Battery-Free Wireless Sensor Networks: A Comprehensive Survey

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***Abstract*—Battery-free wireless sensor network (including energy harvesting network and energy rechargeable network) is a new network architecture that has been proposed in recent years to solve the lifetime limitation problem of conventional wireless sensor networks. Battery-free sensor nodes can harvest energy from environmental energy resources or from artificial power stations. Thus, the lifetime of a battery-free wireless sensor network is unlimited in terms of energy. The specific properties of battery-free wireless sensor networks have brought new challenges in fundamental issues, such as energy management, networking and data acquisition, which means the existing algorithms in wireless sensor networks cannot be adopted directly. The battery-free wireless sensor network can be regarded as a totally new topic in IoT and has attracted much attention from researchers. Many algorithms have been proposed to solve the fundamental problems in battery-free wireless sensor networks. The objective of this survey is to comprehensively summarize and analyze the existing works. In this survey, we first introduce the existing algorithms from three fundamental aspects including energy management, networking and data acquisition. Then we present some specific applications of battery-free wireless sensor networks.**

***Index Terms*—Internet of Things, sensor networks, battery-free, communication, wireless charging, networking, coverage.**

I. Introduction

Internet of Things (IoT) [1] is an effective paradigm to help people access the physical world. It acts as a bridge connecting the physical world and the cyber world. Furthermore, IoT is an indispensable component for the future 6G network [2].

Wireless Sensor Networks (WSNs) are fundamental building blocks in many IoT applications. A WSN consists of sensor nodes which are inexpensive, tiny, powered by batteries, and networked through wireless communications. A WSN can be easily deployed into all kinds of environments to collect sensory data from the physical world and provide data processing services, such as data query [3], data mining [4], data gathering [5] and so on, to the IoT users. WSNs may be employed in many IoT applications, such as environment monitoring [6], battlefield surveillance [7], and industry process control [8]. In the last decades, WSNs have received tremendous attention from both industry and academia. Many researchers and engineers have made tremendous contributions on the design of algorithms, protocols, systems and applications for the development and deployment of WSNs. Modern IoT systems such as edge/fog computing could also benefit from the progress of WSNs. Therefore, the influence of WSNs is profound.

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Although WSNs have many advantages, there is still a barrier which is the battery usage. It causes the following two primary problems: i) Limited network lifetime. The lifetime of a sensor node is mainly decided by its battery's lifetime. A WSN will be non-functional or even dead when a certain number of nodes or some key nodes run out of battery. ii) Environment pollution. Usually, a WSN is deployed in a natural environment, and exhausted batteries may cause environment pollution. Such two problems hinder further development and employment of WSNs. Researchers have spent much effort to solve the problems. One solution is to replace batteries [9], which is almost impossible for large scale networks or inaccessible areas, especially for battlefields and poisoned regions. Another solution is to design energy-efficient algorithms [10] to schedule the working periods of sensor nodes so that network lifetime can be extended to a maximum extent. Unfortunately, for both solutions, the resulted network lifetime is still limited.

In order to completely overcome the challenges caused by battery usage, a new network architecture, Battery-Free Wireless Sensor Network (BF-WSN), has been proposed. It is also known as the *energy harvesting sensor network* or *energy rechargeable sensor network*. Thanks to the energy harvesting capability, a battery-free sensor node can acquire energy from external resources, such as natural energy (solar energy, wind energy, etc.) and artificial energy (RF signal energy). Obviously, natural energy is unlimited. Artificial energy resources, such as RF power stations and RFID readers, always have stable energy supplies. Therefore, the lifetime of a BF-WSN is unlimited in terms of energy. Furthermore, a battery-free sensor node always uses a super capacitor to store energy, which is environmentally friendly [11]. For example, in a wildfire monitoring application, a solar energy powered BF-WSN can be deployed in a forest to monitor the temperature of the surrounding environment.

It seems that BF-WSNs can perfectly prevent the problems emerging in traditional WSNs. Unfortunately, on the other hand, most of the current algorithms for traditional WSNs cannot be adopted in BF-WSNs. There are three fundamental issues in both WSNs and BF-WSNs, which are energy management, networking and data acquisition. As shown in

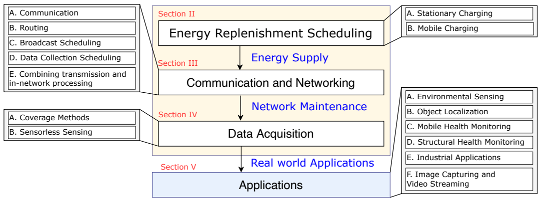

Fig. 1: The structure of this survey.

Fig. 1, energy replenishment resolves the energy supply issue for sensor nodes, networking protocols enable communications among sensor nodes, and data acquisition strategies help a network acquire enough information from the physical world. The corresponding algorithms for WSNs focus on how to save energy and prolong network lifetime [5], [12]–[16]. However, in BF-WSNs, energy supply is infinite and the network lifetime is unlimited in terms of energy. Thus, when designing algorithms for BF-WSNs, the motivation is changed from "how to save energy" to "how to use energy efficiently to improve network performance". Some surveys [17]–[23] have introduced the algorithms in BF-WSNs. However, these surveys only focus on some specific techniques in BF-WSNs, such as backscatter communication [17], [22], visible light communication [21], RFID based sensing [18]–[20] and sensorless sensing [23].

In this article, as illustrated in Fig. 1, we provide a comprehensive survey for the algorithms in BF-WSNs and the following issues are covered:

1) Energy Replenishment Scheduling. We introduce the algorithms for charger placement and scheduling.
2) Communication and Networking. We present the works for broadcasting, data collection, data aggregation, and routing.
3) Data Acquisition. We elaborate the algorithms for sensorless sensing and data coverage.
4) Applications. We summarize some specific applications, such as health monitoring, temperature and humidity sensing, video streaming, object localization, and industrial applications.

The rest of the paper is organized as follows. Section II is dedicated to energy replenishment scheduling. Communication and networking algorithms are introduced in Section III. The data acquisition methods are covered in Section IV. In Section V, some specific applications are presented. Section VI concludes the survey.

II. Energy Replenishment Scheduling

Since sensor nodes in BF-WSNs do not have batteries, energy replenishment becomes a fundamental and essential service to support the continuous operation of a BF-WSN. To charge sensor nodes which may be deployed in any area even with obstacles, Wireless Power Transfer (WPT) has been introduced as a controllable and sustainable way in BF-WSNs. With this technology, energy can be wirelessly transferred from chargers to rechargeable nodes such as RFID tags, sensors, smartphones, and Tesla cars. However, how to charge nodes efficiently considering different utility objectives, such as prolonging network lifetime, maximizing charging efficiency, minimizing energy provisioning cost and charging latency, etc., emerge as the challenging problems in BF-WSNs, and have drawn extensive attentions from researchers.

According to the behaviors of chargers, the existing works for energy replenishment scheduling can be classified into two classes: stationary charging and mobile charging. In stationary charging, a set of chargers (*i.e.* Powercast [24]) is assumed to be located at a set of fixed points to conduct energy transferring. While, in mobile charging, a single charger or a group of chargers is assumed to move around a network to charge all the rechargeable nodes.

A. Stationary Charging

A stationary charger, such as Powercast [24], can recharge devices in a fixed direction within a certain distance. In the stationary charging scenario, generally, there is a set of rechargeable nodes deployed in a target area, and a single charger (or a set of charges) which is responsible for charging these rechargeable nodes and collecting the sampled data from these nodes at a fixed position (or or a group of positions). Since the received charging power of each rechargeable node is related to the distance between it to the chargers, the orientation of chargers, and the power of chargers, thus, how to computed the optimal positions, the orientations, and the power of the chargers, becomes essential for BF-WSNs to support its continuous operation with minimum cost.

For stationary charging, the existing works mainly fall into the following two categories: 1) charger deployment, *i.e.*, how to deploy the chargers to guarantee each rechargeable node can harvest enough energy; 2) charger scheduling, *i.e.*, how to schedule the status of chargers (*i.e.*, active/inactive), the orientations of the chargers, the power of the chargers, etc., to optimize the system utility.

1) Charger Deployment Algorithms in BF-WSNs: Considering the number of chargers and their positions, the charger deployment algorithms in BF-WSNs try to find the minimum number of chargers or the optimal positions of a given number of chargers to satisfy different objectives. The overview of these algorithms is shown in Table 1, and the details of these works are summarized as follows.

Firstly, the charger deployment problem which tries to minimize the number of chargers to (fully or partially) cover the whole area is investigated in [25]–[33]. The main purpose is to ensure that any point in the target area can obtain a sufficient charging power by the rechargeable nodes.

In [25], [26], to ensure that the rechargeable nodes can harvest sufficient energy for continuous operation, two kinds of energy provisioning problems are considered, *i.e.*, point provisioning and path provisioning. In the point provisioning problem, the number of chargers needs to be optimized to ensure that any point in the target area can obtain a sufficient charging rate. For this problem, through exploiting the triangular deployment technique, a lower bound of the optimal solution is firstly derived and then an approximate method based on a designed side length of the triangles is provided. In the path provisioning problem, the rechargeable nodes are assumed that they can move in the network to further

	Optimization Object	Network Performance	Target Area	Direction of Chargers
[25]–[29]	the number of chargers	full coverage	2D area	omnidirectional
[30]	the number of chargers	full coverage	2D area	directional
[31]	the number of chargers	full coverage	3D area	omnidirectional
[32], [33]	the number of chargers	communication latency	2D area	omnidirectional
[34]	the positions of chargers	partial coverage	2D area	omnidirectional
[35], [36]	the positions of chargers	charging utility	2D area	omnidirectional
[37], [38]	the positions of chargers	charging utility	2D area	directional
[39]	the positions of rechargeable nodes	charging cost	2D area	omnidirectional
[40]	the positions of connected chargers	charging utility	2D area	omnidirectional
[41]	the positions and directions of chargers	charging utility	2D area with obstacles	directional
[42], [43]	the positions of chargers	charging utility and EMR safety	2D area	directional

TABLE I: Overview of Charger Deployment Algorithms

reduce the number of required chargers. In this case, some rechargeable nodes can harvest more energy in the power-rich areas. Under such a model, given the mobility pattern of the rechargeable nodes, they try to ensure the cumulative harvested energy in a period is larger than a certain threshold. A triangular deployment based method is also proposed for this problem.

The work in [27] investigates the co-deployment problem of chargers and base stations. In their network model, each rechargeable node has a fixed sampling rate for environment sensing, and the sampled data is required to be uploaded to a base station through either one-hop or multi-hop wireless transmissions. To ensure continuous operation of the rechargeable nodes, a minimum number of chargers and base stations needs to be identified with an optimal deployment strategy and routing path planning. For each sub-problem of deploying chargers or base stations, the authors proved it to be NP-hard. To tackle these problems, the problem of deploying chargers and the problem of deploying base stations are optimized iteratively. In particular, through transforming each sub-problem to a max-flow problem, a set of chargers or base stations are selected based on their contributions to the total flow rate. Then, a greedy algorithm is given for deploying chargers and base stations, respectively. The proposed algorithm is proved to have a guaranteed worst-case bound lnR/ξ, where ξ is a small threshold to ensure the expected data rate can be satisfied and R is the network radius. In addition, the particle swarm optimization based algorithms for the charger deployment problem are studied by [28], [29].

The work in [30] tries to utilize as few directional wireless chargers as possible to cover a whole area, and a heuristic algorithm is proposed. In [31], a more general model is considered, where the rechargeable nodes are deployed in a 3D target area, and each charger is equipped with a 3D-beamforming directional antenna. Two heuristic algorithms are proposed to reduce the number of chargers. In [32], [33], to further reduce the communication latency, the transmission collisions during the deployment of RFID readers are considered. In their works, the RFID readers are regarded as the chargers and the data collection devices simultaneously.

The work in [34] investigates the partial coverage problem. It is assumed that the movement of rechargeable nodes follow some degree of regularity. Under this assumption, the authors try to find the optimal positions of the chargers while the survival rate of the rechargeable nodes is maximized. In this work, to reduce the total deployment cost, the partial coverage approach (some rechargeable nodes may run out of energy) is employed, and the survival rate is defined as the ratio of the number of dead rechargeable nodes to the total number of rechargeable nodes. This problem is proved to be NP-hard by reduction from the Min-Sum Multicenter problem, and a heuristic method is proposed.

Secondly, the charger placement problem which tries to find the optimal positions of chargers considering the harvested energy at rechargeable nodes (*i.e.*, charging utility) is investigated in [35]–[39].

The work in [35] investigates the charger deployment problem which tries to optimize the overall charging utility in a 2D target area. Due to the hardware constraints, each rechargeable node has an upper bound for its received charging power. The charging utility is defined as follows: 1) it is firstly proportional to its received charging power; 2) when the received charging power reaches the upper bound, it becomes constant. Specifically, given a set of candidate points which can be used for placing chargers, the following optimization problem is considered: finding a charger deployment strategy and its corresponding power allocation schedule while the overall charging utility is maximized subject to a power budget. It has been proved that this problem is NP-complete. By assuming a set of adjustable power levels, an approximation algorithm with an ratio of $(1 - 1/\epsilon)/2L$ is proposed, where L is the maximum power level of a charger and ϵ is a much small number. In [36], the authors study the charger deployment problem when the chargers have limited mobility. To reduce the searching space of the proposed problem, they proposed a method to approximate the nonlinear charging power of chargers and an approach to construct the maximal covered set with uniform subareas. A geometrical technique is also proposed to transform the proposed problem to a mixed integer nonlinear programming problem. Then, an approximation algorithm with a ratio $(1/2 - \epsilon)$ is proposed with linear programming.

The work in [37], [38] exploit the same concept of charging utility as in [35]. Different from [35], the directional charging model is employed. In such a charging model, a charger s_i with a orientation vector $\overrightarrow{r_\theta}$ can only charge the nodes which are lying in the shape of a sector with charging angle A_s and charging radius D_c. In their charging model, each rechargeable node is also equipped with a directional antenna which can only harvest energy when its orientation and distance from the charger satisfy a certain condition. To determine whether the target area can be omnidirectionally charged with a set of directional chargers, the authors proposed a minimum coverage set extraction technique with area partition, which reduces the continuous search space to a discrete one. A fast determination algorithm is then proposed. In addition, the problem of computing the probability that the target area can be omnidirectionally charged with a set of randomly deployed chargers is also studied. To address this problem, a group of grid points are used to replace the target area to reduce the searching space, and then a relaxation method is employed to approximate the chargers' power. The upper bound of the probability that the whole area can be omnidirectionally charged is derived. In [39], the authors studied the deployment problem of rechargeable nodes and the routing arrangement problem in BF-WSNs, which tries to minimize the total consumed energy of the charger. The problem is proved to be NP-complete and several heuristic algorithms are proposed to address this problem.

Thirdly, considering the connectivity of chargers, the area with obstacles, and the electromagnetic radiation safety, the charger deployment problem is studied by [40]–[43].

The work in [40] investigates the deployment problem with omnidirectional chargers and assume the deployed chargers are connected. The authors tries to maximize the overall charging utility subject to a group of connected chargers. To address this problem, the proposed algorithm mainly includes the following four steps: 1) region division, the whole area is discretized into uniform regular hexagon cells and then classified into different groups; 2) profit assignment, a greedy algorithm is proposed to assign the obtained utility of the candidate positions where the charger can be deployed; 3) Quota Steiner Tree (QST) construction, a Quota Steiner Tree with maximum charging utility is constructed in the connected graph; 4) subtree seelction: a dynamic programming algorithm is proposed to find the best subtree with the given number of chargers in the QST. The algorithm is proved to have an approximation ratio of 1.5 times better than that of the existing algorithms. In addition, the charger deployment problem under directional charging model is also considered in this work.

The work in [41] investigates the charger deployment problem where there exist several obstacles with arbitrary shapes in a 2D plane. Under such a model, an optimal deployment plan of the directional wireless chargers is expected, including the positions and orientations of these chargers, while the total charging utility is maximized. To address this problem, the authors exploit a piece-wise constant function to approximate wireless chargers' power. An area discretizion method is also given to partition the whole area so that a certain type of chargers have constant approximated charging power in the partitioned subareas and a dominating coverage set based algorithm is employed to reduce the searching space. After these transformation, the problem is proved to fall in the realm of optimizing a monotone submodular function with a partition matroid constraint. A greedy algorithm with an approximation ratio of $(1/2-\epsilon)$ is proposed accordingly.

Other papers consider the charger placement problem with electromagnetic radiation (EMR) safety. In [42], [43], the authors try to optimize the overall charging utility subject to the EMR intensity at any point in the target area is not larger than a threshold. Through dividing the whole area into grids with equal length, the problem is formulated into the Multidimensional $0/1$ Knapsack (MDK) problem. Then, based on the existing algorithms for the MDK problem, an approximate algorithm is proposed. The proposed algorithm is proved to have a performance better than $(1-\epsilon)$ of the optimal solution when the EMR threshold is $(1-\epsilon/2)R_t$ and the EMR coverage radius is $(1+\epsilon/2)D$, where ϵ is an arbitrarily small positive value, R_t is the EMR threshold, and D is the EMR coverage radius of chargers.

2) Charger Scheduling Algorithms in BF-WSNs: Some works try to schedule the status, orientations, and power levels of the chargers to satisfy specific requirements, which are summarized in Table II.

The charger scheduling problem considering the status of wireless chargers is studied in [44], [45]. The authors assume there exist a set of wireless chargers deployed in the target area, and consider a simple charger scheduling model where each charger can be either in the on or off status. The objective is to maximize the overall charging utility subject to the charging safety of the whole field, *i.e.*, to ensure the sum of the intensity of EMR at any point in the network does not exceed a certain threshold. This problem is proved to be NP-hard and a solution which can outperform the optimal solution with a relaxed threshold $(1-\epsilon)R_t$ is proposed, where R_t denotes the EMR threshold. The main idea is to employ a constraint reduction method to reduce the constraints in the non-linear optimization problem, and then transform it to a multidimensional 0/1 knapsack problem.

In [46], [47], it is assumed that a rechargeable node can be either in the working status or charging status, and the rechargeable node cannot work and harvest energy simultaneously. The aim is to schedule rechargeable nodes to achieve a desirable network utility, which is proved to be NP-hard. To address this problem, the authors first study a special case of this problem, where all the rechargeable nodes are only one hop away from the charger. Through employing geometric programming and convex optimization, an optimal solution is obtained. For the general case with a multi-hop network, an algorithm based on the Lyapunov optimization technique is designed, which has a theoretical performance guarantee. The proposed algorithm can decouple the primal problem with a dynamic energy threshold vector, and then obtain the desirable state of each node according to its battery level.

The charging scheduling problem considering the orientations of the directional chargers is studied in [48]–[50]. In [48], the authors consider the charger deployment problem when the rechargeable nodes have limited mobility, *i.e.*, drifting within a certain range. That is, given a set of directional wireless chargers with fixed positions and adjustable orientations, and a number of rechargeable nodes which can drift within a certain range in a 2D area, how to schedule the orientations of wireless chargers so that the overall expected charging utility is maximized. For this problem, they first define the charging power as a random variable which is independent of other chargers. Then, they exploit an area discretization method to partition the target area into grids so that the charging power in each subarea can be approximated and the approximation error can be bounded. To reduce the searching space, they also proposed a method to discretize the orientations of chargers. After that, they propose an approximation algorithm with a

	Optimization Objective	Network Performance	Target Area	Directional of Wireless Charger
[44], [45]	status of chargers	charging utility and EMR safety	2D area	omnidirectional
[46], [47]	status of rechargeable nodes	network utility	2D area	omnidirectional
[48]–[50]	orientation of chargers	charging utility	2D area	directional
[51]	power of chargers	charging efficiency	2D area	directional
[52], [53]	power of chargers	harvested energy and EMR safety	2D area	omnidirectional
[54], [55]	power of chargers	harvested energy and latency	2D area	omnidirectional
[56]–[59]	power of chargers	charging utility and EMR safety	2D area	omnidirectional
[60]	power of chargers	charging fairness	2D area	omnidirectional
[61], [62]	moving speed of rechargeable nodes	charging utility	2D area	directional

TABLE II: Overview of Charger Scheduling Algorithms

ratio of $(1/2 - \epsilon)$. In [49], [50], the authors consider the charger scheduling problem in a 2D target area which tries to maximize the overall charging utility when given a series of charging tasks. For the offline algorithm, they prove the proposed problem is NP-hard, and prove a relaxed version of the proposed problem falls in the realm of maximizing a submodular function subject to a partition matroid constraint. A centralized algorithm with an approximation ratio of $(1 - p)(1-1/\epsilon)$ is proposed, where p denotes the switching delay of the directional chargers. In addition, for the online algorithm, a distributed scheduling algorithm with a competitive ratio of $1/2(1-p)(1-1/\epsilon)$ is also proposed.

The charger scheduling problem considering the power level of chargers is studied in [51]–[60].

The work in [51] tries to improve the energy transfer efficiency by adjusting the directional charging power adaptively. In their charging model, if a wireless charger concentrates the energy from the directions of N sectors into M sectors, the power intensity in the intended directions will be increased N/M times of the omnidirectional one. And there is a tradeoff between the power intensity of the energy beams and the number of nodes being charged. Under such directional charging characteristic, the closed-form function of the distribution metrics of the aggregated received power is derived with the stochastic geometry, and then the Gamma distribution with second-order moment is employed to approximate the complementary cumulative distribution function. In [52], [53], the authors study the scheduling problem of charging power subject to the safety constraints on the EMR incurred. Given a set of wireless chargers and a set of rechargeable nodes, each charger is assumed to have an initial energy and each rechargeable node is assumed to have a battery capacity. The authors try to compute the charging power (charging radius) of each charger to maximize the total harvested energy in the network subject to the constraint that the EMR at any point does not exceed a threshold. They first theoretically analyze the fundamental properties of the proposed problem and prove that even a relaxation of this problem (*i.e.*, exploit a simplified method to approximate the maximum EMR inside the whole area) is NP-hard. To tackle this problem, they propose an approximation algorithm by exploiting the relaxation and rounding technique. An iterative local heuristic search algorithm is also given, which runs in polynomial time. The proposed algorithm can decouple the computation of the objective function from the computation of the maximum radiation, and it can achieve reasonable trade-off between the charging efficiency and the EMR safety.

The works in [54], [55] try to schedule the power of chargers to ensure the total harvested energy of the rechargeable nodes is maximized and the total charging time is minimized. Given a set of wireless charging tasks, including the required harvested energy and charging deadline of each rechargeable node, they try to schedule the power of each wireless charger so that the overall harvested energy and the total charging time are optimized subject to the EMR safety. To address such a problem, the authors first transform it to a linear problem with area discretization and regularization, propose a centralized algorithm. A distributed algorithm, of which the harvested energy is no less than $(1-\epsilon)$ of the optimal one, and the charging time is no more than the optimal one, is also proposed. In [56], [57], the authors try to maximize the overall charging utility under the EMR safety constraint. To tackle this problem, they first propose an approximate algorithm by transforming the proposed problem to a linear programming problem. A distributed algorithm is also given with area partition. The main idea is to divide the whole area into subareas where chargers are lying on the boundaries of these subareas to enable local computation. Two baseline algorithms, which can achieve an approximation ratio of 1/4 and 1/3 are proposed, respectively. Only the communication overhead of the charger with its neighbors are incurred in these two algorithms. The above studies focus on the EMR safety which try to ensure the expected EMR at any point in the area does not exceed a threshold. In [58], [59], the authors consider the scenario that the EMR jitter may exceed the threshold even if the expected EMR does not. They try to schedule the power of chargers to maximize the overall charging utility subject to the probability of the EMR at any point in the area is not exceeding the threshold is no less than a given parameter. Through EMR approximation and area discretization, the proposed problem is transformed to a second-order cone problem. To reduce the computation cost, a second-order cone constraint reduction algorithm is proposed, and then, a centralized algorithm with an approximation ratio of $(1-\epsilon)$ is given. In addition, a fully distributed algorithm with approximation ratio of $(1-\epsilon)$ is also given.

Different from the above methods which focus on optimizing the overall charging utility of rechargeable nodes, the work in [60] focuses on the charging fairness. For fairness, the authors try to maximize the minimum charging utility among the rechargeable nodes on the contrary. An area discretization method is adopted to transform the proposed problem from a nonlinear optimization problem to a linear optimization one. Then, a centralized algorithm is proposed with lagrangian dual. A distributed algorithm is also proposed, which has an approximation ratio of $1-\epsilon$. The main idea is to divide the whole area into subareas, so that the optimization problem in each subarea can be considered independently and safely (the EMR intensity at any location in the target area does not exceed a given threshold). The authors in [61], [62] investigate the energy provisioning problem with mobile rechargeable nodes. In their model, there is a set of wireless chargers and a single rechargeable node, which can move in a region of interest. They state that the continuous operation of the rechargeable node may cannot be ensured under the constraint of the moving speed and battery capacity of the node. Thus, a metric, called Quality of Energy Provisioning, is proposed, which denotes the expected time that a node can keep continuous operation under its node speed and battery capacity constraints. When there is only one wireless charger, the tight upper and lower bounds are derived when a node moves in the 1D scenario based on flow pattern analysis. When there are multiple chargers in the general 1D and 2D scenarios, the tight lower bound and loose upper bound are also analyzed.

B. Mobile Charging

In the mobile charging scenario, generally, there is a set of rechargeable nodes deployed in a target area, a mobile charger (or a group of chargers) which is responsible for moving around in the target area to charge these rechargeable nodes and collect the sampled data from these nodes, and also a base station which acts as the role of data storage and computation and battery replacement of chargers. Once if a rechargeable node finds its residual energy is less than a threshold, it sends a charging request which includes its position, average energy consumption rate and residual lifetime to the mobile charger nearby. When a mobile charger receives a charging request, it will first be stored in the waiting queue. After the mobile charger receives enough requests, it derives a charging plan including a travelling path and the corresponding power allocation scheme. When the mobile charger finishes a charging mission, it travels back to the base station and takes a quick battery replacing service with a negligible delay.

For mobile charging, a lot of works have been proposed with different optimization objectives, such as the number of mobile chargers, charging delay, network lifetime, total energy cost, event covering utility, etc. In the following, we categorize the existing works according to their objectives.

1) Minimizing Number of Mobile Chargers: How to obtain the minimum number of mobile chargers satisfying the energy consumption in the whole network is one of the fundamental charging scheduling problems in BF-WSNs.

The work in [63] investigates the problem of minimizing the number of energy-constrained mobile chargers in a 2D target area subject to all the rechargeable nodes in the network being able to work continuously. The problem is proved to be NP-hard by reduction from the distance constrained vehicle routing problem. To address this problem, they first relax the linear constraints in the optimization problem and transform it to a distance constrained vehicle routing problem, and then propose an approximate algorithm for the relaxed version and then an approximate algorithm is also proposed for the original problem. In [64], the authors remove the energy constraint of mobile chargers and assume a mobile charger can charge only one node at a time. Under such assumption, a greedy algorithm is proposed to minimize the number of chargers.

The work in [65] tries to reduce the number of mobile chargers by jointly scheduling the traveling plans of mobile chargers and the depot positions of the mobile chargers (the position where the chargers replenish its energy). To address this problem, the authors take a mobile charger's charging cycle and the working lifetime of rechargeable nodes into account. That is, they try to ensure the charging cycle of a mobile charger is no larger than the lifetime of rechargeable nodes. In this work, the authors not only try to minimize the required mobile chargers, but also try to improve the energy efficiency of mobile chargers, *i.e.*, the ratio of the charging time of a charger over its traveling time. For a mobile charger with larger battery capacity, a periodic charging scheme is designed, where each mobile charger can serve one tour periodically before it runs out of energy. In such a scheme, the network is first divided into a number of charging tours, and then the depot positions of mobile chargers are determined based on these charging tours. For a mobile charger with limited battery capacity, the authors try to let it serve different charging tours to maximize its energy efficiency. In this case, it can avoid the problem that a mobile charger spends only a short charging time in a particular tour, which results in poor energy utilization.

2) Minimizing Charging Delay: The charging delay, which is defined as the required time for a mobile charger to finish its assigned charging tasks (*i.e.*, satisfying the energy request of each rechargeable node), including the charging time and traveling time of the charger, is an important evaluation metric in BF-WSNs.

The work in [66] studies the problem of finding an optimal traveling plan to minimize the total charging latency while all the rechargeable nodes can harvest enough energy. For such a problem, the authors first propose an optimal algorithm based on linear programming, which requires exponential computation time. To reduce the computation cost, an algorithm with approximation ratio $(1 + \theta)/(1 - \epsilon)$ is proposed by discretizing the charging power in a 2D area, where θ and ϵ denote two system parameters. The proposed algorithm has a computation complexity of $O((N/\epsilon)^2)$, where N denotes the number of rechargeable nodes in the network. In [67], the authors try to jointly optimize the traveling tour of each mobile charger and the location of the base station to further reduce the charging latency. Besides the charging latency, the authors in [68] try to minimize the communication delay between an RFID reader and an RFID tag, which includes the charging time and the transmission time. In this work, two movement patterns of a reader are considered: linear movement and 2D movement. For the linear pattern, an optimization algorithm is proposed. For the 2D pattern, an approximation algorithm is designed.

The work in [69] focuses on the charging problem with directional chargers. Note that, under the directional charging model, the harvested energy at the rechargeable node is related to the distance between it and a mobile charger and the orientations of the rechargeable node and the charger. In their network model, a mobile charger is assumed to travel and stop at a set of planned locations to charge its surrounding rechargeable nodes. The problem is first formulated as a linear programming problem. Then, an optimal solution is obtained by searching all the possible orientations with the LP solver. To reduce computation complexity, a charging power discretization method is proposed to reduce the searching space and bound the charging delay to the optimal one by $1/(1-\varepsilon^2)$, where ε is a power difference threshold. A merging technique is also given to further reduce the charging delay by approximating the neighboring charging sections.

In [70], the authors try to charge the rechargeable nodes in an Area of Interest (AoI) with a directional wireless charger whose charging area is in a shape of a sector. In their model, there is a set of omnidirectional wireless rechargeable nodes deployed in a simple polygon based AoI area with density ρ. An optimal charging plan is expected for a mobile charger to charge the rechargeable nodes inside the AoI while the charging latency is minimized. To tackle this problem, the AoI is first divided into rectangle-like and sector-like subareas. Then a rectangle-based moving strategy and a sector-based rotating strategy are proposed for the rectangle-like and sector-like subareas, respectively. Through calculating the charging time of all the subareas including the rectangle-like subareas and sector-like subareas, they prove that the proposed algorithm can be upper bounded by a value proportional to the size of the AoI. In [71], [72], the authors study the charging latency minimization problem with multiple mobile chargers. In this work, the multi-node charging scheme is employed, where a mobile charger can charge multiple nodes simultaneously, but each node can be charged by only one mobile charger. Since there are multiple chargers in a network, they try to optimize the longest charging delay of these chargers. An approximation algorithm with a constant approximation ratio is proposed.

3) Maximizing Network Lifetime: Since an unpredictable event may occur at any place and anytime throughout the network, the death of any node may lead to event missing, which should be avoided in safety-critical applications.

The work in [73] tries to minimize the number of rechargeable nodes running out of energy to prolong the network lifetime. That is, given a set of charging requests, they try to find an optimal charging plan to minimize the number of dead nodes during the whole charging period. To address this problem, the authors design a temporal-spatial charging scheduling algorithm. The proposed algorithm tries to construct a traveling path from a global view, rather than charging the nodes according to their priorities and orders in the queue. When constructing a travelling path, a short queue is maintained since fewer nodes in a queue may result in a more accurate solution. In addition, the nodes which may dramatically increase the traveling latency are discarded in advance. The optimality of the proposed algorithm is analyzed based on the queuing model. In [74], the authors try to improve the survival rate of rechargeable nodes with a grid-based routing and charging algorithm. In this work, a network is divided into grids of same size, and a mobile charger only stops at the intersections of grids to charge the rechargeable nodes. In [75], the authors also exploit a grid-based method, and a localized algorithm is proposed to compute a traveling plan to prolong the network lifetime.

The work in [76] investigates the online mobile charging problem with multiple cooperative wireless chargers. To improve the survival rate of the rechargeable nodes, they try to take the spatial and temporal correlations of charging requests into account, *i.e.*, the deadline of charging request, and the distance between the nodes and the mobile charger. Each mobile charger is responsible for the charging requests in a designated field, and for computing its charging travelling path independently according to a metric which combines the charging deadlines and distances. They model the problem as a multiple objective joint optimization problem, which tries to maximize the energy efficiency and the survival rate of rechargeable nodes. The theoretical performance is analyzed through an M/M/n/mTS queuing model. Besides the above online scheduling algorithm, some intelligent learning based algorithms for the charger planning problem are studied in [77]–[79] to reduce the number of dead nodes.

In [80], the authors try to maximize the network lifetime for the application of area monitoring. In this work, the network lifetime is defined as the time interval between the time when the target area is fully monitored and the time when a coverage hole appears. The problem is defined as follows: given the energy burden of a mobile charger, find an optimal strategy of a charger's energy transferring plan (*i.e.*, divide its available energy among the rechargeable nodes), and the activation patterns of rechargeable nodes (the active/inactive time of nodes), to maximize the network lifetime. This problem is proved to be NP-complete. An approximate algorithm is proposed by exploiting the minimum set cover technique, An energy dividing strategy is also designed according to the energy consumption rate of each rechargeable node. In [81], the authors try to improve the charging efficiency considering the fact that rechargeable nodes take unproportionally long charging time when their batteries are almost full. A mixed partial and full charging model is introduced, where each rechargeable node can be partially/fully charged by a mobile charger. In this work, a charging schedule is first generated to maximize the overall survival rate (which is defined to quantify the lifetime of rechargeable nodes) by adopting the full charging model. If the optimal survival rate can be achieved, the partial charging model is adopted to maximize the overall survival rate. The shortest Hamiltonian path is used to initialize the traveling path of a mobile charger to reduce the traveling cost.

The authors in [82] try to control the velocity of mobile chargers to maximize the network lifetime. In this work, it is assumed that a mobile charger travels along a pre-planned itinerary. The authors try to maximize the minimum received energy among all the rechargeable nodes to avoid uneven energy replenishment. Different from the above studies, the authors mainly focus on the velocity of the mobile chargers, which also plays a key role in charging scheduling. A simple version of the proposed problem where there is one rechargeable node in a general 2D scenario with any kind of itinerary is first studied. Then, for the proposed problem with multiple rechargeable nodes, an efficient algorithm is also proposed with spatial and temporal discretization. In [83], the authors consider the velocity-control problem when mobile chargers have constrained energy capacity. Additionally, they assume there are several depot positions deployed along the traveling path for the mobile chargers to replenish their energy.

4) Minimizing Energy Cost: Some works try to jointly optimize the movement cost and energy consumption of the mobile chargers during the charging period.

The work in [84] tries to minimize the ratio of the time that a mobile charger stays at the service station over the whole charging period. A cellular based structure is used to divide the whole area into adjacent hexagonal cells and it is assumed that a mobile charger can only stay at the center of these cells to charge the rechargeable nodes. Then, the proposed problem is formulated as an optimization problem considering the traveling itinerary and charging time of the mobile chargers, and the flow routing cost. An discretization and reformulation-linearization based algorithm is proposed. In [85], the authors try to minimize energy consumption subject to keeping continuous operation of each rechargeable node. They formulate the proposed problem as a mixed-integer linear programming problem, which is decomposed into several sub-problems that can be easily solved.

The work in [86] assumes there exist several charging itineraries for mobile chargers. Given a set of rechargeable nodes and a set of candidate travelling itineraries of mobile chargers, they try to find a subset of travelling itineraries while the energy consumption is minimized subject to all the rechargeable nodes being able to be fully charged. The following two factors of energy consumption are considered : 1) the energy loss caused by charging is related to the charging distance and time; 2) the energy consumption caused by moving is used to support the movement of a mobile charger. The problem is proved to be NP-complete by reduction from the set cover problem. To tackle this problem, a relaxed version of the proposed problem where each itinerary can be used only once is first studied. An approximation algorithm with a ratio of $O(lnN)$ is proposed by iteratively choosing the most cost-effective itinerary and removing the covered rechargeable nodes, where N is the number of rechargeable nodes. For the general case where each itinerary can be used several times, an approximation algorithm with a ratio of 10 is proposed with the primal-dual technique.

The work in [87] tries to exploit the concept of bundle charging to reduce the energy consumption. In this work, the rechargeable nodes are assumed to be densely deployed, *i.e.*, several nodes are deployed in a same bundle. In this case, only when the number of nodes running out of energy in a bundle exceeds a predefined threshold, a charging task is activated. Then a mobile charger moves around the network to charge the rechargeable nodes bundle by bundle. Here, not only the number of charging bundles is minimized, but also the total energy cost, including the moving cost and charging cost, is minimized. To address this problem, a greedy bundle generation algorithm is proposed to minimize the number of bundles. Then, a TSP-based algorithm is proposed to reduce the traveling cost of the mobile chargers.

5) Optimizing Event Covering Utility: To avoid mis-detecting the stochastic event, some works try to improve the event covering utility when conducting energy transferring.

The work in [88] investigates the problem of capturing stochastic events in BF-WSNs for the first time. In this work, the authors assume the stochastic events occur around the rechargeable nodes and will stay for a period of time following the exponential distribution. A event is called captured if a rechargeable node is active when the event occurs. Under such a model, the authors try to jointly mobilize chargers and schedule the status of rechargeable nodes to optimize quality of monitoring (QoM), *i.e.*, the ratio of the captured events to all the occurring events. In [89], the authors assume that events occur in a certain area one by one, which are spatially and temporally independent. Since the events come unexpectedly, the recharging tasks cannot be known in advance. Therefore, they try to make some approximation when selecting a set of target nodes to be charged while the event covering utility is maximized. The problem is proved to be NP-complete and several heuristic algorithms are proposed.

In [90], the authors consider a different model to maximize the event covering utility. In their model, a mobile charger moves around the network periodically and the mobile charger repeats its charging plan in every period of time T, which means its charging time and travelling time is less than T in a round. Rechargeable nodes can be either active or inactive in each time slot, and the activation schedule is decided by the mobile charger. Thus, to maximize the event covering utility, there are two issues need to be addressed: 1) how to choose the set of charging nodes and their charging time; 2) how to decide nodes' active/inactive states based on the harvested energy. To tackle this problem, a relaxed version of the proposed problem is first studied where the traveling time of a mobile charger is ignored. Such a relaxed version is also proved to be NP-hard. The authors formulate it as a maximization problem with submodular function under a certain condition. For such problem, an approximation algorithm with a ratio of 1/6 is proposed. Based on this, an approximate algorithm is also proposed for the proposed problem where the traveling time of a mobile charger is considered.

The work in [91] considers the problem of scheduling mobile chargers to maximize the event covering utility with collaborative monitoring. It is assumed that a task can be collaborative monitored by multiple sensors. As a result, charging all the nodes may increase the total energy consumption and degrade the charging utility because of spatial redundancy. In this work, the authors jointly consider the deployment problem of rechargeable nodes and the scheduling problem of mobile chargers, and try to maximize the event covering utility. They formulate the problem as a general convex optimization problem under the energy constraint of the mobile chargers. The area partition and charging discretization methods are given to formulate the proposed problem to an optimization problem with submodular function. An approximation algorithm with a ratio of $(1-\epsilon)/4(1-1/e)$ is proposed, where ϵ $(0 \leq \epsilon \leq 1)$ is an arbitrarily small positive parameter. In [92], the authors assume a rechargeable node may participate in several tasks simultaneously. In this case, different rechargeable nodes may have different energy requirements and charging utility for task execution. To maximize the overall event covering utility, a surrogate function and an approximated traveling cost is employed to formulate this problem as an optimization problem with essentially monotone submodular. An energy allocation scheme is also proposed for task cooperation, and finally, a reward-cost based algorithm is proposed which has an approximation ratio of $(1 - 1/\epsilon)/4$.

The work in [93] investigates the problem of scheduling mobile chargers with the k-coverage guarantee, where each target needs to be covered by at at least k rechargeable sensor nodes. At the beginning, the authors assumed each target is covered by a set of nodes, of which the number is much larger than k. Thus, some nodes can run out of energy to reduce the charging burden of a mobile charger. A theoretical model which analyzes the performance improvement in terms of the charging capability of the mobile charger, is proposed, including the maximum distance it can cover in both the 1-D and 2-D scenarios. Then, a distributed algorithm is proposed by grouping the rechargeable nodes into clusters for target monitoring under the k-coverage constraint.

6) Optimizing Charging Utility: Generally, the energy charging to a rechargeable node is modeled as a utility function, which is a non-increasing submodular function on the residual energy of the rechargeable node. Under such charging scheme, the mobile charging scheduling problem which tries to optimize the overall charging utility is studied by [94]–[102].

The work in [94] tries to find an optimal traveling tour of a mobile charger to maximize the overall charging utility gain. The utility gain of each rechargeable node is defined inversely proportional to its residual battery level, which means a node with less residual battery level has more utility gain. To address such a problem, the authors first consider the charging utility gain maximization problem where the total distance of the traveling tour of the mobile charger per tour is not larger than a given threshold, which is proved to be NP-hard. An approximation algorithm with quasi-polynomial time complexity is proposed. In addition, to further reduce the time complexity, a heuristic algorithm is proposed, which can handle the scenario when the rechargeable nodes exploit a dynamic energy consumption model. Additionally, the online scheduling algorithm when the rechargeable nodes are charging at the fixed time intervals is also studied.

The work in [95] considers a different sub-modular function for charging utility gain, in which the charging utility gain of a rechargeable node is defined proportional to the amount of the received energy of itself and also its neighboring nodes. The authors employ an one-to-many charging scheme, where the mobile charger can charge multiple nodes simultaneously. They first consider the charging utility gain maximization problem under the energy capacity constraint at the mobile charger. A constant approximation algorithm is proposed by ignoring the traveling energy consumption of the mobile charger, and a heuristic algorithm is proposed as well for the proposed problem considering the traveling energy consumption, which is transformed to a length-constrained utility maximization problem. Furthermore, the problem of minimizing the length of the traveling tour subject to all the requesting nodes being charged is studied. An approximation algorithm with a constant ratio is proposed by assuming the mobile charger has enough energy to charge all the requesting nodes and support the energy consumption of its traveling.

The work in [96] assumes each charging request is assigned with a deadline and each node can be charged for many times before its deadline. Given a set of charging requests with deadline constraints, its purpose is to find the optimal charging plan to maximize the overall charging utility, which is related to the amount of nodes' harvested energy before the deadline. In addition, it is assumed that the charging demands of the rechargeable nodes can be divided into several sub-demands. To jointly optimize the charging spots (where the mobile chargers stop to charging the rechargeable nodes) and the traveling path, they formulate the proposed problem as an optimization problem with submodular function subject to a partition matroid constraint. To tackle this problem, an approximation algorithm with a ratio of $1/2$ is proposed to select the charging spots based on spatial and temporal decomposition. Then, a grid-based skip-substitute method is designed to further reduce the traveling time and to increase the overall charging utility.

Based on [96], the authors in [97] distinguish the rechargeable nodes according to the different importance of the data they delivered. Given a set of charging requests with deadlines, an importance-different charging scheduling strategy is proposed to further improve the overall charging utility as well as to improve the performance of data loss. In the proposed algorithm, they first try to compute the candidate charging spots, and then find the mismatch between the deadline and spatial constraints. An area discretization method is also exploited to reduce the infinite candidate charging spots to a finite one. Through using a bipartite graph to combine the spatial and temporal constraints, the authors transform the proposed problem into a maximization problem with monotone submodular function subject to a partition matroid constraint. In the proposed matroid model, the charging requests' deadline and the penalty value of the task are considered. Then, a greedy algorithm with an approximation ratio of $1/2$ is designed where all the charging requests are classified as either the early tasks or the delayed tasks. The more important nodes with an earlier deadline will be assigned a higher priority and are involved in the early tasks. In addition, to maximize the overall charging utility, the authors proposed a method to adjust the sequence of rechargeable nodes by finding a shorter path. In [98], the authors assume the rechargeable nodes can upload data to the fusion center and a mobile charger travels on a pre-planned itinerary to charge these nodes. The data loss rate is defined by the expected number of data packets which are dropped due to lack of energy. In this work, the authors first design an empirical prototype by using an off-the-shelf RF energy transfer hardware. According to the practical performance of the RF energy transfer hardware, they establish an empirical model and use it to jointly optimize the travel planning and charging plan. The optimal traveling and charging plan is derived based on a Markov decision process.

The work in [99] investigates the charging utility optimization with obstacles in the field, which tries to maximize the total harvested energy of all the rechargeable nodes. To measure the impact of obstacles on charging, they first design a new theoretical charging model based on the Fresnel diffraction model and conduct empirical experiments to demonstrate its effectiveness. Then, a spatial discretization method is proposed to obtain a set of finite charging spots of a mobile charger. The proposed problem with energy constraints is formulated as an optimization problem with submodular function and an algorithm with an approximation ratio of $(1-\epsilon)(e-1)/2e$ is proposed. The game theory based algorithm is studied in [100], where a collaborative charging scheduling method is proposed to help a mobile charger to make optimal charging decisions.

Different from the above works which focus on the 2D scenario with mobile chargers moving on the ground, the authors in [101] study the mobile charging problem in a 3D network where an Unmanned Aerial Vehicle (UAV) is exploited. In this work, the authors try to find the optimal trajectory planning to maximize the total harvested energy subject to the energy constraint of the UAV, including the moving, hovering, and charging costs. To address this problem, a spatial discretization method is proposed to obtain a finite number of charging spots for the UAV, and a temporal discretization method is proposed to calculate the charging time for each charging spot. The problem is then formulated as an optimization problem with submodular maximization, and a cost-efficient algorithm is proposed. The work in [102] investigates the period-area coverage problem. Given a target area where a set of rechargeable nodes are deployed for sensing events periodically, the authors try to schedule the traveling path of the UAV to ensure all the target areas can be monitored once in each period. The charging utility is defined as the ratio of the received energy at the requesting nodes over the total consumed energy. It is assumed that the whole target area cannot be covered by the set of rechargeable nodes, and the UAV not only needs to charge the rechargeable nodes, but also needs to move to the vacant region to monitor the area. A hexagonal decomposition scheduling method is proposed to maximize the charging utility and a grid-based scheduling algorithm is proposed to reduce the computation complexity.

III. Communication and Networking

Communication and networking are two main components in BF-WSNs, which indicate the pattern for connecting battery-free sensor nodes and exchanging information among these batter-free sensor nodes. Communication and networking in BF-WSNs include the communication modes for battery-free sensor nodes, routing protocols for transmitting data packets among battery-free sensor nodes, scheduling strategies for data broadcasting and data collection in a network, and in-network processing methods for data transmission. The communication modes for battery-free sensor nodes determine the connections among battery-free sensor nodes in a network. Based on the connections among battery-free sensor nodes, the routing protocols determine the network topology for all battery-free sensor nodes. According to the network topology, scheduling strategies for data broadcasting and data collection could be implemented to improve network performance. Besides, in-network data processing could be combined with data transmission to further improve network performance.

However, according to the energy characteristics of batter-free sensor nodes, it is hard for battery-free sensor nodes to be awake all the time. As a consequence, communication and networking become more challenging in BF-WSNs. In this section, we summarize the works for communication and networking in BF-WSNs.

A. Communication

1) Ambient Backscatter: Ambient backscatter is a promising battery-free communication technology in wireless sensor networks, where transmitters transmit data to receivers by modulating and reflecting the ambient Radio Frequency (RF) signals. There are many common RF sources, such as TV towers, cellular base stations, and WiFi access points, etc. The biggest challenge in ambient backscatter communication is that the RF sources are not dedicated for backscatter communications, which is uncontrollable and unpredictable. Therefore, most works are proposed for efficient data transmission, including antenna design [103]–[107], signal detecting [108]–[112], channel encoding and decoding [113]–[119], modulation and demodulation [120]–[124]. We omit the details of these works since they have been extensively covered in [22] and [125].

2) Wireless Communication: Some works focus on point-to-point wireless communication between two BF-nodes. The work in [126] studies two related problems under offline knowledge of the events: maximizing the number of bits sent by a deadline, and minimizing the time it takes to send a given amount of data. The first problem is solved through a directional water-filling approach. The second one is solved by mapping it to the first problem via the maximum departure curve function. Moreover, by using dynamic programming in continuous time, a throughput optimal policy for the deadline constrained setting under online knowledge of the events is proposed.

Similarly, the work in [127] considers the point-to-point wireless communications in BF-WSN. It investigates the problem of energy allocation over a finite horizon, taking into account channel conditions and energy sources that are time-varying, so as to maximize throughput. Two types of side information (SI) on the channel conditions and harvested energy are assumed to be available: causal SI (of the past and present slots) or full SI (of the past, present and future slots). It can obtain structural results for the optimal energy allocation via the dynamic programming and convex optimization techniques. In particular, if unlimited energy can be stored in a battery with harvested energy and the full SI is available, we can prove the optimality of a water-filling energy allocation solution where the so-called water levels follow a staircase function. Similar work is also seen in [128], which finds a power allocation policy that stabilizes the data queue whenever feasible. Still, for a point-to-point system, using large deviation tools, the effect of finite data queue length and battery size is studied in [129] in terms of scaling results as the battery and queue grow large.

A real sensor node consumes energy not only during transmission but also during executing source coding tasks, such as measurement and compression. The overall energy consumption for source coding is generally comparable to that of transmission, and that a joint design of the two classes of tasks can lead to relevant performance gains. Therefore, the work in [130] considers the problem of dynamically and jointly optimizing source coding and some transmission strategies are formulated for time-varying channels and sources. Specifically, for each node, it can compress its sensory data with different compression rates which leads to differences on the amount of data needs to be transmitted, the energy consumption on coding and the distortion when its sensory data is discovered by the sink. Here, the energy constraint, channel condition and data correlation are considered. The objective is to minimize the cost function of the distortions in the source reconstructions at the sink under queue stability constraints. By adopting perturbation-based Lyapunov techniques, a close-to-optimal online scheme is proposed that has an explicit and controllable trade-off between the optimal gap and queue sizes. The role of side information available at the sink is also discussed under the assumption that acquiring the side information entails an energy cost.

3) Others (RFID, etc.): RFID can be regarded as a kind of BF-nodes. There are some surveys on this topic: the one in [18] focuses on security and privacy, the one in [19] is about applications, and the one in [20] addresses the RFID-based localization methods.

B. Routing

The routing objectives in BF-WSNs include maximizing energy utility, efficiency, throughput, reliability and the minimum sampling rate. Table III compares the different routing algorithms, and the details are summarized as follows.

1) Maximizing Energy efficiency: A model is presented in [131] to characterize the performance of multi-hop networks in the presence of energy constraints and a routing algorithm is designed to optimally utilize the available energy. The energy model can be used to consider different types of energy sources in heterogeneous environment. The proposed algorithm is shown to achieve a competitive ratio (i.e., the ratio of the performance of any offline algorithm that has knowledge of all past and future packet arrivals to the performance of the proposed online algorithm) that is asymptotically optimal with respect to the number of nodes in the network. The algorithm assumes no statistical information on packet arrivals and can easily be incorporated into existing routing schemes (e.g., proactive or on-demand methodologies) in a distributed fashion.

The work in [132] proposes a distributed routing algorithm to improve energy efficiency in solar-powered WSNs. Each node maintains two tables: one table keeps current residual energy, energy harvesting rate and energy density of itself; the other table records those information of its neighbors. The residual energy of a node is divided into different levels. For a node i, its energy harvesting rate is the average EH harvesting rate of its neighbors. Each time a node wants to send out a packet to a target node, when it is selected as the next-hop node, it selects the node with the largest energy density value from the nodes which have the highest energy levels. To avoid the case of ring, a node can only transmit data to those who are closer to the destination node. Comparing the routing algorithms which greedily choose the node with the highest energy harvesting rate, the strength of this algorithms is that a node with higher EH density is likely to choose a neighbor with high energy harvesting rate to be the next relay node.

2) Maximizing Throughput: The work in [133] jointly considers energy allocation and routing in BF-WSNs with the optimization goal of maximizing throughput over a finite-horizon time period. The problem is formulated as a convex optimization problem. A three-step approach is designed. First, a simple network is studied where there is only one node and its energy harvesting rate for the entire time period is known in advance. An energy allocation scheme is proposed and has been proven to be optimal. Then the assumption is relaxed where the future replenishment profile is known and an online algorithm is proposed for the one node case. An approximate algorithm is proposed based on the estimated EH rate, and the ratio bound is $\dfrac{(1-\beta_1)}{(1+\beta_2)}$ where β_1 and β_2 are two constants that describe the inaccuracy of estimation. Specifically, let $\hat{r}(t)$ be the estimated value of the real EH rate whose lower bound is $\underline{r}(t)$ and upper bound is $\bar{r}(t)$. β_1 and β_2 satisfy $\underline{r}(t) = (1-\beta_1)\hat{r}(t)$ and $\bar{r}(t) = (1+\beta_2)\hat{r}(t)$. Finally, for the real energy allocation and routing problem in BF-WSNs, a low- complexity distributed heuristic scheme is proposed and it is proved to be optimal under homogeneous energy harvesting profiles.

The work in [134] studies energy allocation and routing to maximize the total system utility for multi-hop BF-WSNs, without prior knowledge of the replenishment profile. The system utility here is a strictly, concave, non-decreasing and continuously differentiable function of the data transmission rate in each time slot. To address this problem, an upper bound for the utility performance of a BF-WSN is characterized by constructing an infeasible scheme that outperforms the optimal scheme. Then an asymptotically optimal low-complexity online solution is proposed which is provably efficient using estimation of replenishment rate and supply-demand mismatch. The performance gap between this online solution and the infeasible solution for the upper bound diminishes as time tends to be infinity, which implies that it is an asymptotically optimal solution. Moreover, a distributed algorithm is proposed to approximate the asymptotically optimal solution.

3) Maximizing Minimum Fair Rate Assignment: The works in [137] presents a comprehensive algorithmic study of the max-min fair rate assignment and routing problems in energy harvesting networks with predictable energy profile. It is assumed that the harvested energy is known for each node over a finite time horizon. For a routing that is provided as input, the authors design an algorithm that solves the max-min fair rate assignment problem. The algorithm runs in $O(nmT^2)$ time, where n is the number of energy-harvesting nodes, m is the number of edges in the routing graph, and T is the time horizon. Then the problem is to find a reasonable routing of the specified type, where routing is good if it provides a lexicographically maximum rate assignment out of all the

	Optimization Objective	Centralized or Distributed	Energy Harvesting Process
[131]	Energy Efficiency	Centralized	Not specified, but the energy arrivals are known in advance
[132]	Energy Efficiency	Distributed	Solar-Powered
[133]	Maximizing the throughput over a finite-horizon time period	One centralized, one distributed approximate and one heuristic distributed	For the centralized algorithm, the energy replenishment is known in advance; for the distributed approximate algorithm, the energy replenishment is predictable; for the distributed heuristic, the energy replenishment is not known in advance
[134]	Maximizing the throughput	One online and one distributed	No prior knowledge of the replenishment profile
[135]	Energy Efficiency and Reliability	Distributed	No prior knowledge of the replenishment profile
[136]	Latency	Centralized	Not specified, but the energy arrivals are known in advances

TABLE III: Comparison of the existing routing methods

feasible routing solutions of the same type. Specifically, three types of routing are considered: Routing Tree: the simplest form of routing in which every node sends all the data it collects and receives to a single neighbouring (parent) node. Unsplittable Routing: a single-path routing in which every node sends all of its sensed data over a single path to the sink (a routing tree is a special case of the unsplittable routing, in which all the paths incoming into node i outgo via the same edge). Fractional Routing: a multipath routing in which each node can split its data over multiple paths to the sink (unsplittable routing is a special case of fractional routing in which every node has one path to the sink). It is the most general routing that subsumes both routing trees and unsplittable routings, and therefore provides the best sensing rates. All of these routing types are studied in Time-invariable and Time-variable settings. A routing is time-invariable if every node uses the same (set of) path(s) in each time slot to send its data to the sink. If the paths change over time, the routing is time-variable. It is shown that a max-min fair routing tree is NP-hard to approximate within $log(n)$ and that a max-min fair unsplittable routing is NP-hard to find regardless of whether the routing is time variable or not. Relaxing the requirement of the lexicographically maximum rates, a polynomial algorithm is designed that determines a time-invariable unsplittable routing that maximizes the minimum rate assigned to any node in any time slot. For the max-min fair time-variable fractional routing, it is demonstrated that verifying whether a given rate assignment is feasible is at least as hard as solving a feasible 2-commodity flow. That implies it is unlikely that we can determine a max-min fair fractional routing without the use of linear programming (LP). To combat the high running time induced by LP, a fully polynomial-time approximation scheme (FPTAS) is developed. It is also shown that in the special case when the fractional routing is restricted to be time-invariable with rates that are constant over time, the max-min fair routing can be determined in polynomial time with a combinatorial algorithm.

In BF-WSNs, the availability of the node for transmission is hard to determine due to the unpredictable supply of harvested energy. Therefore, it is difficult for a node to determine the operating state of neighbouring nodes. Motivated by this, two probabilistic routing protocols are proposed in [135], called Probabilistic ReTransmission (PRT) and PRT with packet Collision Consideration (PRT-CC), to achieve high efficiency and reliability in data collection in the presence of unsteady power supplied by energy harvesting. Besides, acknowledgements (ACKs) are employed to provide another means to detect packet loss.

4) Others: The work in [138] presents an opportunistic routing and data dissemination protocol for BF-WSNs based on cross-layer constructs that allow cross-layer synchronization and coordination between the routing protocol and the application layer services. The work in [136] considers end-to-end delay as a metric of network-wide QoS in solar-powered WSNs. The authors suggest a low-latency data delivery scheme, which considers harvested energy, deployed location and duty-cycle of neighboring nodes. The scope of the above works is limited to data delivery for delivery-centric WSNs. In many scenarios where sensor nodes are deployed in remote areas, there is limited connectivity to the outside world, thus sensory data have to be stored in the network until the next upload opportunity (e.g., a mobile base station appears). The work in [139] investigates how to enhance storage reliability in storage-centric WSNs where sensory data have to be stored in the network for a long time until next upload opportunity appears. In this work, a storage service, called SolarStore, is developed for solar-powered storage-centric WSNs. The service is novel in its mechanisms for improving the amount of data retrieved from the network in the face of energy constraints and node failures. Maximizing retrievable data in the face of node failures requires implementing reliable storage, where reliability is achieved using redundancy. Since achieving redundancy takes energy, the energy constraints imply that the redundancy level should be dynamically adaptive depending on the available energy. Hence, a main contribution of SolarStore lies in its energy-adaptive and storage-reliable mechanism used to maximize retrievable data.

C. Broadcast Scheduling

The works proposed for broadcast scheduling in BF-WSNs can be grouped into two categories according to network topology, i.e., star-topology and multi-hop topology. Table IV summarizes the different broadcast scheduling methods.

1) Star Topology: The work in [152] considers reliable broadcast in BF-WSNs with a star topology, where all battery-free sensor nodes can directly contact with the base station. The employed energy harvesting model is the Bernoulli model, where a node l can harvest a unit of energy in each slot with probability ρ_l. The forward error correlation technique is applied to guarantee transmission reliability, where N original packets are encoded into $N + K$ packets by erasing coding and the receivers can reconstruct the original N packets if it receives at least N out of these $N + K$ encoded packets. To deal with energy deficiency of battery-free sensor nodes, an energy-aware reception scheme is proposed in this work, where a node can be a receiver only if its stored energy is

	Optimization Objective	Multicast or Broadcast	Energy Harvesting Process
[140] [141]	Minimize latency	Broadcast	Gaussian distribution
[142]–[146]	Minimize latency	Broadcast	Not specified, but the energy arrivals are known in advance
[147]	Minimize latency	Broadcast	Bernoulli process
[148], [149]	Minimize latency	Multicast	Constant harvesting rate
[150]	Maximize throughput	Broadcast	Not specified, but the energy arrivals are known in advance
[151]	Maximize throughput	Multicast	Stationary and ergodic random process
[152]	Trade-off between reality and throughput	Broadcast	Bernoulli process
[153]	Trade-off between reality and throughput	Broadcast	Stationary and ergodic process

TABLE IV: Comparison of the existing broadcast scheduling methods

larger than a threshold B. The trade-off between reliability and throughput is analyzed. Two broadcast policies with different optimization objectives are proposed, i.e., the reliable-first policy and the throughput-first policy.

The work in [153] is an extension of the work in [152]. Besides the Bernoulli model applied in [152], this work employs another energy harvesting model, where the energy harvesting process follows a stationary and ergodic process with mean ρ mJ/slot. Similar to the work in [152], this work applies the forward error correlation technique to enhance transmission reliability, and applies the energy-aware reception scheme to avoid interrupted packet receptions caused by exhausted energy. In addition, an early termination scheme is proposed to enhance energy-efficiency broadcast, where a node stops receiving packets in a time block if it has received enough packets to decode the original packets. Besides reliability and throughput, this work considers energy efficiency to measure the performance of broadcast scheduling policies, which is defined as the expected energy consumption for receiving a packet. Three broadcast policies with different optimization objectives are proposed, i.e., the reliable-first policy, the throughput-first policy and the eclectic policy.

The works in [140] and [141] investigate the broadcast scheduling problem for solar energy based BF-WSNs with a star topology, where all the battery-free sensor nodes are located within the communication range of the base station. It assumes that the energy arrivals and energy consumption of a node follow the Gaussian distribution. Besides, it assumes that the base station has full knowledge about the radio duty cycle and the energy arrivals of each node. Then, the Hidden Markov model for the state (ON/OFF) of each node is built by the base station. Based on the Hidden Markov models, the base station applies the set selection algorithm to derive the broadcast time slots. Finally, the Baum-Welch Estimation Maximization learning algorithm is used to adjust the parameters of the Hidden Markov models to increase the likelihood of achieving the minimum latency.

The work in [150] investigates broadcast scheduling from a battery-free transmitter to its one-hop receivers through a multi-input multi-output (MIMO) broadcast channel, where both the transmitter and the receivers have multiple antennas. Different from other works, it considers the non-ideal circuit power consumption of the transmitter, e.g. the AD/DA converter and signal processor. For the time-invariant channel and the time-varying channel, the authors proposed an optimal broadcast scheduling policy to maximize the weighted sum throughput, respectively. However, these policies are based on the assumption that the energy arrivals are known in advance, including the time and the amount of energy arrivals.

The works in [142] [143] [144] [147] consider the broadcast scheduling policy for a battery-free sensor node to its one-hop receivers over an additive white Gaussian noise broadcast channel. The work in [144] proposes an optimal offline scheduling policy for minimizing the total transmission time of the broadcast from a battery-free sensor node to two receivers in a time window. The authors proposed the DuOpt algorithm which starts with a feasible broadcast schedule and reduces the total transmission time iteratively. They proved the optimality of the DuOpt algorithm under the condition that all data destined to the weak receiver in the time window arrive at the beginning of the time window. However, the proposed algorithms are based on the assumptions that data arrival and energy harvest instants and amounts are known in advance, and the energy capacity and data capacity are infinite. The work in [142] investigates the transmission completion time minimization scheduling problem for the broadcast from a battery-free sensor node to its M receivers. The authors first investigated its dual problem which is the throughput maximization problem with a given deadline constraint. The authors proposed an iterative algorithm to generate the offline broadcast scheduling policy minimizing the transmission completion time of a battery-free sensor node, which optimizes the transmit powers and transmission rates of the battery-free sensor node. However, the proposed broadcast scheduling policy is an offline policy and is based on the assumption that the energy arrival instances of the battery-free sensor node are known in advance. The work in [143] considers the same problem as the one in [142], but it considers an additional constraint where the energy storage capacity of a battery-free sensor node is finite. The work in [147] extends the offline broadcast setting of the works in [143] and [142] to the case of online broadcast. It first considers a special Bernoulli process to formulate the energy arrivals of a battery-free sensor node, where each energy arrival is either zero or its energy capacity. An exactly optimal online power scheduling strategy is proposed for this special energy arrival process. Then, it considers general independent and identically distributed (i.i.d.) energy arrivals, and proposes a sub-optimum strategy coined fractional power constant cut-off policy.

2) Multi-hop Topology: The work in [145] is the first one to consider the broadcast scheduling problem in multi-hop BF-WSNs. In this work, all the nodes are battery-free, i.e., surviving through harvesting energy from other energy sources in ambient environment instead of batteries. It proposes three approximation algorithms for the minimum latency broadcast scheduling problem in BF-WSNs. The latency bound of the broadcast schedules generated by these algorithms are analyzed and proved. Different from other works, the energy arrival process in this work is not specific. The work in [146] further reduces the latency by generating the broadcast tree without relying on predetermined structures, which is proved to be very efficient for tree-structure data communication [154], [155]. It proposes several efficient algorithms by computing the collision-free broadcast schedule and generating the broadcasting tree simultaneously. However, the proposed algorithms are centralized and are based on the assumption that the time consumption function for node v to harvest e amount of energy from 0, $T_v(e)$, is estimated in advance. The work in [151] investigates joint power control, scheduling and routing for multicast of data generated at sensor nodes to a set of sink nodes in a BF-WSN. It assumes that the amount of energy harvested by a node in a time slot follows a stationary and ergodic random process. Three approaches are proposed to maximize network throughput in a fair manner. However, the proposed approaches only guarantee that the average power consumed at each node is slightly less than its average energy harvesting rate in a time slot. Thus, it is not suitable for the scenario where the average energy harvesting rate of each node in each time slot is unknown in advance. The work in [148] investigates the minimum latency multicast scheduling problem in multi-hop BF-WSNs, where all the nodes except the sink node are powered by wireless energy transmitters instead of batteries. It assumes that the energy capacity of each node is infinite and the recharge rate of each node is a constant within a period of time and is known in advance. To generate a collision-free multicast schedule, the authors first proposed a dynamic programming based centralized algorithm, then they proposed an edge-based distributed algorithm. However, these algorithms are heuristic and the multicast latency of these algorithms is not bounded. They further studied the problem of minimum latency many-to-many communication scheduling in [149], where an energy-adaptive and bottleneck-aware algorithm is proposed.

D. Data Collection Scheduling

The works for data collection scheduling in BF-WSNs can be grouped into three categories according to network topology, i.e., one-hop topology, network with a mobile sink node and multi-hop topology. Table V summarizes the different data collection scheduling methods.

1) One-hop Topology: The work in [158] considers data collection in BF-WSNs with a star topology where battery-free sensor nodes directly transmit their data to the base station. In this work, the base station has a cache to store the previously collected sensory data. The nodes only transmit updates to the base station when the data accuracy of a query is not guaranteed, i.e., the stored sensory data in the base station exceed an error margin. They assumed that there is an ideal slot based harvested energy prediction algorithm in each harvesting period, which can predict the amount of energy harvested by a node in each time slot. First, the authors proposed an offline algorithm to solve a linear optimization problem, assigning energy budget to a node for each time slot in a harvesting period. Then, the authors proposed an online algorithm to keep track of the current harvesting rate and battery status adjusting the error margin. To optimize the peak Age of Information at network edge with directional chargers, the authors in [159], [160] studied the first joint scheduling problem of data transmission and energy replenishment at wireless-powered network edge. Several approximate scheduling algorithms are proposed by considering charging and transmitting simultaneously. However, these works only considers the energy constraints of battery-free sensor nodes in data collection but ignores the communication interference among different sensor nodes.

The work in [157] considers data collection from micro-powered wireless rechargeable embedded devices to a receiver (also the charger), e.g., radio frequency identification (RFID) tags and RFID readers. According to the non-linear harvesting rate of each device, a packet scheduling and transmission protocol is proposed with two kinds of predictable delay bounds, per-packet collection delay and total collection delay, for transmitting packets of all devices. The proposed protocol is motivated by the classical uniprocessor real-time sporadic task scheduling problem.

The work in [156] investigates the data collection scheduling problem in mobile BF-WSNs. It considers the monitoring scenario where all the nodes are mobile and the sink node directly collects data from the nodes in one hop. The optimization objective of this problem is to maximize the number of data packets received by the sink node in one data collection period, guaranteeing fairness for all the nodes. Since this problem can be reduced to a typical 0-1 multiple knapsack problem, it is NP-complete. Employing Hello packets and ACK packets, the authors proposed a heuristic algorithm to schedule nodes' transmissions based on energy and fairness constraints. However, the lower bound performance of the data collection schedules achieved by the proposed algorithm is not provided.

2) Networks with Mobile Sinks: To achieve high-rate data collection in BF-WSNs, mobile data gathering emerges which can effectively alleviate non-uniformity of energy consumption among battery-free sensor nodes.

The work in [162] considers delay-tolerant data collection in a BF-WSN with a mobile sink. It tries to find an optimal close trajectory and sojourn time scheduling for the mobile sink to maximize network throughput subject to a specified tolerant delay constraint, which was proved to be NP hard. It assumes that the potential sojourn locations for the mobile sink are fixed and known in advance. Besides, it assumes that the amount of energy harvested in a future time period is predictable based on the source type and harvesting history. An iteration-based heuristic algorithm is proposed for the throughput maximization problem. However, this work ignores the interference among simultaneous transmissions from different nodes to the mobile sink.

Simultaneous transmissions from different nodes to a mobile sink is considered in [163], which investigates the data collection maximization problem in a BF-WSN with a mobile sink. Different from other works, the mobile sink in this work periodically travels along a path at a constant speed without stops to collect data from one-hop nodes. This problem is proved to be NP-hard by reducing it to a well known NP-

	Topology	Static or Mobile Sink	Optimization Objective
[156]	One-hop Networks	Static Sink	Maximize data collection
[157]	One-hop Networks	Static Sink	Minimize latency
[158]–[160]	One-hop Networks	Static Sink	Maximize data accuracy
[161] [162]	One-hop Networks	Mobile Sink	Maximize throughput
[163]	One-hop Networks	Mobile Sink	Maximize data collection
[164]–[167]	One-hop Networks	Mobile Sink	Maximize network utility
[135]	Multi-hop Networks	Static Sink	Maximize delivery ratio in probabilistic data collection
[168]	Multi-hop Networks	Static Sink	Maximize quality
[169]	Multi-hop Networks	Static Sink	Maximize network utility
[170], [171]	Multi-hop Networks	Static Sink	Minimize latency

TABLE V: Comparison of the existing data collection scheduling methods

complete problem, the generalized assignment problem. The authors first proposed an offline approximation algorithm with a provable approximation ratio for the problem based on the combinatorial property of the problem, assuming that the harvested energy of each sensor node is known in advance and link communications in the network are reliable. Then, the authors proposed a scalable online distributed algorithm for the problem without the above assumptions. In this work, the online distributed algorithm is implemented through Probe messages broadcasting by the mobile sink.

The work in [161] also investigates the data collection throughput maximization problem in a BF-WSN with a mobile sink. Similar to the work in [163], the mobile sink in this work has fixed-mobility pattern and moves along a direct path. However, the transmission range of each node in this work is variable rather than fixed. The data collection throughput maximization problem is formulated as an integer linear programming model. This problem is proved to be NP-hard by the reduction from a special case of the generalized assignment problem, which is an NP-hard problem. To cope with the NP-hardness of the problem, time is divided into intervals, where each interval consists of two consecutive time slots. Based on interval partitioning, the authors proposed a scheduling algorithm to improve data collection throughput.

Some works consider the joint of mobile energy replenishment and data gathering, where a mobile sink directly provides energy to nodes through wireless power transfer and collects data from nodes [164]–[166]. In this scenario, energy replenishment of nodes no longer suffers from environmental variations.

The work in [164] investigates the optimal data gathering scheduling problem to maximize network utility. Based on the battery energy status of each node, the authors first proposed an anchor point selection algorithm through binary search and an approximate solution of the traveling salesman problem to generate a data gathering tour for the mobile sink. Then, they investigated the optimal data gathering scheduling problem to maximize network utility, which is defined as the sum of all the nodes' utility functions. The utility function of node i is twice-differentiable, increasing and strictly concave with respect to the total amount of data gathered from node i in a time interval. The optimal data gathering scheduling includes the optimal data rate of each node, the optimal link transmission scheduling based on the interference model, and the optimal routing for data gathering. The authors applied the proximal optimization algorithm and the dual decomposition based subgradient method to solve the problem in a distributed manner. The work in [165] is an extension of the work in [164]. The work considers two tours in anchor point selection, i.e., data gathering tour and recharging tour. In addition, this work considers a special network with regular topology and proposes a simplified solution with lower complexity for it, exploiting the symmetry of regular topology. However, the authors ignored the time consumption for energy replenishment.

The work in [166] and [167] also investigate the optimal data gathering scheduling problem to maximize network utility. However, the works in [164] and [165] assume that only data transmission consumes energy and the recharging rate of each battery-free sensor node is constant. Additional considerations for the energy consumption of data reception and sensing are provided in these works. Besides, the recharging rate of a node is time-varying. They apply the same anchor point selection method as in [164], which can generate a recharging tour for the mobile sink. The optimal data gathering scheduling problem with maximum network utility is formulated as a non-convex optimization problem. The optimal data gathering scheduling includes the optimal data generating and uploading rates of each battery-free sensor node, the optimal scheduling and routing paths of each battery-free sensor node, and the optimal sojourn time for the mobile sink at each anchor point. The authors reformulated the original problem as a convex optimization problem through introducing auxiliary variables, and separated it into a repeated two-level optimization problem by a hierarchical decomposition approach. A distributed algorithm was proposed to solve the two-level optimization problem. However, only a simple interference model is considered, i.e., the node-exclusive interference model, where any two links are not allowed to share a common node to transmit at the same time.

3) Multi-hop Topology: The work in [135] proposes some probabilistic data collection protocols for multi-hop BF-WSNs. The first probabilistic data collection protocol is the Probabilistic ReTransmission (PRT) protocol, where each sender determines its number of re-transmissions for a data packet based on the calculated probability of the data packet being successfully received by a neighbor. However, the PRT protocol ignores the transmission collisions among different nodes. To improve the PRT protocol, the authors proposed the PRT with Collision Consideration (PRT-CC) protocol, which considers the transmission collisions among different nodes. In both protocols, the data packet reception probabilities are exchanged among nodes through piggybacking them onto regular data packets. Moreover, the use of acknowledgements (ACKs) helps detect packet loss.

The work in [168] investigates the weighted, fair data rate allocation and flow routing problem for BF-WSNs. The optimization objective is to maximize the monitoring quality in a time interval, where a time interval consists of a fixed number of consecutive time slots. It is assumed that at the beginning of each time interval, the energy budget of each node in the time interval is instantaneously available. Taking into account the spatial data correlations among nodes, a weight is assigned to the data rate of each node. Then, the original weighted fair data rate allocation and flow routing problem is reduced to the maximum weighted concurrent flow problem, and an approximation algorithm is proposed with a provable approximation ratio. Furthermore, the distributed implementation of the proposed algorithm is provided.

The work in [169] investigates how to maximize data gathering in BF-WSNs (in terms of network utility) jointly optimizing the energy allocation, data sensing and data transmission for each battery-free sensor node. The authors first proposed a balance energy allocation algorithm for battery-free sensor nodes based on the assumption that the harvested energy of each node in each time slot of a period can be estimated with high accuracy, where the length of a period is one day (under solar energy harvesting process). Then, they proposed a dual decomposition method and sub-gradient method based algorithm to optimize the sensing rate and routing control for each battery-free sensor node. However, this algorithm ignores the signal interference among nodes, assuming that it can be eliminated by the underlying MAC layer.

The work in [170] investigates the minimum latency data collection scheduling problem in BF-WSNs. It considers both the protocol interference and the physical interference of data transmission. Different from other works, this work focuses on a more practical scenario, where the nodes can only estimate its own energy harvesting rate in a short period of time. Considering beacon messages containing energy status and partial scheduling strategies, the authors first proposed a distributed latency-efficient data collection scheduling algorithm for line BF-WSNs, where all the nodes are deployed in a line. Then, the authors proposed a distributed latency-efficient data collection scheduling algorithm for general BF-WSNs, where all the nodes are randomly deployed in a two-dimensional monitoring space. Furthermore, the bound of the data collection latency generated by the proposed algorithms is proved. The work in [171] proposes a distributed data collection framework, which uses an adaptive routing strategy. It also enables battery-free nodes to select receivers depending on their status and to provide more transmitting opportunities to achieve high spatial parallelism.

E. Combining transmission and in-network processing

Most BF-WSN approaches focus on sensing and networking algorithm design, and these approaches only consider the energy consumed by sensors and wireless transceivers for sensing and data transmission respectively. But in-network processing (e.g. data aggregation/fusion/compression) is also widely employed in real systems. The work in [172] jointly optimizes sensing (rate control), networking (routing, scheduling, and data forwarding), and in-network data processing for highly dynamic BF-WSNs. The object is to maximize aggregated network utility while guaranteeing sustainable network operation for networks with arbitrary network topology and dynamics. The authors proposed a novel approach called shadow sink to map data processing to virtual data forwarding operations, and to seamlessly combine data processing and wireless networking. As a result, the problem can be seen as a novel networking problem. They developed a lightweight online algorithm called RWE. Through rigorous theoretical analysis, they proved that RWE achieves asymptotical optimality, bounded data queue size, and sustainable network operation. Real-world experiments have been conducted to show that RWE can recycle more than 90% wasted energy caused by battery overflow, and achieve around 300% network utility gain in practical BF-WSNs.

1) Aggregation: The work in [173] proposes an energy-aware data aggregation scheme for BF-WSNs. In this scheme, a node periodically estimates its remaining energy for the next round at the beginning of the round. Then it selects one of the following three modes according to its estimated residual energy:

1) Normal mode: If a node's estimated residual energy is insufficient for sending out all stored data, it does not send any data and only receives and aggregates data received from other nodes and its own data.
2) Transmission mode: If a node's estimated residual energy is more than the battery capacity, it transmits its aggregated data using extra energy.
3) Energy-saving mode: If a node's battery will be exhausted, it transmits its aggregated data and turns to an energy-saving mode. In this mode, the node turns off its radio which is similar to a sleep state, and it does not communicate with other nodes. As a result, it is eliminated from routing because it cannot receive any control packets.

In case the amount of aggregated data of a node in normal mode exceeds the limit of its storage, the node transmits the data regardless of its residual energy. Conversely, if a node in energy-saving mode aggregates the excessive data, the extra data can be discarded.

Minimum Latency Aggregation Scheduling (MLAS) is another important problem for BF-WSNs. The work in [174], [175] studies the MLAS problem in BF-WSNs and three centralized algorithms are proposed where the BF-nodes are scheduled in an adaptive way according to their current energy conditions. However, centralized algorithms are not suitable for WSNs due to high energy consumption and large time complexity in the scheduling process. Moreover, the latency of the algorithms is in proportion to the maximum number of time slots needed for a node to get recharged to receive or transmit a packet. In other words, the latency is determined by the node with the lowest recharge rate, which can result in unacceptable latency. Aggregating data from all the nodes in a whole network is the cause of large time complexity here. However, in practical applications, there are usually multiple nodes being deployed to monitor a target area for higher data precision. It is not necessary to aggregate data from all the nodes in a whole network in the applications with relaxed requirements on precision. To address this, the work in [176] generalizes the MLAS problem to the MLAS problem with q coverage requirement in BF-WSNs (q-BFMLAS) and proves it to be NP-Hard. The first distributed energy-adaptive aggregation scheduling algorithm with coverage guarantee for BF-WSNs is proposed in this work. The works in [177] try to guarantee the covered nodes are evenly distributed in the whole network to further improve the aggregation accuracy. Several efficient aggregation scheduling algorithms are proposed without relying on predetermined structures for aggregation tree construction [178], [179]. Additionally, the MLAS problem when there are multiple aggregation queries is studied in [180]. In the proposed algorithm, a node selection algorithm is proposed to control the number of nodes participating in the aggregation process and connect the target nodes.

IV. Data Acquisition

Different from data collection which aims to transmit sensory data to the network sink, data acquisition investigates how to obtain enough sensory data from the physical world. Therefore, establishing a complete coverage for the monitored region is rather important in data acquisition.

There are two key methods to acquire data from the monitored region. The first method is to use the sensor nodes to form a cover to collect enough sensory data, and the second method is sensor-less sensing which aims to use the Radio-based signals to collect enough sensory data from the physical world. In the following sections, we first introduce the sensor based data coverage methods, and then we briefly introduce the sensor-less sensing techniques.

A. Coverage Methods

A coverage is a set of working sensor nodes that can monitor the environment at a certain time. The coverage quality indicates how well the interested region is being monitored by the network. When designing a coverage method, the following aspects need to be considered, coverage type, objective of the coverage and type of energy supply of a network. Table VI illustrates the comparison of different coverage methods, and the details of these works are summarized as follows. Based on the coverage type, the coverage methods can be divided into two kinds, full coverage and partial coverage.

1) Full Coverage: In [181], [182], the authors considered the Maximum Lifetime Coverage problem in BF-WSNs. The goal is to maximize network lifetime and ensure all the targets are monitored by at least one sensor node during the network lifetime. The authors proved that this problem is NP-Hard. Two approximation algorithms are proposed to solve the problem. The first algorithm (LP-MLCEH) is a linear programming based algorithm in which the problem is formulated as a linear programming problem. The linear programming problem is solved through binary search. The second algorithm (MUA) is a greedy algorithm which aims to minimize energy wastage of sensor nodes due to lost recharging opportunities. In this algorithm, the node with the maximum residual energy is selected to work at each time slot. The experimental results show that comparing with the MUA algorithm, the LP-MLCEH algorithm can obtain longer network lifetime but is time-consuming.

The authors in [183] studied the Distributed Maximum Lifetime Coverage with Energy Harvesting (DMLC-EH) problem. The problem aims to maximize network lifetime of a BF-WSN in a distributed manner. In this work, the authors proposed the **off-duty rule**. The rule implies that if all the targets within the sensing range of node i have been covered by its neighbors, then i can turn itself off without reducing the overall target coverage. Otherwise, node i needs to be active. A distributed scheduling algorithm was proposed based on the off-duty rule.

The work in [186] studies coverage and connectivity of BF-WSNs. The authors aimed to construct a cover in each time slot to maximize coverage quality. A cover is a set of working sensor nodes that can communicate with each other. The coverage quality of a target o is measured by the number of time slots that o can be covered and the number of sensors that can monitor o in a certain time. It is proved that maximizing coverage quality in BF-WSNs is NP-Hard. A heuristic algorithm was proposed to solve the problem. The algorithm uses a forest to predict the working status and connectivity of sensor nodes. Based on the forest, the algorithm greedily selects sensor nodes to work until the monitored duration ends.

The authors in [187] investigated the coverage problem in a new type of BF-WSNs. There are two types of sensor nodes in such networks, non-harvesting nodes and harvesting enabled nodes. Non-harvesting nodes cannot harvest energy and are in charge of sensing and acquiring data from the environment. Harvesting enabled nodes can harvest energy and are adopted as relay nodes to transmit data. The problem is how to place the minimum number of harvesting enabled nodes to cover all non-harvesting nodes and guarantee successful data transmission. This problem is proved to be NP-Hard, and it is solved by adopting connected dominating sets. The algorithm has two major steps. First, a minimal dominating set is constructed in the graph deduced by all the non-harvesting nodes. Second, the harvesting enabled nodes are placed next to the non-harvesting nodes that are in the connected dominating set. The authors also formulated the problem as an integer linear program and proved that the lower bound of this problem is the solution of the program.

The coverage problem in a BF-WSN with a mobile charger is studied in [188]. The authors aimed to schedule a mobile charger to charge sensor nodes and maintain full coverage of the network. The monitoring duration is divided into multiple rounds and the scheduling strategy has three steps. First, the sensor nodes are weighted based on the residual energy. Second, the sensor nodes are classified into three categories, green, yellow, and red, based on their weights. Third, a charging tour is determined based on different classes of the sensor nodes. The mobile charger first recharges the sensors in the red class since they are going to exhaust their energy. A Hamiltonian cycle algorithm is adopted to calculate the charging tour for the red class sensors. The yellow class has the second priority and it means that the sensors can live for

	Coverage Type	Objective	Energy Supply
[181]–[185]	full coverage	maximize network lifetime	natural energy
[186]	full coverage	maximize coverage quality	solar energy
[187]	cover sensor nodes	minimum-cost deployment	natural energy
[188]	full coverage	optimize charging tour	mobile charger
[189]–[191]	full coverage /energy neutral	minimum-cost deployment	natural energy
[192], [193]	k-coverage	optimize the charging tour	mobile charger
[194]	full coverage	minimum-cost deployment	natural energy
[195], [196]	full coverage	minimize energy consumption	RF energy
[197]	partial coverage	maximize coverage quality	solar energy
[198], [199]	partial coverage	maximize coverage rate	natural energy
[200]	energy-data dual coverage	maximize coverage rate/minimum-cost deployment	natural energy and RF energy

TABLE VI: Comparison of the existing coverage methods

more than a round. The charging tour for the yellow sensors is similar to that for the red class. The only difference is that some sensors can be ignored in the charging cycle such that the charging tour is short or the mobile charger can recharge more sensors. Green sensors have enough energy and do not need to be charged.

In [189] and [190], the authors considered maintaining "energy neutral" coverage and connectivity of a network by delicately placing energy harvesting sensor nodes. The energy neutral of a sensor node means the energy consumed to monitor targets is less than its harvested energy. Specifically, the problem investigated in these papers aims to place the minimum number of sensor nodes such that 1) the placement can meet the coverage requirement of each target, 2) each node has a path to the sink, and 3) every node has energy neutral operations. The authors proved that this problem is NP-Hard.

In [189], the targets require perpetual coverage and three algorithms are proposed. The first algorithm is the GMILP algorithm. In the first step, the problem is formulated as a mix integer linear programming (MILP). Then the maximum weighted set cover (MWSC) algorithm is invoked to reduce the search space of MILP. Finally, MILP is solved based on the search space obtained in the last step. The second algorithm, DirectSearch, and the third algorithm, GreedySearch, rely on straight lines from the targets to the sink. In DirectSearch, sensor nodes are only deployed on the points that cover the lines connecting the targets to the sink. On the other hand, GreedySearch considers deploying nodes at other positions to further optimize the performance of the algorithm. It has three steps. First it determines a set of points to place some nodes to monitor the targets. Second, it determines a set of points to deploy some nodes to make the network connected. Third, it computes the number of nodes at each position to maintain the energy neutral operations of the nodes. Witnessed by the simulation results, DirectSearch and GreedySearch are more effective than GMILP while GMILP can obtain better results.

In [190], each target requires a fixed sampling rate, and the monitoring sensor should have enough energy to keep the sampling rate. The authors also formulated the problem as an integer programming problem and adopted the relaxation and rounding method to solve the problem.

Different from [189], [190] in which the authors have assumed that the harvested energy of each sensor node is a constant, the authors in [191] used the hidden Markov model to predict harvested energy. The motivation of this work is to schedule energy harvesting sensor nodes to work to maximize the number of time slots so that all the targets are covered. Based on the energy prediction model, this problem is solved by a Monte Carlo sampling method.

The authors in [192], [193] investigated the k-coverage problem in a BF-WSN with a mobile charger. k-coverage requires that each target should be monitored by at least k sensors at each time. This work aims to schedule the mobile charger to recharge sensor nodes and maintain the k-coverage of all the targets. To do so, the sensor nodes are clustered at first. The objective of clustering is to balance the workloads and energy consumption of nodes so that a single charging round of the mobile charger can cover more energy recharging requests and reduce the moving cost of the charger. After the clustering, a shortest Hamilton path is calculated through clusters. Following the path, the mobile charger recharges sensor nodes.

The authors in [194] studied the target coverage problem in BF-WSNs with directional sensor nodes. A directional sensor node can monitor the targets in a certain direction. The motivation of this work is to study the minimum-cost deployment of sensor nodes for perpetual target coverage. To do so, the deployment should 1) satisfy the coverage requirement of each target, 2) find the communication route from each sensor node to the sink, and 3) achieve the energy neutral operation [189] of each sensor node. The authors proved the NP-Hardness of the problem and proposed three approximation algorithms to solve it. The first algorithm is the linear program-based heuristic (LPBH) algorithm. LPBH modifies the problem into an integer programming problem at first, and then transforms it to a linear programming problem by removing the integrality constrains. In the next step, LPBH solves the linear programming and transforms its solution into a feasible solution of the investigated problem. Obviously, LPBH is time-consuming. The authors also proposed two effective heuristic algorithms, Two-Stage Heuristic (TSH) and Sensing and Routing Integrated Greedy Heuristic (SRIGH). TSH has two stages. The first stage deploys a minimum number of sensor nodes to cover targets, and the second stage places sensor nodes to connect them to the sink. In SRIGH, a sensing node and its communication route to the sink are determined at the same time. Here, the communication route is determined by the shortest path algorithm. Based on the experimental results, TSH is the most effective one. However, the results obtained by LPBH and SRIGH are better.

The authors in [184], [185] investigated the coverage problem in a network with many non-chargeable sensor nodes and a few energy harvesting sensor nodes. The purpose of this kind of BF-WSNs is to use a little number of energy harvesting sensor nodes to further prolong network lifetime. The authors defined a new standard of network lifetime based on the concept connected dominating set. Constructing a connected dominating set is a key method in wireless sensor networks to maintain network coverage and connectivity. In these two works, network lifetime is defined as the number of working connected dominating sets. A working connected dominating set in time slot t is a connected dominating set of the network and the sensor nodes in it can work at t. The motivation of these works is to construct the maximum number of working connected dominating sets to maximize network lifetime. The authors proved that this problem is NP-Hard. Two approximation algorithms were proposed to solve this problem. The first algorithm is a centralized one. It first calculates the upper bound of the actual working time slots of each sensor node. Then a new network is constructed based on the calculated actual working time. Each node in the new graph can work for only one time slot. Based on Theorem 3 in [184], the original problem is equal to constructing the maximum number of disjoint connected dominating sets in the new graph. Thus, in the last step, the algorithm adopts an existing work [201] to construct the maximum number of disjoint connected dominating sets in the new network. The approximation ratio of this algorithm is $\frac{\Delta'}{\lfloor\frac{\Delta'+1}{\beta(c+1)}\rfloor-\epsilon\Delta'|V|}$, where Δ' is the minimum degree of the new network, $c < 11$, $\beta < 2$ are two constants, and V is the set of sensor nodes. The second algorithm is a distributed one which is more suitable to large scale energy harvesting networks. The algorithm first transforms the network into a weighted graph based on the real working time of each sensor node and constructs a connected dominating set in each time slot based on the following two phases. In the first phase, the algorithm distributedly finds a set of sensor nodes to be a dominating set. In the second phase, the algorithm connects the nodes in the dominating set and constructs the connected dominating set. Based on Theorem 6 in [185], the approximation ratio of the distributed algorithm is equal to the minimum vertex cut of the weighted graph.

The works in [195], [196] investigate the coverage problem in BF-WSNs powered by RF energy. The authors call such a network as the "RF-based battery-free sensor network" in which the sensors are modified passive RFID tags and are powered by the RFID Readers. The sensor nodes work in a passive way which means a sensor node can sense and transmit if and only if it has been powered by a RFID Reader. The RFID Readers are equipped with directional antenna and rotate their antenna to recharge sensor nodes and collect the sensory data simultaneously. Rotation and recharging consume a Reader's energy. In order to save energy and maintain the coverage of the sensory data, the Readers only collect the sensory data from the sensor nodes that belong to the dominating set. The problem is how to use the minimum energy to schedule Readers to recharge and collect sensory data from the dominating set in each time slot during the monitoring duration. The authors proved that this problem is NP-Hard. A centralized algorithm and a distributed algorithm are proposed to solve this problem. The centralized algorithm aims to approximately minimize the globe energy consumption by minimizing the energy consumption in each time slot. To do so, the algorithm greedily schedules the Readers in each time slot based on the energy consumption at different rotation angles and the newly dominated sensor nodes. The approximation ratio of the centralized algorithm is $ln(|V_B|)(1+\frac{e_r\pi}{e_b\delta})$, where V_B is the set of sensor nodes, e_r and e_b are the energy consumed by rotation and recharging respectively. The major idea of the distributed algorithm is similar to that of the centralized algorithm. However, in the distributed situation, the Readers can only schedule themselves based on local information. Thus, the performance of the distributed algorithm is not as good as that of the centralized algorithm. The authors in [195] proved that the approximation ratio of the distributed algorithm is $(\frac{(2\pi-R)e_r}{\delta e_b}+\frac{2\pi}{R})(1+\frac{e_r\pi}{e_b\delta})ln(|V_B|)$, where R is the radiation angle of each Reader.

2) Partial Coverage: Different from the full coverage, the partial coverage methods use the coverage ratio (or coverage rate) to measure the coverage quality.

The authors in [197] investigated the coverage problem in a battery-free WSN powered by solar energy. It is assumed that the coverage quality is a submodular function over the set of the sensors providing the service. Furthermore, it is assumed that the recharging rate is stable. The coverage quality maximizing problem in such networks is proved to be NP-Hard. The authors proposed a greedy hill-climbing activation scheduling scheme to maximize coverage quality. In each step, the scheme schedules a node to a proper time slot to maximize the incremental quality together with the previously scheduled sensors. The authors proved that the achieved coverage quality is at least $\frac{1}{2}$ times of that achieved by the optimal schedule.

Instead of specifying the energy source to solar energy, the authors in [198], [199] investigated BF-WSNs powered by general ambient energy. Since ambient energy is always weak and distributes unevenly, sensor nodes may not be able to harvest enough energy to work in any time slot. This implies that maintaining full coverage of the monitored targets all the time is almost impossible. Therefore, in this work, coverage quality is measured by the average coverage ratio. The problem is how to schedule sensor nodes to work to maximize coverage quality during the network lifetime. This problem is NP-Hard. Based on Theorem 2 in [199], the problem has a polynomial time solution if the network parameters satisfy specific sufficient conditions. The work in [199] proposes two centralized algorithms to solve the problem when the sufficient conditions are not satisfied. The first algorithm is the Disjoint Set Cycling (DS-C) algorithm. DS-C first constructs k disjoint node sets to maximize the average coverage rate where k is a variable related to the minimum recharging rate. Then DS-C schedules these sets to work in cycle to cover the monitored region (or targets). Obviously, DS-C is related to the minimum recharging rate and it can predetermine the schedule of sensor nodes in advance. This property implies that DS-C is easy to be implemented but is not adaptive to energy violation. Different from DS-C, the second algorithm Adaptive Local Coverage Quality Maximization (ALCQM) aims to maximize the coverage quality locally to maximize the global coverage quality approximately. In each time slot, ALCQM uses the Predicting Network to predict the working status of each sensor node in the next two time slots and adopts a greedy strategy to schedule sensor nodes to maximize coverage quality in these two time slots. The experimental results show that ALCQM can obtain better coverage quality than DS-C. However, ALCQM is time-consuming.

In [200], the authors further considered BF-WSNs powered by both RF energy and ambient energy. RF energy is supplied by Power Stations. The authors proposed the energy-data dual coverage concept. Energy coverage means to deploy Power Stations to supply stable energy to sensor nodes, and data coverage means to schedule sensor nodes to cover the monitored targets. The authors analyzed the relationship between energy coverage and data coverage, and proposed two heuristic algorithms to meet different user requirements.

B. Sensorless Sensing

Sensorless sensing is a hot topic in the recent years. For a WiFi system with MIMO-OFDM, Channel State Information (CSI) is a 3D matrix of complex values representing the amplitude attenuation and phase shift of multi-path WiFi channels. Time series of CSI measurements capture how wireless signals travel through surrounding objects and humans in time, frequency, and spatial domains, so it can be used for different wireless sensing applications [23]. In this scenario, we can use WIFI "sense" the environment and objects without sensors, so it is called sensorless sensing. The sensorless sensing technique can be used in human behaviors detection [202]–[205] and object movement monitoring [206]–[209]. A detailed survey of the sensorless sensing techniques is presented in [23]. In this paper, we briefly introduce the framework of sensorless sensing.

Sensorless sensing aims to extract information from CSI. In a sensorless sensing system, the input is raw Radio-based signal with the Channel State Information. Then the signal will be processed through noise reduction, signal transformation and signal extraction. Finally, the processed results will be fed into modeling-based, learning-based, or hybrid algorithms to obtain the results for different sensing requirements.

V. Applications

In BF-WSNs, the rechargeable sensor nodes without batteries which can be deployed in practically any area, do not need to be replaced for a long time, and work under extreme conditions, have enabled many new capabilities in the IoT. Currently, BF-WSNs have been employed in many practical applications, such as environmental sensing, object localization, structural health monitoring, mobile health monitoring, video streaming and electrical current sensing, industrial applications, etc. This section provides some examples of these applications accordingly.

A. Environmental Sensing

Several battery-free sensing techniques have been developed for environmental sensing, such as monitoring the ambient environmental parameters (*i.e.*, humidity, temperature, light intensity, etc.) inside a building or in an outdoor environment (*i.e.*, a forest), the health of the ecosystem, the emission of carbon dioxide, etc. Some examples are shown below.

Indoor Air Quality Monitoring: The work in [210] proposes a system with RF-powered wireless sensors for indoor air quality monitoring, which can measure the concentration of volatile organic compounds, ambient temperature, relative humidity, and atmospheric pressure in a building. In the proposed system, an ultra-low power sensor combined with a radio frequency energy harvester is employed, which can harvest the available RF energy from the reader within a maximum distance of 250cm. In [211], the authors try to use passive RFID tags as the battery-free temperature sensors. In their design, the phenomenon that the impedance of an RFID tag changes with temperature is used to sense the temperature. In [212], a battery-free humidity sensor is designed with reasonable sensitivity, reliability, and eco-friendly nature.

Forest Fire Monitoring: Forest fire is one of the most dangerous disasters for the ecosystem, which may cause significant damage to natural resources and economic prosperity. To detect forest fire at an early stage, the work in [213] proposes a forest fire prediction scheme with rechargeable wireless sensors. In the proposed system, it is stated that the rechargeable wireless sensors own the following two superiorities for forest fire monitoring: 1) A large number of low-cost sensors can be deployed in a remote forest field to obtain accurate environmental data (temperature and humidity); 2) Due to the battery-free design, it can harvest energy from solar and wireless power transfer technology to avoid replacing batteries, which greatly reduces the maintenance cost (the monitored area is usually in an untraversed region). The proposed system can collect 24-hour weather data continuously to obtain the status of forest environment accurately and the risk of forest fire.

Insect Monitoring: In [214], an insect monitoring system with batter-free sensors is presented. In the proposed system, a small and lightweight digital telemetry system is designed to record the moving insects, which includes an RF energy harvesting circuit for battery-free operations. The circuit can also communicate with the base station through backscattering. It has a measured flight package mass of only 38mg, which enables recording from insects in flight. The base station includes a RF transmitter to transfer the power to the telemetry circuit wirelessly, and a digital transceiver to collect the sampled data from the telemetry circuit on the insects.

B. Object Localization

Object localization with battery-free devices has become a new hot-spot recently. Many practical applications, including indoor positioning, indoor navigation, object tracking, and even gesture recognition, etc., are proposed.

Indoor Positioning: Indoor positioning is a basic and essential service for many IoT applications. A typical application is called goods positioning in warehouse. The works in [215] introduces an indoor positioning system with battery-free RFID tags, which can obtain the 3-D positions of items in a indoor environment. In the proposed system, the ultrasound detectors and accelerometers are used to estimate the tags' position. In [216], the authors investigate the underwater backscatter localization system for the first time. They present a proof-of-concept prototype and deploy it in the Charles River in Boston. In their prototype, there is a backscatter node and a PCB embedded with a microcontroller to handle the challenges in underwater localization with acoustic backscattering, such as extreme multipath of acoustic signals and slow speed of sound. The battery-free indoor positioning system with visible light is studied in [217]. In their design, the shadow of the target is used to predict its position. The proposed system can position the target when it senses a drop in the intensity of ambient light caused by the presence of a shadow.

Indoor Navigation: Since the accuracy of a current GPS system inside a building is not enough for indoor navigation, a BF-WSN based indoor navigation system, which can work for a long time without replacement and can be deployed in anywhere, would be beneficial [218]. In [219], the authors present a battery-free parking system with visible light. The battery-free tags are instrumented on the vehicles and the parking places to obtain the vehicle positions and status of parking spaces in a low-cost manner. The authors also design a lighting infrastructure to conduct data communication based on the visible light backscatter communication. The authors in [220], [221] try to obtain the accurate positions of the rechargeable sensor nodes with the unique Time of Charge (TOC) sequences when the charger stops at different point to charge them.

Object Tracking: Recently, device-free object tracking has become a promising solution for many local tracking systems with non-cooperative objects which do not carry any transceivers [222]. In [223], the authors propose a tracking system with passive RFID tags, which try to detect the targets moving inside an unconstrained indoor environment. In the proposed system, they leverage the relationship between the received signal strength indicator (RSSI) value and the moving status of the object to estimate the target positions. To improve the accuracy, a signal noise reduction method is used to clean and normalize the original data, and then a particle swarm optimization based algorithm is proposed to obtain its initial position. A trajectory prediction method is also given for continuous tracking. The system can achieve an accuracy of 1m in an unconstrained indoor environment. In [224], [225], the authors propose an intrusion detection system with the commercial off-the-shelf RFID readers and tags. In their design, the interference among passive RFID tags is leveraged to detect moving objects. The proposed system has a low positioning error of 0.75m in average, which is effective to detect moving objects.

C. Mobile Health Monitoring

Wireless and battery-free sensors can also be employed to support reliable and long-term health monitoring with minimal intervention. Some examples are shown below.

Battery-free Body-Area Networks: The work in [226] implements a prototype of a battery-free body-area sensor. In their designed battery-free sensors, there is an energy management module, a microcontroller chip, a small triple-band rectenna, and a sensing and communication module. To support continuous operation of the sensors, an electrically small triple band rectenna is designed to harvest energy for RF signals at GSM-900, UTMS-2100, and TD-LTE bands. In [227], the authors try to power the wireless battery-free body-area networks from a long distance. In their proposed system, there is a cellphone-like power source and a passive relay node which transfers energy from the power source to multiple battery-free sensor nodes on the body. The star network topology is leveraged to support continuous connection of these sensor nodes and the sink station. In the design, the wireless power transfer source can power up to 6 sensor nodes from a distances at 60cm with a sample rate of 20Hz.

Wearable Bio-sensing: Wireless battery-free wearable bio-sensors can enable noninvasive health monitoring, which has gained an increasing attention from researchers. In [228], the authors design a wireless wearable bio-sensing platform which can harvest energy from body motions to support robust and continuous bio-sensing. In their platform, a triboelectric nano-generator with a flexible printed circuit board is designed as the energy source to support bio-sensing and data transmission via Bluetooth. In [229], the authors design a wearable tag to monitor multiple physiological signals, which can also emit an alarm when it detects an emergency signal of the patient. The tag consists of a self-designed integrated circuit, an RF-Powered antenna for energy harvesting, and several sensors for bio-sensing. The total cost of the designed wearable tag is less than 2 dollars.

Mobile Health Care: In [230], a hospital nurse calling system is proposed with the RF-powered sensors. In their system, each patient carries a wireless battery-free call device, which is used for making requests and providing patient positioning. For patient positioning, several reference nodes are deployed in the hospital and the trilateration positioning method is leveraged to estimate a patient's position with the received signal strength indicator values at the reference nodes. Once a patient's position is obtained, the nearest nurse will get an alarm when an emergency occurs. In [231], the authors design a wearable battery free sensor for falling detection, which is one of the most serious medical concerns for elderly patients. The designed sensors can not only harvest energy from RF wave of an off-the-shelf reader but also transmit their sampled data to the reader wirelessly. To improve the detection accuracy, the authors combine the values of the accelerometer with the received signal strength indicator values of wireless signals for prediction. The proposed system can work in an operating range of up to 2.5m.

D. Structural Health Monitoring

For structural health monitoring, *i.e.*, monitoring the health status of civil and mechanical structural infrastructures [232], including the high-tall buildings, long suspension bridges, railway and subway tunnels, etc., there have been many studies taking BF-WSNs as a promising solution.

Bridge Health Monitoring: The work in [233] presents a prototype of the battery-free and LoRa based sensor node to monitor the occurrence of ice on a large bridge. A LoRa transceiver is leveraged in their design although it consumes much more energy than other short-range wireless transmission techniques, such as Bluetooth. This is mainly due to it enables the monitoring of a large bridge from a long distance. To support the energy consumption of the batter-free sensor nodes, a low cost electromagnetic vibration energy harvester is designed, which is more cost effective, longer lasting, and easily scalable to different level of power consumption. The Halbach array of permanent magnets are employed in their design to reduce the sizes of the designed energy harvester. The harvested energy is stored in a supercapacitor, which is used to support a ARM Cortex M0+ microcontroller and the LoRa radio frequency module. In [234], two prototypes of RF-powered sensing nodes are implemented, which are powered by an RF energy source operating in the ISM 868MHz frequency band with the far-field wireless power transfer technique.

Building Monitoring: The work in [235] presents a battery-free sensor node with commercial off-the-shelf components for building monitoring. In their proposed system, an indoor battery-free sensor node which can support Bluetooth communication is designed, including an ambient light energy harvesting module. To maximize the lifetime of the designed nodes under dynamic lighting conditions, a predictive algorithm is proposed to achieve a trade-off between node-lifetime, quality of service and light availability. In [236], a battery-free sensor node with sensing and communication capabilities is wirelessly powered by a dedicated radio frequency source which can transfer energy at a long distance. A prototype of such a sensor node is implemented, including a temperature sensor and a relative humidity sensor, the communication model which can enable LoRa WAN uplink wireless communication, and an energy harvesting model. It is shown that the designed sensor node can achieve periodicity of measurement and communication with the wireless power transfer source.

Structural Damage Localization: The work in [237] leverages battery-free sensor nodes for damage localization and quantification in gusset plates. Gusset plates are usually used as as a critical component to connect different structural members (*i.e.*, diagonals, chords, and vertical members) in the structural system (*i.e.*, bridges and trusses). Because of the corrosion, there may exist typical damages of gusset plates at intersections of different members. In this work, the authors design a prototype of battery-free sensor nodes for damage localization and quantification in gusset plates. A network of battery-free sensor nodes is deployed on the surface of the plate. With the fusion of the sensing data from self-powered sensor nodes in the network, they proposed a crack localization and quantification method to detect the damage and measure the crack size.

E. Industrial Applications

Some works try to employ the novel battery-free design in the Industrial Internet of Things (IIoT) applications, such as industrial monitoring and leakage detection.

Industrial Monitoring: The work in [238] introduces a prototype of battery-free sensor for industrial monitoring with a designed Ultra High Frequency (UHF) RFID integrated circuit. The designed circuit can harvest and store energy from RF signals based on a low cost CMOS. It also incorporates a serial peripheral interface in order to communicate with two commercial digital sensors, which can monitor temperature and pressure. In [239], the authors design a battery-free goods quantity monitoring system in a small warehouse, which act as a link in the logistics process. For smart warehouse, it needs to ensure the speed and accuracy of the data input in each link of warehouse management. The proposed system is aimed for counting the number of goods in each column in the smart warehouse with a small number of RFID tags. The correspondence between the quantity of goods and the radio frequency signal is used to identify the quantity of goods with the K-Nearest Neighbors (KNN) classification algorithm.

Leakage Detection: Leakage detection is an essential issue for factories with numerous pipelines. In [240], the authors propose a battery-free and low-cost system for liquid leakage detection with backscattered signals. In their design, the commercial off-the-shelf RFID tags are used. The intuition is that the leaked liquid around tags will change the phase and the RSSI values of the emissioned signals of tags, which then can be used to detect the presence of liquid leakage. To make the proposed system work functionally, the authors mainly focus on the following two challenges : 1) how to detect the slight signal variation which is changed by the leaked liquid; 2) how to eliminate the multipath and interferences between different tags. It is shown that the proposed system can achieve 90.2% true positive rate while keeping the false positive rate is not larger than 14.3%.

F. Image Capturing and Video Streaming

Although the RF-powered devices face great energy limitations for performing arbitrarily complex sensing and computation, the energy-consuming sensing and computation tasks in a battery-free design, such as battery-free image capturing and video streaming, are also investigated recently.

Image Capturing: In [241], the authors design a passive UHF RFID camera tag to support reliable image capturing and transmission. The passive UHF RFID camera tag is designed based on the wireless identification and sensing platform and powered by an RFID reader. To utilize the harvested energy efficiently, they leverage a charge-storage scheme to support the operation of the image sensor, in which they try to balance capacitance and leakage of the energy-harvesting model to improve efficiency. They also proposed a data storage and communication method to transmit the image data to the RFID reader. Two practical applications, *i.e.*, mechanical gauge reading and surveillance, are implemented with the designed tag. In [242], the authors further improve the battery-free image capture tag. They propose a novel data storage and bi-directional communication method to support reliable image data transmission even under the scenario with packet loss. The designed system also can support periodic updates on the charging state of the tag before it has accumulated enough energy for image capturing.

Video Streaming: Video streaming is an extremely energy-consuming operation, which needs power-consuming hardware and computationally intensive video codec algorithms. This makes it seemly impossible for battery-free implementation. In [243], the authors present a novel architecture which can support HD video streaming with a battery-free camera which can transmit the video data to a nearby mobile device. In their design, to remove the power-consuming hardware components including ADCs and codecs, they proposed an "analog" video backscattering method to feed analog pixels from the photo-diodes directly to the backscatter hardware. It is shown that their system can achieves 60fps 720p video streaming with a power of 321uW and 1080p HD video streaming with a power of 806uW. The empirical results also show that their system can support battery-free 30fps 1080p video streaming at a distance up to 8 feet.

VI. Conclusion

In this survey, the existing algorithms for BF-WSNs are summarized and analyzed where a BF-WSN is a solution to address the energy limitation of conventional wireless sensor networks. The algorithms are classified into three categories, energy management, networking, and data acquisition. We first introduce the existing works for energy replenishment scheduling, including charger deployment, charger placement and charger scheduling. Then we present the algorithms for communication and networking, such as broadcasting, routing, data collection and data aggregation. Furthermore, we summarize the works in data acquisition, including sensorless sensing and coverage. Finally, we introduce some specific applications in BF-WSNs.

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