WIRELESS CHARGING PADS IN SENSOR NETWORKS WITH RECHARGEABLE BATTERY TECHNOLOGY

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Abstract: Innovative vehicle energy solutions and technological advances using wireless sensor networks are being brought about by fast development of wireless power transfer technologies (WSNs). Sensor nodes are typically served by one or more wireless charging vehicles (vehicles) in most current systems for wireless rechargeable sensors networks (WRSNs) (SNs). These plans do a good job of dealing with the energy problem, but because of vehicle speed and off-road restrictions, some SNs will never be fully charged, which will shorten the networks' lifespan. When the drone can't make it to the next stop, it will be charged using several wireless charging pads (pads) that we've developed as part of our research as a new WRSN model. Our design addresses the problem of the drone's limited battery capacity while also solving the charging issue. Consequently, a wireless charging pad deployment problem is developed, which seeks to apply the lowest number of pads such that the drone may create at least one viable routing route for every SN in the specified WRSN to reach. This issue is addressed using four different heuristics: three based on graph theory, one on geometry. The shortest multi-hop route method is also created for the drone to fulfil charging requests with the use of pads, which is a new drone scheduling technique. We do comprehensive simulations to check the suggested plans. When looking at network density, area, and maximum flying distance, the findings compare and show the efficacy of the various methods presented. Keywords: Wireless power transfer, wireless charging drone, wireless charging pad, sensor node, wireless rechargeable sensor networks.

1.INTRODUCTION

Wi-Fi sensor networks (WSNs) using cutting-edge technologies are extensively utilised in a variety of applications requiring system monitoring, such as metro operations, military operations, and environmental monitoring [1]. WSNs have a serious energy challenge since sensor nodes (SNs) at remote locations are difficult and expensive to replace. The wireless rechargeable sensor network (WRSN) was created as a result of recent advancements in wireless power transmission (WPT). This new network has rapidly drawn the attention of many academics. According to the most current findings, wireless charging vehicles (vehicles) equipped with high-capacity batteries and WPT devices may be used to power sensor nodes. They allow a vehicle to travel near to an SN and wirelessly charge it without making any contact with the SN at all. Existing vehicle-related research includes using many SNs at once [2], developing mobile charging protocols [3], simultaneously charging multiple SNs [4], and arranging optimum collaborative charging schedules for numerous cars to improve sensor network performance [5]. These plans have the potential to alleviate the world's energy crisis to some degree. However, there are two critical flaws with automobiles that are often overlooked: As a result, it's obvious that WRSNs' biggest challenges will be off-road and travel speed restrictions. Drones for wireless charging of SNs in WRSNs have recently been explored in certain research [14]. When the drone's battery gets low, it must return to the base station (BS) to refuel, which necessitates repeated flights between the sensor nodes and the base station to keep the drone running. Furthermore, advances in drone wireless charging technologies have been made [6]–[13]. There may be an automated landing wireless charging pad (pad) for a drone used in conjunction with a highpower and high-efficiency WPT system to charge a drone quickly, eliminating the need for repeated visits back to the base station [6].

One drone and many pads are proposed as a new sensor network model to overcome off-road and travel speed constraints in this study. Sensor nodes send charging requests to the base station, which computes and schedules the drone's best scheduled trip, according to the new method. It leaves the base station to charge sensor nodes in accordance with its designated timetable after getting a charging mission. The drone must fly to a nearby pad for energy replenishment before visiting the next node if its energy falls below a certain level while on the journey. After completing the job, the drone returns to the station, where it sits in anticipation of its next assignment. However, the low battery capacity limits the use of drones in the WRSN today. As a result of drones' limited battery capacity, they can only fly a fraction of the distance of vehicles. During a mission, a drone with an assigned charging tour may need to land on several charging pads in order to meet all charging demands.

II. RELATED WORK

In this part, we'll take a look back at past WRSN and drone-specific wireless charging research. The first step is to go through past research on energy-resolution methods for WRSNs. After that, we'll look at current research on drone wireless charging to see where we're at now. Most prior efforts have used one or more MCs to wirelessly charge the network's nodes. The architecture of the schemes relies heavily on how well the MCs are scheduled in order to ensure improved network performance. Periodical charging schemes and on-demand charging schemes are the two major types of charging schedules used today. On the basis of periodic charging, these methods assume that the MCs move along a certain route in the sensing region, periodically charging the SNs wirelessly. Wireless charging and data gathering were suggested by Zhao et al. [2] using multifunctional MCs (MFMCs). To solve the scalability issue in a dense WSN, the authors of Xie et al. [3] proposed using WPT technology to charge MCs as they move along an optimal route within the WSN.

Fu et al. [18] devised a mobile reader charging route that minimised the overall charging time. A new energy-synchronized mobile charging protocol (ESync) was also suggested in [4], which lowers the travel distance of MCs and the charging delay of sensor nodes simultaneously. Based on different nodes' energy usage, they created nested TSP charging tours by picking out the most energy-hungry. Guo et al. [19] explored a WRSN architecture for combined wireless energy replenishment and anchor-point based mobile data collecting, which was framed as a network utility maximisation issue. A distributed method was also developed, in which the sojourn duration at each anchor point is constantly adjusted by the MC. The optimum velocity issue was originally discovered by Shu et al. [20] when an MC travels along a specified route on a regular basis. In the meanwhile, they devised a strategy to maximise the charged energy in SNs by using arbitrary, irregular paths in a two-dimensional environment. As a result of this, Liu et al. [21] developed a new metric called the criticality index (CI) to measure how critical nodes are to the overall system. Then they chose SNs with the greatest possible total number of CIs in the charging tour while keeping MC's travel distance to a minimum. In order to improve data arrival rate and transmission latency in solar energy harvesting wireless sensor networks, Liu et al. [22] proposed a security disjoint routing-based verified message system. Sensor data was collected from a rendezvous location using a mobile sink, according to Liu et al. [23]. They developed a fast rendezvous planning method based on a convex hull for complete connectivity and reducing multihop communication energy consumption by building a near-convex hull trip. The energy issue in WRSNs is solved by optimum route planning in on-demand systems. The schemes, on the other hand, presuppose that the MCs are aware of the SNs' current energy consumption status. He and his colleagues [24] established the theoretical groundwork for a mobile charging issue where MC charges the SNs that submit charging requests when their energy drops below a particular threshold. This is known as an on-demand mobile charging problem. Afterwards, they put forth the NJNP (nearest-job-next with preemption) algorithm, which prioritises charging the node that is closest to it in terms of distance. In their study, Lin et al. suggested a number of alternative pricing schedules. According to [25], there should be two warning levels with a two-tiered preemption fee structure. Two criteria and comparison procedures were developed in the system to determine charge request scheduling priority. For real-world features of WRSN, two preemption methods have been developed. For improved performance, the researchers in [26] developed a temporal and distantial priority charging scheduling method that took into account how far nodes were from the MC and how quickly charging requests arrived. A main and passer-by scheduling method was devised in [27] in which the MC charged adjacent nodes while charging the primary ones. By eliminating many unnecessary nodes, they came up with the OPPC (Optimal Path Planning Charging) system in [28]. This assesses the scheduleability of charging jobs and makes them scheduleable. According to [5,] a temporal-spatial charging algorithm was developed in order to minimise the number of dead nodes while maximising energy efficiency in multi-MC collaborative charging systems. The issue of scheduling one MC in an on-demand WRSN was originally formulated in linear programming by Kaswan et al. [29]. Then they developed a charging scheduling technique based on a gravitational search algorithm and an efficient fitness function that takes into account SNs' temporal and geographical preferences as well as a new agent representation methodology. An innovative new concept developed by Wang and colleagues (30) enables the mobile charger to collect data and refill energy at the same time, using small communication distances to do so. Models with separable charger arrays like the one suggested by Xu et al. [31] have emerged. The MC doesn't have to wait for charging before unloading charges to an SN's position. There are still energy and mobility limitations for mobile chargers in large-scale WRSNs even with on-demand charging methods that are more practical for a complex network environment than other systems.

III. SYSTEM MODEL AND TERMINOLOGIES

In this part, we'll take a look back at past WRSN and drone-specific wireless charging research. The first step is to go through past research on energy-resolution methods for WRSNs. After that, we'll look at current research on drone wireless charging to see where we're at now. Most prior efforts have used one or more MCs to wirelessly charge the network's nodes. The architecture of the schemes relies heavily on how well the MCs are scheduled in order to ensure improved network performance. Periodical charging schemes and on-demand charging schemes are the two major types of charging schedules used today. On the basis of periodic charging, these methods assume that the MCs move along a certain route in the sensing region, periodically charging the SNs wirelessly. Wireless charging and data gathering were suggested by Zhao et al. [2] using multifunctional MCs (MFMCs). To solve the scalability issue in a dense WSN, the authors of Xie et al. [3] proposed using WPT technology to charge MCs as they move along an optimal route within the WSN. Fu et al. [18] devised a mobile reader charging route that minimised the overall charging time. A new energy-synchronized mobile charging protocol (ESync) was also suggested in [4], which lowers the travel distance of MCs and the charging delay of sensor nodes simultaneously. Based on different nodes' energy usage, they created nested TSP charging tours by picking out the most energy-hungry. Guo et al. [19] explored a WRSN architecture for combined wireless energy replenishment and anchor-point based mobile data collecting, which was framed as a network utility maximisation issue. A distributed method was also developed, in which the sojourn duration at each anchor point is constantly adjusted by the MC. The optimum velocity issue was originally discovered by Shu et al. [20] when an MC travels along a specified route on a regular basis. In the meanwhile, they devised a strategy to maximise the charged energy in SNs by using arbitrary, irregular paths in a two-dimensional environment. As a result of this, Liu et al. [21] developed a new metric called the criticality index (CI) to measure how critical nodes are to the overall system. Then they chose SNs with the greatest possible total number of CIs in the charging tour while keeping MC's travel distance to a minimum. In order to improve data arrival rate and transmission latency in solar energy harvesting wireless sensor networks, Liu et al. [22] proposed a security disjoint routing-based verified message system. Sensor data was collected from a rendezvous location using a mobile sink, according to Liu et al. [23]. They developed a fast rendezvous planning method based on a convex hull for complete connectivity and reducing multihop communication energy consumption by building a near-convex hull trip. The energy issue in WRSNs is solved by optimum route planning in on-demand systems. The schemes, on the other hand, presuppose that the MCs are aware of the SNs' current energy consumption status. He and his colleagues [24] established the theoretical groundwork for a mobile charging issue where MC charges the SNs that submit charging requests when their energy drops below a particular threshold. This is known as an on-demand mobile charging problem. Afterwards, they put forth the NJNP (nearest-job-next with preemption) algorithm, which prioritises charging the node that is closest to it in terms of distance. In their study, Lin et al. suggested a number of alternative pricing schedules. According to [25], there should be two warning levels with a two-tiered preemption fee structure. Two criteria and comparison procedures were developed in the system to determine charge request scheduling priority.

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IV.DEPLOYMENT OF PADS

The new charging model's use of pads has a significant impact on the WRSN's performance. Because of this, the use of as few pads in the sensing region as feasible without delaying the charging process is critical. The author looked into this issue for his article. Definition 1: Given a base, how do you deploy a pad? station and an aircraft filled with SNs and their locations, the objective is to determine the bare minimal number of pads while such that there is at least one pair of coordinates for each SN. The route taken by the drone to go from BS to SN is shown below. M sites in the sensing region must be chosen and one pad must be placed at each of the m selected locations such that the deployed pads support for every SN there must be at least one direct flight route from base station drone, since it may be required to fly to each sensor using to the padding. When flying near sensor nodes, a drone should be as close as possible charging it by sending a charging request. as a result of the drone's flying range is restricted [15] after it has been fully charged drone's remaining power must guarantee the sensor node's success. May go to the closest power station to top up their batteries. If not for dmax was chosen as the maximum to take into account any billing requests. The greatest distance a drone can fly is different for each model. We have a formal definition. a charging flight path is shown below. Let r = dmax /2 be the radius of the disc used to represent the service area of a deployed pad. A drone must be able to fly to the designated charging station (s) and return to the charging station (pi) with enough energy for the job at hand. The pad cover issue employs the smallest amount of discs to cover all sensor nodes, which makes intuitive sense. Condition (2), on the other hand, guarantees that a drone can reach every deployed pad.

To save battery life, drones may fly from one pad to another without stopping. They can then recharge and continue flying to their next destination. Sections 2–4 examine a simplified pad deployment issue, where only SN sites are considered for pad placement (with a drone flying distance restriction). Since the deployed SNs are assumed to form a network, a simplified pad deployment issue always has a solution. There are four distinct plans that are brought forward and examined in detail. For the simplified pad deployment, three schemes are used: MSC, TNC, and GNC. The DC scheme works by putting pads at certain locations, which may or may not be

SNs in the deployed region. In the beginning, the pad cover issue allowed pads to be deployed anywhere in the specified region without restriction. However, in this study, the algorithms MSC, TNC, and GNC solely consider sensor location when determining where the pads should be placed throughout a mission. In many ways, the simplified pad deployment issue is the same as the NPcomplete geometric linked dominant set [34]. This strongly suggests that all of the pad deployment problems studied in this paper is NP-complete. As a result, we're thinking about coming up with heuristic methods for pad placement. A significant number of sensor nodes are assumed to be evenly distributed and scattered across the study area, thus sensor sites are assumed to be good candidates for the pad's placement.

V. SIMULATION RESULTS

Detailed simulations are performed in this part in order to assess the efficacy and efficiency of the algorithms presented in Sections IV and V. We start with a simple simulation and then compare and contrast the outcomes. This project's key performance measure is the number of pads. A variety of network characteristics, such as dmax, network density, and the sensing area's size, are utilised to compare how many pads the four methods require. The built flying networks are integrated with the three scheduling algorithms EDF, NJNP, and SFF once the pads have been deployed. With the use of SMHP, the new network model's advantages may be verified. Afterwards, a second simulation setup is given, followed by a comparison and a discussion of simulation findings, utilising metrics such as the life expectancy, the number of successfully charged SNs, the average range of flights, and the overall range of flights. Visual Studio C# 2017 was used to develop the algorithms and run simulations on a PC with an Intel i5 CPU and 16 GB of RAM parameters dictating how many pads are needed. To begin, Fig. 14 (a)-(d) shows snapshots for the MSC, TNC, GNC, and DC. Pads and SNs are shown in these images as tiny black and violet circles, respectively.

The BS is represented by the red triangle. The drone's range from pads is shown by the big grey dotted-line circles. We used a 6000m 6000m deployment area with N SNs and a dmax = 2000m maximum flying distance. MSC, TNC, GNC, and DC all received different numbers of deployed pads and locations in Fig. 14 (a)- (d).

To evaluate the effect of network density on the number \sof deployed pads, the number of SNs changes between 100 and \s800 in the simulations. Figure 15 shows that for all four suggested systems, as the number of SNs rises, so does the number of deployed pads.

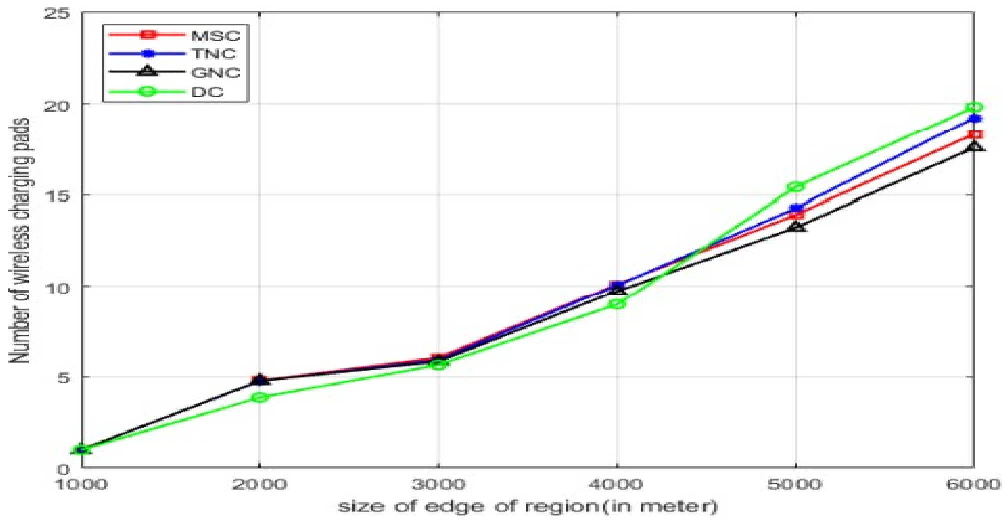

FIGURE 1. Number of required wireless charging pads

when region size changes

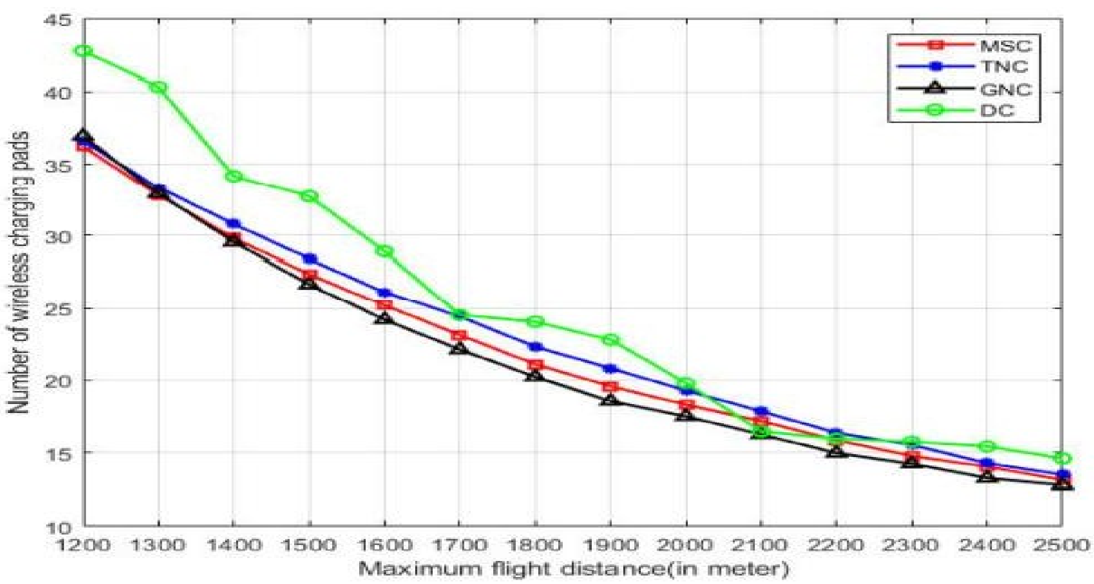

FIGURE 2. Number of deployed wireless charging pads

when maximum flight distance varies

TABLE 1. Simulation parameters of second simulation

Parameters	Values
Region size (m^2)	6000×6000
Number of SNs	200
d_{max} (m)	2000
Speed of drone (m/s)	10~50
Energy threshold of SNs (s)	200~1300
Energy consumption rate (KJ/s)	0.002
Initial energy (KJ)	10

In the context of fulfilling a charging request, the average drone flying distance is defined as the distance a drone travels from its current charging SN to the next charging SN in the schedule.

Next, we evaluate the suggested algorithms' performance by varying the drone's speed from 10 to 50 m/s, while maintaining dmax = 2000m and a 300s energy threshold. The related simulation results are shown in Figs. 18 and 19.

Notably, drone speed improves WRSN life expectancy and SN charge success rates. This is good news. This is due to the fact that a faster drone has shorter flight duration, enabling it to service more SNs with charging requests more quickly. In terms of lifespan and number of successfully charged SNs, SFF has the best results. In contrast, EDF has the worst results. That's because a drone uses the SFF technique to fly quickly and the EDF way to fly slowly.

VI.CONCLUSION AND FUTURE WORK

We provide a new WRSN model for charging low-power SNs using a drone and pads in this paper. A difficulty with the pad deployment must be solved to overcome the drone's disadvantage of restricted flying range.

In order to optimise the efficiency of pad placement, the algorithms MSC, TNC, and GNC use a variety of factors including replenishment energy, flight duration, distance flown, and geometric distribution of nodes. In addition, a static deployment method for pads is also suggested to illustrate the benefits of the proposed algorithms, DC. According to the findings of the simulations, the three suggested methods yield fewer pads than DC does. Using MSC, TNC, and

GNC findings, we next suggest a charging scheduling method for SMHP that takes into account the maximum flying distance. Charge schedules generated using EDF, NJNP, and SFF have all been coupled with the proposed method in a number of simulations. SFF beats NJNP and EDF in simulations, according to the findings.

There is still a need to develop more effective and optimum methods for the WRSN model's pad deployment issue despite the fact that the presented algorithms are mainly aimed at solving that problem. The features of deployed pads will be scrutinised more closely in the future. The robustness of the suggested model will also be extrapolated under different configurations and situations by considering scenarios where one wirelessly charged vehicle and numerous drones are used.

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