, or turned into sleep mode whenever possible in order to obtain energy savings.

- In some specific application scenarios, the sensing subsystem might be a significant source of energy consumption. So, this subunit should not be completely neglected during the design of energy efficient mechanisms.

- The use of low-power hardware components that are specifically designed for the WSN's mission is highly recommended. It allows to discard unnecessary performances at the different sub-units, which significantly reduces the node's energy dissipation.

At the network level, energy efficiency is measured through its *lifetime*. The latter represents the defacto metric used to evaluate the impact of energy conservation mechanisms on the whole network. Network lifetime is usually defined as *the time interval from network initialization until failure of the first node or portion of nodes, due to battery outage*. The portion (number of depleted nodes) can vary depending on the context of the sensor network [ZH06, CT04]. This definition is the simplest form under which one can make the problem tractable. However, a more complete definition of network lifetime is the *total time over which the network remains operational, and hence supports the application requirements* [YCEHH17]. Indeed, every sensor network is deployed to achieve the tasks required by application. The network is considered "alive" as long as it is able to fulfill the application requirements, even if few sensors remains operational.

Consequently, we conclude that the energy efficiency is seen from the global network standpoint as a compound of two aspects that jointly reflect the application performance and the energy expenditure. To optimize these two aspects, three general approaches have been adopted in the literature [CLCS18]:

- *Bits per Joule maximization*: focuses on the data delivered by the network. It tends to optimize both energy expenditure and network capacity in terms of transmitted data (throughput). With such optimization, both energy consumption and data capacity are combined as a single function with clean physical meaning. However, this function is generally nonlinear. So the existence of optimal solution is not guaranteed.

- *Energy minimization with guaranteed performances*: this optimization approach reflects the notion of energy efficiency from the viewpoint of Quality of Service(QoS), or user's Quality of Experience (QoE). Hence, the goal is to provide the required level of QoS/QoE using the less energy as possible, resulting in minimization problems with QoS/QoE constraints.

- *Performance optimization under energy constraints*: represents the most common approach in WSNs, since the energy budget is limited by the node's battery capacity, and the batteries are usually hard to replace. Hence, the problem of energy efficiency concentrates on delivering the best performances in terms of QoS/QoE using the available energy budget.

Based on the aforementioned optimization approaches, a large number of research works have been devoted to the design of services and protocols that allow sensor networks to operate in energy efficient manner. The proposed solutions rely on some energy conservation techniques that are studied in the following.

2.3 Energy conservation techniques

In this section, we review the existing energy conservation mechanisms by summarizing their mains features and design principles. Our objective is to provide the reader with a background on state-of-the-art techniques that are commonly adopted, without necessarily enumerating the protocols or frameworks that have used them.

A couple of papers in the literature have surveyed energy efficiency mechanisms in WSNs [ACDFP09, RBC14, YCEHH17]. In these papers, the mechanisms have been classified regarding their common design principles. For example, in [ACDFP09] three categories have been identified namely, duty-cycling, data-driven, and mobility-based approaches. In the following, we adopt a different classification based on the networking layer targeted by each energy conservation technique. This allows designers and practitioners, intending to develop a new protocol, to acquire a clear and comprehensive view on the possible ways to achieve energy efficiency, depending on the targeted layer.

We categorize the studied techniques with respect to the three main layers of the WSN's protocol stack namely, physical, data link and network layers. Concerning the transport layer, most of the proposed protocols are designed for specific applications. Hence, their main focus is to guarantee the QoS performance, relying on lower layers to achieve energy efficiency. On the other hand, the application layer data is usually processed at the network layer, and related energy saving mechanisms are tightly coupled with those in the network layer.

2.3.1 Physical layer

In this category, energy conservation mechanisms aim to enhance the node's energy consumption through efficient hardware design. They also address the elementary and low-level network operations that are in close interaction with the sensor node's hardware, such as sensing, signal modulation and transmission. Depending on the targeted subsystem, low-level mechanisms can be divided into data sensing and data communication techniques, targeting the sensing and communication subsystems respectively.

Directional antennas

Conventional design of a sensor node relies on omnidirectional antennas, which allow every node within the sender's communication range to receive the transmitted data, even when the data packet is intended to a single node. To mitigate the unnecessary energy consumption used in propagating the signal in all directions, the use of directional antennas has been proposed as a viable alternative for the design of energy-efficient communication units. With directional antennas (beam antennas), the signal is transmitted in the specific direction towards the intended receiver. Although directional communications may require positioning techniques for antenna orientation, they have multiple advantages compared to omnidirectional antennas. Indeed, and in addition to energy consumption minimization for a given transmission range, they allow multiple transmissions to occur in close proximity, resulting in spatial reuse of the bandwidth and throughput increase. Also, the overhearing problem (when a node wastes power in receiving uninteresting packets) is limited, which improves the communication reliability.

Authors of [MKL+15] studied the impact of using directional antennas in sensor network through both experimental and simulation measurements in outdoor environment. A significant improvement has been noticed, compared to omnidirectional antennas, in terms of multiple performance metrics (energy efficiency, packet error rate, etc.). For example, the experiments revealed that unidirectional antennas can enhance the node's lifetime by 40 hours while achieving comparable performances in terms of packet error rates. To benefit from these advantages, new MAC protocols have been designed, as in [CYRV06, NSR+17]. However, these works are confronted to some challenges that are specific to directional antennas, such as antennas orientation and deafness problem [SD10].

Passive wake-up radios

For successful data delivery in WSNs, the destination node must be listening to the wireless medium when the sender starts data transmission. However, continuous idle listening for incoming data packets results in unnecessary energy dissipation. To mitigate this drawback, the receiver can be put into a sleep state, and a rendezvous scheme is employed to achieve synchronization with the sender. One of the most energy-efficient rendezvous schemes consists of utilizing a secondary passive wake-up radio in addition to the main communication transceiver. This additional hardware is used to awake the destination node only when it needs to receive a packet, while the power-hungry radio serves for actual data reception. Similarly to the idea used in RFIDs, passive wake-up radios do not require any power supply, since they use the energy spread by transmitters to trigger an interruption that wakes up the node. While this makes passive wake-up radios energy efficient, it limits their operational range because of a low reception sensitivity.

Gu et al. developed in [GS05] a passive radio-triggered circuit that is connected to one of the interrupt inputs of the sensor node processor. The wake-up process is selective, i.e, a node remains in the sleep state unless a wake-up signal is present at its assigned radio frequency. Experimental results of this basic radio-triggered circuit have shown a considerable energy savings which are about 70% to 98%, compared to duty-cycled and always-on communication schemes respectively. However, the maximum wake-up range did not exceed $3m$. In addition, the addressing mechanism necessitates a different frequency for every single node, which requires an additional hardware per frequency. More recently, Ba et al. [BDH13] presented a novel node design, called WISP-mote, that integrates the programmable RFID tags WISP [SYP$^+$08], with Tmote sky sensors as a passive wake-up radio. This combination allowed the maximum achievable wake-up distance to be extended up to $5m$, by disabling the WISP-to-reader communications. In practice, it is impossible to equip all sensors in the network with RFID readers, because of their high energy consumption. This major shortcoming, coupled with the short wake-up distance of passive wake-up radios restricts their application to single-hope network only. To demonstrate the potential benefit of passive wake-up radios in practical applications, authors suggest the use of WISP-motes in sparse and delay tolerant networks using mobile sinks equipped with RFID readers. Simulations have shown an important improvement in energy conservation, at the cost of extra hardware and minor increase of data delivery latency, especially if an adapted MAC protocol is employed, such as those surveyed in [DD17].

Cognitive radios (CR)

A wireless sensor network operates in the unlicensed frequencies of Industrial, Scientific, and Medical (ISM) bands. These frequencies are always shared with other networks. Furthermore, certain applications like crowd sensing, require a large number of sensor nodes to be deployed. As a consequence, the available bandwidth in ISM bands may not suffice to support all the transmissions, which entails increasing packet loss and retransmission, and results in higher energy consumption. This spectrum inefficiency can be overcome using a cognitive radio (CR)[AKE09]. The latter is an intelligent radio that is able to dynamically and opportunistically access spectrum holes (available channels), and adapts its transmission and reception parameters accordingly. The underlying Software-Defined Radios (SDR) technology replaces hardware components of traditional radios including, mixers, modulators and amplifiers, with intelligent software. This is expected to create a fully reconfigurable wireless transceivers that automatically adapt their communication performance to the network demand, allowing a better context-awareness.

To exploit the potential advantages of cognitive radios in extending WSNs lifetime, multiples challenges must be addressed. One of these challenges is the design of suitable radio resource allocation scheme. Indeed, wireless channels undergo a wide range of impairments like fast fading, shadow fading, etc. The channel strength also vary with time, frequency and space. Hence, it is crucial to exploit this diversity to devise a dynamic allocation of the channel resources (time slots, frequency bands, transmit antenna, transmit power, etc.) that adapts to the state of the selected channel, in order to optimize communication performance [AARH15]. Other open issues related to cognitive radio sensor networks include the development of upper layer protocols (MAC and routing) that are aware of the opportunistic channel access offered by cognitive radios.

Transmission power control (TPC)

The node's transmission power determines the range over which the signal can be coherently received. At the same time, it considerably impacts the network performance in terms of energy efficiency. Indeed, the energy consumed by the radio is directly proportional to the power of the transmitted signal. Reducing the transmission power (range) plays a significant role in reducing the energy required to deliver a packet. However, the radio hardware of a sensor node is usually set to a fixed and maximum transmission power, which induces an unnecessary high energy usage, especially when communications are performed over short distances. Therefore, selection of the best transmission power has been investigated extensively in the literature as a mean to enhance the energy consumption of the network at the physical layer [KML04, CL18b]. The idea is to adopt a dynamic transmission power that is controlled by the node, considering a number of parameters like the neighbors positions (communication distance) and their residual energy capacities. For instance, authors of [CS15] introduce a distributed TPC algorithm, based on a game theoretic approach that configures the transmission power of sensor nodes, considering their uneven energy consumption profiles. To extend the network lifetime, the proposed algorithm leverages cooperation between nodes such that energy-rich nodes tend to make more sacrifices by increasing their transmission powers, and helping other nodes to reduce their energy consumption rates.

Globally, TPC algorithms differ according to their dynamics in transmission power selection. *Node-level* TPC allow each node to compute one adequate transmission power for all neighbors. *Neighbor-level* solutions target different transmission powers for different neighbors, while more dynamic solutions go further to support *packet-level* TPC tuning in pairwise manner. Nevertheless, these algorithms do not impact the network lifetime only but also links quality, data delivery latency and interference. While reducing transmission power helps in eliminating interference and overhearing problems, it results in longer data delivery delays, since shorter communication ranges result in increased number of hops. Ensuring the best trade-off between energy efficiency and other TPC effects has been considered in multiple works like in [LMZ+16].

Energy-efficient signal modulation

Similarly to the transmission power selection, the modulation process of the signal can also affect the energy consumed per transmitted bit. Hence, notable research efforts have been dedicated to find optimal signal modulation schemes that result in the minimum energy consumption. In traditional wireless networks, energy-efficient modulation is developed with a special emphasize on transmission energy, which is dominant in the total energy consumed during long-range communications (>100m). In contrast, WSN's are characterized with high densities, and the average distance between nodes is usually below 10m. In this scenario, the circuit energy consumption along the signal path becomes comparable to, or even dominates the transmission energy in the total energy consumption. Thus, in order to find the optimal transmission scheme, the overall energy consumption including both transmission and circuit energy consumption needs to be considered [CGB05]. In this context, authors of [CO10] derived an energy-efficient transmission scheme, for point-to-point communications in WSNs, considering three digital modulation types (MQAM, MPSK and MFSK). The objective is to choose a suitable modulation type and compute, through numerical analysis, its optimal parameters like the constellation size (number of symbols used) and information rate(number of bits per symbol). Among considered modulation approaches, it has been shown that MQAM and MPSK are very similar in terms of energy dissipation for all distances, while MFSK has poor performance for shorter distances.

Adaptive sampling

In some WSN applications, the sensing subsystem becomes a significant source of energy dissipation, due to different factors such as: the use of power-hungry transducers, continuous sampling for long periods, or the use of active sensors that need to send out signals in order to acquire sensed data. For such applications, optimizing data transmission is not sufficient. Additional energy conservation mechanisms are necessary to reduce the number of sensor readings via adaptive sampling. Data sampling refers to the measurement of the signal that represent the sensed phenomenon at regular intervals. It is obtained by reducing a continuous signal to a discrete-time signal (a sequence of samples). The challenge of adaptive sampling is to compute the optimal sampling rate (frequency) that provides an accurate picture of the sensed phenomenon, with a minimum energy consumption. It is worth pointing out that adaptive sampling is not intended exclusively to reduce the energy consumption of the sensing subsystem, but it helps in decreasing the number of transmissions as well.

As measured samples can be correlated across time and space, adaptive sampling techniques exploit such similarities to reduce the amount of data sensed by the transducer. When sensed data changes slowly with time, the sampling rate can be adjusted to acquire samples at significant epochs only. *Temporal* analysis of data samples has been discussed in [AAG+07]. Authors propose an adaptive sampling scheme for avalanche forecast. The scheme dynamically sets the sampling rates after estimating F_{max}, the current maximum frequency in the power spectrum of the considered signal, based on the trend of the sampled data.

Adaptive sampling can also be useful when the sensed phenomenon does not change sharply between areas covered by neighboring nodes. Here, *spacial* correlation is utilized to reduce the number of sensor readings. Backcasting [WMN04] is a prominent method that takes advantage from spatial correlation to adapt sensing process. It operates by activating only a small subset of nodes that communicate their information to the sink. The communicated information represents a coarse-grained spatial distribution of the phenomenon. It provides an initial estimate of the sensed environment, and guides the allocation of additional network resources. The sink then selectively activates additional sensor nodes in order to achieve a target error level based on approximating signal activity.

In a large number of adaptive sampling solutions, sensors cannot take actions autonomously to switch their rates and intervals. They rely on an omniscient central unit or a sink that performs heavy computations for analyzing the signal complexities of all nodes, and periodically transmits suitable sampling rates to them. Consequently, such solutions induce extra communication overhead. Furthermore, they suffer from a limited capability to capture highly dynamic changes, which affects monitoring quality. To cope with this problem, a recent paper proposed a distributed adaptive sampling scheme, in which nodes can decide to switch between high- and low-frequency intervals, in order to reduce the resource usage, while minimizing false negative detections [BWW+17]. The solution has been applied to applications with high frequency events like Fire Event Monitoring, and notable performance enhancement has been demonstrated through experimental and simulation results.

2.3.2 Data link layer

The objective of energy conservation techniques in data link layer is to minimize the energy dissipated for data frame detection, medium access and error control. This is mainly achieved through duty cycling approaches that are implemented as standalone modules or integrated in MAC protocols.

Duty-cycling

As an alternative to wake-up radios, discussed earlier, duty-cycling mechanisms offer different approach to implement sleep/wake-up schemes, at the data-link layer, to ensure energy conservation [ODC$^+$16]. While the former mechanism allows the complete node to be switched off, duty cycling deals with the radio component only. The radio state is alternated between sleep and wake-up periods, based on the network activity, with the objective to optimize the communication performance in terms of energy consumption. This is mainly achieved by reducing two negative sides of wireless transmissions, namely: idle listening (i.e. the radio keeps waiting in vain for a frame) and overhearing.

Duty-cycling schemes can be divided into *synchronous* and *asynchronous*, in relation to the mechanism used to coordinate motes' schedules. Synchronous schemes are those where nodes are time synchronized, although the degree of synchronization varies greatly. Nodes are waking-up and sleeping simultaneously, according to a schedule that can take the form of either a global and single rendezvous, or staircase pattern. The latter is used when a hierarchical topology is adopted. It defines wake up periods based on the node's level in the network topology, aiming to achieve a tradeoff between energy and end-to-end data delivery delays. In asynchronous methods, nodes are not required to keep a common clock.[CPMA14]. Instead, other methods are used to guarantee that neighbors always have overlapped active periods within a specified number of cycles. For example, in preamble-sampling methods, the transmitted frames are preceded by preambles, ensuring that a destination waking up periodically will detect it, and stays active to receive the frame.

Since pair-wise synchronization is easier to achieve than global synchronization, it makes sense to group neighbors into synchronized clusters and have the clusters interact with each other asynchronously. This results in a semi-synchronous scheme (also called hybrid or semi-asynchronous)

Table 2.1 presents un overview on different types of duty cycling schemes with their advantages and drawbacks. From this overview, it can be noticed that the techniques differ in terms of their ability to achieve a tradeoff between energy efficiency and other performance metrics like end-to-end delays. Hence, choosing a convenient duty-cycling scheme for a given scenario relies on a set of considerations that are mainly related to the desired application. For example, if the application's data flow is expected to rely on broadcast traffic, the use of synchronous mechanisms is highly recommended. On the other hand, each duty cycling mechanism is sensitive to a set of parameters, such as sleep/wakeup periods, preamble length or cluster size, that can considerably influence the network performance. For instance, a short wake-up time saves a large amount of energy but penalizes end-to-end delays. Tuning these parameters is a challenging task that can be performed once, prior to network deployment for sake of simplicity. However, this approach lucks of flexibility. For better adaptation to network states, some works choose to change duty-cycling parameters dynamically as a mean to enhance their performance. For example, authors in [TKT+18] propose a receiver-initiated duty cycling technique that adapts intermittent sleep/wakeup intervals, according to the remaining amount of harvested energy, and the number of active sensors in the coverage. Both simulation and experimental results of this work confirmed the effectiveness of duty cycle adaptation in achieving lower packet loss rate and higher energy savings compared to conventional methods.

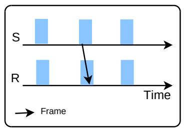
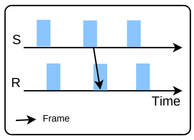
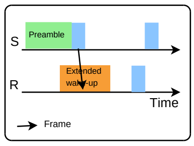
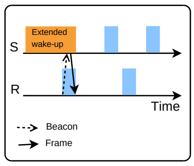
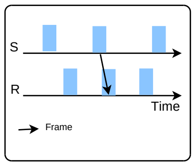
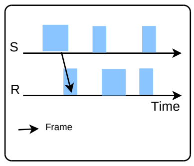
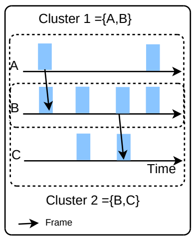
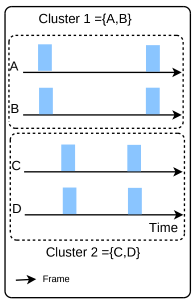
	Sync	Principle	Pros	Cons	Illustration
Rendezvous	Yes	Simmultanous wakeup and sleep time for all nodes in the network	- Low duty cycles - Intuitive - Supports broadcast	- Requires guard-times to deal with synchronization errors	
Skewed	Yes	Staircase wakeups according to node depth	- Reduced end-to-end delays	- Topology dependant - Requires guard-times to deal with synchronization errors	
Preamble sampling	No	Frames are preceded by preamble ensuring that the receiver will detect it once awake	- Minimize overhearing	- Long channel occupation - Inefficient for broadcasts	
Receiver-initiated	No	Sender transmits the frame after hearing a beacon from the receiver	- Less channel occupation than preambles - Adapted for high traffic load	- High end-to-end delays	
Random	No	Wake-ups and sleeps are performed randomly, relying on the probability that the receiver is active when the transmission begins	- Equal destribution of trafic load	- Efficient in dense topologies only - Low delivery rate	
Schedule-based	No	Wakeup schedule guarantees that active periods overlap	- Resilient to topology changes - Do not require control messages	- Low duty cycles result in high latency	
Spantaneous clustering	Semi	Clusters are formed following synchronization among neighbors	- Easier synchronization compared to global schemes - Simple to maintain	- Nodes may participate in multiple clusters, which increases duty cyles	
Elected cluster-head	Semi	Cluster-head is elected and neighbors synchronize with it	- Easier synchronization compared to global schemes	- Additional overhead for cluster maintenance - Require additional mechanisms for inter-cluster communication	

Table 2.1: Duty cycling mechanisms in WSNs

Low-duty MAC protocols

As duty cycling solutions have been integrated with medium access protocols, research on duty-cycled MAC has evolved towards two main directions : TDMA- and contention-based protocols. TDMA stands for Time Division Multiple Access. With this class, the channel access is performed on slot-by-slot basis. Nodes need to turn on their radios only during their active slot, relying on a synchronized duty cycling mechanism. This enables them to reduce the energy consumption to the minimum required for transmitting and receiving data. In contention-based protocols, nodes randomly poll the transmission channel during their active slot until gaining access. The integrated duty cycling mechanisms can be synchronous [DDBB14] or asynchronous like in B-MAC [PHC04].

Both TDMA and contention-based MAC protocols have their strengths and weaknesses. The former are naturally energy-efficient as nodes possess dedicated slots to switch-on their radios and use the channel. In addition, they can solve interference problems by appropriately scheduling wake-ups of neighboring nodes in different slots. However, TDMA-based protocols suffer from several drawbacks. First, they have limited flexibility and scalability, especially in highly dynamic topologies where slot allocation may be problematic. Second, they inherit the shortcoming of synchronized duty-cycling that requires tight synchronization among nodes. Finally, they exhibit low performance in low traffic conditions. On the other hand, contention-based MAC protocols entail higher energy consumption than TDMA-based protocols. Nonetheless, they are generally more robust and scalable. Also, some of them can achieve low end-to-end delivery delays, which favors their adoption for many WSNs applications.

2.3.3 Network layer

In the network layer, energy conservation approaches aim at minimizing the overhead caused by network-wide communications required for data collection from sensors to the sink node. This is mainly achieved by optimizing the underlaying topology, and reducing the energy consumed by routing protocols.

Topology control

Thanks to the self-organization feature of WSNs, it is possible to deploy the network randomly, e.g., by dropping a large number of sensor nodes from an airplane. In such case, it maybe convenient to use a number of nodes greater than necessary in order to cope with possible failure that may occur during and after the deployment. Furthermore, if the field of interest is hard to attain, it is much easier to initially deploy a high number of nodes than re-deploying additional nodes when needed. For the same reason, redundant deployment may be convenient even when nodes are placed deterministically by hands [YA08]. However, with redundant deployment, the sensing data reported by adjacent nodes will tend to be similar. Thus, the concurrent activity of "redundant" nodes in the network will not be entirely necessary. Further, having redundant nodes active may become undesired because of the energy wastage when retransmitting unnecessary packets, inducing a high collision rate due to the augmented traffic volume.

Topology control protocols are meant to deal with redundancy problems by dynamically adapting the network topology, based on the application needs, so as to maintain network operations while minimizing the number of active nodes or communication links (and, thereby prolonging network lifetime). The network topology is constructed and reorganized either by modifying nodes transmission powers or their operation modes (active, sleep). In this regard, existing techniques can be classified into two categories: power control (PC) and sleep scheduling (Figure 2.4)

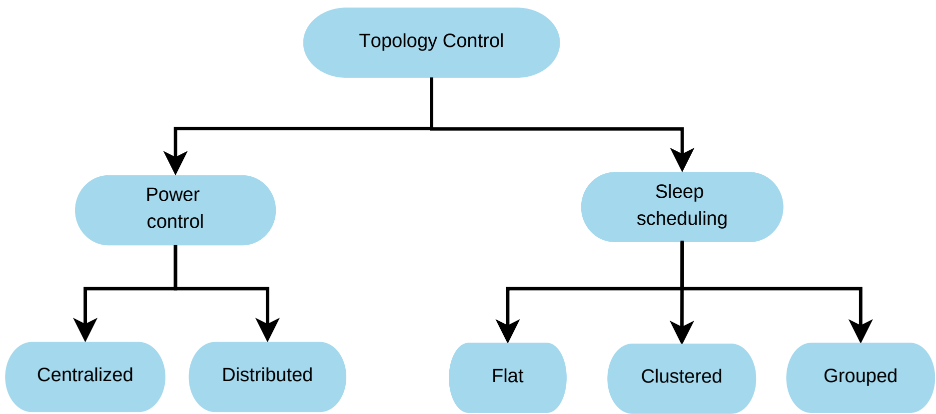


Figure 2.4: Topology control techniques in WSNs.

PC-based techniques build energy efficient topologies by controlling the nodes' transmission power. This can be done in either centralized or distributed manner. The former is the most adopted approach. Under this approach, there are two well-known problems: The Critical Transmission Range (CTR) problem, which finds the minimal communication range for all the nodes in the network while preserving network connectivity, and the Range Assignment (RA) problem, which goes further in the goal of saving energy by finding the optimal transmission power for each individual node. Both problems have the goal to compute optimal topologies. On the other hand, distributed PC-based techniques are more concerned with a practical construction of "sub-optimal" topologies based on efficient methods requiring less energy, computational and message complexity. Here, a tradeoff is considered between the implementation overhead and the performance gained after topology construction. In [LW10], existing solutions for distributed PC-based topology control have been categorized, according to the type of information they utilize, into location-, direction-, neighbor- and routing-based

With *sleep scheduling* approaches, the topology control is performed by defining coordinated sleep/wakeup schedules among nodes in the network. Ideally, nodes are kept in sleep state as long as possible. They should be switched-on only when needed, which results in important improvement in energy conservation. The objective of sleep scheduling topology control is to compute the optimal subset of nodes that need to be turned on, in order to ensure connectivity and sensing coverage with minimum energy consumption. The state-of-the-art contributions in this category can be divided into flat, clustering and grouping solutions.

The first category of sleep scheduling solutions (flat schemes) considers the entire network when selecting the set of active nodes that form the communication backbone. SPAN [CJBM02] represents one prominent example in which coordinator nodes are elected periodically based on a global network view. In cluster and group-based sleep scheduling, nodes are organised first, either in clusters or in groups. Then, active nodes are elected from each cluster or group. Cluster-based solutions elect three types of nodes: cluster-heads, primary gateways, and secondary gateways. These nodes should remain active to ensure connectivity while other nodes can go into energy saving mode. On the other hand, group-based approaches organize the topology into groups, either statically, based on nodes position, or dynamically using connectivity information. In a recent work, Zebbane et al. [ZCBB18] proposed RTCP, a group based topology control protocol that employs two-neighbor connectivity information for identifying redundant nodes and grouping them according to their degree of redundancy. The sleep schedules are set subsequently within each group. To prevent weak connectivity in the resulting topology, authors define eligibility rules allowing conservative identification of redundant nodes.

Overall, the efficiency gained through topology control mechanisms is tightly related to node density and the actual number of redundant nodes. Consequently, their use in sparse deployment scenarios maybe insufficient to guarantee an acceptable energy efficiency, and requires the adoption of additional energy consumption mechanisms like those discussed next. On the other hand, reducing the network topology for the sake of energy conservation may induce some side effects, such as a weak tolerance to link and node failures. A tradeoff between positive and negative effects of topology control mechanisms need to be considered at the early design stage of WSNs.

Energy-efficient routing

Routing represents a crucial service in WSNs, since it is responsible of collecting data from sensor nodes to the sink, via multi-hop communication. However, this service introduces a heavy burden on the network performance in terms of energy consumption, because of many network-wide operations during route discovery and maintenance. The high energy dissipation caused by routing protocols can be continuous throughout the network life span, especially in dynamic topologies that undergo frequent changes caused by node/link failures or mobility.

Extensive research has been conducted to optimize the energy dissipated by the routing service. For a comprehensive review on existing energy-efficient routing protocols, the reader can refer to the works in [AY05, PNV13]. In the following, we discuss the common energy conservation mechanisms that have been adopted by these protocols.

1. **Hierarchical organization:** takes into account the heterogenous energy capacities of sensor nodes. In hierarchical routing, nodes are generally organized into clusters, where energy-rich nodes are assigned the role of cluster heads (CH) and others become members. The CH is responsible for coordinating activities inside the cluster, processing the data received from members and forwarding it to the sink via multi-hop communication with other CHs. The members are mainly responsible for the sensing task only. Hierarchical routing contributes to extend the overall network lifetime by various means. Firstly, it enables data aggregation and fusion at the CH, which decreases the number of messages transmitted to the sink. Secondly, it balances energy consumption among nodes by assigning heavy tasks to the CHs (energy-rich nodes), and periodically rotating the CH role. Finally, it allows to switch-off some cluster members when they are not required for sensing.

   LEACH [HCB00] is by far the most popular cluster-based routing protocol for sensor networks. In this protocol, a node becomes cluster head by randomly choosing a number that is smaller than a threshold value. The threshold is calculated, at each round, based on a set of parameters such as the current round number, the set of nodes that didn't become CH yet. The optimal number of cluster heads has been estimated to be 5% of the total number of nodes. After CH designation, the other nodes form the clusters in distributed manner, based on the signal strength received from different CHs. It has been shown that LEACH achieves over a factor of 7 reduction in energy dissipation, compared to direct communication. Based on LEACH, a multitude of protocols have been derived as an enhancement for particular application scenarios [AJR+12]. A taxonomy and general classification of hierarchical routing schemes can be found in [AY07].

2. **Energy cost functions:** Many routing protocols in WSNs rely on the shortest path method allowing data collection through a minimum number of hops. However, this method is not always efficient in terms of energy consumption. An alternative approach is to adopt energy-aware routing that uses a cost function (energy metric) reflecting the energy efficiency of the employed route. This function is calculated during the route discovery phase in order to help the sink or forwarding nodes to select the path with the a minimum cost.

   The main difference among proposals on energy-aware routing resides in the design of the cost function. Ok et al. [OLMK09] introduce a new metric, called Energy Cost(EC), that balances the energy consumed on each transmission link in the route with the residual energy of corresponding nodes. EC takes the best values when transmission energy on a given link is low and the sender's available energy is high. Using this metric, a localized routing algorithm, named Distributed Energy Balanced Routing (DEBR) is proposed. Liu et al. [LRL+12] enhanced the DBER cost function which was proven to be suboptimal. Authors proposed a double cost function routing (DCFR) that considers energy consumption rates, in addition to end-to-end energy consumption and nodal remaining energy. The resulting cost function is shown to achieve a better energy balancing and longer network lifetime, thanks to its rapidly increasing slope, which is very sensitive to small changes in energy consumption rate or available energy level. In a more recent work [AKFV+18], authors argued that traditional cost functions based on rigid computations of input metrics are unable to capture all dynamics in network states. For example, remaining energy metric is important only when node's energy level is low. As a more adaptive solution, they proposed to model energy-awareness in routing decisions using the tools of fuzzy logic.

3. **Multipath routing:** In contrast with single-path routing, multi-path routing allows the use of several disjoint or braided paths towards the sink to deliver data. The adoption of this technique may be motivated by different design goals. For example, data can be simultaneously collected through multiple paths to enhance the bandwidth utilization in high traffic applications like multimedia sensor networks[CL18a]. A complete survey discussing different categories of multi-path routing protocols with corresponding design objectives

can be found in [RDBL12, SGG13]. For the objective of energy efficiency, multi-path routing is adopted to prevent the rapid battery outage for nodes belonging to optimal routes. Consequently, it leverages the use of sub-optimal routes in order to balance the energy consumption rates among all nodes, which extends the network lifetime.

Authors of [MD13] devised a heuristic approach for constructing multiple paths between a target sensor and the sink. The paths are formed by choosing nodes that consume less power in packet forwarding. The energy consumption is estimated according to the neighbors distance and Received Signal Strength (RSSI). As soon as several paths reach the sink, this latter performs an energy balancing strategy by computing the size of data flow to transmit on each path. The multi-path routing protocol described in [LDB+17] is also designed with the objective of balancing energy consumption. Authors exploit the model of Ant Colony Optimization (ACO) in discovering multiple paths that avoid the use of nodes with low residual energy. The set of selected paths(cloud) is found using two metrics: the nodal remaining energy and the hop count. These metrics represent the pheromone for the ACO algorithm.

Its worth mentioning that multi-path routing can also indirectly contribute in enhancing the energy efficiency of the routing service, even when the designers are motivated by different goals. For example, in case of nodes failure, it enables a fast recovery without re-execution of the path discovery phase, which allows significant energy savings.

Network coding

Is a promising energy conservation technique that can complement traditional routing, especially in the case of multicast-based applications. In this technique, intermediary nodes (coders) reduce the amount of data delivered to the destination by sending a combination of received packets, instead of simply forwarding them.

To explain the principle of network coding, we consider the example depicted in Figure 2.5. Suppose that the two source nodes (1 and 2) must deliver their respective data (a and b) to multiple sinks (5 and 6). With conventional routing, intermediary nodes must forward a and b separately, leading to a total number of 6 transmissions. However, if network coding is employed, the coder (node 3) will send a simple combination of the received data (for example the sum) to node 4. With this manner, both sinks will be able to collect the original data values, while saving

2 transmissions. For instance, node 5 can deduce b by subtracting a from the coded data. In addition, it can be noted from the illustration, that network coding allows an improvement in end-to-end delays as well. Indeed, communicating entire data - at once - over the link $3 \rightarrow 4$ will shorten the delivery time, compared to the case where two packets must be transmitted sequentially, which delays the arrival time for one of them.

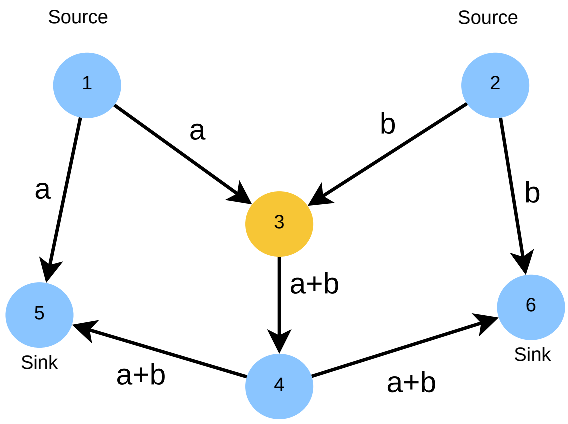


Figure 2.5: Network Coding mechanism.

Due to the multiple benefits of network coding, a large research community has been attracted to its application in the context of WSNs. Adapcode [HTAG08] is one of the first network coding schemes that have been specifically tailored for sensor networks. Packets on every node are coded by linear combination and decoded by Gaussian elimination. Contrary to previous works destined to general wireless networks, Adapcode takes into account the resource limitations of WSNs by using small memory for Guassian elimination. Moreover, it adapts to network conditions by changing the number of packet coded in one messages, according to the node density, in order to enhance reliability. The evaluation shows that AdapCode uses up to 40% less packets than conventional data propagation schemes. The design of novel routing protocols based on network coding has also been explored in [WYZ12, WHW+12]. In a more recent work, Lee et al. [LKC16] investigated the combination of Random Linear Network Coding (RLNC) with duty cycling, to solve the problem of bottleneck zones in multimedia sensor networks.

Data aggregation

Similarly to network coding, data aggregation methods aim to optimize energy consumption by reducing the amount of data that flows across the network [RV06, FRWZ07]. However, these methods are not limited to broadcast or multi-cast schemes. They can be used in unicast communications as well. In addition, the employed data reduction methods are closely related to the data semantics defined by the application. For example, if the application needs to measure the average temperature of a given area, aggregation can be used to calculate the average value, while raw data packets are routed to the sink. Each intermediary node can aggregate received data packets into one message containing the average value, and send it to upstream nodes. This will facilitate the final task for the sink, while reducing the number of messages in the network.

The performance of data aggregation schemes is strongly dependent on two components namely: the *aggregation function* and the *routing protocol*. The latter are mainly distinguished from traditional routing schemes by the *scheduling algorithm*, which synchronizes the waiting periods elapsed by each intermediary node before packet retransmission. The paper in [BCK$^+$14] is dedicated to the detailed review of scheduling mechanisms for data aggregation in WSNs. On the other hand, routing functions must be implemented on top of a suitable topology that maximizes aggregation opportunities. For instance, the authors in [LCKH15] use Genetic Algorithm (GA) to calculate the optimum tree which is able to balance the data load and the energy consumption.

As for aggregation functions, the main design challenge is to eliminate data redundancies and achieve maximal compression, without loss of accuracy. Preserving information precision is particularly important if the sink needs to recover original values from aggregated messages. Harb et al. [HMTC17] present and compare three different aggregation functions that focus on identifying data redundancies. The proposed methods are based on the sets similarity functions, the one-way Anova model with statistical tests and the distance functions respectively. Real experiments confirmed the important role of aggregation functions in extending the network lifetime. Nonetheless, the choice of the most suitable scheme follows the application needs in terms of data accuracy and latency.

Sink mobility

Communication in a WSN often has the many-to-one property. Indeed, data from a large number of sensor nodes needs to be concentrated to one or a few sinks. If the network is static, the nodes near the sink can be burdened with relaying a large amount of traffic from other nodes. This phenomenon is sometimes called the “crowded center effect” or the “energy hole problem”. It results in premature energy depletion at the nodes located in the vicinity of the sink, potentially disconnecting the sink from the remaining sensors. One possible solution to this problem consist in exploiting controlled mobility. A mobile sink can be used to move around the network and collect data. Sensor nodes wait for the passage of the sink and route messages towards it, so that communications take place in proximity (Directly or at most with a limited multi-hop traversal). As consequence, energy will be saved thanks to reducing transmissions, links errors and contentions. Furthermore, energy holes will be mitigated with enhanced balancing of the message forwarding task.

Among research topics raised by the introduction of mobile sinks in WSNs, mobility management has drawn much attention. The proposed solutions aim to endow the sink with optimal mobility pattern that allow maximum optimization in network performances. In [GRJL16], Gu et al. classified related schemes based on the employed mobility pattern into four categories: uncontrollable mobility (UMM), path restricted mobility (PRM), location-restricted mobility (LRM) and unrestricted mobility (URM).

2.4 Discussion and open directions

Our study on energy conservation techniques has led us to a couple of conclusive remarks. Firstly, many techniques share the same energy conservation approach that is implemented differently, depending on the targeted networking layer. Alternating the node's subsystems between *sleep and wake-up* states is by far the most adopted approach. It represents the basic idea of passive-wakeup radios, duty-cycled MAC protocols and topology control schemes. *Data reduction* is another approach that has been identified as an efficient way to decrease the communication overhead. It has been essentially implemented through adaptive sampling, data aggregation and network coding. In addition, the techniques of transmission power control, directional antennas and cognitive radios share all the same idea of *radio optimization*.

Secondly, achieving a good level of energy efficiency often necessitates the use of multiple energy conservation techniques that are implemented concurrently, in order to simultaneously target different network services and procedures. Despite of the high number of solutions based on multiple mechanisms, research addressing the mutual influence between these mechanisms, as well as the design guidelines allowing their optimal combination remains insufficiently explored. Furthermore, and since it is practically hard to guarantee an optimal energy consumption for every network service, designers must prioritize those with the most significant impact on the network lifetime, such as routing protocols addressed in the next chapter.

Finally, the choice of energy conservation techniques must be derived by the application's design constraints and requirements. In fact, each WSN's application has a set of inherent requirements that need to be considered, in addition to energy

efficiency. For example, sensor networks for healthcare applications are constrained by hard data delivery delays. For this case, the use of techniques that introduce additional communication delays, such as asynchronous duty cycling, is not recommended. With this perspective, the next chapter investigates energy conservation in routing protocols within the application context of Internet of Things (IoT) characterized by specific design constraints such as high deployment densities.
On the other hand, and for a given application scenario, designing an energy conservation technique that positively impacts all performance metrics is a difficult task, especially for recent WSNs applications known by their complex requirements. This objective is even harder to achieve if the deployed network is intended to support multiple applications like in Software-Defined Sensor Networks. In such scenario, the application requirements can dynamically change throughout the network lifetime, which requires a continuous balancing between energy consumption and other performance metrics. Hence, investigating the tradeoff solutions that timely adapts to dynamic application requirements is an interesting area of research.

2.5 Conclusion

Since the early research investigations on wireless sensor networks, energy efficiency has been identified as the primary design objective. Achieving this objective is still challenging because of the growing complexity of WSNs applications from one side, and the continuous miniaturization of sensor nodes from the other side.

In this chapter, we reviewed the main energy conservation techniques that have been adopted for the design of energy efficient services in WSNs. The studied mechanisms have been classified according to their implementation layer at the networking stack. One of the lessons learned from this review is that the usefulness of a given energy conservation mechanism can not be measured by its contribution in energy savings only. It also depends on its positive or negative impacts on other performance metrics, required by the network application. By taking into account this strong dependence between energy conservation and application requirements, we will focus in the next chapter on achieving energy efficient routing in the context of high network density, imposed by several emergent applications of WSNs in the era of Internet of Things (IoT).

Chapter 3

Energy-efficient Routing in Dense IoT WSNs

3.1 Introduction

The era of Internet is witnessing a mutation from Internet of people to Internet of Things (IoT), where a large number of heterogeneous devices could seamlessly interoperate in globally integrated communication platforms. In this mutation, Wireless Sensors Networks are expected to assume a crucial role, thanks to their ubiquity and low cost. Nevertheless, the integration of WSNs in complex IoT applications requires a rethinking of employed communication protocols, to ensure their efficiency in new application scenarios [KABG14, MPV11].

Motivation

One of the design challenges raised by the emergence of IoT-WSNs applications is the high density of deployed nodes [Lla15]. For example, the network density in urban IoT, based on crowdsensing, will be extremely high when each person sitting in a stadium contains hundred of sensors that are embedded in his body, clothing, shoes,...etc [BCCF13]. Such a high density might be very useful to the application in terms of enhanced quality of sensed data and node failures mitigation. However, it negatively impacts the underlying networking protocols and penalizes their performance, especially in terms of *energy efficiency*.

Routing protocols are considered as a pilar networking service in WSNs, due to their major role in enabling communication between sensor nodes and the end-user or even between nodes themselves. Optimizing the energy efficiency of routing protocols will considerably impacts the overall network performance, because of two reasons. First, routing is based on network-wide procedures that impose the participation of all nodes, especially in the route discovery phase. Improving these procedures will inevitably enhance the global energy consumption of the network. Second, at the node level, the routing service comes in a top layer of the networking protocol stack. This means that each routing operation triggers several other operations in the underlying protocols at the data link or physical layer. Considering this relationship in the design of a routing protocol helps significantly in achieving energy efficiency for each node in the network.

Contributions

In this chapter, the issue of energy efficient routing is investigated in the context of new IoT applications of WSNs characterized by the *large scale* and *dense* deployment. To this end, we propose the use of a power-aware topology control technique, in order to mitigate the performance degradation of routing protocols in dense networks. The proposed solution is built on a well-known WSNs routing scheme, namely Directed Diffusion. Despite of the suitability of Directed Diffusion to the IoT applications, thanks to its data centric-paradigm, it has been shown in [KB07] that it encompasses several operations, like network-wide broadcasts, which strongly affect its performance in dense networks.

In addition to the topology control mechanism, a new energy consumption metric is adopted for route selection. This metric takes benefit from the power-awareness feature of topology control phase, to estimate the energy expenditure of each discovered path, and select most energy efficient path.

Outline

The remainder of this chapter is organized as follows: In Section 3.2, we briefly overview the issue of routing in WSNs. Then, Section 3.3 describes Directed Diffusion protocol and highlights its performance in dense deployment scenarios. In Section 3.4, the power-aware topology control mechanism is presented, and the improved routing protocol using this mechanism is detailed in Section 3.5. The performance of the proposed protocol is evaluated and compared to Directed Diffusion in Section 3.6. Finally, Section 3.7 provides concluding remarks and possible area of extension.

3.2 Routing protocols in WSNs

Routing protocols for Wireless Sensor Networks can be classified as hierarchical, location-based, QoS-aware and Data-centric [AY05].

- **Hierarchical routing** organizes the network into clusters, that are managed by elected nodes called clusterheads. Cluster formation is typically based on the energy reserve of sensors and their proximity to the cluster head. To enhance the routing performance in large networks, hierarchical protocols limit the task of low-energy nodes to sensing and local data transmission within a particular cluster only, while clusterheads are responsible of data fusion and multi-hop routing towards the sink.

- **Location-based routing** utilize node's position information to relay the data to the desired regions rather than the whole network. For instance, if the region to be sensed is known, using the location of sensors, the query messages can be routed only to that particular region which will significantly reduce the number of transmissions.

- **QoS-aware routing** consider end-to-end delay requirements, as well as other performance metrics while setting up the paths. This class of protocols are mainly destined to some critical applications that are highly sensitive to the quality of service, such as target tracking and multimedia WSNs.

- **Data-centric routing** makes abstraction of all forms of physical identification among the network nodes. Instead, communications are established using query-response model, based on attributes of the data requested by application. This allows a more efficient selection of requested nodes, without the use of global identification schemes, which demonstrated a limited scalability. In addition, data-centric approaches leverage in-network data aggregation that reduces considerably the energy overhead resulting from redundant data transmission. SPIN [HKB99] was the first attempt towards data-centric routing protocol. It considers data negotiation between nodes in order to eliminate redundant data and save energy. Later, Directed Diffusion [IGE+03] has been proposed and was recognized as breakthrough in data-centric routing.

Data generated by sensors, especially in IoT applications, is considered as a precious asset that requires an efficient management in all architectural levels. At the routing level, data-centric routing and more particularly Directed Diffusion, has been recognized as a promising alternative. This protocol has the potential of efficient energy consumption and bandwidth utilisation thanks to the possibility of in-network data processing [TS13].

3.3 Directed Diffusion

In Directed Diffusion [IGE+03], sensed data is named by a list of attribute-value pairs. These attributes are used to describe the type of the sensed phenomenon, their locations, duration, etc. To ensure data collection and communication with the sink node (base station), Directed diffusion relies on three main steps namely, interest propagation, data dissemination and path reinforcement.

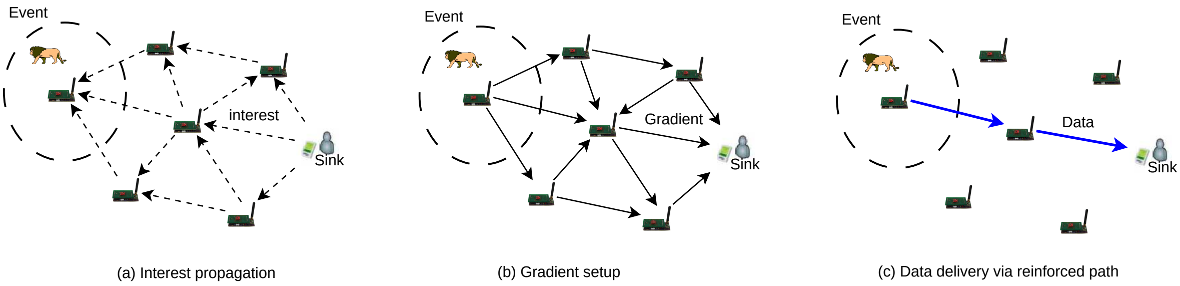


Figure 3.1: main phases of Directed Diffusion.

Interest propagation

In this first step, the *sink* node floods the network with an *interest* message. An interest represents a task assignment message that contains a detailed description of the event data in which the end-user is interested. For example, in animal tracking WSN application, an interest asking the sensors to report locations of four-legged animals may take the following form (Figure 3.1 (a)):

```
type = four-legged animal       /* Type of tracked animals*/
timestamp = 01:20:40
interval = 1 s               /* Data sending rates */
duration = 10 s                 /* Interest validity period */
rect = [-100,100,200,200]       /* Data from sensors within rectangular region */
```

When the interest is received by an intermediary node, this latter creates a *gradient* entry to the neighbor from which interest was received. If the same interest is captured from several neighbors, a separate gradient will be set up for each neighbor. Basically, a gradient is local state stored at the relay nodes that points to the neighbor from which the interest has been received (Figure 3.1 (b)). It intuitively shows the direction that facilitate "pulling down" eventual reported data flows towards the sink node. After rebroadcasting the interest to other neighbors, the receiving node that meets the interest attribute triggers its local sensors to begin collecting samples and performs the sensing task.

Data dissemination

Once a node detects a matching target, it tasks the sensor subsystem to generate event samples following the rates specified in the gradient entry. Based on the samples, this *source* node starts sending an event description of the form :

```
type = four-legged animal          /* type of animal seen */
instance = elephant                /* instance of this type */
location = [125, 220]              /* node location */
intensity = 0.6                    /* signal amplitude measure */
confidence = 0.85                  /* confidence in the match */
timestamp = 01:20:40               /* local time when event was generated*/
```

This data event is sent to all neighbors for which a gradient has been setup. Intermediary nodes undertake the same operation, and follow the gradients to forward the received data towards the sink node. The first data packets are always sent with low rates (e.g. 1 *event/sec*) and are flagged as *exploratory*. Their main mission is to identify existing paths between discovered sources and the sink.

Path reinforcement

Upon the reception of exploratory data, possibly via multiple paths, the sink replies with *reinforcement* message. This latter is sent to one particular neighbour from which an exploratory packet meets a particular QoS criteria. For example, for low-delay routes, the sink reinforces the first neighbor from which a data message was heard. In the example illustrated by Figure 3.1-(c), the sink reinforced the path with a minimum number of hops.

The structure of reinforcement message is similar to the initial interest message, with a modified transmission rate that is requested to be higher. Each intermediary node that receives a reinforcement follows the same local rule that consists in selecting an empirically low-delay neighbor.

After reception of reinforcement message, source nodes start sending data, over the reinforced route, with a higher rate (e.g. 20 *event/sec*). Meanwhile, alternative paths are maintained through continuous transmission of exploratory data. They are used as a replacement if link failure is detected in the reinforced path. Gradients are, in their turn, refreshed by the sink through periodical flooding of interest messages, for the purpose of fault tolerance.

It is worth mentioning here that Directed Diffusion provides also a data caching mechanism in order to limit exploratory data flooding, which guarantees the selection of single and loop-free reinforced path.

3.3.1 Directed Diffusion performance in dense WSNs

The analysis of Directed Diffusion mechanisms reveals that the protocol encompasses several resource-demanding operations, especially during the propagation of interest and exploratory data steps. Depending on the network topology and its deployment density, the employed techniques, like network-wide flooding, may lead to a significant and unnecessary overhead that degrades the protocols performance, especially in terms of energy efficiency, reducing the lifetime of the whole network.

These remarks are consolidated in [KB07], where the impact of network density on the performance of Directed Diffusion has been evaluated. The study demonstrates, through extensive simulation, that Directed Diffusion is heavily based on operations that requires participation of all neighboring nodes (such as gradient maintenance and data cashing). Despite of their localized nature, the execution performance of these operations decreases considerably with higher densities, due to an augmentation in the number of broadcasted messages. Concerning the network-wide operations, higher densities resulted in higher number of flooded interests and exploratory data messages, which penalizes the performance of forwarding nodes. Also, the number of alternative paths is increased, which requires additional overhead for maintenance. In addition, it has been pointed out that both local interactions and high number of flooded messages caused a more aggressive contention on the communication channel, as well as a more frequent interference between simultaneous transmissions. These factors participated in the degradation of the protocol performance in terms of energy expenditure, end-to-end communication delays, and delivery ratio.

As a result, we conclude that the performance degradation of Directed Diffusion in dense networks represents a serious obstacle preventing its adoption in emergent WSNs applications, despite of the efficient data management brought by its data-centric mechanisms.

To address this issue, we propose to improve Directed Diffusion with a density-adaptation technique, based on a Power-Aware Topology Control (PATC). In the following, the PATC mechanism is detailed, and its impact on the performance of Directed Diffusion is studied.

3.4 Power Aware Topology Control (PATC)

The design of the Power-Aware Topology Control (PATC) mechanism is inspired from the work in [RM99]. In the latter, authors propose MECN protocol that selects energy-efficient routes after extracting a minimum-energy graph from the actual network topology. Here, our aim is to investigate the use of similar techniques for different purpose, which consists in reducing the high network connectivity while preserving the energy-efficient routes between the sink and sensors.

The PATC technique relies on the power consumption model of wireless communications. The model states that the transmitted signal power P_{tx} falls as $\frac{1}{d^n}$, where d denotes the distance between the transmitter and the receiver, and n is the path-loss exponent that depends on the transmission environment ($n \geq 2$ for outdoor propagation models) [Rap96]. Hence, a sender is required to transmit at least with a power $P_{tx} = Td^n$, in order to allow correct reception at the receiver. Here, T is the pre-detection threshold (in mW) at each receiver, which is related to the minimum transmitted signal power, required for correct reception of packets.

The principals of the aforementioned model conducts us to the main observation that motivates the PATC technique, which is : *Since the transmission power P_{tx} depends on a power n of the desired transmission distance (d); relaying messages between multiple nodes may induce lower transmission power (energy consumption) than communicating them over large distances.*

Based on this observation, the PATC objective is to *"disable"* a direct communication link between every two neighbors, if a third node is found such that relaying communication via this node consumes less energy than the direct transmission.

To this end, every node i in the network calculates the *relay region* associated to each of its neighbors r. A relay region $R_{(i,r)}$ is defined as the set of all neighbor j of i to which the direct transmission of packets from i costs more energy than its relay through r. Figure 3.2 illustrates a typical relay region in a propagation environment with a path-loss exponent of 4. One of the characteristics of the relay region is its asymptotic behavior to the median line $y = \frac{d_{ir}}{2}$

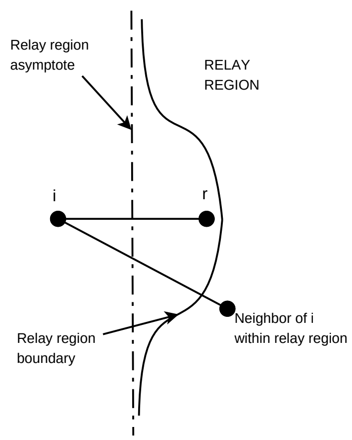


Figure 3.2: Relay region of node i.

When the relay regions, associated to all neighbors are calculated, the node i combines them in order to define a surrounding region where it is not power efficient for node i to maintain a direct communication link with neighbors which are outside.

This region is called the *enclosure* of i, and only the nodes belonging to it will be considered for direct communication with i (Figure 3.3).

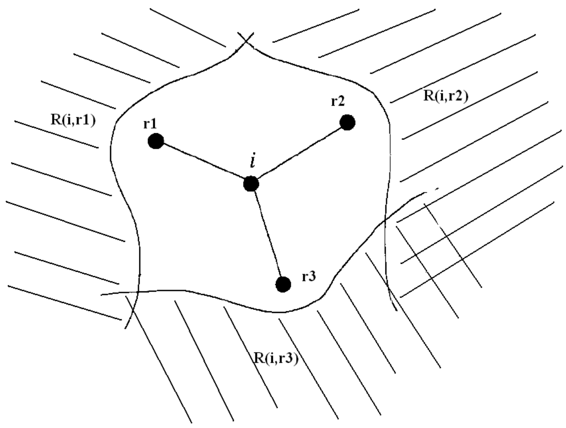


Figure 3.3: Enclosure of node i.

3.4.1 PATC distributed algorithm

The distributed algorithm for PATC topology calculation will consist in the following steps. First, each node in the network starts by broadcasting a beacon containing its position, using the maximum transmission power. When a node i receives the location of a given neighbor r, the relay region associated to this neighbor is calculated by solving the following system of equations[1]:

$$\begin{cases} d_{ij}^4 \geq d_{ir}^4 + d_{rj}^4 + \frac{C}{T} \\ \\ d_{ij}^2 = d_{ir} + d_{rj}^2 - 2d_{ir}d_{rj}\cos\theta \end{cases}$$

Above, $d_{i,j}$ defines the distance separating node i with every node j located in its corresponding relay region. θ denotes the angle between vectors $\overrightarrow{ri}$ and $\overrightarrow{rj}$, C is the reception power cost, and T is the pre-detection power threshold.

After calculation of all relay regions, the node i eliminates the neighbors which are located within these regions, and their corresponding communication links are disabled. In practice, this can be done by reducing the transmission range of node i, to covers only its enclosure.

The execution of the PATC algorithm by every node in the network results in a sparse topology with a considerably reduced node density. It has been proven in [RM99] that the resulting topology, called *enclosure graph*, is strongly connected.

[1]The equations are derived assuming a specific model described in [RM99], with a path-loss exponent $n = 4$

Moreover, this topology maintains all minimum energy consumption that exist in the original topology.

3.5 Directed Diffusion with PATC

3.5.1 System model

Let us assume a sensor network with a high number of nodes that are densely deployed over a two-dimensional area. Each node is equipped with a global positioning system (GPS), which permits the node's awareness of its absolute location within the deployment field. Embedding GPS hardware on sensor nodes has become a viable option thanks to recent implementations of low-power GPS receivers that offer an improved positioning precision [BSB12]. Moreover, we assume that the nodes' transceivers can control the transmission power, allowing a dynamic adjustment of the communication range. Nowadays, most radio transceivers integrate this functionality. For instance, the Chipcon CC2420 [cc2] radio used in Tmote Sky and TelosB nodes [PSC05] can be programmed to operate on 31 transmission power levels.

3.5.2 General idea

In order to enhance directed diffusion performance for the network model stated above, we propose the integration of PATC as a density-adaptation mechanism. In fact, PATC would be proactively executed as a first configuration stage before Directed Diffusion. This allows the calculation of the sparse enclosure graph, which will have a considerably lower connectivity. After the computation of the enclosure graph, only this latter will be considered by Directed Diffusion to execute the rest of the routing procedures (Figure 3.4).

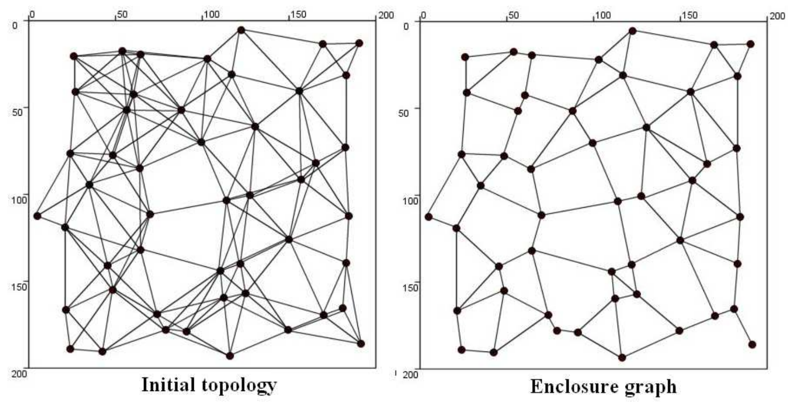


Figure 3.4: Network Topology with PATC.

Another advantage of PATC resides in its power-awareness feature gained from the mechanisms that identify energy-hungry communication links. Hence, in addition to PATC configuration step, we propose to take advantage of this feature in order to allow the selection of an energy efficient route among the discovered paths. The new routing protocol is described below.

3.5.3 Power-Aware Directed Diffusion (PADD)

From the combination of Directed Diffusion and PATC, we derive a new protocol named Power-Aware Directed Diffusion (PADD). In PADD, the power-awareness feature of the first configuration stage is exploited by the rest of protocol operations in order to enhance its energy efficiency. In fact, each node can evaluate, during the PATC phase, the minimum transmission power required to communicate with each of its neighbor. This will allow the calculation of an energy consumption metric during the route discovery phase, which reflects the power expenditure of each discovered path. The computed metric will then be used by the sink to reinforce the path that minimizes the energy expenditure of the data dissemination phase.

In the following, we explain in detail calculation method of the power consumption metric, which is performed during the first two steps of PADD.

PATC configuration phase:

In addition to its density-adaptation purpose, the first configuration step in PADD serves to evaluate the energy consumption induced by packet transmission over each communication link in the network. For that, every sensor node, after reception of its neighbors' positions, calculates P_{tx}: the minimum transmission power required to communicate with each of its neighbors. This is done using the path-loss model, described in section 3.4, which models the minimum necessary transmission power as a function of the distance between the sender and the receiver. Recall that PATC phase allows every node to know the positions of all its neighbors, and thus their relative distances. The calculated minimum transmission power is then transformed into an energy consumption cost for a given link, based on the characteristics of the node transceivers. At the end of the PATC configuration phase, only energy-efficient links are maintained, and each of them is weighted with the related transmission energy cost.

Interest Propagation:

In this step, we emphasize two main differences between PADD and the original Directed Diffusion. First, the interest in PADD is not broadcasted using the node's maximum power. In fact, every sensor broadcasts the interest using the minimum transmission power that covers its enclosure only, as calculated in the PATC configuration phase. Second, every node receiving the interest saves in the corresponding gradient the minimum transmission power related to the link on which the interest was received. This cost is called the *link cost* (C_l), and is used for the calculation of the overall energy communication cost of the explored path.

Data Dissemination:

Similarly to Directed Diffusion, exploratory data messages in PADD are sent to all nodes for which a gradient has been previously established. However, these data messages contain an additional field denoting the total energy cost, entailed by their delivery through the explored path. The value of the total cost is initially set to $C_l(n)$: the energy required to send the data message from the source node to its neighbor n. Afterward, the cost of the explored path is calculated as follows:

Each intermediary node maintains all similar data messages [2] that it receives in a data cache entry. After a given timeout, the node can determine the neighbor that offers a path to the data source with a minimum communication energy C_{min}. Only the ID of this neighbor is saved in the data cache, along with the corresponding energy cost. The intermediary node computes then the new path cost $C_p(n)$ related to every neighbor n for which a gradient exists:

$$C_p(n) = C_{min} + C_l(n) + C_r(n).$$

Such as $C_l(n)$ is the transmission energy cost of the link with the neighbor n, and $C_r(n)$ is the energy spent by the neighbor n during packet reception.

The path cost value is then updated in the data message, and this latter is forwarded to the corresponding neighbor.

After sending the data messages, it is possible that an intermediary nodes receives a data packet that offers a new path with a lower energy consumption. In this case, we choose to simply ignore the message. Because if considered, we would have to reevaluate the entire path cost, and resend it to all concerned neighbors. We believe that this would cause a considerable communication overhead and additional energy expenditure.

Path reenforcement:

The path reenforcement approach in PADD remains identical to the original Directed Diffusion, except that the sink reinforces the neighbor that offers a path with a

[2] messages describing the same event

minimum energy cost. Similarly, intermediary nodes use their data cache in order to identify the neighbor to which the path reenforcement message should be forwarded.

3.6 Performance Evaluation

To evaluate the performance of the proposed protocol, we performed simulation experiments using GloMoSim [ZBG98]. For this, the simulator has been extended with the implementation of three main modules, namely the power control capability at the radio level, Directed Diffusion (DD) routing protocol and Power Aware Directed Diffusion (PADD).

In this section, we first describe the simulation metrics and methodology. Then, we evaluate the performance of PADD in dense scenarios, and compare it do the original Directed Diffusion.

3.6.1 Methodology and metrics

The performances of Directed Diffusion and PADD are compared using an energy model where the node's transmit, receive and idle power consumption are set to 0.66W, 0.395W and 0.175W respectively. We use IEEE 802.11 DCF as the underlying MAC protocol, to which we introduced random backoffs as a mean to reduce packet collisions that result from simultaneous transmissions in high densities. The sensor nodes are uniformly deployed over a square sensing area of a variable size, which depends on the desired network density. The default network configuration contains 5 sinks and 5 sources that are randomly chosen in a different positions of the simulation area. The sink sends his interest every 30 sec. A source answers with 1 exploratory data packet per minute. After a path reinforcement, the data sending rate is raised to 12 packets per minute. The packet sizes for query and data messages are 36 and 64 bytes respectively. The performance evaluation and comparison is performed regarding three metrics.

- *Average energy consumption* per node reflects the energy efficiency of the protocol and its impact on the network lifetime.
- *Success rate* is the ratio of the number of successfully received data packets at a sink to the total number of data packets generated by a source, averaged over all source-sink pairs. This metric shows the reliability of the protocol in terms of data delivery.
- *End-to-end delay* is defined as the average duration between the time of data packet transmission at the source node and its reception by the sink. The

latter metric indicates the protocol ability to preserve data freshness.

3.6.2 Simulation results

To study the impact of network density on PADD, we vary the size of the network deployment field, while maintaining the number of nodes constant. The network density is expressed as the resulting average number of neighbours per sensor node.

Energy consumption:

Figure 3.5 shows that the energy consumption of PADD remains almost constant in spite of density augmentation. This is mainly due to the use of the PATC technique. By eliminating the communication links considered as redundant in terms of energy consumption, PATC allows PADD to preserve almost the same connectivity degree in the network, regardless the actual deployment density.

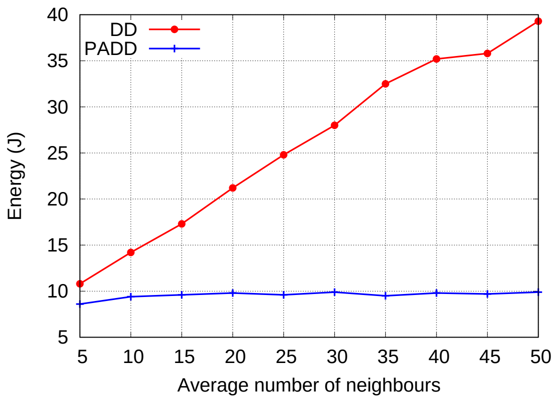


Figure 3.5: Energy Consumption *vs* network density.

In contrast, the energy consumption of DD increases considerably for higher network densities, although the number of nodes is kept constant. In fact, the increase of the deployment density in DD is immediately translated into a higher connectivity in the network. This leads to a high number of the costly "send and receive" operations between neighbours, a more complex operations for gradient setup, data caching and aggregation, and more alternative paths to maintain. All this factors participate in the "linear" increase of the energy dissipated by DD in high network densities.

Moreover, we notice that PADD consumes less energy than DD in all simulated densities. In fact, the use of transmission power control for unicasted packets allows a considerable saving in dissipated energy, thanks to the use of minimum transmission power. Moreover, the energy consumption metric allows PADD to reinforce an energy-efficient path rather than a delay-efficient one, as in DD. Although this may penalize the protocol performance in delay-sensitive applications, it permits to preserve the scarce energy resource of sensors, and increases substantially the overall network lifetime.

End-to-end delays:

As emphasized earlier, the energy-efficient reinforcement rule in PADD may penalize its performance in terms of reported data freshness. The choice of a delay-efficient path in DD enables a faster data reporting than in PADD (Figure 3.6). However, this drawback is noticed only in low network densities (i.e. when the number of neighbours is lower than 20). Starting from 25 neighbours per node, PADD outperforms DD by keeping the reporting delays almost constant. Again, this is explained by the constant connectivity degree ensured by the PATC configuration stage in PADD. Concerning DD, the augmentation of the network density results in a more aggressive contention for the communication channel. This contention forces the concerned nodes to delay the transmission of queued messages for longer time, until acquisition of the communication medium, which explains the additional end-to-end delays.

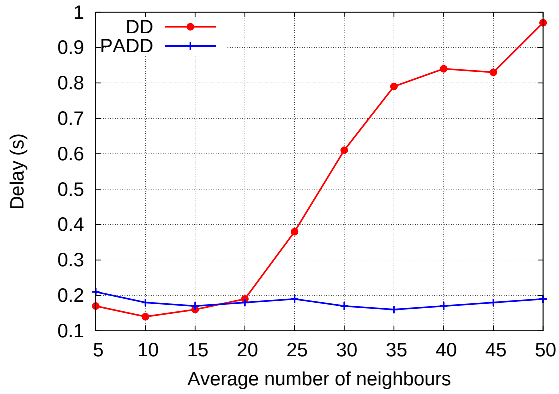


Figure 3.6: Reporting delay *vs* network density.

Success rate:

Simulation experiments showed that most of packet losses experienced by DD in high densities are caused by the congestion resulting from the high traffic overload. This congestion lead to a transmission buffer overflow at the sending nodes, constraining them to ignore additional incoming packets. The congestion was avoided in PADD, thanks to the PATC configuration stage that eliminates additional traffic overhead in dense networks. In fact, PADD guarantees a success rate near to 100%, even in high density scenarios (Figure 3.7).

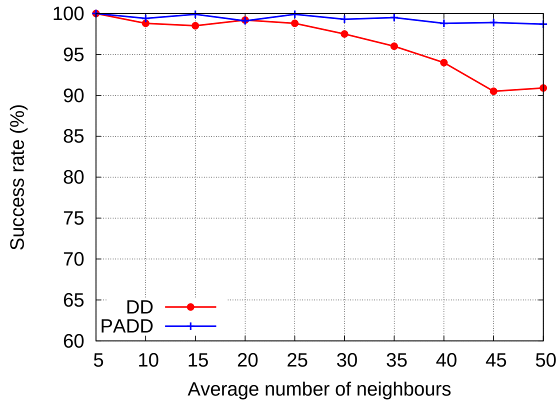


Figure 3.7: Success rate *vs* network density.

3.7 Conclusion

In this chapter, we investigated the issue of energy efficiency in WSNs routing protocols. In particular, we addressed the challenge of high node density noticed in emergent IoT applications of sensor networks. For such applications, we showed that Directed Diffusion is a suitable routing protocol because of its data-centric paradigm. However this protocol fails to preserve its performance in high densities.

In order to cope with the performance degradation of Directed Diffusions, a new routing protocol is proposed with two main improvements: First, a position-based topology control technique (PATC) is employed to reduce the high connectivity in dense networks, allowing a better performance, especially in terms of energy consumption. The execution of this proactive technique induces an additional energy cost during initialization, but this cost is rapidly compensated by the gain in energy consumption during the data transmission phase.

Second, a simple energy consumption metric is introduced to allows the reinforcement of an energy efficient routes. The metric calculation is devised without the need of any additional message exchanges. Also, it effectively evaluates the energy consumption of all network paths, including those involving multiples sources and/or destinations. However, the introduced energy consumption metric does not consider the residual energy level of sensor nodes. This entails a fast battery exhaustion of nodes that belong to the optimal routes. The integration of a more complex metric that takes into account this shortcoming represents a possible extension of this work.

Chapter 4

Energy harvesting with wireless power transfer

4.1 Introduction

Energy conservation methods, discussed in previous chapters, can only slow down the energy dissipation caused by WSN's protocols and services, but are unable to guarantee their perpetual functioning. Energy harvesting solutions have been recognized as a sound alternative [ZKRSR14], where ambient energy such as solar, vibrational or wind energy, is used to recharge the sensor nodes. However, the major drawback of these solutions is the high uncertainty associated with the harvested energy, which often shows an erratic behavior. For example, in solar harvesting systems, the energy output of the charger depends on the amount of solar radiations received at the panel, which varies with the time of the day and weather conditions.

Recent research developments in Wireless Power Transfer (WPT) technology opened up interesting perspectives for more reliable and deterministic energy provision, compared to the use of ambient energy. Additionally, and contrary to the usual battery charging process that requires wired power plugs, WPT technologies allows energy transfer between the power source and the battery using a wireless medium. Hence, they avoid the hassle of interconnecting wires during energy replenishment and enhance the flexibility of the charging operation. The benefit is especially noticed in devices for which replacing batteries or connecting cables is costly, hazardous or infeasible (e.g., body-implanted sensors).

This chapter introduces the concept of energy harvesting through wireless power transfer and shows its usefulness for WSNs. For this, it starts with a brief historical review in Section 4.2. Then, existing WPT technologies namely: radio frequency, magnetic induction, capacitive coupling and magnetic resonance coupling are studied in Sections 4.3, 4.4, 4.5 and 4.6, respectively. Section 4.7 compares these tech-

Figure 4.1: Teslas Wardenclyffe Tower (1904)

nologies in order to bring out the ones that can be applied in WSNs. Section 4.8 highlights the concluding remarks.

4.2 History

The idea of transferring power over a wireless medium can be dated back to the early 20^{th} century, before the appearance of electric power grids. At that time, Nikola Tesla performed the first experiments on large scale wireless power distribution by building the world's first power station in Long Island, New York [Tes14]. This Station, called "Wardenclyffe Tower" (Figure 4.1), was designed to transmit wireless electricity. Unfortunately, it was never been put into practical use because of its magnetic fields that considerably lowers the electricity transfer efficiency. Since the $1999s$, the need for Wireless Power Transfer (WPT) reemerged with the proliferation of electronic mobile devices, such as cell phones and laptops. In addition, the rapid development of electrical and hybrid vehicles contributed to the high demand on WPT technologies.

As a result of this fast-growing demand, there have been many active efforts towards the development of efficient technologies for WPT. For instance, several consortiums like *Wireless Power Consorsium* [WPC] and *Airfuel Alliance* [AIR] have been created in order to set the international standards for inter-operable wireless charging. Currently, those consortiums include leading manufacturers from wide range of industries, and the total number of wireless powered devices is estimated to evolve from 4.5 billion in 2106 to 15 billion by 2020 [NR2].

In the following, we discuss the different categories of WPT technologies [LWN+16, DL15, XSHL13]. For each category, we review its physical characteristics, then discuss its strengths, weaknesses as well as its suitability for wireless sensor networks.

4.3 Radio Frequency charging

This technique consists in using electromagnetic radiations in the form of radio frequency (RF) waves as a medium to carry energy. The power transmission process starts with the conversion of Direct Current (DC) into radio frequencies, which are transmitted by the charger's antenna and propagated over the space. When RFs are captured by the harvested device, they are rectified into electricity using a special antenna, called *rectenna*, which encompasses RF-to-DC conversion circuits (Figure 4.2).

Depending on the employed frequencies, the RF-based wireless charging can be classified into two sub-categories:

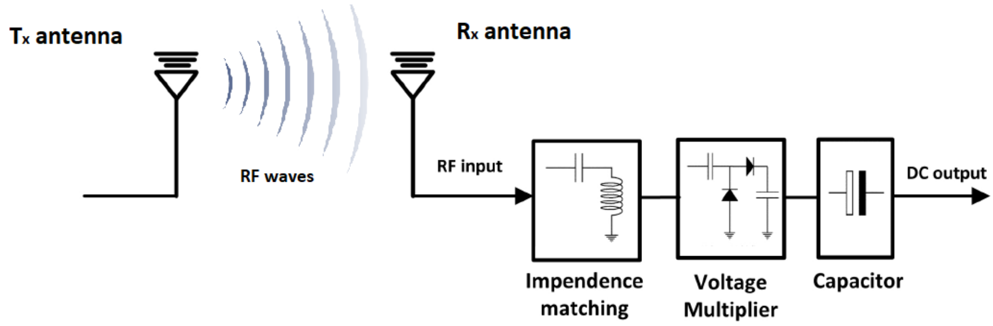


Figure 4.2: RF power transfer scheme.

4.3.1 Far-field power beamforming

A unidirectional radiation technique that requires a clear line-of-sight (LOS) between the charger and the harvested device. The charger employs super or extremely high frequency bands (microwaves) in order to produce an energy beam. This later is generated through an antenna array (or aperture antenna) that allows power transfer over long distances, which may attain several kilometers.

The equipments and technologies used in power beamforming impact the efficiency of energy transfer. A good efficiency can be achieved using massive antenna arrays that improve the sharpness of energy beamforming, and produce high power microwaves. However, the cost of such high efficiency equipments limit their use on military and industrial applications only. An example of such applications is discussed in [BE92], where authors propose a design of beamed microwave charging platform for low-earth-orbit-to-geostationary-orbit (LEO to GEO) transportation system.

4.3.2 Near-field RFs

Contrary to power beamforming, near-field RF charging is omnidirectional and relies on radio frequencies within unlicensed ISM bands (e.g, 915 MHz , 2.4 GHz). Although suitable for data transfer, omnidirectional RFs suffer from a poor efficiency in energy transfer, since the emitted electromagnetic waves decay quickly over short distances. For example, the achieved efficiency in the commercial product *Powercast* is under 1% when the receiver is $3m$ away from the RF transmitter [POW]. Moreover, to prevent potential health hazard to humans from EM radiations, the transmitted power are constrained by RF exposure regulations, like in the C95.1-2005 standard [IEE06]. Therefore, this technique is only suitable for low-power devices such RFID tags and wearable sensor nodes.

Despite of the aforementioned limitations, near-field RF charging offers the potential of compatibility with existing communication systems. In fact, the amplitude and phase of the employed frequencies can modulate data, while their radiations serve to carry energy. This concept is known as Simultaneous Wireless Information and Power Transfer (SWIPT)[PJS$^+$18] and represents a trending area of research.

4.4 Magnetic induction

The central principle behind magnetic induction charging is the Faraday's law that defines the interaction of electromagnetic fields with electrical circuits. The charging process in this technique is triggered by alternating current in a primary coil, which generates a varying magnetic field. The latter induces a voltage across the terminals of a distant secondary coil, connected to the harvested device. The separation, alignment and sizes of the respective coils determines the “coupling factor”, which has a significant influence on the efficiency of the energy transfer. Perfect coupling, whereby all the flux generated by the primary coil is captured, has a coupling factor of 1. Practical closely-coupled systems typically have a coupling factor of 0.3 to 0.6 (Figure 4.3)

Thanks to its safety, convenience and ease of implementation, magnetic induction charging has been rapidly commercialized to a number of products like cell-phone charging pads and electrical toothbrushes. This led also the WPC consortium to approve the first wireless charging standard (called Qi), which uses magnetic induction [WPC]. Nonetheless, the major drawback of magnetic induction resides in the short charging range that should not exceed the coils diameter, in order to maintain a high power transfer efficiency. Despite of this drawback, this technique has been successfully used in applications like electrical vehicles wireless charging, where a Kilowatt-level power charging is achieved [WGSB12].

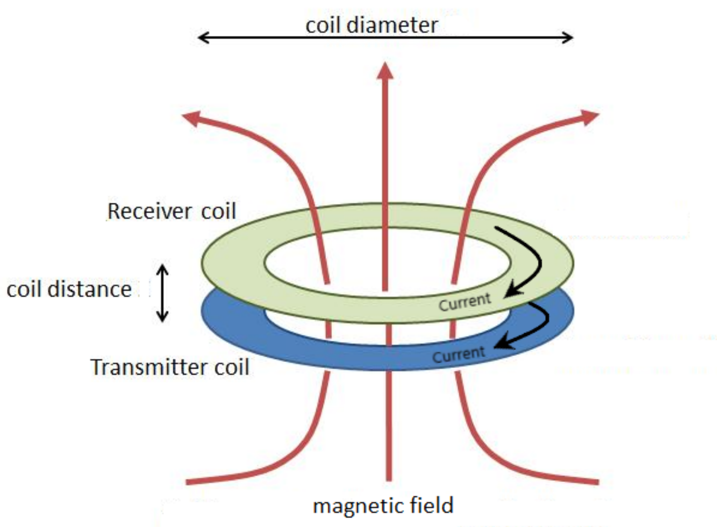


Figure 4.3: Coupled coils in magnetic induction.

Very recently, MIT scientists have announced the invention of a novel wireless charging technology, called MagMIMO [JK14], which can charge a wireless device from up to 30cm away. It is claimed that MagMIMO can detect and cast a cone of energy toward the harvested device, even when the latter is behind an obstacle.

4.5 Capacitive coupling

Unlike the previous technique that relies on magnetic field, capacitive coupling delivers energy using electric field between transmitter's and receiver's electrodes (metal plates), which form a *capacitor* [KIBS11]. As depicted in Figure 4.4, the alternating voltage V_s, generated by the charger, is applied to the transmitting plate, which results in an oscillating electric field. When this latter penetrates the receiver's plate, it induces a potential and causes an alternating current to flow in the load circuit.

The use of electric field in capacitive coupling offers few advantages, compared to magnetic induction. The field is largely confined between the capacitor plates, alleviating the need for magnetic flux guiding and shielding components, which add bulk and cost to system design and implementation. Also, alignment requirement between the transmitter and receiver is less critical, and allows charging in the presence of metal obstacles.

However, this technique suffers from major drawbacks. Its practical use remains limited on few low power applications, because of the high voltage required to deliver acceptable amount of energy, which may have unpleasant side-effects on users and environment. In addition, the achievable efficiency in energy transfer depends essentially on the capacitance between electrodes, which is proportional to the area of the used metal plates. In other words, enhancing the systems charging efficiency requires the use of capacitance with large area. For example, in [CSK+15], a recent prototype of capacitive WPT system has been built and shown to transfer $30W$ across two $5cm \times 5cm$ metal plates separated by an air-gap of $0.5cm$. The achieved power transfer per unit capacitance is equal to 5.5 W/pF. Such efficiency is considered insufficient, and prevents the wide use of capacitive coupling in consumer electronics and portable device charging.

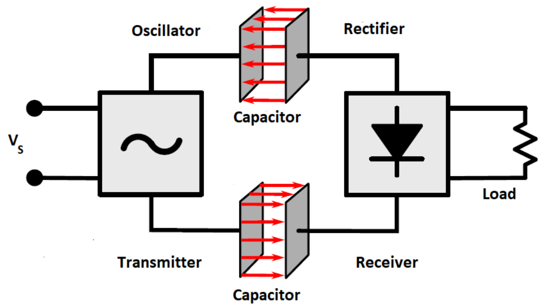


Figure 4.4: Capacitive wireless power system.

4.6 Magnetic resonance coupling

Magnetic resonance coupling is a special form of magnetic induction charging; i.e., it relies on magnetic field for power transfer. Its specificity consists in adding resonant circuits to the magnetic coils (Figure 4.5), and making them operate at the same resonance frequency, so that they become strongly coupled. The effect of magnetic resonance is analogous to the classical mechanical resonance, where a structure can be excited to vibration by a distant sound generator, when there is a match between their respective resonance frequencies. Thanks to strong coupling feature, enhanced power transfer efficiency and extended charging range are achieved [HWFS11]

The basic concept of this charging technique has been discovered by Nikola Tesla during its pioneering experiments on wireless power transfer, at the beginning of the 20^{th} century [HZL14, Whe43]. However, its use as mean to enhance power transmission range has been explored recently in [KKM+07]. This work, conducted by an MIT research group, represents a breakthrough in mid-range wireless power transfer technologies. In fact, the demonstrated technology, called Witricity, allowed the transmission of $60W$ of power over a distance of 2 meters (8 times the coil diameter) at around 40% efficiency.

In addition to the enhanced power transfer efficiency and charging distance, magnetic resonance coupling has two important advantages. First, it is immune to neighboring environment and line-of-sight transfer requirement. This enlarges its application field to systems within harsh and noisy environment. Second, magnetic resonance can be performed between one transmitting and many receiving resonators, enabling thus concurrent charging of multiple devices.

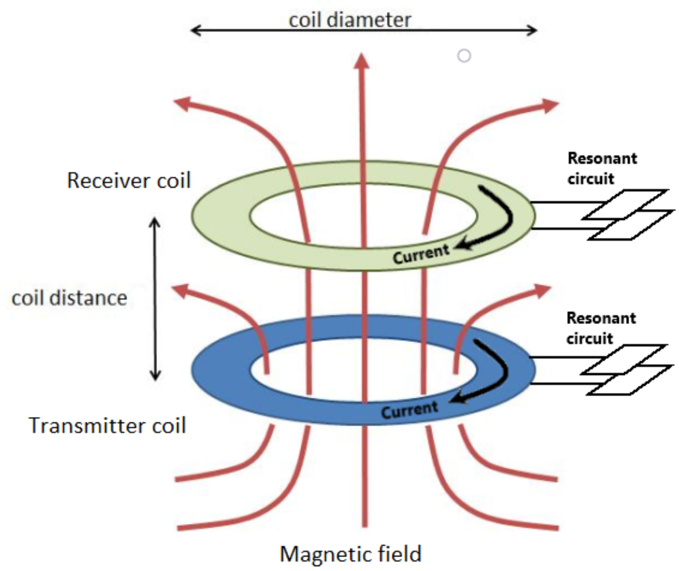


Figure 4.5: Coupled resonant coils.

	Typical Range	**Efficiency**	**Alignement**	**Advantages**	**Drawbacks**
Near-field RFs	$50cm$ to 3 meters	$< 1\%$ for $3m$ distance	- Omnidirectional - Possible obstacles	Simultaneous data transfer	Suitable for ultra low-power devices
Far-field RFs	$100m$ to several Km	$> 50\%$	- Directional - Line-of-sight	High efficiency for long ranges	- Health hazard - High cost - Strict positioning
Magnetic induction	$< 1cm$	$30\% - 60\%$	- Precise - No obstacles	- Safety - Simplicity	Short distances
Capacitive coupling	$< 1cm$	$> 50\%$	- Flexible - Possible obstacles	Low cost	- Electrode size - Short distances - Possible hazard
Magnetic resonance	2m-10m	$40\% - 60\%$	- Flexible - Possible obstacles	- Efficiency for mid-ranges - Safety - Simultaneous charging	- Low efficiency for extended ranges

Table 4.1: Comparison of WPT technologies

4.7 Which WPT for Sensor Networks?

After a detailed review of the existing WPT technologies, we notice that each of them has its distinct characteristics that are translated into advantages or drawbacks.

These characteristics determine the technology suitability for different applications, depending on the corresponding requirements. In Table 4.1, we provide a comparison between the most important features of these technologies and summarize their advantages as well as their drawbacks.

For wireless sensor networks, the use of wireless charging system is constrained by a couple of mandatory requirements that must be satisfied, namely:

- **Flexible alignment:** In most WSNs, sensor nodes are deployed according to the application needs in terms of sensing and monitoring. The deployment may be performed without knowing the nodes' absolute positions, or their antenna orientation. Moreover, the initial nodes location may change over time. Even in case of static deployment, the node's positions may be altered due to an external environmental factor (like wind). Consequently, the employed WPT technology must have flexible positioning requirements, since it is impractical to guarantee an accurate alignment between the charger and all charged nodes.

- **Small circuit size:** Maintaining the small size of nodes in WSNs is a primary design challenge, which permit their use in a wide range of ubiquitous applications like in wearable IoT. To enable wireless charging, these nodes need to be equipped with additional circuits, allowing them to receive energy wirelessly and convert it into current load. The added circuits can be plugged into the node as an external module, or integrated as internal built-in component. In both scenarios, the volume of additional circuits should not impact the sensor node size allowing it to preserve WSNs ubiquity.

- **Scalability:** Depending on the WSN application, the number of sensor nodes deployed may be in the order of thousands. The employed WPT technology must be able to work efficiently with the high number of nodes, by allowing simultaneous charging of multiple nodes. WPT should also consider the high density nature of WSNs, avoiding interference between concurrent charging processes, or between a charging and data communication signals.

Considering the aforementioned requirements, it is remarked that some WPT technologies are naturally excluded from being used in WSNs. In capacitive coupling, the achievable amount of capacitance depends on the available area of the device. Nonetheless, the small size of sensor nodes make it hard to generate a sufficient power density for charging, and imposes a serious design challenge for this technology in WSNs. As for far-field RF power beamforming, the limitation lies in the constraint that the charger is required to know the exact location of the charged devices. Moreover, microwaves are difficult to generate due to the quite large size of the employed transceivers, which makes them unfitting for WSNs. Similarly, the use inductive coupling is also impractical because of the constraint of precise alignment, and the short charging distance, which force the charger to be very close and correctly positioned with the harvested nodes.

As a result, only two WPT technologies are suitable to be applied in WSNs, namely near-field RFs, and magnetic resonance. In the following, we briefly describe some wireless charging systems that have been designed for WSNs, and we review their advantages and drawbacks in this context.

4.7.1 Application of Near-field RF charging in WSNs

Wireless charging using omnidirectional RF waves may be necessary in applications where the positions of sensor nodes are either unknown or dynamic. Based on this technique, various WSNs charging systems have been proposed.

In [SYP+08], wireless identification and sensing platform (WISP) was developed by Intel. WISP nodes (Figure 4.6) upload sensory data to querying readers via backscatter modulation. When they do so, they are also capable of harvesting energy from the RFID reader signals. The harvested surplus energy is stored in a capacitor. It can be used for data sensing, logging, and computing when the readers are unavailable. WISP platform has been adopted by several research works to investigate the design and deployment of static wireless chargers for energy provisioning in WSNs [HCJ+13].

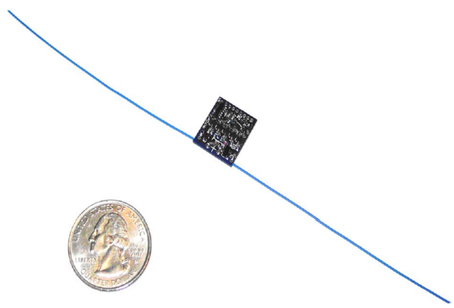


Figure 4.6: WISP node [SYP+08].

Tong et al. [TLWZ10] conducted a field experiment to demonstrate the feasibility of applying near-field RF wireless charging in WSNs. For this, they used *Powercast* chips which are commercially available RF-based WPT products [POW]. The results showed that the power transfer efficiency drops drastically (under 1%), when a single node is charged within a distance of $20cms$. Also, it has been pointed out that low efficiency can be enhanced by considering the scenario where multiple nodes are charged simultaneously.

In [ZH13], authors explore the use of RF signals to achieve simultaneous wireless information and power transfer, using MIMO antennas. Specifically, they studied a simplified three nodes setup where one receiver harvests energy and another receiver decodes information separately from the signals sent by a common transmitter. Based on this setup, authors present theoretical tradeoffs in designing practical MEMO broadcasting systems that maximize transfer rates for both energy and data. The results demonstrated the concept of multi-antenna energy beamforming as a mean to improve the power transfer efficiency of near-field RF charging. However, this technology is still in its infancy and further investigations are needed to fully understand its potential for WSNs, and other wireless communication networks in general.

Recently, the use of RF charging in the special case of Cognitive Radio WSNs (CRWSN) has been studied in [RHZ+18]. CRWSNs enables sensor nodes to opportunistically access licensed frequency channels in order provide a spectrum-efficient networking. To address the challenge of additional energy consumption caused by continuous spectrum sensing and switching, authors propose a new framework of RF-powered cognitive radio sensors, in which sensor nodes can dynamically access the vacant licensed channels for interference-free data transmission, while they utilize the strong signals over the occupied licensed channels for energy harvesting.

To sum up, near-field RF charging has some potentials that favor its use in WSNs, thanks to its omnidirectional nature as well as the possibility of concurrent information and power transfer. However, this technology still faces a major bottleneck that prevents its widespread adoption in all WSNs. In fact, its low charging efficiency limits the possibility of using simultaneous charging to the case of extra-high density where multiple nodes can be charged within small range, which is not a common application scenario.

4.7.2 Application of magnetic resonance in WSNs

Wireless charging via magnetic resonance has gained a lot of interest among WSN's research community. This interest is a result of various advantages compared to RF charging, in terms of power efficiency, charging range and immunity to neighboring environment.

Most of the literature dealing with magnetic resonance in WSNs addressed the design of charging strategies that ensure perpetual operating of sensor nodes. Based on the WPT technique proposed in [KKM+07], the early-proposed strategies was limited to charging one node at time and was not scalable as the number of nodes or their density increases. Kurs et al. identified this problem and developed an enhanced magnetic resonant coupling technology that allow multiple devices to be charged simultaneously [KMS10]. Motivated by this technology, a plethora of new charging schemes have been proposed, enlarging thus the adoption of magnetic resonance WPT in WSNs application. These schemes are reviewed in details in the next chapter.

4.8 Conclusion

With the advent of wireless power transfer technologies, battery-powered WSNs have manifested new challenges out of the necessity to manage finite energy budgets against sensing, computation, and communication needs. These technologies fundamentally redefined the design challenges, as the assumption of a finite energy budget is replaced with that of potentially infinite, yet intermittent, energy supply. This profoundly impacts every aspect of wireless sensor networking, ultimately including the pattern of operation. The new operational mode will transform from sense-compute-transmit to a harvest-sense-compute-transmit-share, that is, beginning and ending with energy- and not data-related tasks [BASM16].

In this chapter, we reviewed the existing power transfer technologies, and compared them in terms of their suitability to the particular context of wireless sensor networks. As concluded, radio frequency (RF) charging and magnetic resonance coupling have offered a significant potential for their utilization in energy-harvested WSNs. As a result, multiple research effort have been attracted to the design of charging strategies using RF and magnetic resonance charging. These efforts are detailed in the next chapter.

Chapter 5

Strategies of wireless charging

5.1 Introduction

Advances in wireless charging technologies, particularly in magnetic resonance coupling, have opened up new perspectives for efficient energy provisioning in sensor networks. However, a successful integration of wireless power transfer in WSNs faces a number of design challenges. Some of these challenges, are related to the hardware implementation and system architecture such as circuit size, antenna alignment, etc. These challenges have been covered in section 4.7 of the previous chapter.

Yet another important challenge that highly impacts the performance of wireless charging in WSNs is the design of an efficient charging strategy. The latter defines the approach adopted to distribute energy among sensor nodes, in terms of number of chargers used, their placement, the time of the charging operations, etc. Due to the importance of this issue, we can find in the literature a rich body of works that focused on the design of wireless charging strategies. Although different in terms of optimization objectives, all proposed solutions targeted an efficient scheduling of the charging operations while ensuring sustainable operating of sensor nodes by preventing their failures.

In this chapter, we aim at providing a detailed review of literature on wireless charging strategies in WSNs, in order to assess their strength, weaknesses and possible ways for improvements. Existing solutions are classified depending on weather the employed charger is static or mobile. Consequently, the chapter is organized as follows. In section 5.2 we study the static charging strategies and related issues like charger deployment. Then, section 5.3 presents the mobile charging approaches and highlights corresponding challenges, such as charger's path planning and time scheduling of the charging operations. Section 5.4 summarizes the main outcomes of our study and provides the open research directions. Finally, section 5.5 concludes the chapter.

5.2 Static charging strategies

A trivial approach to wireless energy provision in WSNs is to deploy a number of static chargers throughout the network field. Each charger can supply energy for one or multiple nodes located within its charging range. Depending on the employed WPT technology, the charging operations can be scheduled for one node at a time, or simultaneously for multiple nodes. In this section, we review the state-of-the-art solutions based on static chargers. Typically, two types of wireless chargers are considered :

1. *Dedicated Chargers (D-CH):* Their mission is limited on providing energy to requesting nodes using a suitable WPT technology.
2. *Hybrid Chargers (H-CH):* are able to perform data communication with nodes, in addition to charging them wirelessly. This can be done in either full or half-duplex. A full-duplex *H-CH* allows for simultaneous charging and information transmission in the downlink and the uplink directions, respectively. By contrast, a half-duplex *H-CH* requires coordination between energy charging and information transmission, since these two operations are undertaken in different time slots. In addition, a full-duplex *H-CH* relies on an *out-of-band* charging. i.e., the frequency used in power transmission is different from the one serving for data communication. Half-duplex *H-CH* can use a charging frequency that overlaps with the information transmission frequency band. This form of charging is referred to as *in-band* charging

Based on the two types of wireless chargers, the existing literature dealing with the field of static chargers adopted two main variations of power transfer models, which can be described as follows:

- Single-hop charging: This model is based on direct power transmission from the charger to every sensor node in the network. Depending on wether an *H-CH* or *D-CH* is used, data communication is conducted with the charger or with a separate data sink, using one-hop or multi-hop relayed transmissions.
- Relay-assisted charging: In networks with relatively sparse topologies and low densities, it is hard to find clusters that covers a high number of nodes that can be charged by the same charger. A single-hop charging strategy will tend to deploy a charger for every few nodes. This considerably increases the number of deployed chargers and penalizes the effectiveness of the solution in terms of cost. To address this issue, an alternative cost-effective approach, apart

from dense charger deployment, is to motivate sensor nodes to cooperate by relaying power for each other, or to deploy dedicated passive relay stations.

In the following, we review the charging strategies according to the adopted charging model.

5.2.1 Single-hop static charging

The majority of research works based on static chargers adopted the scheme of single-hop charging. In these works, different design issues have been addressed. They can be broadly categorized as follows:

Cost-effective charger deployment

In order to make the charging solution practical, it is primordial to optimize the deployment cost by reducing the number of deployed chargers. Hence, significant research efforts focused on methods for calculating the minimum number of chargers needed to recharge a given WSN, and their optimal deployment positions.

The study in [LJ14] assumes the case where wireless chargers can be deployed only on grid points, at a fixed height from the sensor nodes. The considered chargers are equipped with 3D-beamforming directional antennas that provide a cone-shape charging space called charging cone. To achieve a minimum number of deployed chargers, authors propose two algorithms namely: the node-based greedy cone selecting (NB-GCS) and the pair-based greedy cone selecting (PB-GCS). Both algorithms rely on a heuristic that generates charging cones whose apexes are located at grid points. However, the former algorithm generates cones on a node-by-node basis, while in the latter the cones are on a node-pair-by-node-pair basis. In each iteration, cones covering the highest number of unmarked sensors are greedily selected, and the algorithms stops when all nodes are marked. Although NB-GCS has a significantly lower complexity than PB-GCS; it has been shown through simulations that PB-GCS achieves a lower number of deployed chargers. The performance gap between the two algorithms increases with a larger number of nodes.

Compared to [LJ14] where the search space of chargers positions is limited to a predetermined grid points, authors in [PLPL14] define the charger minimization problem as charging cover optimization problem on all the Euclidean plane that represents the network deployment field. To mitigate the computation complexity of the optimal solution, they devised an approximation solution based on network partition algorithm. In this algorithm, the deployment field is divided into small cells of equal size. The deployment location of the chargers are computed by solving the charging cover problem for each cell. Finally, the solutions of all cells are merged resulting in the global approximate solution of the original optimization problem. Moreover, the order of approximation has been theoretically defined under the condition that all target sensors are evenly distributed. The authors also introduced a shifting strategy to prove the performance lower bound of the proposed algorithm.

QoS-constrained charger deployment:

Some applications of sensor networks are sensitive to the network quality of service (QoS). For example, in target tracking WSNs, a continuous packet stream should be guaranteed toward the end-user to ensure efficient surveillance, and prevent critical data loss. In such scenarios, the WSN's wireless charging strategy needs to consider the application design requirements, and the scheduling of the static charger should achieve the tradeoff between the deployment cost and network performance optimization.

In this perspective, the problem of maximizing the flow rate at the sink node has been investigated in [HCS16]. Authors noted that the data flow rate at the sink is penalized by the transmission rates of nodes with insufficient energy resources (*bottleneck* nodes). As a solution, they propose to select an optimal subset of bottleneck nodes to be charged by placing the static chargers next to them. The number of selected nodes is equal to the number of available chargers, which is an input parameter to the deployment problem.

To illustrate the impact of charger deployment on data flow rate, let us consider the scenario in Figure 5.1. Node A and C are sources that generate 1 and 6 pkt/s, respectively. The energy resources of node B, D and E allow them to forward 3, 2 and 10 pkt/s, respectively. Without the deployment of chargers, we see that the total flow at the sinks is 3 pkt/s. Now consider the case where two wireless chargers are available. The problem is to determine the locations to deploy these chargers. The aim is to improve the energy capacity of some nodes such that the sinks observe a higher flow rate. In this example, the search space contains 10 possible node pairs. Assume the chosen nodes are A and D. Source A can increase its data generation rate to 13 pkt/s. Node D has sufficient energy to forward all data from source C. Consequently, the total flow rate of the sinks becomes 19 pkt/s.

The problem of identifying the data flows and calculating the set of $\mathcal{N}$ bottleneck sensors that need to be charged is formulated as a Mixed Integer Linear Program (MILP). Due to NP-hardness of the MILP model, three heuristics have been devised, namely *Path*, *Tabu* and *LagOP*. The first heuristic preferentially charges nodes on the shortest path among paths from sources to sinks. *Tabu* uses *Path* heuristic as a first step then searches for a neighboring solution that yields a higher max flow. Finally, *LagOP* approximates the initial MILP using Lagrangian and sub-gradient

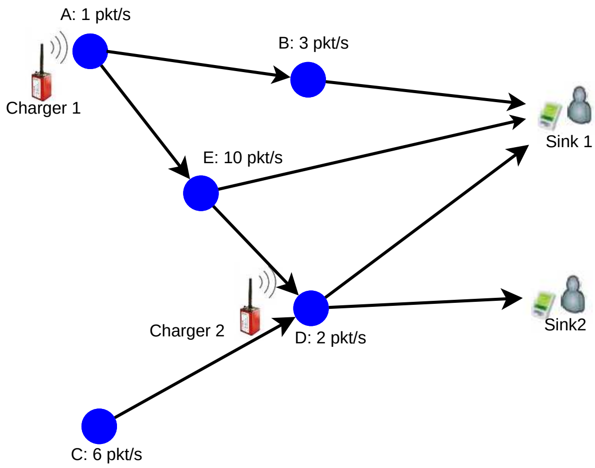


Figure 5.1: A WSN with two static chargers.

optimization. It has been shown through simulation experiments that *Tabu* has the best performance since it is able to attain 99.40% of the optimal max flow rate delivered by MILP model.

A key drawback in the aforementioned solution resides in maximizing the flow at sinks that causes a bias in rate allocation among source nodes, and does not guarantee fairness. In fact, nodes with a higher power consumption rate, or those located far away from the sink are allocated a lower rate. This shortcoming is investigated in [HCS17] and an improved approach is proposed, which is based on maximizing the minimum flow rate at sources. Two alternative algorithms are devised. The first, called greedy node deployment (GND), iteratively selects a node that yields the highest increase in max-min rate. However, this method incurs a high computational cost, especially in large network since it searches all non-selected nodes. The second algorithm ($OUED$) attempts to decrease the computational cost by relaxing the initial optimization model. Although this algorithm runs at least 5 times faster than GND, the simulation results revealed that the gap between the two algorithm does not exceed $0.191kb/s$ in large networks.

Safe charging:

When sensor networks are deployed in an urban environment, the use of wireless charging solutions based on radio frequencies may cause a safety concern for human health, due to the high electromagnetic radiations (EMR). High EMR exposure has been shown to associate with risks like tissue impairment, mental diseases and brain tumor [NSKM13]. It can be even more dangerous to pregnant women and children[GMdS$^+$12]. Due to concerns about adverse consequences of EMR exposure, exposure limits have been established in regulations like Title 47 of the Code of Federal Regulations (CFR) in the United States, and standards published by the International Commission on Non-Ionizing Radiation Protection (ICNIRP) [ABB+98] in most of Europe.

Although initially neglected, the issue of safety has been recently considered by few research efforts in the field of wireless charging strategies. In [DMLC18], author's objective was to find locations to place the static chargers so that there is no region in the network deployment field where the aggregate EMR exceeds a given safety threshold. For a given position in the deployment field, the aggregated EMR value is proportional to the cumulated power received from multiple chargers.

Figure 5.2 illustrates two deployment scenarios of 3 static chargers within a network of 5 nodes. In scenario (a), a person located at position p within the greyed region will perceive a high amount of EMR, since this region is covered by three chargers. Consequently, a safer strategy is to place the charger $C3$ closer to nodes $n4$ and $n5$ like in scenario (b). This will eliminate the high EMR region, and allows a more efficient charging of $n4$ and $n5$.

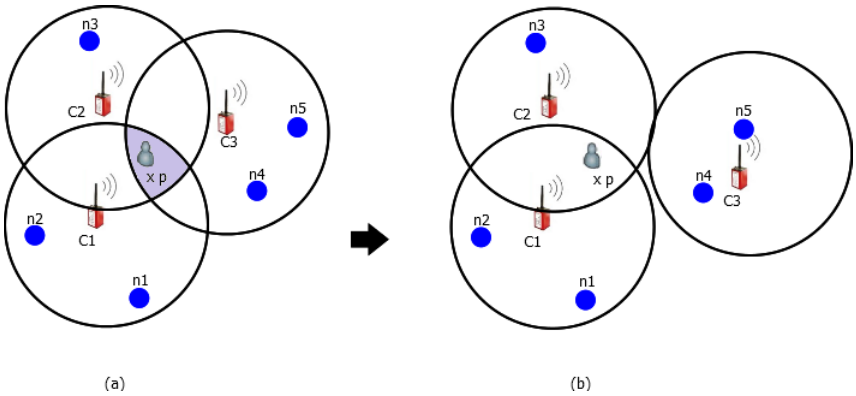


Figure 5.2: An illustration of safe chargers deployment.

The approach adopted in [DMLC18] for safe charging consists in the following steps. First, the whole network area is discretized and the problem is formulated into the Multidimensional 0/1 Knapsack (MDK) problem [FRE04]. Second, an approximation algorithm to the MDK model is proposed in order to deal with the absence of an FPTAS solution (Fully Polynomial-Time Approximation Scheme). Three schemes have been adopted to eliminate the redundant constraints namely bounds method, linear programming method and heuristic method. In the third phase, the computational effort of the basic scheme is further reduced via double partition methods of the charging plane. It has been proven through theoretical analysis that the output of the resulting algorithm is better than $(1 - \epsilon)$ of the optimal solution with a smaller EMR threshold and a larger EMR coverage radius. Moreover, both simulation and real-field experiments showed that the proposed algorithm outperforms prior works, in terms of charging utility, by up to 45.7%.

The focus of [DLC+17] was on a slightly different problem, compared to safety-constrained charger placement. That is, given a set of already deployed chargers, how to select the ones to be activated so that the charging utility is maximized and no location in the planar field exposes to an EMR exceeding a predefined limit. For a given node, the charging utility is calculated as the total power received from chargers. This problem is baptised as Safe Charging Problem (SCP).

Since the radiation limit in SCP applies to every point in the field, it inevitably results in an infinite number of constraints. The authors demonstrate that, even after constraint reduction, searching for the optimal set of chargers to be activated remains NP-hard. Consequently, the original problem is broken down into two phases (subproblems). The first phase consists in computing Maximal EMR Point (MEP), then the constraints of SCP are actually derived based on the outputs of MEP in a second step. The two subproblems are, in turn, transformed into known models, *i.e*, multidimensional 0/1 knapsack problem [FRE04] and Fermat-Weber problem [APHSW75]. For each of them, an approximation algorithm with a provable near optimal solution was devised. The simulation results showed that the gap between the proposed solution and the optimal one is only 6.7%, while a naive greedy algorithm is 34.6% below the near-optimal performances.

Nonetheless, such solution to the SCP problem suffers from complex and resource demanding operations, especially for area discretization, as the number of obtained constraints explodes with the network scale and with the granularity of discretization. The centralized nature of the algorithm also contribute to the deterioration of computational performances. In addition, the formulated problem is limited on one-time optimization, and does not consider the practical scenario where nodes dynamically request for charging.

The study in [DLC+18] discusses an extension of the safe charging problem (SCP), where deployed chargers can continuously adjust their power level within an appropriate range. In Safe Charging with Adjustable PowEr (SCAPE), the solution is not limited on turning on/off the chargers. Instead, the objective is to compute the optimal power levels that maximize the charging utility under EMR exposure constraints. Similarly to SCP, the infinite number of EMR constraints result in NP-hard solution.

In attempt to make the SCAPE problem traceable, authors propose an approximation method to reformulate it as a classical Linear Programming (LP) model with limited constraints. Also, an approximation algorithm is proposed in order to provide a solution with a reduced computational burden. This algorithm relies on distributed procedures between the sink and a subset of chargers, named square heads. A square head is dynamically elected and serves as an interface between the sink and the chargers located in given square subarea of the deployment field. Theoretical analysis demonstrated that the distributed algorithm has an approximation ration of $(1-\epsilon)$ to the optimal solution. Moreover, a performance comparison have been conducted with respect to the centralized SCP algorithm through simulation experiments, and results showed an average performance gain of 41.1%

Mobile nodes charging:

In some WSN applications, nodes can be mobile or coupled to mobile entities such as vehicles or people. For example, in wearable sensor networks used for health monitoring, the sensors are usually worn or implanted into patient's body. For such applications, the charging strategy must take into consideration nodes mobility, as well as the resulting dynamics in network topology.

Authors of [HCJ+13] considered both scenarios of static and mobile node charging for the wireless identification and sensing platform (WISP). This platform is built from RFID tags that serve as sensors, and are able to harvest energy from RFID readers. The WISP platform has been described in details in section 4.7.1. Since the RFID tags can be either static or mobile (e.g., those carried by human users), the problem of optimal reader/charger deployment have been investigated in two forms: *point provisioning* and *path provisioning*.

Point provisioning uses the least number of readers to ensure that a static tag placed in any position of the network field will receive a sufficient recharge rate for continuous operation. On the other hand, path provisioning exploits the potential mobility of tags to further reduce the number of necessary readers. In fact, if a tag can gain energy only at a low rate along parts of its path, there may be no loss of operation as long as the tag can harvest enough extra energy along other parts of the path and, has a large enough capacitor to store the extra energy. The path provisioning then aims to determine how to deploy readers so that the average recharge rate of a tag over time is high enough to sustain its operation given the tag's mobility pattern.

As shown in Figure 5.3(a), a point provisioning deployment requires 3 chargers to harvest the 3 nodes in the network. However, when nodes are mobile and their traveling paths are considered, two chargers can be sufficient (Figure 5.3(b)). The two chargers are able to cover most traveling paths allowing mobile nodes to harvest energy that will ensure continuous operating, especially in uncovered regions.

To solve the point and path provisioning problems, authors rely on an empirically derived wireless charging model, where the recharge power received by a tag is a decreasing function of the distance between the tag and the reader that charges it. In addition, the power received from different readers is additive at the same

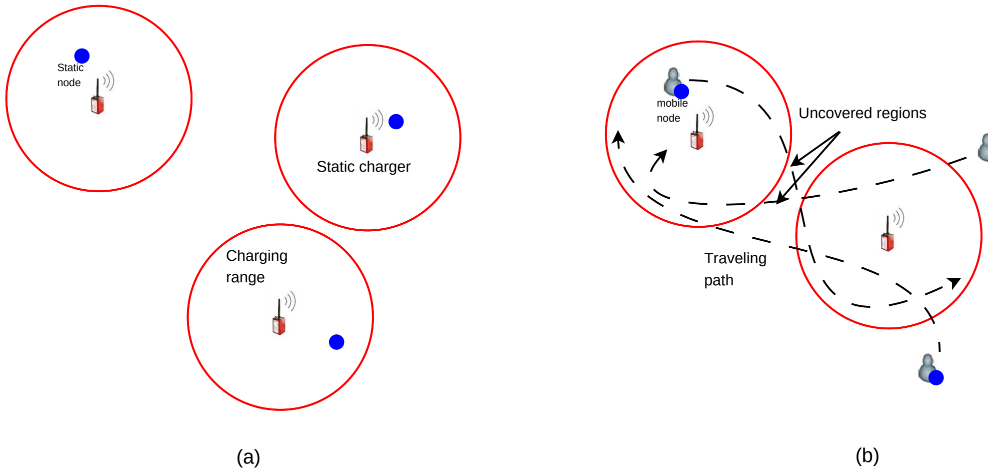


Figure 5.3: Point provisioning *vs* Path provisioning.

tag. Under these properties, it has been remarked that the point provisioning problem is different from the classical sensing coverage problem where sensing range is characterized by a perfect binary disk [BKX+06]. Hence, authors show that the number of readers needed for a region of interest can be greatly reduced, compared to the well-known solution of sensing coverage based on triangular deployment. This improvement is done by increasing the side length of equilateral triangular lattice.

Concerning path provision, authors assume that the distribution of nodes positions that results from their mobility pattern is a uniform distribution. Based on this assumption, the average recharge power received by mobile nodes within a given region is calculated. It has been concluded that the triangular solution proposed for point provisioning can be improved by further extension of the triangles' side length.

For both problems, the upper bound asymptotic approximation ratios of the proposed solutions to the optimal ones are given analytically. The analysis is also supported by simulation results showing that the proposed deployment method considerably reduce the number of readers compared with solutions based on binary disk models. However, this work does not discusses new methods to devise deployment strategies depending on different mobility models of nodes. Rather, the study is limited on the triangular deployment solution and investigates its improvement considering the difference between classical sensing models and wireless charging models, as well as nodes mobility. Its worth noting here, that triangular deployment solutions target the full coverage of the network field, which maybe inefficient in large-scale networks. A more efficient path provisioning approach can leave some regions uncovered while ensuring continuous operating of mobile nodes (Figure 5.3(b)).

To mitigate the inefficiency of full coverage methods in large-scale networks, the work in [CSP+12] exploits the idea of partial coverage to develop a cost-effective charger deployment strategy for mobile nodes. Particularly, authors target applications where sensor nodes are worn by humans. Based on the observation that human mobility patterns has some degree of regularity [SQBB10], the goal is deploy a minimum number of chargers with partial coverage, while still maintaining good survival rate of sensor nodes. This problem is referred to as Mobility-Aware charger Deployment(MACD).

MACD has been formulated as a graph problem, considering a grid-based map where the grid points represents the potential deployment locations of chargers. By using the mobility historical data collected for grid points, each points is associated with a weight denoting the total number of mobile nodes passing by. Authors prove that the problem of $\mathcal{N}$ charger placement that maximizes the number of mobile nodes avoiding battery depletion is NP-hard. Consequently, they designed a low-complexity MACD heuristic based on a greedy approach.

The proposed heuristic consists of two phases : The predict position (PRE) phase searches for points where the nodes' battery draining-out is most probable to happen. These points are defined as the charger deployment positions. If the number of selected location is less than the number of available chargers $\mathcal{N}$, the second phase (POP) selects additional positions based on the principal that charger deployment in popular places, i.e., places that are frequently visited by nodes, can improve nodes' survival rate. The worst case time complexity of both phases have been estimated to $\mathcal{O}(|\mathcal{V}|log|\mathcal{V}|)$. In addition, simulation results showed that, compared to full-coverage algorithm discussed earlier [HCJ+13], MACD manages to achieve a better survival rate with significant less number of chargers, thanks to the use of nodes mobility patterns and partial coverage principle.

In addition to charger deployment issues discussed above, another line of work in the area of static charging focused on the scheduling of charging operations. These works deal with the design of charging protocols that are executed by the chargers and the harvested nodes, to ensure an efficient coordination with other network functionalities like data communication and improve the network performance. Hereafter, we present the relevant research efforts based on the type of chargers used.

Static Dedicated Charger scheduling:

The system model considered in this category is based on two different entities:

- Dedicated charger (D-CH) that performs downlink wireless charging of sensor nodes.
- Base station (BS) that is responsible for uplink information reception from

sensor nodes. This operation can be established via direct transmission or via multi-hop communication. In the example depicted in Figure 5.4, the uplink data for node A consists of two hops, since this node is not within the communication range of the BS.

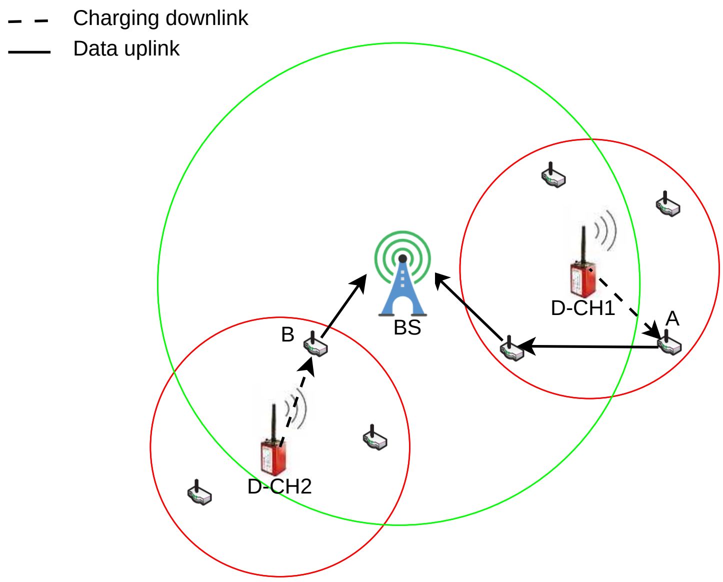


Figure 5.4: Network model for D-CH scheduling.

The main focus of D-CH scheduling is to define time allocation and power control strategies adopted in wireless charging, in order to maximizes some targeted network performances.

The study in [ZWC16] considers the elementary network scenario of a single node that harvests energy from a D-CH in the downlink, in order to be able to execute information transfer in the uplink with the BS. Based on this simple harvest-then-transmit protocol, the study proposes a time allocation scheme that achieves maximal throughput by balancing the time duration between the wireless power transfer phase and the information transfer phase. The optimization problem is defined and solved under the following constraints:

- *Limited time duration:* The operations of energy harvesting and data transmission are conducted over finite time slots.
- *QoS guarantee:* The symbol error rate must be lower than a target value
- *Energy causality:* The total energy consumed for information transmission until any given time should be less than the total harvested energy so far.

Unlike [ZWC16] where energy and information transmissions are performed over different time slots, the work in [ZHZ16] considers a full-duplex system based on Orthogonal Frequency-Division Multiplexing (OFDM). In this system the total bandwidth is divided into multiple orthogonal sub-channels (SCs). As a result, data transmission and energy harvesting can be scheduled at the same time over orthogonal SCs. Authors' objective is to maximize the achievable rate at the BS, by jointly optimizing the SC allocation over the time on one hand, and the power allocation over time and SCs on the other hand, for both energy and information transmission links.

Under the assumption that the channel state information is fully-known a priori, the problem is solved in two stages. First, with given SC allocation, the optimal joint power allocation over time and SCs is obtained for both energy and data links. Second, two heuristic schemes for the SC allocation are proposed using dynamic and a static SC allocation. Afterwards, the assumption of full availability of sub-channel information is relaxed by considering a partial CS information regarding the past and present slots only. For this case, an online scheme is proposed based on an observe-then-transmit strategy. The performance gap between the considered D-CH system and an H-CH system with random energy arrivals was examined by numerical simulations. Furthermore, the performance evaluation showed that even the use of partial information on SC for energy links brings significant benefits to the achievable data rate.

In previous works related to D-CH scheduling, only a single node have been considered, which left the case of charger scheduling for multiple nodes an open issue. Reference [BA12] addressed D-CH power allocation for multiple nodes in Passive Opportunistic Distributed Sensing (PODS). The considered network is composed of passive sensors that are powered by D-CH. The power received from chargers is immediately reflected towards the BS to communicate data using modulated backscattering. Each D-CH employs cognitive radio to detect vacant channels that are used in charging the passive sensors. Consequently, the received data quality at the BS, measured by the estimation distortion, is directly affected by the opportunistic spectrum access as well as the power levels used at the D-CHs. Driven by this relationship, authors proposed a power control strategy for the D-CHs to minimize the energy consumption of the charging operation, while satisfying estimation distortion requirement at the base station. Simulation results assessed the energy consumption performance achieved by the proposed scheduling approach for various estimation requirements, channel noise levels, and spectrum opportunities. A key limitation of the proposed approach is that the computed power values are identical for all chargers. Considering a different charging power for each D-CH may make the problem more complex, but it allows improved performances in terms of energy saving and estimation distortion.

Static Hybrid Charger scheduling:

The use of dedicated chargers and base stations to separate energy transmission from data communication offers a good option for flexible design of wireless rechargeable sensor networks. However, this option induces an additional deployment cost and requires coordination between D-CHs and BSs, in order to achieve improved network performance. To avoid these shortcomings, many research efforts adopted the concept of hybrid chargers (H-CHs) that are responsible for both wireless energy transmission and data communication. The major challenge addressed by these efforts is to determine the resource allocation scheme that balances wireless power transfer, and wireless information transmissions (WITs), so that the network performance is optimized.

The work in [JZ14b] aims to maximize the sum-throughput of all nodes in the network by optimizing time allocation for WIT versus WPT operations. For this, authors propose a "*harvest-then-transmit*" protocol where each node first harvests the wireless energy broadcasted by the H-CH in the downlink (DL) and then sends its independent information to the H-CH in the uplink (UL) by time-division-multiple-access (TDMA). By applying convex optimization, the closed form expressions for the optimal time allocations is obtained. However, the study revealed the "*doubly near-far*" phenomenon where nodes that are far from the H-CH harvest less energy than closer nodes, but have to transmit with higher power for reliable data delivery. This led the proposed solution to unfair rate allocation among nodes, by favoring the ones close to the H-CH. To overcome this problem, a new metric, called common-throughput, is proposed to ensure equal rates among all network nodes. In addition, a new iterative algorithm that maximizes this metric is devised, based on simple bisection search. Simulation results demonstrated the effectiveness of the new algorithm in maximizing the common–throughput metric, but at the cost of sum-throughput degradation.

Reference [JZ14a] extends the problem in [JZ14b] to the case of full-duplex H-CH. In this case, the charger is able to transmit wireless power and receive data simultaneously over the same channel, which doubles its spectral efficiency and allows significant time saving, compared to half-duplex chargers. Despite of these advantages, full-duplex operating of chargers introduces the challenge of self-interference cancellation (SIC), in which the H-CH must reduce interference between the transmitted power and the received data signals.

In order to address this challenge, a new charging protocol is proposed, assuming a network of nodes that operate in half-duplex mode for data transmission, using a TDMA channel access. Under the proposed protocol, the maximum weighted-sum rate (WSR) is characterized for these nodes, by joint optimization of WET time, WIT time, and H-CH transmit power. Unlike [JZ14b] that assumes a constant transmit power at the H-CH, the optimization problem in this work is subject to both the average and peak transmit power constraints. The study is performed on two steps: First, the ideal case of perfect SIC at the H-CH is considered. The maximization problem is found to be convex, and the closed-form solution for the optimal time and power allocations is obtained by applying convex optimization techniques. In a second step, authors considered the practical case with imperfect SIC. In this case, the WSR maximization problem is shown to be non-convex, and thus is difficult to be solved optimally. Accordingly, an iterative algorithm is derived, based on optimal solutions in ideal case. The simulation results showed that full-duplex H-CH charging is more beneficial than the half-duplex H-CH, when the SI can be more effectively cancelled.

Large-scale WSNs are usually deployed randomly, due to the high number of nodes. In such networks, it is infeasible to achieve a scalable charger scheduling based on deterministic nodes locations, like in the solutions presented above. The authors in [CDZ15] took a different approach to design a charger scheduling solution for randomly deployed networks, by adopting stochastic geometry tools. The solution aims to maximize the spatial throughput of the wireless nodes. This parameter measures the total throughput achieved by nodes, per unit area, averaged over all information transmission phases (bps/Hz/unit-area). To this end, authors first extended the "*harvest-then-transmit*" protocol proposed in [JZ14b], taking into account the stochastic node positions, and using the model of Poisson Point Process (PPP) [SKM95]. With the new protocol, the problem of spatial throughput is defined as joint optimization of time frame partition between the WET and WIT phases on one hand, and the wireless nodes' transmit power on the other hand. To theoretically analyze the impact of battery storage on the network throughput performance, the solution is presented for two cases: battery-free and battery-enabled nodes. In the former case, the nodes are found to prefer small transmit powers at the optimality, for obtaining large transmission opportunity. Whereas in the last case, only an approximate solution is derived, based on the ideal case of infinite-capacity batteries.

Different from the above works, the objective in [LND$^+$18] is to design a charger scheduling approach that minimizes the packet loss caused by the transmission buffer overflow at the sensor nodes. A buffer starts overflowing once the maximum queue length is reached, while the transmission is withheld due to insufficient energy harvested from the H-CH. The scheduling problem is first formulated as a centralized Markov Decision Process (MDP) model, where data transmission orders, modulation level, WPT duration are jointly optimized. The proposed solution, named EHMDP, assumes that the complete state of nodes in terms of queue length and battery level is known in real-time by the H-CH. This assumption is further relaxed in a semi-decentralized approach wherein nodes can make their own decisions on wether they transmit data during a given time slot, as well as on the modulation level they use for transmission. The numerical analysis characterized the performance gap between the semi-decentralized approach and EHMDP. The latter is presented as the upper bound of packet loss rate in the considered WSN model.

Liu *et* al.[LWJ16] investigate the special case of wirelessly powered underground sensor networks (WPUSNs), where sensor nodes are buried under the soil to monitor geological data . The nodes run a TDMA-based protocol with the HCH for energy harvesting and sensory data transmission. WPUSNs suffers from two majors problems: i) the high path loss resulting from soil influence on data transmission signals, and ii) the diversity in data traffic demands caused by heterogonous geological characteristics. Thus, the quality of service (QoS) in terms of both communication reliability and diverse data traffic should be considered in the design of a charger scheduling strategy for WPUSNs. Under this motivation, authors target an H-CH scheduling strategy that maximizes throughput under reliability and data traffic requirements. After the problem formulation, the QoS requirements have been further mapped into signal-to-noise threshold constraints, in order to transform the model into convex optimization with linear constraints. The closed-form solution for the transformed problem is obtained through a problem decomposition of the Karush-Kuhn-Tucker (KKT) conditions. The theoretical results demonstrated the impact of the wireless channel states, reliability requirements, and data traffic demands on the optimal resource allocation. Moreover, a simulation-based comparison with other scheduling scheme like sum-throughput optimization with equal time allocation is presented to highlight the effectiveness of QoS-aware time allocation strategies in WPUSNs.

5.2.2 Relay-assisted static charging

All works addressed above considered single-hop wireless charging wherein power is directly transferred from a static charger to sensor nodes. Another interesting solution is to equip the nodes with WPT devices, allowing them to mutually charge each other. This solution enables a new paradigm in static charging termed relay-assisted charging. In this paradigm, the power can be *relayed* by intermediary nodes to destination node, if this latter is not within the charger's range. As a result, energy-rich nodes can send they extra power to energy-poor nodes, and charge them via multi-hop wireless transmission.

The feasibility of multi-hop wireless charging has been demonstrated for the first time by *Watfa et al.*[WAHS08]. Authors show that the power transfer efficiency can be as high as 20%, when the charged node is 8 hops away from the sender. Depending on the application scenario, three multi-hop power transfer techniques are identified and their corresponding efficiency is computed. In the first technique, called *store and forward*, each node on the path from the source to the destination receives the energy and stores it in its battery, before forwarding it to the next node. The second technique (*Direct Flow*) takes advantage from the possibility of simultaneous multiple coupling between transmission coils in WPT. Hence, each intermediary node that receives energy can forward it directly to the following node in the path without the need to store it temporarily in its battery. This avoids the energy losses resulting from battery charging and discharging in the store-and-forward technique. Finally, the third technique is a combination of the previous ones where energy is stored only in some nodes. These nodes will serve as intermediary accumulation points of energy received from multiple sources.

Based on the above techniques, *Watfa et al.* propose two charging strategies for flat and clustered network topologies. In the flat topology, the node observing a critical energy level floods a charging request packet throughout the networks. The energy-rich nodes respond by sending back the request message and transmitting power (eventually along a multi-hop path). In clustered architecture, the request is first sent to the cluster-head (*CH*). If the latter can not charge the requesting node, the message is broadcasted to the cluster members. If no energy-rich node exist in the cluster, the *CH* floods a charging request on its behalf over the rest of the network, in order to receive energy and satisfy the demand of requesting node.

Dedicated charger deployment

The charging strategies proposed in [WAHS08] suffers from the absence of reliable energy sources (dedicated chargers) that guarantee energy provision for requesting nodes. Indeed, these strategies are rather based on an energy sharing model between sensor nodes, and the charging requests may remain unsatisfied. A more practical energy provision scheme is proposed in [RBC13]. In this scheme, a set of dedicated static chargers are deployed over the network such that each node can be harvested by one charger, directly or via multi-hop transmission (Figure 5.5). Consequently, the feature of multi-hop power transfer is exploited to devise a cost-effective charger deployment strategy with reduced number of chargers. The number of required chargers and their locations are calculated according to the energy-demand of the nodes, the energy loss that occurs during multi-hop transfer, and the capacity of the chargers.

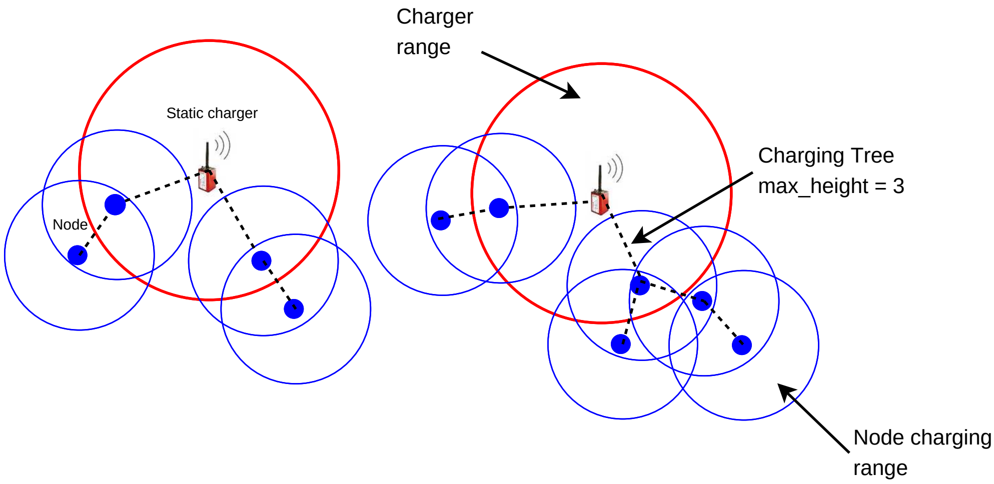


Figure 5.5: Relay-assisted static charging.

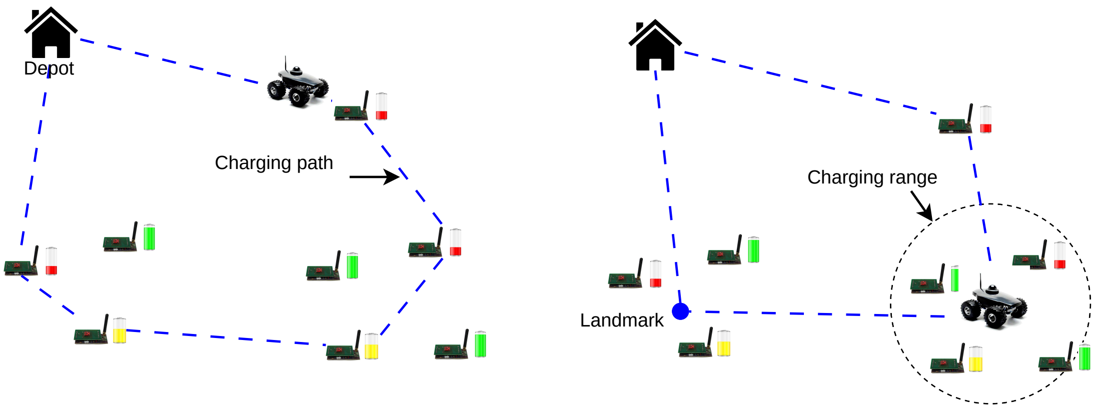
Assuming that the possible charger locations are restricted to the set of nodes positions, authors solved the charger deployment problem in a two-step approach. The first step constructs, for each possible location of the chargers, a shortest path tree rooted at this location and covering all nodes in the network (using Dikjstra's algorithm). The power losses induced throughout each path of the tree is calculated as a multiplicative cost of the edge's weight instead of an additive one. At the second step, authors propose a Mixed Integer Linear Programming (MILP) model that determines the minimum number of chargers required to recharge all nodes, given the constraints related to the limited energy capacity of chargers and the energy loss that occurs during power transfer. The MILP uses the trees constructed at the first step to return the minimum number of *disjoint shortest trees* where the maximum number of hops on each path does not exceed a given value. This value represents the maximum height of the searched trees, and is considered as an input parameter to the optimization problem.

Compared to single-hop charging, simulation results in [RBC13] showed that multi-hop energy transfers allows a significant reduction in the number of required static chargers, especially when their energy capacity is large. In addition, authors highlighted a tradeoff between the number of required chargers and the maximum height parameter. However, the work misses an analytical study that helps in setting this parameter based on the network topology and energy losses on different paths.

5.3 Mobile charging strategies

In general, event-based applications of WSNs observe a significant disparity among nodes in terms of energy consumption rate. The latter varies according to the nodes positions as well as the events' geographical area and their time frequency. In such applications, the permanent deployment of static wireless chargers becomes ineffective, since most of the chargers may remain unexploited during several periods of the network lifetime, due to a low energy consumption of the covered nodes.

Instead of deploying static chargers, a more efficient solution consists in using a mobile charger that visits the collection of nodes with low battery levels, and recharge them wirelessly. The mobile charger (MC) can be designed as a multi-functional vehicle that can either be manned by a human or be entirely autonomous. The MC carries a high-capacity battery pack in addition to resonant coils or RF antennas for wireless charging. When the charger's own battery is low, it returns to a depot for battery replacement and maintenance. (Figure 5.6).



(a) Point to point charging

(b) Multi-point charging

Figure 5.6: Mobile charging in WSNs.

Typically, a mobile charging strategy for WSNs aims to prolong the network lifetime by ensuring that all nodes can be charged before they run out of energy. In addition, some strategies target the optimization of additional network performance parameters related to data gathering/routing or energy consumption. To achieve the optimization goals, the following issues are commonly addressed :

- *Landmark selection*: Given the set of sensor nodes that need to be charged, the strategy selects the best charging locations to be visited by the MC, allowing it to cover the nodes in need. Depending on the employed WPT technology (point to point or point-to-multipoint), the charger can charge one or multi-ple nodes from each landmark. Consequently, the selected landmarks will be confined to nodes' locations in the case of point to point charging, as shown in

Figure 5.6(a). However, in point-to-multipoint charging, the process of landmark calculation optimizes the power transfer efficiency of all nodes located within the MC's charging range (Figure 5.6(b)).

- *Path construction*: Once the optimal landmarks are chosen, the best traveling path needs to be defined by determining the landmark visiting order. Note that the optimal order is not always equivalent to the shortest path. The path optimization is subject to the global objective function targeted by the charging strategy, which sometimes differs from the distance traveled by the MC.

- *Charging durations*: In addition to path construction, the charging strategy computes the optimal sojourn durations for the charger to dwell in each landmark so that none of the nodes will be under/extra-charged.

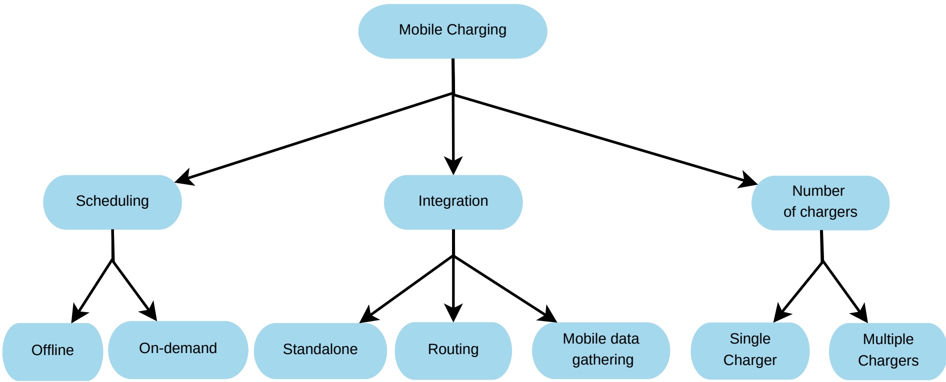


Figure 5.7: Taxonomy of mobile charging in WSNs.

Figure 5.7 depicts the taxonomy of mobile charging strategies in WSNs. Existing solutions can be categorized based on different criteria. The most notable criteria is the *scheduling type*. From the scheduling perspective, the strategies can be classified either as offline or on-demand solutions. In offline scheduling, the charging plan is computed one time for all nodes in the network. The energy replenishment is then performed in a periodic manner, using the same schedule, and without considering disparities in terms energy requirements, for different nodes and different charging cycles. In contrast, on-demand scheduling relies on nodes requests that are continuously received by the MC. As a result, the calculated charging plan changes dynamically according to the subset of requesting nodes and their energy consumption.

Alternatively, the classification can be performed in terms of integration level. This parameter reflects the charging approach interactions and its awareness for other operations at the network or application layers. Three main categories can be distinguished. Standalone approaches are limited on optimizing the performance of charging schedules independently from other network tasks. The second class takes into account the adopted routing mechanisms, which significantly impact the energy consumption patterns of nodes. The idea is to modify the communication schemes in terms of transmission rates and employed routes to achieve a better synergy between energy consumption patterns and mobile charging schedules. The last class exploits the MC mobility for data collection task. Consequently, the charger's strategy target the joint optimization of energy provisioning and data gathering services. In addition, mobile charging strategies can be perceived as single-charger or multiple-chargers approaches. The latter class is intended for large-scale networks where a single charger can not solely recharge a high number of nodes.

In the following subsections, we review the state-of-the-art research on mobile charging based on the adopted scheduling type (offline and on-demand solutions). Within each class, we consider the integration level by shedding light on solutions that address routing and mobile data gathering issues. Similarly, the criteria of number of chargers used is emphasized by discussing multiple charger solutions separately.

5.3.1 Offline mobile charging

The larger part of literature on mobile charging strategies focus on offline scenarios where the MC executes periodically a fixed schedule to recharge every node in the network. The schedule calculation is performed only once for a given network setup.

The common optimization goal in offline charging is to minimize the total charging time that includes the charger traveling time and the sojourn durations in each landmark of the path. In some models, this objective has been expressed in equivalent forms like maximizing the ratio of the charger's vacation time (time spent at the depot station) over the charging cycle duration [XSHS12], or minimizing the total charing energy. The different optimization models are defined under a large variation of constraints such as the chargers battery capacity, the minimum energy level tolerated at each node, the application requirements, etc.

Joint offline charging and routing

The idea of periodic offline charging has been investigated first, by *Xie et al.* [XSHS12], in the context of joint optimization of routing and mobile charging. In this work, authors motivated the periodic charging by introducing the concept of *renewable energy cycle* where the remaining energy level in a sensor node's battery exhibits some periodicity over a time cycle (Figure 5.8). Assuming that the data flow routing and rates in the network are invariant with time, both necessary and sufficient conditions for a renewable energy cycle are identified. The feasible solutions satisfying these conditions are shown to achieve unlimited network lifetime thanks to periodic charging.

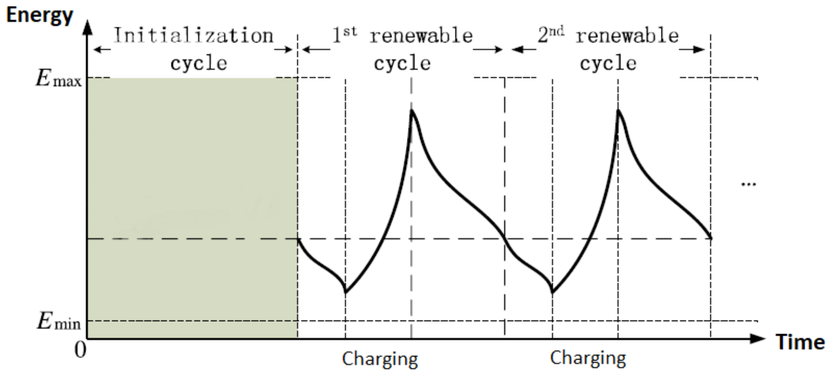


Figure 5.8: Node's energy consumption in renewable cycle.

To devise the scheduling strategy, the optimization problem has been initially limited on maximizing the ratio the MC's vacation time over the cycle period. Authors theoretically proved that an optimal traveling path in each charging period is the shortest hamiltonian cycle. Under the optimal traveling path, the problem is then reformulated to jointly optimize flow routing and charging schedule, taking into account the data flow rates of nodes. The new problem is shown to be NP-hard. Hence, a piecewise linear approximation technique is applied for each nonlinear term in order to obtain a linear relaxation. Based on this linear relaxation, authors derived a feasible solution and proved its near-optimality for any desired level of accuracy, through both theoretical proofs and numerical results.

One major limitation noticed in the above solution resides in the assumption of time-invariant routing flows. This assumption is impractical in most WSNs applications that are characterized with high dynamics in node's reported data rates and routing flows. To overcome this limitation, the work in [SHH+14] investigates methods that jointly optimize a dynamic multi-hop data routing and mobile charging. Similarly to [XSHS12], authors aims to maximize the ratio of the MC's vacation time over a charging cycle.

The key challenge that has been identified when considering dynamic routing is related to the integration and differentiation terms that appear in the problem formulation, which yield a non-polynomial program. To remove these non-polynomial terms, the concept of $(N + 1)$-phase solution has been proposed. The principle is to splits the network lifespan into $N + 1$ phases such that each phase corresponds to a state where the MC is charging one of the N nodes in the network, in addition to the resting state where the MC is in the depot station. With the assumption of static flow routing and rate within each phase, authors prove that an optimal $(N+1)$-phase solution can achieve the same objective value as that by an optimal time-varying solution. Subsequently, the original problem has been reformulated as a linear programming (LP) model that can be solved in polynomial time. Compared with previous results for static routing, numerical results showed that the proposed mobile charging solution for dynamic routing guarantees a larger objective value with a lower complexity.

Multi-node charging

One important issue that has not been addressed in the two previous works is scalability. That is, as node density increases in a WSN, it will be extremely hard for the mobile charger, using single-node charging, to ensure that each node is charged in a timely manner before it runs out of energy.

To solve this problem, *Xie et al.*[XSH+15] extended the work in [XSHS12] by proposing a new mobile charging strategy based on multi-node power transfer technique. In contrast to single-node scenario in which the charging locations are confined to node's positions, the use of multi-node power transfer involves the selection of charging landmarks where the MC stops by to charge a subset of nodes. For this, and given the limitation of MC's charging range, the proposed solution start by partitioning the two-dimensional plane that represents the network field into hexagonal cells. To charge all sensor nodes in a cell, the MC needs only to visit the center of the cell that represents the charging landmark.

Similarly to the single-node case, the objective in [XSH+15] is to maximize the ratio of the MC's vacation time over the cycle duration. However, authors argue that the idea of renewable energy cycle can not be extended to multi-node charging due to a saturation phenomena that is observed when MC is simultaneously charging nodes within the same cell. In fact, the difference in residual energy levels among these nodes causes some nodes to finish their charging earlier and run into saturation for the rest of the charging period. Consequently, the multi-node mobile charging problem is formulated taking into account the cell-based energy constraints that minimizes the saturation phenomena, in addition to the other constraints related to data-flow rates and energy consumption. The formulated non-linear programming problem (NLP) was shown to be NP-hard. By applying discretization and reformulation-linearization techniques described in [SAD98], the NLP was first converted to 0-1 Mixed-Integer NLP, then to Mixed-Integer Linear Programming (MILP). The resulting approach was proven to be near-optimal. Moreover, simulation results highlighted a considerable performance improvement of the proposed scheme over point-to-point charging.

The paper in [FCG+16] also considered multi-node charging, with a different goal of optimizing the total charging delay. This goal is primordial for sensors with small energy storage capacity like RFID sensors [SYP+08]. In such devices, the charged energy should attain a given threshold in order to enable sensing, computation and communication tasks. Therefore, minimizing charging delays helps in completing these tasks more efficiently and in shorter time. The paper models the charging delay minimization problem as a linear programming problem, which can be optimally solved to identify the charger's stop locations and durations. It was shown that considerable reduction in the searching space for the optimal solution can be achieved by utilizing the concept of smallest enclosing space [Wel91] and charging power discretization. However, it has been noticed that the optimal solution may result in a large number of stop positions, which incurs a long travel distance for the mobile charger. To deal with this shortcoming, a point merging heuristic based on k-means clustering [Llo82] was used to reduce the number of stop locations, while maintaining the total delay cost to $(1 + \theta)$ upper bound [1]. Simulation results showed that the proposed approach largely outperforms a baseline design relying on the concept of Set-Cover [AMS06], which maximizes the number of under-charged devices nearby each stop.

Joint offline charging and data gathering

As shown in chapter 2, data gathering via a mobile base station has been recognized to achieve significant energy saving in WSNs [GRJL16]. This fact has naturally led researchers to explore the possibility of collocating the mobile charger and base station in a single entity that is responsible of both energy provisioning and data gathering. The undertaken efforts resulted in a new class of mobile charging strategies, namely *joint mobile charging and data gathering.*

In mobile charging schemes that we reviewed thus far, the data is routed to a static base station that is totally independent from the mobile charger. Thus, the data flow routing and energy consumption rates do not depend on the charger's movement. In contrast, joint mobile charging and data gathering approaches consider a different system model based on an Hybrid Mobile Charger (HMC) that performs both data collection/forwarding and wireless power transfer. Data can be forwarded to the HMC when it visits the charging location either in single-hop or multi-hop manner. Figure 5.9 depicts an example scenario where nodes N_2 and N_3 are sending data via single-hop and multi-hop paths respectively, while the HMC is charging N_1. In such scenario, the charging strategy needs to optimize the dynamic routing that varies according to the HMC location.

[1] θ is the merging threshold for k-means clustering heuristic

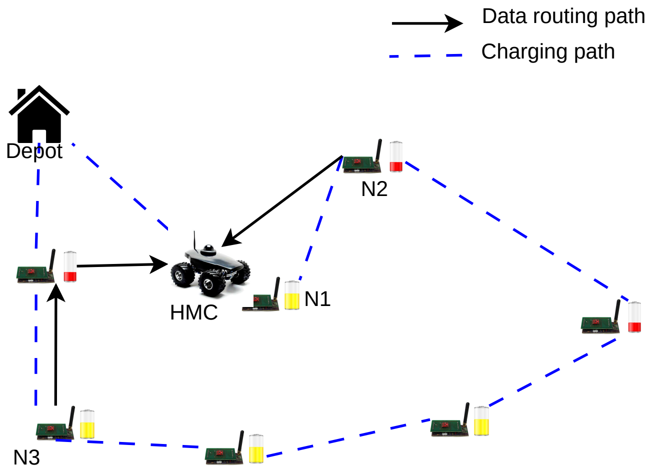


Figure 5.9: Joint mobile charging and data gathering.

Reference [XSH+13b] explores the problems centered around the design of joint mobile charging and data gathering strategies, with the objective of minimizing the energy consumption of mobile charger. As the HMC's location changes over time, the data flow routing needs to be optimized dynamically. To this end, authors developed a time-dependent optimization problem (OPT-t) assuming that HMC follows a predefined path that is known a priori. Noticing the high complexity of OPT-t, an interesting simplification is proposed. It considers a special case of OPT-t where the optimization variables (data flow routing and energy consumption rates) depend on the HMC locations only. The new space-dependent model (OPT-s) is shown to offer the same optimal objective value as OPT-t with a lower complexity. Consequently, an iterative $(1-\varepsilon)$-optimal algorithm is devised. In each iteration, the HMC path is discretized into a finite number of segments and each segment is represented as a logical point. Given the set of logical points, the lower bound and an upper bound for OPT-s are calculated by solving two linear programs (LPs). If the gap between the computed bounds doesn't meet the required accuracy ε, another iteration is executed involving path discretization into smaller segments.

The previous work has been extended in [XSH+13a] by considering a more complicated model where the traveling path is initially unknown and should be optimized, along with stopping locations, charging times, and data flow routing. To deal with the nonlinearity of the optimization problem , authors assume first an idealized case with zero traveling time for the charger (i.e., infinite traveling speed). They compute a near-optimal solution for this case by applying discretization on node's energy reception rates and energy consumption rates. Also, the smallest enclosing disk (SED) covering all nodes is partitioned based on upper energy consumption bounds and lower energy reception bounds. Each subarea is represented by a logical point as its "worst-case" energy reception and energy consumption behavior. Based on this solution, authors further obtained the travel path of the original problem. The path is the Hamiltonian cycle that connects all logical points having a non-zero sojourn time in the ideal case. With this path, a feasible solution is derived. In addition, the performance gap between the feasible and the unknown optimal solution has been theoretically quantified.

Both [ZLY14] and [GWY14] aim to maximize a network utility function that characterizes the amount of data gathered by sensors. Maximizing such utility functions becomes particularly important when a large amount of data is generated in the network. In this case, not all data can be successfully collected by the HMC, due to the limited energy of nodes and the constrained bandwidth of wireless links.

In [ZLY14], the proposed scheme (J-MERDG) operates periodically in two steps. First, the location of a subset of sensors are selected as anchor points, and a first tour is performed by the HMC on these anchors to recharge corresponding sensors. During the charging tour, the HMC can also collect available data from nearby nodes using multi-hop routes. To ensure a tradeoff between charging efficiency and data gathering latency, the anchor selection algorithm searches for the maximum number of locations where sensors hold the least battery energy, while keeping the tour length below a given threshold.

After anchor selection and first charging tour, the second step comes with a number of tours that are optimized for data collection. As mentioned earlier, authors formulate the optimization problem as a network utility maximization model, which is found to be NP-hard. Consequently, they propose a distributed algorithm that allows each sensor to self-adjust its data transmission rates, link scheduling and flow routing so as to adapt with its energy status. The algorithm is based on Proximal Approximation method that is proven to achieve a system-wide optimum [BT97]. The numerical results verified the convergence of the charging strategy and its effectiveness under random and regular topologies. However, the charging durations of sensors are ignored and the HMC's sojourn time at each anchor point is supposed to be manually configured, based on the application requirement. Additionally, the considered energy model does not take into account the energy consumption induced by data reception and sensing operations.

The work in [GWY14] extended J-MERDG by considering all types of power consumption, including sensing and data reception energy. In addition, the recharging rates are regarded as time-varying instead of constant. The optimization approach of the proposed scheme named (WerMDG) is similar to J-MERDG in that it is performed in two steps. The first step defines non-convex optimization framework under the constrains of flow conservation, energy balance, link and battery capacity and the bounded sojourn time. Then the second step converts the original formulation into convex one. In the distributed algorithm, each sensor adaptively tunes its optimal data rates and routing paths based on the current energy replenishment status. At the same time, the HMC dynamically adjusts its optimal sojourn time at each anchor point such that the entire network utility can be maximized. The simulation results showed that WerMDG can converge in case of small level of node failure. Also, the proposed scheme outperforms J-MERDG in terms of network utility and lifetime.

Collaborative offline charging

Prior offline charging strategies assumed that a mobile charger has a sufficient amount of energy to not only replenish an entire WSN, but also to make a round-trip back to the base station. Unfortunately, this model becomes invalid for large-scale networks that are deployed in a widely extended and remote areas. In such scenarios, an individual mobile charger with limited energy can hardly reach and charge all sensors. To solve this problem, multiple chargers can be dispatched from one or several power stations allowing them to cooperate in fulfilling the network charging task. Compared to single-charger dispatch problem, collaborative charging further involves coordination among mobile chargers. Therefore, the design of the charging strategy entails two issues: minimization of the number of chargers required to cover a given network area, and scheduling the optimal dispatch given the minimum number of chargers.

Beigel et al. [BWZ14] investigated the idea of collaborative charging in the simple case of one-dimensional (1D) line and ring topologies, considering negligible charging time. An optimal solution with linear complexity is provided to compute the minimum number of necessary chargers and corresponding schedules, given homogeneous sensors with the same recharging frequency. Here, the schedules refer to the area coverage and the speed selection of each MC over a period of time. Afterwards, the case of heterogeneous sensors has been examined and a greedy algorithm is proposed. The authors showed by mathematical proof and simulation experiments that the algorithm has a an approximation order of two to the optimal solutions.

Authors in [DWC^{+}14] considered a more practical scenario of two-dimensional (2D) sensor network with energy constrained chargers. Authors' formulation to find a minimum number of MCs in 2D networks was proven to be NP-hard. Hence, the original model has been relaxed by removing linear constraints, then reduced to a Distance Constrained Vehicle Routing Problem (DVRP)[NR12]. Based on the obtained result, authors derived two algorithms for the original model and their corresponding approximation bounds have been computed. Simulation results showed an improvement in terms of minimum number of MCs, compared to a baseline scheme. However, since this work aimed to guarantee a performance ratio for worst case, its average performance is far from optimal. Furthermore, the energy consumption rate of each sensor node is assumed constant and uniform, which makes the new strategy impractical in general scenarios where nodes have different energy consumption rates.

Reference [ZWL15] was the first work discussing the idea of enabling MCs to intentionally transfer energy between themselves for a better collaboration. Given a sufficient number of mobile chargers, the formulated problem consists in computing the schedules that maximizes Energy Usage Effectiveness (EUE). This metric is defined as the ratio of energy transferred to sensors over the total energy consumed by the MCs for traveling and charging. To better understand the problem structure, authors considered first an elementary case that satisfies three conditions: (K1) all sensor nodes are distributed along a one-dimensional (1D) line; (K2) the recharging cycles of all sensor nodes are the same; (K3) there is no energy loss during power transfers. For this case, the designed solution named "PushWait" relies on the following idea: each MC charges a portion of nodes, *pushes* other MCs to continue the task by providing them with additional energy, then *waits* for their return to share back the remaining energy so that all chargers can reach the base station (Figure 5.10). PushWait strategy has been proven to be optimal and can cover a 1D WSN of any length. Further, the three initial conditions (K1,K2 and K3) have been removed one by one to gradually build a final solution for charger scheduling in two-dimensional WSNs. Simulation results showed that the introduction of energy sharing between MCs improves energy usage effectiveness over traditional multi-chargers schemes. However, the total cost of collaborative charging strategies is determined also by the number of employed chargers that has been neglected in this work.

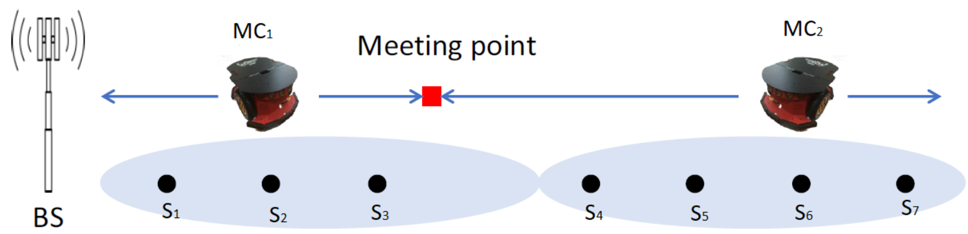


Figure 5.10: Illustration of PushWait strategy for collaborative charging.

The work in [LWWP17] pointed out that the number of chargers used under PushWait strategies increases dramatically with the number of nodes. Authors also showed that it is impossible to simultaneously achieve a maximum energy usage effectiveness and a minimum number of chargers. Consequently, their proposed approach starts with computing the minimum number of chargers needed for collaborative charging with energy sharing. Once this number is identified, the chargers scheduling is designed with the objective of minimizing the MCs' traveling distance. This approach led to Push-shuttle-back (PSB) algorithm, in which the MC is allowed to shuttle between its current and previous positions to carry more energy. Authors formally proved that PSB achieves the minimum number of chargers and the optimal shuttling distance in a 1D scenario with negligible energy loss. Concerning the 2D network scenario, authors improved the reference solution proposed in [ZWL15] with a new circle-based shortcutting algorithm. In addition, the problem of energy loss in real application scenario has been solved by exploiting detachable battery packs that can be swapped among chargers. Despite of the improvements in overall network cost shown in the performance evaluation study, the additional cost of introducing a battery exchange system, as in [WQG+12], for each mobile charger has been omitted.

In contrast to single-depot multi-charger strategies, the work described in [JLS+17] investigates the possibility of using several charging depots to replenish the MC's batteries. In this scenario, developing an efficient strategy requires a joint optimization of the chargers number, their related schedules and the depots locations. To do so, the proposed scheme partitions first the network into minimal number of un-rooted charging tours, without considering the locations of depots. Depots' locations are then determined based on the charging tour distribution. Finally, multiple charging tours/MCs are assigned to the same depot with the objective of maximizing energy efficiency, which is measured by the ratio of charging time over traveling time. The performance comparison has been carried out against a single-depot baseline approach for both cases of limited- and unlimited-capacity depots. Simulation results revealed that the joint optimization of depots locations and chargers tours led to an average reduction in the number of MCs by 64%, and an average increase of 19.7 times on the ratio of total charging time over total traveling time.

5.3.2 On-demand mobile charging

In offline strategies, the charging of nodes is based on *a priori information* and carried out in a *periodic* and *deterministic* manner. However, in practice, WSNs are in continuous and close interaction with the surrounding environment. As a result, the energy consumption profiles of nodes demonstrate high diversity. With such uncertainty and variation in network demand, existing periodic charging solutions lack of adaptability and may suffer from non-negligible performance degradation. Furthermore, most of the literature discussed in previous sections rely on the assumption that the mobile charger requires the acquisition of a perfect *global knowledge* on the entire network state, which incurs a large communication overhead, and thereby, considerable energy consumption.

Observing the limitations of offline strategies, researchers have been oriented towards online, mostly known as on-demand charging schemes. An on-demand strategy allows the mobile charger to serve only nodes that are in real need for energy, after receiving charging requests from them. Based on these requests, the strategy adjusts the charger's path and schedules the energy replenishment in on-demand basis. In the following, standalone on-demand charging solutions are divided into two main categories, depending on weather they employ single or multiple chargers. In addition, we distinguish a third category wherein charging is integrated with routing operations.

Single-charger strategies

A relatively large portion of the solutions proposed for on-demand mobile charging belongs to this category. Existing schemes differ essentially in terms of their primary design goals. For example, the objective of reference [RLX14] was to maximize the network charging throughput, defined as the number of charged nodes per travel tour. The offline formulation of this problem is first given under the constraint of bounded tour period, and with the assumption that all charging requests are known in advance for each period. This problem is shown to be NP-hard using a reduction from the well-known orienteering problem with time windows [GLV87], and an approximation solution is derived. Then, for the online version with one-by-one charging requests arrivals, a naive solution was proposed. In this solution the MC iteratively adjusts its schedule by serving the node requiring a smallest processing time, which is the sum of the traveling and charging time. Noticing a sub-optimal utilization of the charging tours, an enhanced cluster-based solution is devised. It consists in grouping the requesting nodes into clusters according to their locations. Then for each iteration, the charger chooses the cluster to serve, based on a new metric called charging gain. Nevertheless, both solutions are location-biased and may prevent nodes that are far from the depot from being charged. In addition, the charging time is assumed constant for all nodes. However, in practical scenarios, this time varies from a node to another and impacts significantly the performance of the charging strategy.

Fu et al. [FHC+16] propose an energy synchronized (ESync) mobile charging protocol with the aim to simultaneously reduce the charger travel distance and the sensors charging delays. *ESync* starts with constructing a set of nested Traveling Salesman Problem (TSP) tours, based on the energy consumption rates of the sensor nodes. Then for each round of the charging process, the charger selects the tour involving nodes with low residual energy. The tour construction is dynamically adjusted according to the continuous estimation of the sensors' consumption rates, which relies on the frequency of corresponding charging requests. To further enhance the charger's travel distance, a new concept of energy synchronization is adopted for the execution of charging rounds. It consists to proactively harmonize the future nodes charging requests sequence with their actual order in the TSP tour. This is achieved by carefully controlling the amount of energy charged to individual nodes. The performance of *ESync* is compared with two baseline schemes, namely, TSP and Nearest-Job-Next. Simulation results demonstrate that the charger travel distance and nodes charging delays can be reduced by up to 30% and 40% respectively. However, we believe that proactive charging of non-requesting nodes for synchronization purpose limits the charger's capacity to adapt with unpredictable augmentation in number of requests that may occur in event-based WSNs applications.

The on-demand approaches studied so far have alleviated some drawbacks of offline methods. However, they still necessitate significant (or even global) network knowledge, and the solutions are centralized. To tackle this issue, authors of [ANR14] proposed a distributed on-demand charging scheme that employs only local and limited information. To establish an order of charging priority among requesting nodes, a new "criticality" metric is introduced. This metric reflects the node's importance within the network by measuring it energy consumption rate, as well as the size of data traffic that it serves. The charger's path scheduling is implemented by two distributed algorithms, assuming different levels of network knowledge. The first algorithm elects a subset of reporter nodes that perform limited sampling on the network state to the sink, which in turn guides the mobile charger to the subarea with critical alerts. In the second protocol, charging requests are propagated throughout a tree that is rooted at the requesting node. The depth of the constructed tree gradually grows as the criticality of the corresponding root increases. The mobile charger patrols the network following a spiral trajectory until detecting a tree. The latter indicates the path towards the root node to be charged. Additionally, a partial charging method is adopted by the charger to determine the amount of energy that should be transferred to individual nodes for a better sharing of the MC's energy budget. The performance evaluation study demonstrated the effectiveness of the proposed scheme in terms of robustness (i.e., the average number of alive nodes). However the MC's traveling energy is completely neglected and is expected to increase dramatically due to continuous patrolling.

Similarly to [ANR14], the work described in [HKG$^+$15] studied the issue of On-Demand Mobile Charging (DMC) in absence of a priori knowledge on node's charging demands. The DCM problem has been theoretically investigated using the discipline of Nearest-Job-Next with Preemption (NJNP), which takes into account both spatial and temporal properties of incoming requests. Under NJNP, re-selection of the next node to be charged is automatically trigged upon either completion of the current charging task, or the arrival of new charging request. At that time, the mobile charger selects the spatially closest requesting node as the next node to charge. The performance bounds of NJNP are theoretically analyzed regarding two metrics: charging throughput that is the number of requests served during a given period, and charging latency that defines the time separating the request emission and node charging. It has been demonstrated that the asymptotic performance of NJNP is within constant factors of the optimal results under both light and heavy charging demands. In addition, both numerical and system-level simulations showed that the proposed strategy outperforms the First-Come-First-Serve discipline. Nonetheless, NJNP-based charging is also location-biased. This engenders service unfairness and may leave distant requesting nodes without being charged.

Multi-charger strategies

In an attempt to improve the scalability of on-demand charging in large-scale networks, few works have investigated possible ways of using multiple chargers in such scenarios. In [JWCL14], author's goal was to devise an on-demand charging approach aiming at optimizing the quality of event monitoring, through maximizing a covering utility metric. The problem formulation has been initially established for a single charger, and was proven to be NP-complete. Then, two heuristics are devised: Maximal next coverage utility first (MNCUF) and Maximal average coverage utility first (MACUF). They both adopt a greedy approach in choosing the next node to be charged, based on different coverage-related metrics. Finally, the use of multiple chargers has been investigated. The suggested solution is to dispatch the charging requests among the MCs, which will process them following MACUF discipline. After each service completion, the charger broadcasts a notification message that helps other MCs in tracing the information used to calculate MACUF metrics. Despite of its simplicity, the proposed multi-charger approach lacks of real coordination between chargers. For example, splitting requests based on their order of arrival may results in suboptimal performance in terms of coverage. This is because the spatial attribute of these requests is not considered, while the notion of coverage is closely correlated with space.

As opposed to [JWCL14], reference [LWL$^+$16] considers scalability as the primary design objective, and the solution is totaly built on multi-charger on-demand scheduling. The problem has been modeled via game theory as a collaborative game wherein each chargers seeks for maximum profit when fulfilling the charging task. Concepts related to the game model (GTcharge) such as contribution degree, charging priority and profits have been formally defined, considering the objective to maximize the ratio of charged energy over total consumed energy. A typical round of GTcharge algorithm proceeds as follows. First, each MC sends a query to the sink for obtaining information about its service region (i.e. a circle centered at MC's coordinates). Subsequently, the contribution degrees corresponding to nodes and chargers located in the service region are calculated and sent to the charger. For nodes, a contribution degree is computed by the sink using the information transmitted in charging requests. Concerning MC's, their contribution degree reflects their energy status and their participation in charging other devices. After that, the charging priority is computed, and the MC calculates profits gained by charging sensor nodes or other mobile chargers. In deed, a mobile charger can decide to charge another one in order to reduce repetitive traveling to the depot. Finally, the MC chooses the next device to charge, based on the strategy that maximizes its profits. The proposed scheme have been compared to PushWait offline solution discussed earlier. Simulation results demonstrated an improved performance of GTcharge in terms of energy usage efficiency, despite of the highly preemptive nature of the game plays, which entails under-optimal traveling paths.

Joint on-demand charging and routing

The impact of on-demand charging strategies on dynamic routing decisions is highlighted in [PLZQ10]. Experiments have been conducted using a charger that adopts a simple but greedy strategy to replenish nodes with lowest residual energy (bottleneck sensors). In this context, two well-known routing approaches are examined, namely energy-balanced and energy-minimum routing. It has been concluded that energy-balanced routing achieves longer network lifetime when the power transfer efficiency is low or the charger's on-board energy is small. By contrast, when both the charging efficiency is high and the amount of energy carried by the mobile charger is large, the energy-minimum routing is superior in extending the network lifetime.

Inspired by the aforementioned findings, the authors of [LPZQ11] design a joint routing and charging scheme (J-RoC) for practical scenarios. The system model is constrained by limited charging capacity of the MC, time-varying energy consumption rates for nodes and imperfect communication channels. The key idea of J-RoC is to combine energy-minimum and energy-balanced routing in order to benefit from their strength as well as mitigate their shortcomings. For this, J-RoC requires periodical information exchanges between sensor nodes and the charger. Transmitted information specify the node's energy consumption rate, residual energy level, data packet generation rate and the set of parents on the energy-minimum paths to the sink. Based on these information, the MC keeps track of the global energy status of the network, schedules its charging activities accordingly, and disseminates the charging schedule back throughout the network. While being aware of the charging schedule, sensor nodes employ charging-aware routing metrics to make their routing decisions. The routing metrics take into account the effects of future charging operations on the transmission link quality for better estimation of costs in terms of residual energy. The simulation results show that J-RoC can approach the upper bound of network lifetime under some configurations. However, it suffers from performance degradation in large-scale networks, due to the lack of scalability.

5.4 Summary and research directions

The literature on wireless charging strategies in sensor networks suggested two main ideas. The first idea consists in the deployment of static chargers that can replenish the sensors' batteries either directly or through multi-hop power transfer. The proposed deployment strategies differ essentially in terms of primary design goal (cost-effectiveness, safety, QoS insurance, etc.). These goals were mostly formulated by an objective function within an optimization model. Clearly, the field of relay-assisted static charger deployment has been less investigated. This is explained by the relatively high loss of energy in case of multi-hop transfers. Nonetheless, power transfer efficiency is continuously improving with the development of new wireless charging hardware. Hence, the area of relay-assisted charger deployment should be further explored in order to minimize the cost of charger deployment and leverage the emergent paradigm of wireless charging networks. Additionally, it is important to study the system when each node can simultaneously receive energy from multiple transmitters. For such scenario, new challenges need to be considered like interference avoidance, safety and coordinated scheduling of power transfer operations.

The second idea of wireless charging adopts a mobile charger (MC) in order to cope with the problems of under-exploitation and the lack of flexibility remarked in static charging solutions. Earlier works investigated the offline and periodical scheduling of mobile chargers. In Table 5.1 we summarize the prominent works related to offline mobile charging. The reviewed schemes are compared in terms of number of chargers used, information control method (centralized or distributed), integration level (standalone or with other network function), targeted objective function, optimization parameters, the type of power transfer (P2P: point-to-point or P2M:point-to-multipoints) and the set of system assumptions. As the table shows, a significant variation is remarked in the considered assumptions and constraints, which represents a real obstacle to apply these solutions in real life scenarios. In fact, most of the solutions were proven to achieve near-optimal performances against a set of theoretical assumptions, but few only have been evaluated through real experiments, or via system-level simulations. With the abundance of commercialized wireless charging equipments, there is a real need for future research to conduct more assessment through test-bed experiments, in order to understand the real performances.

Additionally, methods for distributing the control and reducing the use of global information in the offline charging have not been sufficiently studied. Only references [ZLY14] and [GWY14] adopted distributed algorithms that are run by the nodes to attain certain synergy with the mobile charger. Consequently, an additional effort need to be invested into the integration of distributed processing in offline strategies, to improve their flexibility. This research direction is particularly important in cooperative charging, where all state-of-the-art solutions are based on a central entity responsible for guiding the mobile chargers. In this scenario, we can notice also that all strategies utilize point-to-point power transfer. Consequently, investigating the use multi-node charging represents an interesting idea that allows further improvement of scalability gained with multi-charger utilization.

On the other hand, the principle of on-demand charging has been presented as a mean to build more practical solutions that adapts to the dynamic nature of sensor networks. Table 5.2 summarizes the mains features of reviewed solutions. Here also, the use of multiple chargers represents a promising option to enhance the solution's responsiveness in case of heavy requests load. However, all existing solutions rely on centralized and limited coordination. The design of novel schemes that balance an improved coordination with the required communication overhead is an interesting research issue. Finally, the review of on-demand charging strategies revealed that none of them considered the use of point-to-multipoint power transfer. We believe that such possibility is able to significantly enhance the charging strategy in terms of both dissipated energy and charging delays.

Literature	Number of chargers	Control/ Knowledge	Integration level	Optimization parameters				Objective functions	Assumptions/ Constraints	Power Transfer
				Path	landmarks	Charging time	Others			
Xie et al. [XSHS12]	Single	Centralized	Routing	✓		✓		MC's vacation time per cycle	Static data flows, Renewable energy cycle	P2P
Shi et al. [SHH+14]	Single	Centralized	Routing	✓		✓		MC's vacation time per cycle	Dynamic data flows	P2P
Xie et al. [XSH+15]	Single	Centralized	Routing	✓	✓	✓		MC's vacation time per cycle	Static data flows, Node's battery saturation	P2M
Fu et al. [FCG+16]	Single	Centralized	Standalone		✓	✓		Cumulative sojourn durations	charged energy must attain a threshold σ	P2M
Xie et al. [XSH+13b]	Single	Centralized	Mobile data gathering		✓	✓		HMC's energy consumption	Predefined traveling path	P2P
Xie et al. [XSH+13a]	Single	Centralized	Mobile data gathering	✓	✓	✓		HMC's vacation time per cycle	Uknown traveling path	P2P
Zhao et al. [ZLY14]	Single	Distributed	Mobile data gathering		✓		Data rates, routing flows	Utility function of data collection	Charging durations are negligible compared to data gathering	P2P
Guo et al. [GWY14]	Single	Distributed	Mobile data gathering		✓	✓	Data rates, routing flows	Utility function of data collection	Time-variant charging rate	P2P
Beigel et al. [BWZ14]	Multiple	Centralized	Standalone		✓		Chargers speed	Number of chargers to cover all nodes	1-dimentional topologies, predefined paths	P2P
Dai et al. [DWC+14]	Multiple	Centralized	Standalone		✓			Number of chargers to prevent failures	Identical energy consumption for all nodes	P2P
Zhang et al. [ZWL15]	Multiple	Centralized	Standalone	✓	✓			Energy usage effectiveness	Power transfer among chargers	P2P
Liu et al. [LWWP17]	Multiple	Centralized	Standalone	✓	✓			Number of chargers, and MC's traveling distance	Chargers with battery swap system	P2P
Jiang et al. [JLS+17]	Multiple	Centralized	Standalone	✓	✓		Depots positions	Number of chargers, and depots	Chargers with different capacities	P2P

Table 5.1: Summary of offline mobile charging strategies

Literature	Design objective	Number of chargers	Knowledge/ Control	Integration level	Power Transfer
Ren et al. [RLX14]	Number of nodes charged per tour	Single	Centralized	Standalone	P2P
Fu et al. [FHC+16]	Charger travel distance and nodes charging delays	Single	Centralized	Standalone	P2P
Angelopoulos et al. [ANR14]	Average number of alive nodes	Single	Destributed	Standalone	P2P
He et al. [HKG+15]	Charging thoughput and delays	Single	Destributed	Standalone	P2P
Lintong et al. [JWCL14]	Coverage utility	Multiple	Centralized	Standalone	P2P
Lin et al. [LWL+16]	Energy usage effeciency	Multiple	Centralized	Standalone	P2P
Li et al. [LPZQ11]	Time to first node failure	Single	Centralized	Routing	P2P

Table 5.2: Summary of on-demand mobile charging strategies

5.5 Conclusion

The last years have witnessed a growing interest in the design of wireless charging strategies for sensor networks. This confirms the potential of wireless power transfer technologies to provide perpetual network operation in WSNs. In this chapter, we have provided a comprehensive survey on wireless charging approaches. The literature has been broadly classified into two main categories namely static and mobile charging solutions. In addition, the strengths and weaknesses of each category have been emphasized. We concluded that on-demand mobile charging approaches are the most appropriate for real-life applications of WSNs, which are characterized by permanent dynamics in energy consumption and data flows. In addition, the study revealed several interesting research directions that remain unexplored. For example, all on-demand mobile charging solutions are limited to charge a single node at a time, which penalizes their scalability in large networks. Using multi-node charging in on-demand strategies represents an important topic for future investigations.

Chapter 6

On-demand and Multi-node Wireless Charging

6.1 Introduction

As concluded in the previous chapter, most of the charging scheme rely on offline and deterministic scheduling of the mobile charger, in order to carry out periodically the charging tour and visit every WSN node [XSH$^+$12, XSHS12, FCG$^+$16]. However, in many real-world applications, the energy consumption of sensor nodes is highly dynamic. Consequently, offline solutions may lead to unnecessary visits of energy-rich nodes. This will not only result in a higher energy consumption of the mobile charger due to useless displacements, but it also causes high waiting times for those nodes with critical energy levels and possibly results in their exhaustion.

Considering this shortcoming, some works proposed the use of on-demand approaches allowing the charger to serve requesting nodes only [HGPZ13, JWCL14, HKG$^+$15]. However, all the proposed approaches in this category are limited to charge a single node at a time. This may induce low performance of the mobile charger and make the approaches hard to scale up. However, the interesting results of Kurs et al. [KMS10] proved that by properly tuning the magnetic resonance coupling, it is possible to perform a wireless energy transfer to *multiple* receivers simultaneously. Moreover, it has been empirically demonstrated that the overall output efficiency of charging multiple devices was better than that of charging every device individually.

Inspired by these new findings, we propose a novel *on-demand* wireless charging scheme for WSNs that considers the following challenges: i) avoiding node failure by ensuring a bounded charging delay for each requesting node, ii) optimizing the energy consumption of the mobile charger in terms of power transfer efficiency and traveling energy, iii) ensuring the scalability of the charging scheme with a high number of requesting nodes.

To address these challenges, we explore the use of *simultaneous multi-node charging* in on-demand scenarios. We use a simple but efficient scheduling of the charging operation via *threshold-dependent request grouping*. In addition, a path planning strategy is proposed, based on minimizing the stopping points in the charging tour.

The main contributions of our work are as follows:

- While simultaneous energy transfer has largely been used in off-line solutions, no on-demand approach uses it thus far. The present work investigates the use of simultaneous energy transfer in *on-demand* wireless charging. This has the advantage of improving the charging performance and assures higher scalability, as compared to charging based on one node at a time.

- We propose a novel on-demand charging solution that uses the concept of threshold-based tour launching (TTL). Contrary to existing schemes that focus on shortening the charging delays, we demonstrate that it is possible to delay the charging operation of requesting nodes to maximize the benefit from multi-node simultaneous charging without affecting the sensors' operations.

- To show that the proposed approach does not impact the sensor operations, a new metric called cumulated failure time is defined. The latter is shown to be more relevant than the charging delay metric that is traditionally adopted by existing solutions.

- At the tour planning level of the proposed strategy, a new modeling approach is used. It leverages simultaneous energy transfer to multiple nodes, with the aim of maximizing the number of nodes that are charged at each stop. Giving the NP-hardness of the problem formulation, we approximate it to a clique partitioning problem, and a simple heuristic is proposed. The resulting charging algorithm is shown to have a cubic time complexity in the number of nodes, with a good approximation ratio.

- The proposed mechanisms are evaluated in offline and on-demand scenarios. First, and to illustrate the performance of the path planning strategy in terms of energy consumption in the presence of a high number of nodes, the strategy is compared to a recently proposed offline solution that is also based on multi-node simultaneous energy transfer. Afterwards, the whole solution including the threshold-based launching is evaluated in an on-demand scenario against NJNP [HKG+15].

The remainder of this chapter is organized as follows. Section 6.2 presents the wireless power transfer (WPT) technology used in our solution and gives the problem statement. Section 6.3 introduces the proposed solution, while section 6.4 and section 6.5 describe each of its building blocks. Section 6.6 analyses the computation complexity of the proposed algorithm, as well as the approximation ratio of the enclosed heuristics. Section 6.7 presents a thorough simulation study, evaluating the proposed techniques against state-of-the-art solutions. Section 6.8 concludes the chapter.

6.2 Preliminaries

6.2.1 Employed WPT technology

In chapter 4, we provided a detailed review on the existing WPT technologies and concluded that magnetic resonant coupling is one of the most promising technologies for the special context of wireless sensor networks applications. In fact, the experiments conducted by Kurs et al. [KKM+07] demonstrated the possibility to power a 60 W device from a distance of 2 m with an energy transfer efficiency of 40%. Furthermore, the inventors proposed an interesting enhancement allowing simultaneous power transfer to multiples devices [KMS10]. They showed that proper tuning of the coupled resonators enables a better power transfer efficiency than for a single charged device. Therefore, this technique allows a significant performance enhancement compared to other technologies in terms of received power and charging distance. This opens up new possibilities for wireless charging in WSNs, especially in applications that require **medium or high deployment density** such as IoT-WSNs, military/border surveillance, or smart cities [HKL+06].

Giving the usefulness of magnetic resonant coupling for those WSN applications, as well as its scalability enabled by multiple simultaneous charging, we use this technology in our charging scheme. Nevertheless, the proposed model and solutions are not exclusively related to magnetic resonant coupling, but apply to all charging technologies where the mobile charger can perform simultaneous wireless charging of multiple nodes. For the current technology, multiple simultaneous charging with magnetic resonant coupling is only efficient in applications of medium to high deployment density (i.e., short distances between the charger and the nodes), but not in applications with sparse deployment such as [LHL+13].

However, abstracting away from the limitations of present charging technology, our solution can take advantage from any future technology that may offer better efficiency of multi-node charging over longer distances. This will extend the application range of our charging strategy to low-density WSNs as well. In the rest of the chapter, the employed charging technique is referred to as Multi-node Wireless Charging (MWC).

6.2.2 Problem Statement

We consider a network with a mobile charger (MC) and a set of static sensor nodes that are randomly scattered over a two-dimensional deployment area. Each sensor is equipped with an onboard battery of limited capacity. Nodes send out charging requests to the MC when their energy level falls below a certain threshold. Dealing with routing request is out of the scope of this work, but similarly to data, the necessary communication scheme for this operation can be performed using state-of-the-art routing protocols for mobile destination [GSZ$^+$16]. Furthermore, the time needed for request delivery is assumed to be negligible compared to the MC's travel and charging time. The MC maintains a service queue to store the received charging requests that are served according to the adopted on-demand charging strategy. Here, by *serving* a request we mean that the charger travels to the requesting node and replenishes its energy supply. As emphasized earlier, we assume the use of MWC technology for power transfer between the MC and the visited nodes. This means that the MC has the ability to simultaneously charge several nodes if more than one requesting node is located within its charging radius.

Contrary to offline approaches, where the charging operation is triggered periodically taking into account every node in the network, on-demand charging exhibits highly dynamic properties in both the *temporal* dimension, i.e., the arrival time of a new charging request, and in the *spatial* one, i.e., the location of requesting nodes. These yield additional design challenges compared to offline approaches that mainly focus on optimizing the path of the charging tour. In fact, the design process of on-demand mobile charging must consider the following challenges to guarantee efficiency for the requesting nodes and the mobile charger:

- **Bounded charging delays**: for requesting nodes, charging delays measure the time from when these nodes send out their charging requests to when their energy supply is replenished. An efficient charging strategy ensures that each requesting node can be served within a limited charging delay, so as to prevent its battery exhaustion. It is worth mentioning that contrary to all existing on-demand solutions, the one proposed herein does not target the minimization of the charging delay. Instead, its objective is to keep the delay sufficiently low in order to mitigate node's failures due to battery depletion.

Our new approach in dealing with the charging delay metric is further detailed in section 6.3.

- **Optimized MC's energy consumption**: from the mobile charger perspective, achieving an efficient charging scheme requires optimization in its energy consumption. This includes the energy spent to recharge the requesting nodes (*charging energy*), in addition to the *traveling energy*, necessary to visit those nodes. As shown in section 6.4, optimizing the MC's energy consumption can positively or negatively influence the charging delay of the requesting nodes, depending on the employed technique. Hence, it is vitally important to consider this challenge in the early design stages of the on-demand charging strategy. Yet, existing solutions either neglect it to the detriment of other utility metrics [HKG+15, JWCL14], or consider it as a secondary objective that amounts to reducing the traveling energy by minimizing the length of the charger's path.

- **Scalability**: Most WSN applications envisage a large-scale deployment over a widely-extended area with high number of nodes. A viable charging process must ensure scalable performance when used in such application scenarios, especially when the requesting load becomes heavy. One trivial solution to enhance scalability in on-demand wireless charging is to rely on cooperation of multiple mobile chargers, similarly to [LWL+16]. However, the scalability objective becomes more challenging with the use of a single charger.

6.3 Solution Overview

We propose a new on-demand charging scheme that aims at improving the scalability by relying on MWC for simultaneous power transfer. Nevertheless, the high dynamics exhibited by requesting nodes in terms of locations and request time make it less probable for the mobile charger to find a subset of requesting nodes that are close enough to be charged simultaneously. This complicates the use of MWC in on-demand scenarios. The objective is to explore the available design choices that better integrate MWC into an on-demand charging strategy, and to maximize its benefit. The employed techniques must also optimize the MC's traveling and charging energy consumption, without neglecting the solution performance in terms of bounded charging delays.

From the perspective of requesting nodes, we think the efficiency of an on-demand charging strategy is *not necessarily achieved by minimizing the charging delay.* A more flexible definition of this efficiency is *the prevention of node's failures by serv-*

ing requesting nodes before their battery depletion. Hence, the time available for the mobile charger to serve a given requesting node is equivalent to the period between request issuing and battery exhaustion. This period depends on the requesting node's energy consumption and becomes longer if this node experiences low communication and sensing loads after issuing the request. Previous on-demand charging solutions do not take into account this variance in terms of charging delay requirement and tend to minimize it for every requesting node. Although this may help prevent battery exhaustion for energy-hungry nodes, it imposes unnecessary constraints on the mobile charger strategy for serving other nodes that can tolerate a longer charging delay. The consideration of such unnecessary constraints may foster the use of some greedy charging approaches that negatively influence other performance metrics such as the MC's traveling and charging energy.

The objective of charging delay optimization is relaxed in our approach to maximizing the benefit from MWC, while preventing the depletion of node batteries. Hence, the MC is no longer constrained to start the charging process immediately upon receiving the first request. Instead, the MC waits and keeps on collecting additional requests for a period that ends when a predefined threshold is reached. This waiting period is intended to enable the collection of the maximum number of requests, which allows for a more efficacious simultaneous multi-node power transfer during the charging tour.

Driven by these considerations, we build the charging strategy on charging tours that are triggered based on a waiting threshold. The choice of this threshold and its impact on the solution's performance is discussed in the next section. Each time the waiting threshold is reached, the mobile charger proceeds to the second step, which consists in the *charging path planning*. In this step, the MC computes an optimized charging path represented by a set of stopping locations, along with their corresponding stop durations.

While a conventional on-demand strategy may choose, at each round, the next optimal charging position to serve one or a subset of the existing requests without the need for path planning, the MC in the proposed approach considers all requests received before starting the charging tour. Moreover, charging is performed without preemption, i.e., any request that may arrive during the charging tour will not be served until the next round. This is for the sake of fairness and to avoid penalizing some waiting nodes upon the reception of new requests coming from better candidates (e.g., being in a better location). These facts justify the need for an online path planning mechanism that seeks to optimize the charging of the requesting nodes within each round, while adapting to the dynamic nature of the charging requests.

The planned path is intended to ensure the MC ability to serve all requesting nodes before their battery depletion. In addition, it must optimize the energy expenditure related to the charger movement and the charging energy. To this purpose, we propose a design that takes benefit from MWC through computing a charging path with the *minimum number of stopping points*. The advantage of minimizing of the number of stop locations in the charging path is twofold. First, it allows maximizing the number of nodes that are simultaneously charged at each stop. This reduces the overall amount of energy spent by the mobile charger to charge all the requesting nodes. Second, it helps reduce the length of the charging path, as well as the energy and time needed to stop and resume movement. This contributes to limiting the delays consumed by the mobile charger to serve the requesting nodes, and reduces the energy expenditure associated with the MC mobility.

Once the charging path is calculated, the MC starts visiting requesting nodes and charging their energy supplies, following the computed schedule. Meanwhile, It continues receiving possible charging requests from other nodes in the network. Upon finishing the current tour, the mobile charger begins a new charging round if its queue contains new requests with at least one being below the waiting threshold.

6.4 Threshold-based Tour Launching (TTL)

As emphasized earlier, the proposed charging solution seeks to collect as many requests as possible, so as to group them in the upcoming charging tour. For this, the mobile charger needs a mechanism to decide about the time to launch a new charging tour. The choice of a suitable time for tour launching represents an important design challenge that considerably affects the solution performance in terms of charging delays and energy consumption. If the charging tours are carried out frequently, the service delay experienced by the requesting nodes is reduced. However, a low number of nodes would be served in each tour and this reduces the possibility for the MC to find subsets of requesting nodes that can be charged simultaneously via MWC. As a result, the mobile charger efficiency in terms of traveling and charging energy consumption is expected to be rather low. On the other hand, prolonging the waiting time, so as to serve a higher number of nodes in each charging tour, leads to a higher energy consumption efficiency due to simultaneous charging and traveling path optimization, but it increases the service delay, which may result in node's failures due to battery exhaustion. Thus, the decision mechanism by which the MC chooses the launching time of subsequent charging tours needs to balance the energy consumed by the MC and the time spent to charge requesting nodes.

A simple but efficient strategy for such decision mechanism is to rely on a characteristic value that may reflect the state of requesting nodes or that of the mobile charger's queue. A new charging tour is launched when this value reaches a predefined threshold. Depending on the application requirements, the threshold definition can be either fixed or adaptive. For example, one could use the MC's waiting time since the reception of the first request as a tour launching metric. In this case, the MC may launch a new tour when this time reaches a given threshold value, say T. However, the use of a fixed temporal threshold is not convenient in dynamic WSNs, where the generation of charging requests varies considerably with time and location. In fact, whenever the time threshold is exceeded, the MC may undertake a new charging tour even for a single requesting node. This may lead to an unsatisfactory performance in terms of energy consumption and traveling path planning.

To cope with this, our solution relies on an adaptive threshold that allows the mobile charger to monitor the energy level of the requesting nodes battery. The mechanism uses two energy thresholds, L_c and L_r with $L_c < L_r$ and the following procedure applies to each WSN node.

When the energy level of any of the nodes falls below L_r, this node sends a *request* message to the MC. When the battery level decreases below the second threshold L_c, the node then issues an ALERT message, as an indicator for a critical battery condition. The MC keeps collecting requests and starts a new charging tour as soon as it receives the first ALERT message, at which point all the nodes that have issued a request are served (charged) by the MC using path planning and multi-node charging for each stop location. The use of these two thresholds allows the mobile charger to prolong the request collection phase in an attempt to maximize the benefit of MWC, without neglecting the time needed to serve the requesting nodes before their battery depletion. Hence, scheduling charging tours based on battery criticality threshold will help the MC to adapt its charging strategy to the varying rates of charging requests. This tends to reduce energy consumption, while preventing node's failures due to long charging delays.

6.5 Minimum-Stop Path Planning

The path planning phase is executed each time the mobile charger decides to launch a new charging tour. Its objective is to schedule a charging strategy that allows the MC to recharge the set of nodes from which a request has been received before tour launching. Specifically, the goal is to find optimal stop locations and the corresponding stop durations that minimize the total energy consumed by the mobile charger. The energy optimization technique must take into account the objective of preserving a bounded charging delay in order to prevent node's failures due to

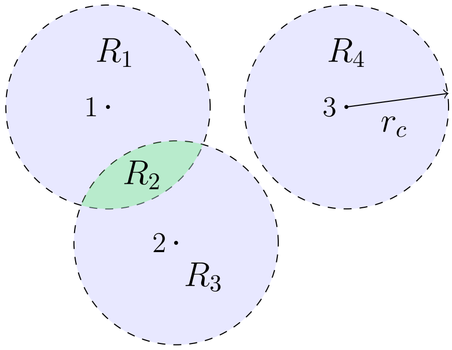


Figure 6.1: Illustrative example of stop regions.

battery depletion. For this purpose, we formulate the path planning calculation as a minimum stop planning (MSP) problem that computes a charging path to recharge requesting nodes with a minimum number of stops. As emphasized earlier, minimizing the number of stops is expected to maximize the number of nodes that are charged simultaneously using MWC power transfer. This allows decreasing the energy consumed in power transfer. Furthermore, planning a charging path with a reduced number of stops helps decrease the distance traveled by the mobile charger, which also reduces the traveling energy and limits the charging delays.

6.5.1 Problem Formulation

The MSP problem is formulated as follows. Let $\mathcal{N}$ be the set of n requesting nodes from which a charging request has been received by the MC at the time when a decision is made to launch a new charging tour., i.e., $|\mathcal{N}| = n$. Each node, i, has a *power reception disk*, D_i. The latter is defined as the set of possible locations where the MC can stop by and charge the node. D_i is centered at the node i position with a radius equal to the maximum energy transfer distance of the mobile charger, denoted by, r_c.

We consider all potential stop regions, R_j, from where the mobile charger can simultaneously charge a different set of nodes. To clarify the concept of stop regions, let us consider the example in Figure 6.1 that illustrates a scenario of three nodes represented by their respective power reception disks. Depending on the location of each node, its power reception disk may (or may not) intersect with other node's power reception disks. For example, the power reception disks of nodes 1 and 2 intersect, thus the resulting stop regions for these nodes are R_1,R_2 and R_3. R_1 and R_3 are the regions from where the mobile charger can charge either node 1 or 2, while R_2 is the region where both nodes can be charged simultaneously. For node 3, only one region, R_4, can be defined. It is equivalent to its power reception disk. This is because the latter does not intersect with any other region in the network.

Generally speaking, each region R_j is either resulting from the intersection of several node's power reception disks, or equals an entire node's power reception disk if this latter does not intersect with any other region. In our model, each geometric region R_j is associated with the set of nodes that can be charged from that region, say, $\mathcal{N}_j$. This is defined as,

$$\mathcal{N}_j = \bigcup_{i=1}^{n} \{i | R_j \cap D_i \neq \emptyset\}. \tag{6.1}$$

Obviously, the union of all regions' representative sets $\mathcal{N}_j$ is equal to the set of nodes in the network, i.e.,

$$\mathcal{N} = \bigcup_{j=1}^{m} \mathcal{N}_j \tag{6.2}$$

where m is the number of regions.

Since the number of nodes that can be charged from a given region, R_j, is unrelated to the MC's position (provided it is inside the region), the region's centroid (s_j) is chosen to be the stop location of the mobile charger when R_j belongs to the charging path. For the ease of presentation, the terms stop region and stop location are used interchangeably.

Given the calculated sets $\mathcal{N}_j$, $j \in 1, \cdots, m$, of possible stop regions, we define an $n \times m$ matrix, $A = [a_{ij}]$, as follows:

$$a_{ij} = \begin{cases} 1 & \text{if node } i \in \mathcal{N}_j \\ 0 & \text{otherwise .} \end{cases} \tag{6.3}$$

Minimizing the number of stop locations that allows to recharge the n requesting nodes is equivalent to solving the following optimization problem:

$$\begin{aligned} \min \quad & \sum_{j=1}^{m} x_j \\ \text{subject to} \quad & \sum_{j=1}^{m} a_{ij} x_j \geq 1 \qquad \forall\, i \in \{1, \cdots, n\} \\ & x_j \in \{0, 1\}\,, \end{aligned} \tag{6.4}$$

where x_j is a binary decision variable that is equal to 1 if region R_j belongs to the minimum stop path, and to 0 otherwise. Also, the n inequality constraints ensures that every node must belong to at least one stop region in the minimum stop path. (6.4) is a Binary Integer Linear Programming (BILP) problem, which is known to be NP-hard. In the next section, this problem is solved through a simple heuristic allowing to find a charging path with a small number of stop locations.

6.5.2 MSP Algorithm for Path Planning

Finding the optimal solution by solving the BILP defined in (6.4) is an NP-hard problem that cannot be achieved with an acceptable computing time for a high number of requesting nodes. In on-demand charging scenarios, the mobile charger needs to perform the path planning phase frequently and cannot afford costly and complex computations. To deal with this problem, we propose a Minimum Stop Planning (MSP) algorithm. The objective is to compute a charging path with a small number of stop locations, using low complexity mechanisms that scale well with the number of requesting nodes.

The main idea is to transform the MSP problem into a minimum clique partitioning problem, and to take advantage of a simple but efficient heuristic to find a reduced number of stop locations in the charging path. Before explaining the problem reformulation, we briefly introduce some notions related to the general problem of clique partitioning and possible ways to solve it.

Clique partitioning

Let $G = (V, E)$ be an undirected graph with a set V of vertices and a set E of edges.

Definition 6.1 *A* ***clique*** *is a set of vertices that form a complete subgraph of G, i.e, a set where every pair of distinct vertices is adjacent. A clique is* ***maximal*** *if it is not properly contained in another clique of G. The maximal clique of the greatest cardinality is called the* ***maximum*** *clique.*

Definition 6.2 *A* ***clique cover*** *of G is a set of cliques A_i for i=1,2,...,c that covers the entire graph: $V = A_1 \cup A_2 \cup ... \cup A_c$. A* ***clique partitioning*** *of G is obtained if vertices are deleted from A_i such that $A_i \cap A_j = \emptyset, \forall i \neq j$. A clique partitioning is called* ***minimum*** *if c is the smallest possible.*

Based on the above definitions, the clique partitioning of the graph depicted in Figure 6.2 can results in multiple partitions:

- Partition 1 : $V_1 = \{1\}$, $V_2 = \{10\}$, $V_3 = \{2, 8, 9\}$, $V_4 = \{6, 7\}$, $V_5 = \{3, 4, 5\}$
- Partition 2 : $V_1 = \{1, 2\}$, $V_2 = \{3, 4, 5\}$, $V_3 = \{6, 7, 8\}$, $V_4 = \{9, 10\}$

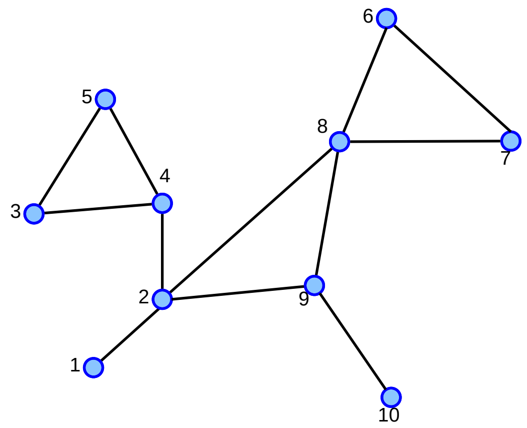


Figure 6.2: illustration of clique partitioning.

The size of clique partition $\{V_1, V_2, ..., V_k\}$ refers to the number of partitioned sets k. The clique partitioning of minimum size is called **minimum click partition**.

The problem of minimum clique partitioning has been proven to be NP-complete for general graph structures [GJ90]. Therefore multiple near-optimal algorithms have been proposed to deal with the high complexity in computing the optimal solution[BS91, KS02]. One of algorithms that have a simple implementation and small derivation from optimal solutions has been proposed by Tseng et al.[TS86]. The idea is to find maximal cliques so that the number of cliques can be minimized. In the proposed heuristic, the edge with the maximum number of common neighbors is chosen first as a primary edge to initiate a search for a maximal clique, and he cliques are found one by one. Tseng's algorithm was developed for the synthesis of data paths at the register-transfer level of processors. The addressed problem was to minimize the number of allocated registers, data operators and interconnection units, which was modeled as a minimum clique partitioning. The proposed algorithm is described in Figure 6.3.

MSP reformulation

The problem is reformulated as follows. Let $G(V, E)$ be the undirected graph where each node in the network is represented by a vertex in the set V. An edge between two vertices is activated iff the power reception disks of the corresponding nodes intersect. The clique partition problem applied to $G(V, E)$ consists in finding the minimal number of cliques that partition the graph, where each clique represents a subset of V, such that every two vertices in this subset are connected by an edge. As emphasized earlier, this problem is NP-hard. Consequently, we adopt the popular heuristic of Tseng that allows to compute near-optimal solutions in polynomial time.

1. Pick the edge (p, q) which has the maximum number of common neighbors (a vertex is a common neighbor of an edge if it is connected with both vertices of the edge).
   - Tie-breaking: select p and q such that the sum of node degrees is maximum;
   - If the graph has no edges, then Stop.
2. Cluster p and q into a clique.
3. Delete edges from p and q that are not connected with their common neighbors.
4. Combine p and q in the original graph and call it r.
5. If vertex r is isolated, Goto 1.
   - Else pick an edge s which includes r as a vertex and which has the maximum number of common neighbors.
6. Rename r and s as p and q.
7. Goto 3.

Figure 6.3: Tseng's clique partitioning algorithm.

The intuition behind partitioning graph G into a number of cliques is that when a set of nodes forms a clique, it is highly probable to have a single intersection region between their power reception disks. Thus, the algorithm considers this region as stop region from where the mobile charger can charge all the nodes in the clique. As a result, finding a minimum number of stop locations where the mobile charger can stop and charge all requesting nodes is equivalent to computing a minimum number of cliques.

However, it is possible that a set of nodes form a clique but their power reception disks do not intersect in a single common region. Figure 6.4(a) illustrates an example of four nodes represented by their power reception disks. Following the proposed model, these nodes form a clique, but no common intersection region exist between their power reception disks. When such a special case is met, MSP proceeds iteratively to find a minimal set of stop regions from which the nodes of this clique can be charged. It starts by isolating a single node from the clique and checks if the resulting new clique has a common intersection region. If this is the case, the algorithm considers two stop regions; namely, the intersection region of the new clique and the power reception disk of the isolated node. Otherwise, if no common intersection is found in the new clique, the algorithm proceeds to the next iteration by isolating a higher number of nodes. Figure 6.4(b) shows that by isolating node 4 from the clique, a common intersection region can be found for the remaining nodes (dark blue region on the left). The algorithm considers, for this case, two stop regions (colored regions).

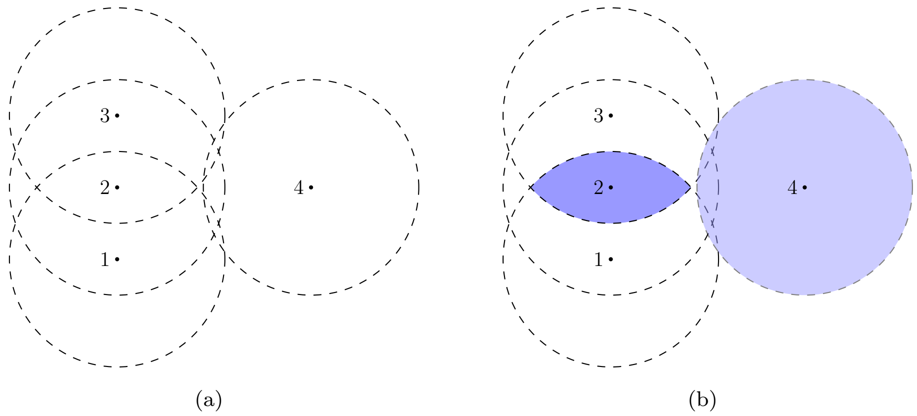


Figure 6.4: An example of a 4-nodes clique. (a) No common intersection region exist for all nodes. (b) Two stop regions are identified after isolating node 4.

Path calculation

The minimum stop path produced by the algorithm is defined by the set, Π, that includes all stop regions related to each clique of the graph G. Upon obtaining Π, the MSP algorithm computes the best path allowing the MC to travel around the calculated stop positions in order to charge all nodes. For this, we apply a Polynomial Time Approximation Scheme (PTAS) for the Traveling Salesman Problem (TSP) on the set Π. The aim is to obtain a minimum-length charging path that includes all the calculated stop positions.

Sojourn durations

Finally, the last step of the MSP algorithm consists in calculating the stop durations so that the MC can fully charge the nodes within each stop region. This duration, which is calculated upon the MC arrival to each stop location, depends on the requesting nodes' battery levels and on the distances separating every node to the stop location. It is calculated as follows.

Let s_j be one of the stop locations in the calculated charging path. The MC simultaneously charges all the nodes that are reached by its charging radius. The received power $p_i(s_j)$ by a sensor node i located at a distance $d_{i,j}$ from this stopping point is:

$$p_i(s_j) = \mu(d_{i,j})p_t, \tag{6.5}$$

where p_t denotes MC's transmission power for wireless recharging, and $\mu(d_{i,j})$ reflects the efficiency of the wireless energy transfer operation using MWC. The value of this efficiency is always smaller than 1 and polynomially decreases with the distance separating the charging node and the mobile charger [KMS10]. To fully charge a node battery of capacity σ_i, the received power at this node needs to be accumulated during a charging time, $t_i(s_j)$, such that:[1]

$$t_i(s_j) = \frac{\sigma_i}{p_i(s_j)}. \tag{6.6}$$

Since the mobile charger needs to charge all the nodes covered by the current stop point before moving to the next one, the stop duration, $t(s_j)$, of the mobile charger is:

$$t(s_j) = \max_{i \in \mathcal{N}_j}(t_i(s_j)). \tag{6.7}$$

Algorithm 1 summarizes the main steps of the proposed On-demand Multi-node Charging (OMC) scheme including the collection of charging requests, threshold-based tour launching (TTL), and minimum stop path planning (MSP).

Algorithm 1 On-demand Multi-node Charging (OMC).

threshold = FALSE
while NOT threshold **do**
    Receive msg from nodes in set $\mathcal{N} = \{i(x_i, y_i)\}, i = \{1, .., n\}$
    if msg == ALERT **then**
        threshold = TRUE
    else
        Add msg to queue
    end if
end while
$\mathcal{D} = \emptyset$
for $i = 1$ to `length`(queue) **do**
    Compute D_i of node $i(x_i, y_i)$
    $\mathcal{D} = \mathcal{D} \cup D_i$
end for
Calculate graph $G(V, E)$ given $\mathcal{D}$
Find minimum number λ of cliques in G(V,E) using the heuristic of Tseng
$\Pi = \emptyset$
for every clique C_j, $j = 1$ to λ **do**
    Find the set $\mathcal{S}_j$ of k stop regions using iterative routine, $k \geq 1$
    $\Pi = \Pi \cup \mathcal{S}_j$
end for
Π' = ordered set by applying TSP PTAS on Π
for each s in Π' **do**
    Go to s
    Calculate the stop duration $t(s)$ using Eqs. (6.5)-(6.7)
    Charge neighboring nodes for $t(s)$ seconds
end for

[1] A linear model is assumed for the charging time, i.e., non-linearities in the charging process are neglected in this study.

6.6 OMC Algorithm Analysis

In the following, we analyze the worst-case computation complexity of the OMC algorithm and demonstrate that it runs in polynomial time with respect to the number of requesting nodes. In addition, we show through simulation experiments that the used heuristics for clique partitioning makes it possible to deal with the NP-hardness of the optimal BILP solution, while keeping the number of stop locations close to the minimum.

6.6.1 Computation Time Complexity

To calculate the computation time complexity of OMC (Algorithm 1), we assume the worst case where the mobile charger receives the first ALERT message after all the nodes have sent a charging request. Thus, the number of requests received at the mobile charger will be equal to the total number of nodes n. In such situation, the MC starts by executing the first block (lines $1-9$) that consists in verifying wether the received request is an ALERT message or not. The number of steps in this block is bounded by the number of nodes, i.e., a complexity of $\mathcal{O}(n)$.

In the second step (lines $10-15$), the MC calculates the power reception disk for each requesting node and constructs the graph $G(V,E)$ based on the intersection of each disk with the others. Given n power reception disks, mutual intersection verifications can be done in $n(n-1)/2$ steps, i.e., $\mathcal{O}(n^2)$.

Concerning the complexity of the Tseng's clique partitioning heuristic (line 16), we also consider the worst case where the graph resulting from the second step is complete and contains $n(n-1)/2$ edges. The result of the heuristic will be then one clique. For this case, and following the steps detailed in Figure 6.3, the mobile charger starts by searching in $n(n-1)/2$ edges the one with the vertices having the maximum number of common neighbors. When found, the corresponding two vertices will be combined into one vertex, and the resulting graph will contain $n-1$ vertices and $(n-1)(n-2)/2$ edges. Following a similar rationale, the computations in the i^{th} iteration will entail a complexity of $(n-i+1)(n-i)/2$, which represents the number of edges in that iteration. Since the algorithm ends when the graph contains no edges (i.e., $i=n$), the total number of iterations is n. Consequently, the overall complexity of the clique partitioning heuristic is obtained by summing the computation complexity along the n iterations:

$$\sum_{i=1}^{n} \frac{(n-i+1)(n-i)}{2} = \mathcal{O}(n^3). \tag{6.8}$$

The forth step (lines $17-21$) is only executed if the resulting clique, which in our case has n vertices, does not have a common intersection region for all the nodes' reception disks. In this case, the routine starts searching for two stop regions instead of one, by choosing one node and isolating it. This will take a maximum of n iterations. If the two stop regions are not found, the MC iteratively chooses two nodes and isolates them, and so on. The heuristic terminates when finding two intersecting regions or by isolating $n-1$ nodes in one iteration. Hence, the maximum number of computations for this step is $\mathcal{O}(n^2)$.

Finally, once the stopping regions are obtained, a quasilinear heuristic for Euclidean TSP in $\mathbb{R}^2$ is used to compute the shortest path that covers all the stop regions. It has been shown in [Aro97] that such a scheme has a complexity of $\mathcal{O}(n(\log(n))^{\mathcal{O}(c)})$ with an approximation ratio of $1 + 1/c$. In our algorithm, we set $c = 2$.

As a result, we conclude that the computing time complexity of OMC is dominated by the clique partitioning heuristic, which leads to a polynomial time complexity of $\mathcal{O}(n^3)$ for the whole algorithm.

6.6.2 Approximation Ratio of the Clique Partitioning Heuristic

The polynomial time complexity of our charging algorithm has been essentially achieved by using a clique partitioning heuristic. The latter allows overcoming the NP-hardness when calculating the minimum number of stop locations within a BILP formulation. In order to show that the enhancement in the computation complexity preserves an acceptable approximation ratio to the optimal number of stop locations, we performed simulation experiments to compare, for different numbers of requesting nodes, the number of stop locations found by an optimal BILP solver and by the adopted clique partitioning heuristic.

As shown in Figure 6.5, the heuristic gives results very close to the optimal solution and the ratio between the two solutions remains within the interval $[1.33, 1.38]$.

6.7 Performance Evaluation

The performance evaluation is conducted in two stages. First, the proposed strategy is simulated in offline scenarios, where each experiment considers a fixed number of requesting nodes for which a charging tour is planned and executed. The objective is to evaluate the effectiveness of minimum stop planning (MSP) neglecting the dynamics of charging request arrivals. In the second stage, the entire OMC scheme (including TTL) is evaluated in on-demand scenarios, and its performance

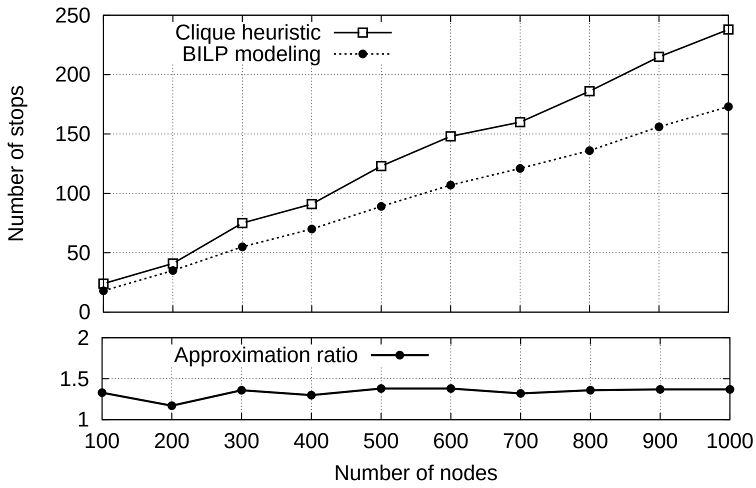


Figure 6.5: Approximation of clique partition heuristic.

is compared to a popular state-of-the-art solution.

6.7.1 Performance of MSP in Offline Scenarios

Offline mobile charger scheduling has been largely dealt with in the literature, and many solutions based on MWC have been proposed. However, some of them, due to their assumptions such as static flow routing and nodes' fixed transmission rates, are limited to a specific application context [XSH+12]. The most related and recent work that can be compared to our solution in an offline scenario is the one by Fu et al. [FCG+16], which we call hereafter Minimum Charging Time (MCT). Similarly to the proposed approach, MCT employs multi-node simultaneous charging and aims at optimizing the charging path (stopping locations) without prior assumptions on the network operations. This solution is described in more details in the previous chapter (section 5.3.1).

Simulation Settings

In offline scenarios, the mobile charger considers a fixed number of nodes that need to be charged periodically. Hence, the performance in such case is unrelated to the MC strategy for tour launching and solely depends on the effectiveness of the path planning strategy in terms of charging and traveling energy drained by the MC.

To evaluate the performance of the proposed minimum stop planning (MSP) algorithm, a set of nodes with different battery capacities ($\sigma_i \in [25, 50]$ J) is considered. The energy consumed in charging operations is computed using the experimental measurements on the efficiency of simultaneous wireless energy transfer [KMS10].

By undertaking a curve fitting on these experiment results, the equation that computes the energy efficiency transfer $\mu(d)$ as a function of the distance between the mobile charger and charged node is:

$$\mu(d) = -0.0958d^2 - 0.0377d + 1.0 \tag{6.9}$$

Assuming $p_t = 5$ W (MC transmission power), and a minimum received power threshold allowing a sensor node to be charged, $p_{\min} = 1$ W. The maximum charging range for the mobile charger following the previous equation would be, $r_c = 2.7$ m.

Furthermore, to reflect mobility in a realistic environment, the motion characteristics of the Pioneer 3DX robot are considered for the mobile charger MC [Pio]. Hence, to travel from a charging point to another, the MC increases its traveling speed with an acceleration of $a = 0.3$ m/s^2. If the maximum velocity $v_{\max} = 2$ m/s is reached, the MC keeps traveling with this constant speed before decelerating to stop at the destination. To measure the energy consumed by the MC for traveling along the charging path, we use the study presented in [MLHL06] on the Pioneer 3DX robot. There, it has been experimentally shown that the traveling power consumption varies linearly with the robot speed following the equation: $p_{\text{travel}} = 7.4v + 0.29$. Finally, in the following plots, the results are presented with error bars of 95% confidence interval.

Results for Low and Medium Scale Networks

In the following, the performance of MSP is compared against MCT [FCG+16] by varying the network size from 10 to 100 nodes. For each simulation scenario, the nodes are randomly deployed within a square area of 25×25 m^2.

Figure 6.6 shows the number of stop locations on the charging paths for MSP and MCT. As shown, the number of stop locations with MSP increases very slowly with the number of nodes. It remains low compared to the number of charged nodes in the network (25 stops for 100 nodes). In contrast, the number of stops in MCT increases linearly but much faster than MSP and reaches high values for higher number of charged nodes. In fact, since MCT only focuses on optimizing the charging energy, the mobile charger tends to visit each node individually to perform the charging operations from shorter distances. This explains the high number of stops in MCT.

In MSP, minimizing the number of stop points makes it possible to optimize the charging energy, but in a different way. In fact, rather than minimizing the charging energy by enhancing the efficiency of energy transfer, MSP tends to maximize the

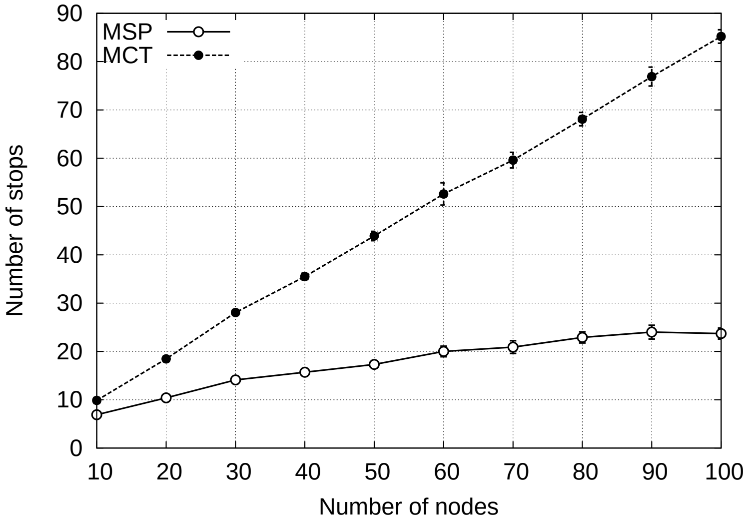


Figure 6.6: Number of stop locations *vs* network size.

number of nodes that can be charged simultaneously in order to reap the full benefits of simultaneous multi-node charging technology. This is shown in Figure 6.7, where MSP is shown to consume more energy for charging the nodes, but the measured values remain relatively close to MCT that consumes a near-optimal charging energy, as demonstrated in [FCG+16]. Moreover, the plots show a similar rise shape for an increasing number of nodes. It is worth noting that the difference between MCT and MSP in this figure is smaller than that in the previous one.

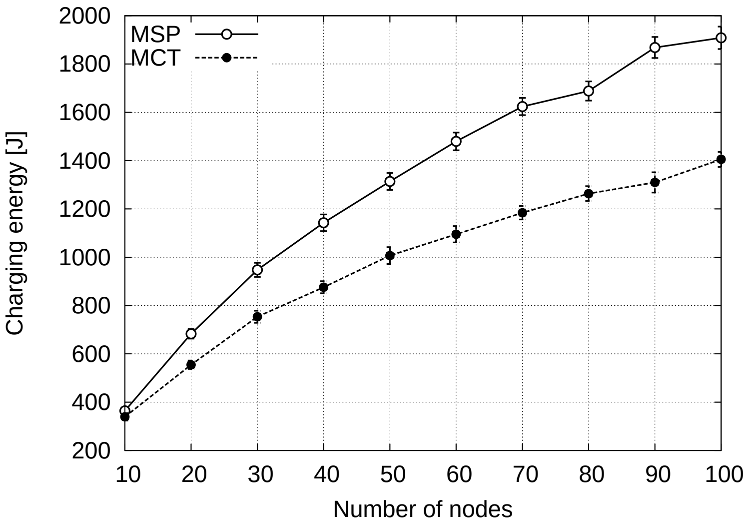


Figure 6.7: Charging energy *vs* network size.

From Figure 6.8, it can be seen that MSP considerably reduces the traveling energy *vs* MCT. This is due to the low number of stops of MSP, which helps reduce the length of charging paths and, in turn, the energy expenditure for traveling. Also, minimizing the number of nodes in the charging path optimizes the motion of the MC, which then drains less energy (note that a higher number of stops entails a higher energy consumption for the MC due to repeated accelerations and decelerations, and high dynamics in traveling speed).

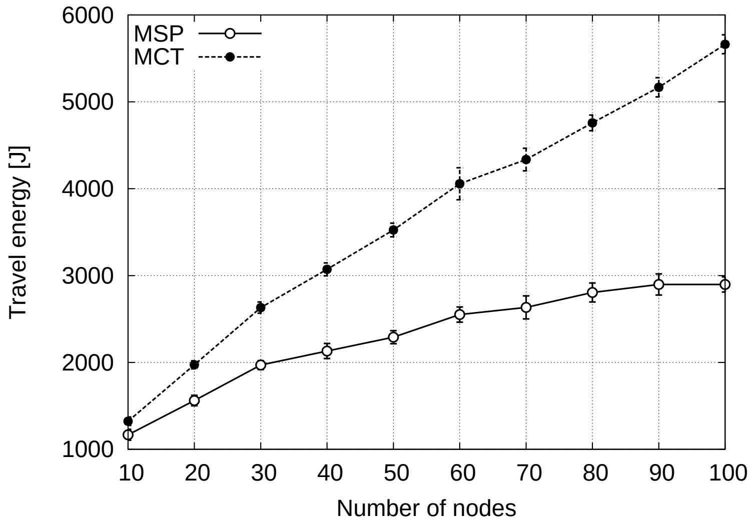


Figure 6.8: Travel energy *vs* network size.

Figure 6.9 illustrates the total energy consumed by the mobile charger for both charging nodes and traveling around the path. We remark that for a relatively low number of nodes ($n \leq 20$), the two schemes consume almost the same amount of energy. However, this amount becomes higher as the number of nodes increases. This is explained by the fact that the optimization on charging energy in MCT cannot compensate for the high traveling energy expenditure due to charging a high number of nodes. Consequently, we conclude that for large-scale networks, and when using simultaneous multi-node recharging, the total energy expenditure of the mobile charger is more impacted by the traveling energy than by the charging one, and that our technique effectively tackles this fact.

The scalability of a wireless recharging scheme for an increasing number of nodes should not only be measured in terms of its energy efficiency. It is also important to consider the complexity entailed in the computation of charging path and stop durations. The entity responsible for these calculations in rechargeable WSNs is the MC. Although the latter is assumed to be more powerful in terms of computation and memory capacity compared to the sensor nodes, the computing overhead of the charging path and stop durations needs to remain acceptable to make the solution practical. In Figure 6.10, the time to compute the charging path and stop durations is shown. The experiments are performed on a desktop computer with an Intel Core i3 CPU and 4 GB of RAM, running Windows8. As it can be noted, MCT is very demanding in terms of computing time. For example, calculating the charging path

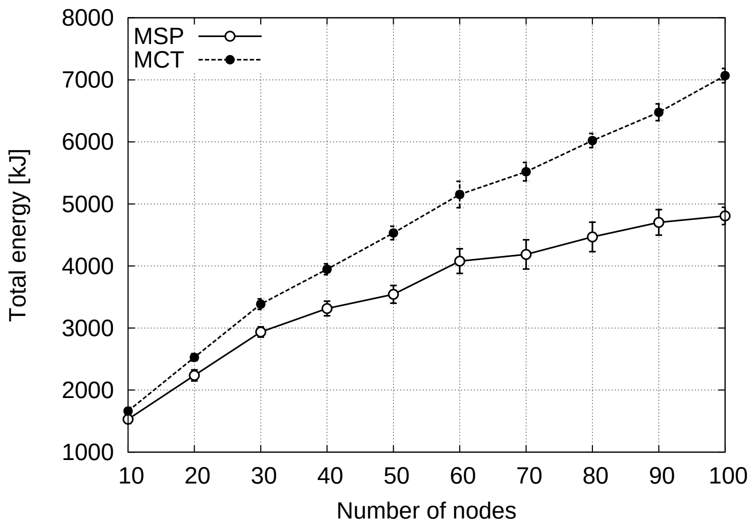


Figure 6.9: Total energy *vs* network size.

for 100 nodes takes longer than 7,000 s, while the MSP calculation time did not exceed 10 s. This considerable gap is due to the difference in the two approaches to compute the charging path. MCT solves a linear programming optimization problem where the number of variables increases exponentially with the number of nodes. Instead, MSP uses a low-complexity heuristics that scales with the problem size.

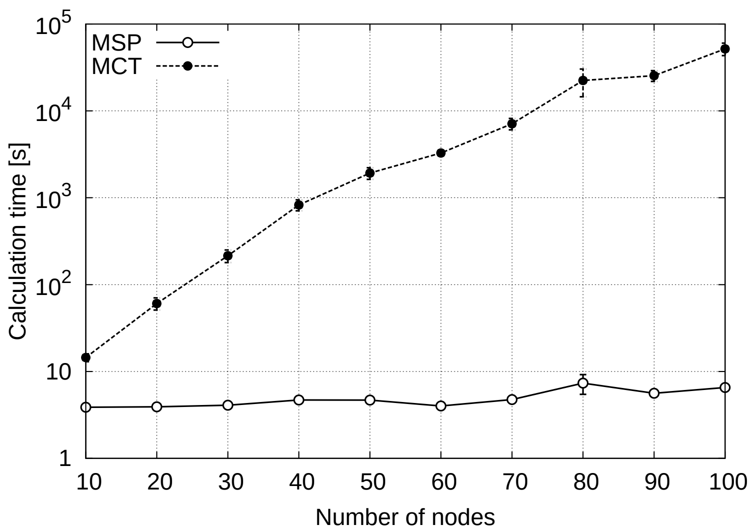


Figure 6.10: Computing time *vs* network size.

Results for Large-Scale Networks

To better demonstrate the scalability of MSP in large-scale networks, we vary the number of charged nodes from 100 to 1,000. The nodes are randomly deployed in a square area of 100×100 m^2. Due to the high complexity of MCT, we were unable to execute it within an acceptable computing time. As shown in Figure 6.11, the total energy consumption of MSP increases smoothly as the number of charged nodes increases, which demonstrates its scalability in large-scale sensor networks.

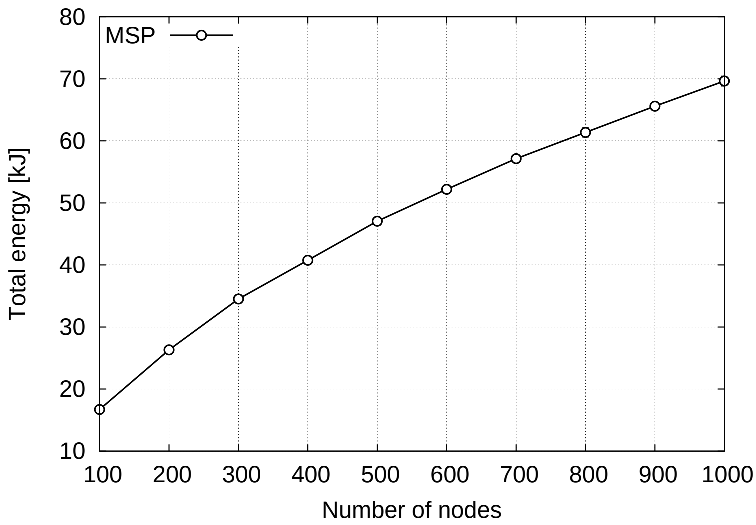


Figure 6.11: MSP performance in large scale networks.

6.7.2 Solution Performance in On-Demand Scenarios

Simulation Settings

Next, the performance of the entire OMC charging algorithm is studied in the context of on-demand charging scenarios. Each experiments considers a WSN with a different number of nodes that varies from 50 to 500. To emulate a sensible energy consumption model, we simulate an event-based sensing application where events are generated and detected by a random subset of sensors. Energy is consumed as a result of communication and sensing operations. The number of nodes participating in the event detection and reporting is proportional to the total number of nodes in the WSN. This allows us to study the scalability of OMC with respect to a higher charging request load and an increasing network size. The energy consumption models for motion and energy consumption are the same as those considered in the offline scenario.

Since none of the existing on-demand charging solutions uses multi-node simultaneous power transfer, the proposed scheme is compared against a popular approach and our own variation of it. The two schemes are: i) Nearest Job Next with Preemption (NJNP) [HKG+15], ii) a modified version of NJNP, with added MWC capabilities (called MWC-NJNP).

As emphasized in section 5.3.2, NJNP was shown to achieve near optimal charging delays using point to point wireless power transfer. It prioritizes the requesting node located at the nearest position from the MC. Moreover, the MC is forced to preempt its motion towards the next scheduled node if a new request from a closer node is received meanwhile. In MWC-NJNP, the MC charges all the requesting nodes within its power transmission range upon arriving to the scheduled node.

In the following, OMC, NJNP and MWC-NJNP are compared in terms of energy consumption and ability to serve the requesting nodes within a bounded delay. For this, we define a new metric that measures the total failure time due to battery exhaustion. We believe that this metric better reflects the service quality of on-demand charging techniques (see our discussion in section 6.2.2) than the traditionally adopted average charging delay. Energy and delay metrics are measured for a simulation duration of 500 seconds.

Results and Discussion

Figure 6.12 depicts the total energy consumption, including charging and traveling energy, for the three strategies. This figure shows that MWC-NJNP enhances the MC's performance in terms of energy consumption. This is mainly due to the reduction in charging energy obtained through MWC, while NJNP charges each node individually, even when requesting nodes are close enough to be simultaneously charged. The figure clearly shows that OMC outperforms, not only NJNP, but also MWC-NJNP. This is explained as follows:

- In MWC-NJNP, the mobile charger starts charging as soon as the first request is received (in order to reduce as much as possible the charging delay). This lowers the number of requesting nodes to be charged in the MC's queue and makes it difficult to group them into subsets to take advantage of simultaneous charging. On the other hand, the adoption of a request collection period, along with threshold-based tour launching of OMC increases the number of requesting nodes in the MC's queue. This provides more aggregation opportunities and a better exploitation of MWC.

- In MWC-NJNP, the mobile charger tends to stop by a location that is close to the next scheduled node only. This prevents the MC from covering other requesting nodes that could be simultaneously charged, and leads to additional traveling and charging energy consumption. In OMC, the stop positions computed through MSP allow the MC to cover the maximum number of requesting nodes within each stopping point. This plays an important role in the optimization of charging and traveling energies.

- The greedy approach of MWC-NJNP forces the MC to proceed with serving any request, even if the position of the nearest requesting node is relatively far. This usually results in a "zigzag" movement of the MC across the WSN, e.g., when receiving a new request from a node located in the vicinity of its initial position. Conversely, the charging tours in OMC make it possible to prevent these undesired back-and-forth movements and shorten the total traveled distance.

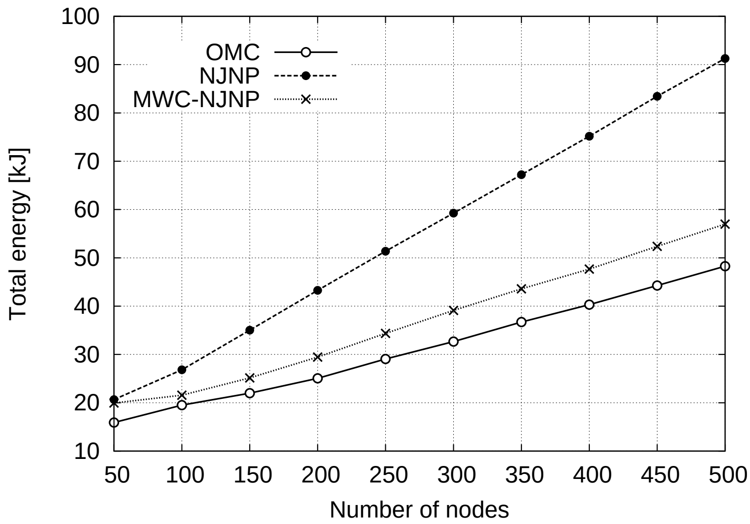


Figure 6.12: MC's energy consumption *vs* number of requesting nodes.

Finally, we notice that the energy consumption of OMC increases sublinearly with the network size and the charging request load. This demonstrates the scalability of the proposed on-demand scheme in terms of energy consumption.

Concerning the total failure time, a considerable improvement in OMC is to be noted, compared to NJNP and MWC-NJNP (Figure 6.13). The gap between OMC and the other schemes becomes larger for higher number of nodes. This confirms the fact that the objective of minimizing charging delays, traditionally adopted in existing on-demand schemes, is practically inefficient. For example, NJNP and MWC-NJNP prioritize the nearest requesting nodes in order to optimize the overall charging delay. Consequently, all requesting nodes that are located in the MC's vicinity will see their requests served in a short time, even if they do not need such a prompt recharge. This entails that farther nodes will be penalized by waiting longer times, which causes their failure due to battery exhaustion. The TTL mechanism of OMC forces the mobile charger to proceed in a new charging tour as soon as one of the requesting nodes sends an ALERT message, without considering new requests. This guarantees a bounded charging delay for all requesting nodes and avoids battery depletion failures.

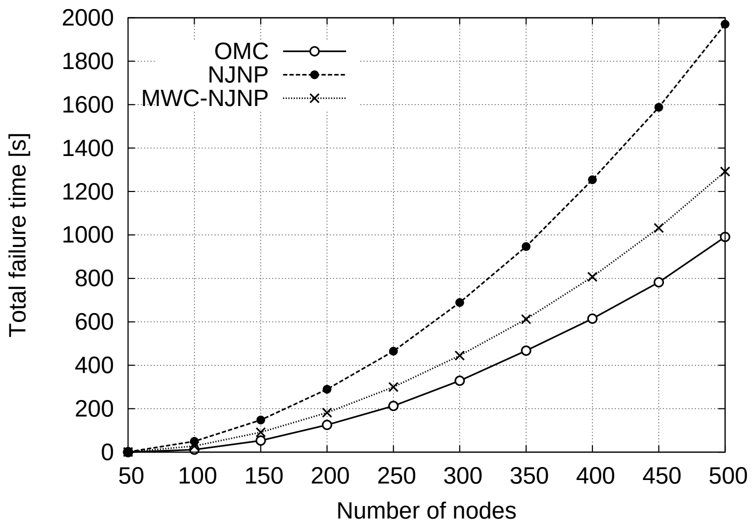


Figure 6.13: Total node's failure time *vs* number of requesting nodes.

6.7.3 Design Choice for TTL Thresholds

The practical design of OMC relies on a TTL mechanism that uses the nodes' energy level thresholds L_r and L_c to trigger charging requests and ALERT messages. These thresholds influence the behavior of the mobile charger and of the requesting nodes, and their choice considerably impacts the solution performance. However, L_c has a more important role as compared to L_r, since it determines when the MC stops collecting requests and starts a new charging tour. Consequently, a judicious approach that we adopt consists in fixing the value of the charging request threshold L_r, and empirically choosing a suitable L_c, so as to obtain a suitable tradeoff between competing performance objectives.

The empirical calculation of L_c for a given network scenario can be attained through numerical simulation. For example, Figure 6.14 shows simulation results for a sensor network of 50 nodes. L_r is fixed to 0.3 (expressed as a ratio of the battery capacity) and L_c is varied from 0.1 to 0.26. The performance of OMC is then measured in terms of MC's average energy draining rate (EDR) per unit of time, and average node failure probability (NFP). As expected, EDR decreases with an increasing L_c. In fact, if we set $L_c << L_r$, we allow for collection of a high number of requests before starting a new charging tour. When a new tour is launched, The MC has an opportunity of aggregating more nodes, thus increasing the charging efficiency (or equivalently decreasing EDR). The tours, on the other hand, will tend to start late because of a longer request collection period. Moreover, they will last longer as a large number of nodes is to be charged, implying the visit of many locations. This has the impact of increasing NFP, since requesting nodes have a long time to wait before being served. As L_c increases and gets closer to L_r, the number of collected requests decreases. This implies the following facts: 1) the tours will take a shorter amount of time (NFP decreases) and 2) a smaller number of nodes will be charged within each tour, resulting in fewer aggregation opportunities (EDR increases).

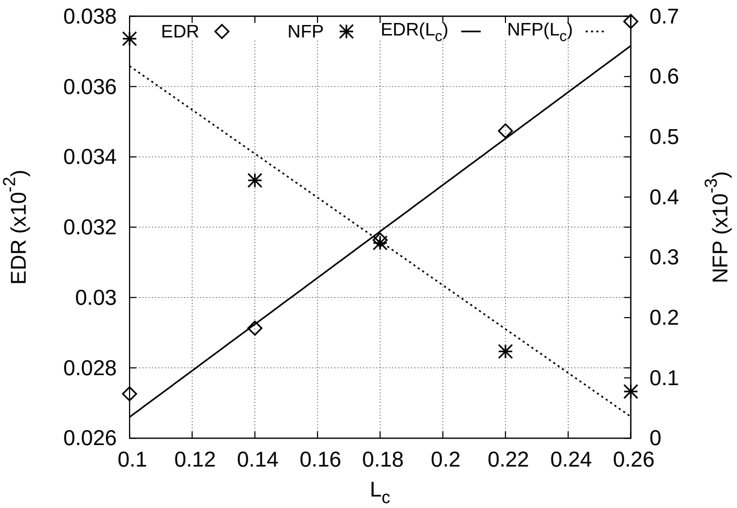


Figure 6.14: L_c variation impact on EDR and NFP.

One sensible way to pick the L_c value that optimizes both EDR and NFP consists in using multi-objective optimization approaches [Ehr05]. For this, we apply curve fitting to the simulation results in order to derive the functions expressing EDR and NFP in terms of L_c. As shown in Figure 6.14, the resulting curves are linear, since $\text{EDR}(L_c) \approx= a_1 L_c + b_1$, and $\text{NFP}(L_c) \approx a_2 L_c + b_2$, with $a_1 = 0.066$, $b_1 = 0.020$, $a_2 = -3.636$ and $b_2 = 0.981$.

Minimizing EDR and NFP simultaneously implies their combination in an objective function to be minimized considering a weight factor $w > 0$, which encodes the designer's preference for one of the metrics. As an example, we adopt the quadratic sum formula used in the *least square optimization* method, as follows: $f(w) = (\text{EDR})^2 + w(\text{NFP})^2$. Here, the designer may choose $w > 1$ if NFP is preferred. Otherwise w needs to be less than 1, if a preference is accorded to EDR.

As a result, the optimal L_c value is the one that minimizes the objective function $f(w)$, leading to:

$$L_c(w) = -\frac{a_1 b_1 + w a_2 b_2}{(a_1)^2 + w(a_2)^2}\,. \tag{6.10}$$

6.8 Conclusion

Scheduling of a mobile charger that performs wireless charging of sensor nodes has been considered in this chapter, exploiting multi-node power transfer and devising a new scheme for on-demand scenarios. The proposed technique is based on grouping the charging requests and appropriately launching and planning the charging tours. For the tour launching, threshold-based tour launching (TTL) has been proposed, whereas for the tours, a new path planning strategy has been presented, based on minimizing the number of stopping points. Compared to previous on-demand solutions, the proposed technique postpones the launching of the tours in an attempt to maximize aggregation opportunities for requesting nodes, for their simultaneous charge. We numerically found that this has a very positive impact on energy efficiency and reduces failures due to battery depletion. As a drawback, the waiting time increases slightly, but this can be tolerated as long as the nodes receive energy before their batteries drain out. A new performance metric is defined to clarify this aspect. At the tour planning level of the proposed strategy, a new modeling approach is used. It leverages simultaneous energy transfer to multiple nodes by maximizing the number of sensors that are charged at each stop. As the problem is NP-hard, we model it through a clique partitioning approach, which is solved through lightweight heuristics. The resulting charging algorithm is shown to run in cubic time with respect to network size, while ensuring a good approximation to the minimum number of stops.

The proposed scheme has been evaluated by extensive simulations in offline and on-demand scenarios, and its different parts have been compared to relevant solutions from the literature. Simulation results show that the proposed path planning strategy reduces the number of stops in the charging tours and the energy consumed by the mobile charger, while also being computationally efficient. The results in the on-demand scenario demonstrate the effectiveness of the path construction strategy, TTL, and multi-node charging, in reducing node failures, as well as the total energy consumed by the mobile charger. Clear improvements against state-of-the-art solutions have been demonstrated.

Chapter 7

Conclusion & Perspectives

7.1 Summary

Efficient energy management in wireless sensor networks endows them with desired availability and reliability, which strengthens their dependability and considerably enlarges the span of market opportunities.

In this thesis, we investigated the two fields related to energy management, namely energy conservation and energy harvesting, which are both important and complementary. Indeed, while the former field aims to optimize the consumption of the available energy resource among the different network services, the second field provides efficient algorithms to continuously renew this energy resource, in order to ensure sustainable service execution.

Concerning energy conservation, a special interest has been accorded to routing protocols, considered as a pilar networking service in WSNs. Based on the scheme of Directed Diffusion, we proposed a novel protocol with the objective to achieve energy efficiency in dense deployment scenarios that characterizes IoT-WSNs. To minimize energy consumption, two techniques are proposed. Firstly, a power-aware topology control technique (PATC) is employed as a configuration phase. PATC reduces the network connectivity by dropping inefficient transmission links, while maintaining energy efficient routes between the sink and sensor nodes. Secondly, a simple energy consumption metric is introduced allowing the choice of the route with the minimum energy consumption among available paths. The metric calculation is performed using the energy information collected during the PATC phase, without the need of any additional message overhead. The simulation results showed a considerable improvement of routing performance in terms of energy consumption, compared to the original scheme of Directed Diffusion

As for energy harvesting, we started our study with a comprehensive survey on existing strategies for energy provision in WSNs, using wireless power transfer technologies. It has been concluded that the model relying a mobile charger and on-demand scheduling represents the most suitable alternative that fits the dynamic and large-scale nature of WSNs. However, it has been noticed that none of the solutions based on this model employs the multi-node wireless power transfer that allows charging multiple nodes simultaneously. This entails low scalability in large-scale and dense networks. To cope with this problem, we proposed a on-demand mobile charging strategy, based on multi-node power transfer. Our strategy consists in grouping the charging requests from nodes with low-battery levels, then appropriately planning and launching the charging tours. The Threshold-based Tour Launching (TTL) technique is designed to postpones launching of the charging tour until reception of sufficient number of requests, which maximizes simultaneous charging opportunities. Despite of the slight increase in charging delays, the numerical results demonstrated the positive impact of this strategy on reducing node failures caused by battery depletion. At the tour planning level, our model also leverages simultaneous energy transfer by maximizing the number of sensors that can be simultaneously charged at each stop of the tour. Given the NP-hardness of the solution, the initial model has been reformulated as a clique partitioning problem and lightweight heuristic has been developed to calculate the charging path. The proposed charging techniques have been evaluated with extensive simulation experiments and compared to relevant approaches in both scenarios of offline and on-demand scheduling. The results demonstrated the effectiveness of our path construction strategy, TTL launching mechanism, and multi-node power transfer in enhancing the network dependability by reducing the nodes' battery exhaustion rate, as well as the total energy consumed by the mobile charger.

7.2 Perspectives

We would like to extend our charging strategy by investigating the means to model the optimal launching of the charging tours that guarantees the best tradeoff between charging delays and energy consumed by the mobile charger. The current TTL mechanism is designed to postpone charging tours until reception of the first critical request from a previously requesting node. However, this strategy relies heavily on the selected values of the battery level thresholds. Hence, it only provides an empirical indication on the time criticality of charging operation, which does not necessarily meet the optimal charging opportunity in terms of mitigating node's failures and minimizing energy consumption.

Indeed, a node that emitted a critical alert, or even other requesting nodes that haven't observed the critical threshold, can die before being charged during the launched tour, due to an unusually fast battery depletion. In this case, waiting for critical request message to launch the charging tour will be inefficient for the mobile charger in preventing nodes failures. In contrast, the nodes' energy consumption rate may slow down after attaining the critical threshold. Hence, launching the tour immediately after reception of a critical request might be under-optimal in terms of energy consumption, since the mobile charger can postpone the charging tour until reception of additional requests, to maximize the multi-node charging opportunities. Consequently, it is important for the charger to compute the best time when it should make a decision for optimal tour launching. We would like to model this decision problem using the stochastic tools of Markov Decision Process (MDP). We believe that solving the tour launching problem through this modeling allows an improvement of our charging strategy in terms of energy consumption, and nodes failures mitigation.

As for energy conservation, the design of routing protocols that cooperate with the employed energy provision strategy represents an interesting area of research. More precisely, the idea consists in a routing protocol that adapts to our charging strategy by selecting the routes that are geographically close to each others. Although this may results in the use of sub-optimal routes, it can reduce the number of charging requests coming from scattered locations. This is expected to leverage multi-nodes charging via our approach, and consequently enhances the energy efficiency of the whole network.

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