International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 05 | May - 2023 SJIF 2023: 8.176 ISSN: 2582-3930

EFFICIENT WIRELESS CHARGING PAD DEPLOYMENT IN WIRELESS RECHARGEABLE SENSOR NETWORK

Mr. Sivakumar, M.Lavanya

Abstract: Rapid progress in wireless power transfer technologies (WSNs) is enabling novel energy solutions for vehicles and new technical achievements that make use of wireless sensor networks. In most modern setups for WRSNs (SNs), one or more wireless charging vehicles (vehicles) provide service to sensor nodes. However, some SNs will never be completely charged due to vehicle speed and off-road limitations, which will reduce the longevity of the networks. As part of our study towards developing a new WRSN model, we have designed various wireless charging pads (pads) that will be used to recharge the drone when it runs out of juice before it reaches the next stop. Our solution takes into account the fact that the drone's battery life is limited and handles the problem of charging at the same time. As a result, we formulate a wireless charging pad deployment problem with the goal of using the minimum possible number of pads to ensure that the drone can establish at least one feasible routing path to every SN in the given WRSN. Three graph-theoretic heuristics and one geometric heuristic are used to solve this problem. As an additional innovation in drone scheduling, we provide a shortest multi-hop path mechanism for the drone to complete charging requests through pads. To ensure the proposed strategies are sound, we run extensive simulations. The results compare and demonstrate the effectiveness of the proposed methodologies with respect to network density, area, and maximum flying distance. Sensor node, wireless rechargeable sensor networks, and wireless power transfer are some examples of keywords.

1.INTRODUCTION

Modern Wi-Fi sensor networks (WSNs) are widely used in a range of system monitoring applications, including metro operations, military operations, and environmental monitoring [1]. Because sensor nodes (SNs) in outlying areas may be so difficult and costly to repair, WSNs have a significant energy problem. Thanks to recent developments in wireless power transmission (WPT), the wireless rechargeable sensor network (WRSN) was born. Many scholars have already become interested in this new network. Recent research suggests that sensor nodes might be powered by wireless charging vehicles (vehicles) fitted with high-capacity batteries and WPT devices. They make it possible for a car to drive close to an SN and charge it wirelessly without really touching the SN. There is already a lot of study into improving the performance of sensor networks by employing a large number of SNs concurrently [2], creating mobile charging protocols [3], charging many SNs at once [4], and planning the best collaborative charging schedules for a large number of automobiles [5]. These proposals may help ease the global energy shortage in various ways. However, there are two major problems with cars that people tend to ignore: Therefore, it is evident that the major difficulties for WRSNs will be off-road and travel speed limitations. Drones have lately been investigated in some studies [14] for the purpose of wirelessly charging SNs in WRSNs. Due of the drone's need to recharge at the BS, many trips between the sensor nodes and the BS are required to maintain the aircraft operational. Drones may now be charged wirelessly, and related technologies have advanced [6–13]. A high-power and high-efficiency WPT system, in combination with an automatic landing wireless charging platform (pad) for a drone, may allow for rapid recharging of a drone without the need for many trips back to the base station [6].

In this research, we present a novel sensor network paradigm in which one drone and many pads are used to circumvent off-road and travel speed limitations. The new system involves sensor nodes sending charging requests to the base station, which then determines and arranges the most efficient flight path for the drone. After receiving a charging mission, it departs the base to charge the sensor nodes at the allotted period. If the drone's battery life drops below a specific threshold, it will have to return to the nearest pad to recharge before continuing on to the next node. After finishing up, the drone flies back to base, where it waits for its next mission. Unfortunately, drones' current utility in the WRSN is limited by their batteries' inadequate power. Drones can't go as far as cars since their batteries don't last as long. If the drone's allotted charging tour doesn't include enough charging pads, the drone may need to make many landings throughout the operation.

.

II. RELATED WORK

In this section, we will review earlier studies that focused on wirelessly charging WRSNs and drones. Examining earlier studies on energy-resolution techniques for WRSNs is the first step. Then, we'll assess the present state of wireless drone charging by reviewing the most recent studies in the field. Traditionally, a single or more MCs have been used to power the nodes of a network wirelessly. Scheduling the MCs effectively is crucial to the success of the scheme's design and, by extension, the network's performance. The most common forms of modern charging schedules are periodic charging and on-demand charging. These strategies imply that the MCs follow a predetermined path inside the sensing zone, stopping at certain intervals to wirelessly charge the SNs. Zhao et al. [2] proposed employing multifunctional MCs (MFMCs) for wireless charging and data collection. Xie et al. [3] suggested employing WPT technology to charge MCs as they moved along an ideal path inside the WSN, which would address the scalability problem in a dense WSN.

A mobile reader charging path that reduces total charging time was developed by Fu et al. [18]. To reduce the time it takes to charge sensor nodes and the distance they have to travel, a new energy-synchronized mobile charging protocol (ESync) is proposed in [4]. Nesting TSP charging tours were developed by selecting the most power-hungry nodes. As a network utility maximisation problem, Guo et al. [19] investigated a WRSN architecture for concurrent wireless energy recharging and anchor-point based mobile data collection. The sojourn time at each anchor point is dynamically modified by the MC in a distributed approach that was also devised. When an MC consistently follows the same path, the optimal velocity problem was first identified by Shu et al. [20]. Meanwhile, scientists came up with a plan to maximise the charged energy in SNs by having them take random, erratic routes on a flat plane. Due to this, the criticality index (CI) was created by Liu et al. [21] as a means of quantifying the importance of individual nodes within a network. Then, to maximise the number of CIs in the charging tour while minimising MC's travel time, they choose SNs. Liu et al. [22] suggested a security disjoint routing-based verified message system for solar energy harvesting wireless sensor networks to increase data arrival rate and decrease transmission delay. According to Liu et al. [23], sensor data was acquired from a rendezvous point utilising a mobile washbasin. They made something up

A fast, convex-hull-based approach for arranging rendezvous that ensures full connection while cutting down on the energy needed for multihop communication. Optimal route planning in on-demand systems is a viable solution to the WRSNs' energy problem. The strategies, on the other hand, assume that the MCs know how much energy the SNs are currently using. The theoretical foundation for a mobile charging problem was laid by him and his colleagues [24], who proposed that when an SN's energy decreases below a certain threshold, the MC should charge the SNs that make charging requests. This is what's known as a "mobile charging on demand" issue. After that, they proposed the NJNP (nearest-job-next with preemption) method, which gives financial preference to the node that is geographically closest to it. Lin et al. proposed many different price structures in their research. Two degrees of notice and two tiers of preemption fees are called for in [25]. The system uses a pair of criteria and a set of comparison methods to decide the order of scheduling charge requests. Two preemption strategies have been created for use with real-world WRSN functionality. Researchers in [26] created a charging scheduling algorithm that prioritised both the speed with which charging requests were received and the distance from the MC to the nodes. In [27], the MC established a main and passer- by scheduling approach in which it taxed neighbouring nodes while exempting the principal ones. The OPPC (Optimal Path Planning Charging) method was developed by reducing the number of intermediary nodes in [28]. In this way, charging tasks may be evaluated for scheduleability and made scheduleable. In order to maximise energy efficiency while minimising the number of dead nodes in multi-MC collaborative charging systems, a temporal-spatial charging algorithm was devised [5, 6]. Kaswan et al. [29] first formalised the challenge of scheduling a single MC for an on-demand WRSN as a linear programming problem. Next, they devised a novel form of agent representation and a charging scheduling strategy based on a gravitational search algorithm that accounts for the temporal and geographical preferences of SNs. The mobile charger may now gather data and replenish energy at the same time thanks to a novel approach developed by Wang and colleagues (30). Separate charger arrays in models have evolved, such as the one proposed by Xu et al. [31]. The MC may immediately dump charges to an SN's location without waiting for charging to complete. Even if on-demand charging techniques are more practicable for a complex network environment than other systems, there are still energy and mobility limits for mobile chargers in large-scale WRSNs.

III. SYSTEM MODEL AND TERMINOLOGIES

In this section, we will review earlier studies that focused on wirelessly charging WRSNs and drones. Examining earlier studies on energy-resolution techniques for WRSNs is the first step. Then, we'll assess the present state of wireless drone charging by reviewing the most recent studies in the field. Traditionally, a single or more MCs have been used to power the nodes of a network wirelessly. Scheduling the MCs effectively is crucial to the success of the scheme's design and, by extension, the network's performance. The most common forms of modern charging schedules are periodic charging and on-demand charging. These strategies imply that the MCs follow a predetermined path inside the sensing zone, stopping at certain intervals to wirelessly charge the SNs. Zhao et al. [2] proposed employing multifunctional MCs (MFMCs) for wireless charging and data collection. Xie et al. [3] suggested employing WPT technology to charge MCs as they moved along an ideal path inside the WSN, which would address the scalability problem in a dense WSN. A mobile reader charging path that reduces total charging time was developed by Fu et al. [18]. To reduce the time it takes to charge sensor nodes and the distance they have to travel, a new energy-synchronized mobile charging protocol (ESync) is proposed in [4]. Nesting TSP charging tours were developed by selecting the most power-hungry nodes. As a network utility maximisation problem, Guo et al. [19] investigated a WRSN architecture for concurrent wireless energy recharging and anchor-point based mobile data collection. The sojourn time at each anchor point is dynamically modified by the MC in a distributed approach that was also devised. When an MC consistently follows the same path, the optimal velocity problem was first identified by Shu et al. [20]. Meanwhile, scientists came up with a plan to maximise the charged energy in SNs by having them take random, erratic routes on a flat plane. Due to this, the criticality index (CI) was created by Liu et al. [21] as a means of quantifying the importance of individual nodes within a network. Then, to maximise the number of CIs in the charging tour while minimising MC's travel time, they choose SNs. Liu et al. [22] suggested a security disjoint routing-based verified message system for solar energy harvesting wireless sensor networks to increase data arrival rate and decrease transmission delay. According to Liu et al. [23], sensor data was acquired from a rendezvous point utilising a mobile washbasin. In order to speed up the process of arranging a meeting, they came up with a

convex hull for full connectivity and minimising the energy required for multihop communication by constructing a nearly convex hull journey. Optimal route planning in on-demand systems is a viable solution to the WRSNs' energy problem. The strategies, on the other hand, assume that the MCs know how much energy the SNs are currently using. The theoretical foundation for a mobile charging problem was laid by him and his colleagues [24], who proposed that when an SN's energy decreases below a certain threshold, the MC should charge the SNs that make charging requests. This is what's known as a "mobile charging on demand" issue. They then proposed the NJNP (nearest-job-next with preemption) method, which gives preference to billing the node that is geographically closest to it. Lin et al. proposed many different price structures in their research. According to [25], there should be two different types of preemption fees and two different types of warning levels. The system uses a pair of criteria and a set of comparison methods to decide the order of scheduling charge requests.

Two preemption strategies have been created for use with real-world WRSN functionality. Researchers in [26] created a charging scheduling algorithm that prioritised both the speed with which charging requests were received and the distance from the MC to the nodes. In [27], the MC established a main and passer-by scheduling approach in which it charged neighbouring nodes in addition to the principal ones. The OPPC (Optimal Path Planning Charging) method was developed by reducing the number of intermediary nodes in [28]. In this way, charging tasks may be evaluated for scheduleability and made scheduleable. In order to maximise energy efficiency while minimising the number of dead nodes in multi-MC collaborative charging systems, a temporal-spatial charging algorithm was devised [5, 6]. Kaswan et al. [29] first formalised the challenge of scheduling a single MC for an on-demand WRSN as a linear programming problem. Next, they devised a novel form of agent representation and a charging scheduling strategy based on a gravitational search algorithm that accounts for the temporal and geographical preferences of SNs. The mobile charger may now gather data and replenish energy at the same time thanks to a novel approach developed by Wang and colleagues (30). Separate charger arrays in models have evolved, such as the one proposed by Xu et al. [31]. The MC may immediately dump charges to an SN's location without waiting for charging to complete. Even with on-demand power and more mobility, mobile chargers still face challenges in large-scale WRSNs.

IV. DEPLOYMENT OF PADS

The effectiveness of the WRSN is greatly affected by the new charging paradigm, which makes extensive use of pads. That's why it's crucial to employ as few pads in the sensing area as possible without compromising charging speed. For his essay, the author did some research on this topic. Meaning No. 1 / How does one place a pad on a base? station and an aeroplane loaded with SNs and their locations, the goal is to find the fewest possible pads needed to guarantee that every SN has at least one set of coordinates. Below is a map depicting the drone's flight path from BS to SN. To ensure that every SN is supported by the pads deployed, m sites within the sensing zone must be identified and a pad installed at each of the m designated locations. Since the drone could have to travel to each sensor utilising the padding, there needs to be at least one straight flight path from the base station. Drones should be as close as possible to sensor nodes while delivering a charging request from the air. Due to its limited range of flight [15], the remaining power of the drone after it has been completely charged must ensure the success of the sensor node. They could go to the nearest power plant to get a charge. To allow for potential billing needs, dmax was selected as the upper limit. The maximum range of a drone varies depending on the make and type. The term has been formally defined. The flight path of a charging bird is seen below. The service area of a deployed pad may be represented as a disc with a radius of r = dmax /2. A drone has to be able to fly to its assigned charging station (or stations) and back with enough juice to complete its mission. It seems to reason that the simplest solution to the pad cover problem would include using the fewest possible discs to cover all sensor nodes. However, if condition (2) holds true, then every pad will be within drone range.

Drones may be programmed to go directly from one landing pad to another in order to save power. After landing, they may get some rest before continuing on to their next destination. In Sections 2–4, we look at a streamlined version of the pad deployment problem, whereby pad insertion is restricted to SN locations (with a drone flying distance constraint). Since it is believed that the deployed SNs constitute a network, every pad deployment problem may be reduced to a simpler one. Four separate proposals are presented and discussed in length. Three methods (MSC, TNC, and GNC) are employed for the streamlined pad deployment. Pads, which may or may not be stationary, are what make the DC system operate.

SNs in the area of deployment. Pads may initially be placed anywhere within the designated area because of the pad cover problem. In contrast, MSC, TNC, and GNC only take sensor position into account when deciding where to install pads during a mission. The NP-complete geometric linked dominating set [34] is quite similar to the simplified pad deployment problem. The results of this research clearly imply that all pad deployment issues are NP-complete. Therefore, we are contemplating developing heuristic approaches to pad positioning. Sensor sites are presumed to be suitable for the pad's location because a large number of sensor nodes are thought to be uniformly dispersed around the research region.

V. SIMULATION RESULTS

In this section, we run extensive simulations to evaluate the performance of the algorithms discussed in Chapters IV and V. We begin by running a quick simulation and comparing the results. The quantity of pads produced is the primary indicator of success for this project. To evaluate the relative need for pads among the four approaches, we use measures of network properties such maximum data rate (dmax), network density, and the size of the sensing region. Once the pads have been set up, the created flying networks are merged with the three scheduling algorithms (EDF, NJNP, and SFF). It is possible to confirm the benefits of the new network model by using SMHP. Next, a second simulation setup is provided, and the results are compared and discussed according to a variety of criteria, including the number of SNs that were successfully charged, the average flight distance, and the total flight distance. The algorithms and simulations were built in Visual Studio C# 2017 and executed on a computer with an Intel i5 CPU and 16 GB of RAM, with the number of pads determined by the simulation's settings. Figure 14 (a)-(d) displays stills of the MSC, TNC, GNC, and DC, respectively. In these pictures, the pads and SNs appear as small black and violet circles.

That triangle in red indicates the BS. Big grey dotted-line circles represent the drone's range from the pads. We employed N SNs spread out across a 6000m 6000m region, with a maximum flying distance of dmax = 2000m. Pads were distributed differently amongst the MSC, TNC, GNC, and DC, as shown in Fig. 14 (a)–(d).

In the simulations, the number of SNs is varied from 100 to s800 to examine how network density influences the total number of deployed pads. As can be seen in Figure 15, the number of deployed pads increases with the total number of SNs in each of the four proposed systems.

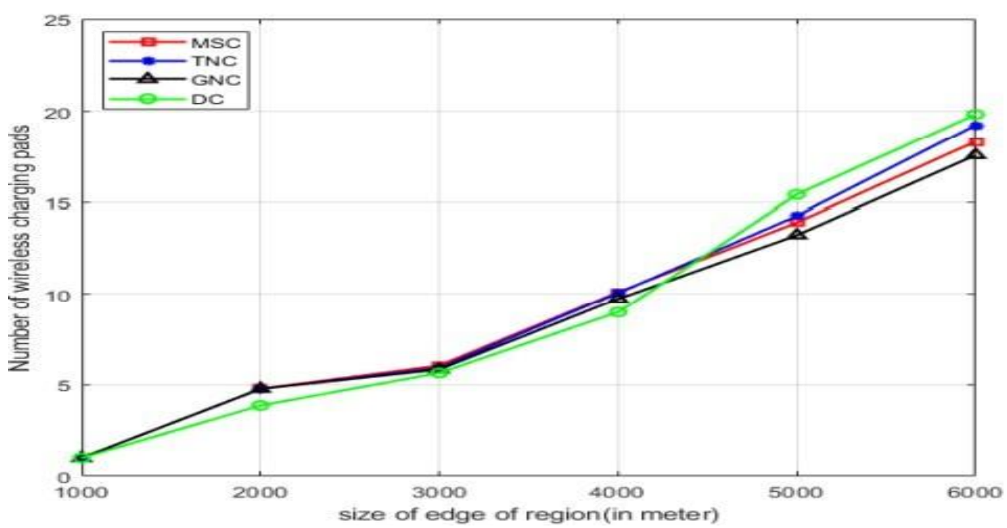

FIGURE 1. Number of required wireless charging padswhen region size changes

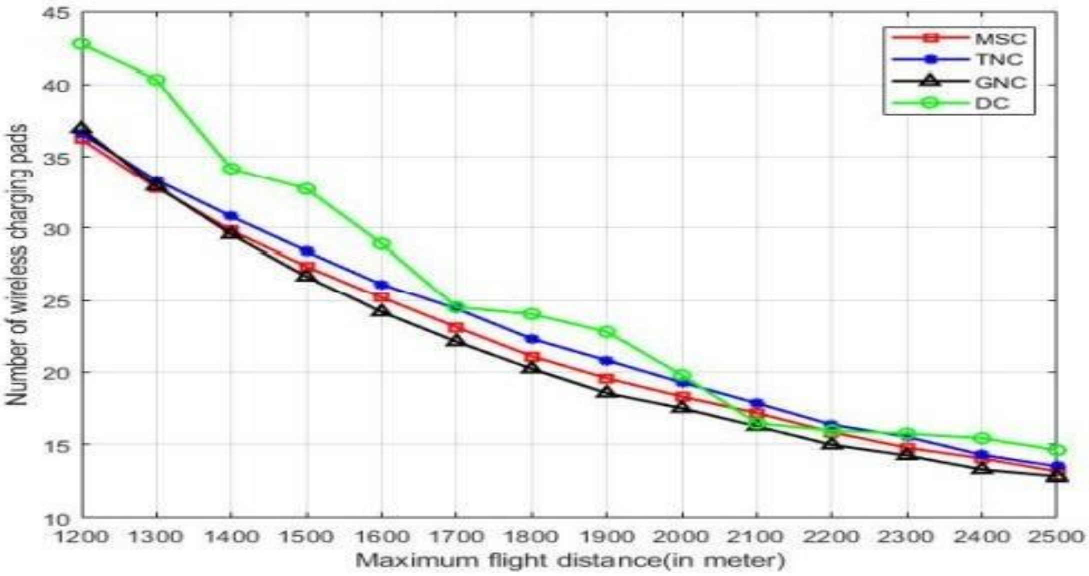

FIGURE 2. Number of deployed wireless charging padswhen maximum flight distance varies

TABLE 1. Simulation parameters of secondsimulation

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

The average drone flight distance is the distance flown by a drone from its current charging SN to the next charging SN in the schedule in order to complete a charging request.

We next test the effectiveness of the proposed algorithms by changing the drone's speed from 10 to 50 m/s while keeping dmax = 2000m and the energy threshold at 300s constant. Figures 18 and 19 show the same simulation findings.

The longevity of WRSNs and the success rate of SN charges are both enhanced by increased drone velocity. It's fantastic to hear this. This is because a quicker drone can complete its flight in a shorter amount of time, allowing it to charge a greater number of SNs in a shorter amount of time. SFF achieves the greatest performance in terms of longevity and the number of successfully charged SNs. On the other hand, EDF has the poorest performance. Because a drone may switch between the SFF and EDF flight modes, allowing for both fast and slow flight.

VI. CONCLUSION AND FUTURE WORK

In this study, we provide a novel WRSN paradigm for recharging low-power SNs using drone and pads. To compensate for the drone's short range, a problem with the pad deployment must be fixed.

The algorithms MSC, TNC, and GNC all consider aspects including energy replenishment, flight time, travelled distance, and geometric distribution of nodes in order to maximise pad placement efficiency. To further demonstrate the advantages of the presented algorithms, DC suggests a static deployment approach for pads. The results of the simulations show that the pad yields for the three proposed approaches are lower than those for DC. Next, based on the results of the MSC, TNC, and GNC, we propose a charge scheduling approach for SMHP that accounts for the greatest possible flight distance. Numerous simulations have combined the suggested technique with charge schedules developed using EDF, NJNP, and SFF. The results show that in simulations, SFF performs better than NJNP and EDF.

Despite the fact that the offered algorithms are primarily intended to address the pad deployment issue in the WRSN model, there is still a need to create more effective and optimal techniques for doing so. In the future, there will be a closer look at the characteristics of currently installed pads. One wirelessly charged car and several drones will be used as examples to generalize the model's resilience across configurations and conditions.

REFERENCES

[1].L. M. Borges, F. J. Velez, and A. S. Lebres, ‘‘Survey on the characterization and classification of wireless sensor network applications,’’ IEEE Commun. Surveys Tuts.,vol. 16, no. 4, pp. 1860– 1890, Apr. 2014.

[2].M. Zhao, J. Li, and Y. Yang, ‘‘A framework of joint mobile energy replenishment and data gathering in wireless rechargeable sensor networks,’’ IEEE Trans. Mobile Comput., vol. 13, no. 12, pp. 2689–2705, Dec. 2014.

[3]. L. Xie, Y. Shi, Y. Thomas Hou, W. Lou, H. D. Sherali, and S. F. Midkiff, ‘‘Multi-node wireless energy charging in sensor networks,’’ IEEE/ACM Trans. Netw., vol. 23, no. 2, pp.437–450, Apr. 2015.

[4]. L. Fu, L. He, P. Cheng, Y. Gu, J. Pan, and J. Chen, ‘‘ESync: Energy synchronized mobile charging

in rechargeable wireless sensor networks,'' IEEE Trans. Veh. Technol., vol. 65, no. 9, pp. 7415–7431, Sep. 2016.

[5].C. Lin, J. Zhou, C. Guo, H. Song, G. Wu, and M. S. Obaidat, ''TSCA: A temporal-spatial real- time charging scheduling algorithm for on-demand architecture in wireless rechargeable sensor networks,'' IEEE Trans. Mobile Comput., vol. 17, no. 1, pp. 211–224, Jan. 2018.

[6]. H. Chae, J. Park, H. Song, Y. Kim, and H. Jeong, ''The IoT based automate landing system of a drone for the round-the-clock surveillance solution,'' in Proc. IEEE Int. Conf. Adv. Intell. Mechatronics (AIM), Busan, South Korea, Jul. 2015, pp. 1575–1580. M. Simic, C. Bil, and V. Vojisavljevic, ''Investigation in wireless power transmission for UAV charging,'' Procedia Comput. Sci., vol. 60, pp. 1846–1855, Jan. 2015.

[7]. C. H. Choi, H. J. Jang, S. G. Lim, H. C. Lim, S.H. Cho, and I. Gaponov, ''Automatic wireless drone charging station creating essential environment for continuous drone operation,'' in Proc. Int. Conf. Control, Autom. Inf. Sci. (ICCAIS), Ansan, South Korea, Oct. 2016, pp. 132–136

[8]. C. Wang and Z. Ma, ''Design of wireless power transfer device for UAV,'' in Proc. IEEEInt. Conf. Mechatronics Autom., Harbin, China, Aug. 2016, pp. 2449–2454.

[9]. T. Campi, F. Dionisi, S. Cruciani, V. De Santis, M. Feliziani, and F. Maradei, ''Magnetic field levels in drones equipped with wireless power transfer technology,'' in Proc. Asia– Pacific Int.