energies

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On Increasing the Energy Efficiency of Wireless Rechargeable Sensor Networks for Cyber-Physical Systems

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Abstract: In recent times, wireless energy transfer has become an effective solution to charge devices due to its efficiency and reliability. In a typical Wireless Rechargeable Sensor Networks (WRSN), wireless energy transfer technique can solve the energy depletion problem with the aid of a Wireless Charging Vehicle (WCV), thereby enabling the network to extend its lifetime. However, sensor nodes in a WRSN still have their energies depleted before it gets replenished by the WCV. In this paper, we proposed a scheme that prioritizes sensor nodes for charging and also developed efficient algorithms to improve on existing charging schemes so as to extend the lifetime of the WRSN. Firstly, an inspection algorithm was developed to visit and inspect sensor nodes in the network so as to determine the sensor nodes to charge. Secondly, a greedy charge algorithm was introduced to ascertain the shortest distance the WCV needs to travel and, lastly, an energy for nodes' algorithm was proposed to determine the stopping point and when the WCV needs to return to the base station. Simulation experiments were also conducted to determine the performance of our scheme. The simulation experiments revealed that our proposed scheme made significant improvements when compared to other schemes in literature using several metrics.

Keywords: charging; energy efficiency; charging efficiency; WRSN; cyber-physical systems; WCV

Citation: Orumwense, E.F.; Abo-Al-Ez, K. On Increasing the Energy Efficiency of Wireless Rechargeable Sensor Networks for Cyber-Physical Systems. *Energies* **2022**, *15*, 1204. https://doi.org/10.3390/en15031204

Academic Editors: Hugo Morais and Rui Castro

Received: 16 November 2021
Accepted: 9 December 2021
Published: 7 February 2022

1. Introduction

As the need for a more sustainable network continues to become more influential and significant, Wireless Sensor Networks (WSNs) in cyber-physical systems are seen as an ideal technology for data collection in various fields ranging from agricultural, military, and medical services to industrial production [1]. However, the network energy constraint and battery power drain in sensor nodes has been the key issues that prevents WSNs to be operational for an unlimited period of time and also limits its applications [2,3]. Replacing sensor nodes when energy is depleted is not only a cumbersome task but a very expensive venture and sometimes quite harmful to the environment [4]. A WSN that possesses a battery recharging capabilities technique, which is a Wireless Rechargeable Sensor Networks (WRSNs), has appeared to be a smarter technological choice as a result of lots of recent research.

With the recent breakthrough in technology leading to the emergence of WRSNs, Wireless Energy Transfer (WET) technology ensures that energy is easily transferred to sensor nodes in a WRSN without difficulty. The fundamental principle of WET is dependent upon magnetically coupled resonance [5] in which two self-resonators that possess similar resonance frequency can easily and efficiently transfer energy over a considerable amount of distance. This technology has been widely used in body sensor networks, transportation systems, cellular phones, and many more. Remarkably, this innovative technology is considered safe and not vulnerable to the surrounding environment. When matched with similar wireless energy transfer technologies such as electro-magnetic radiation [6], it is observed that magnetic resonant coupling has several advantageous features including no line-of-sight requirements, higher energy conversion, and higher transmission distance.

In a typical WRSN, wireless charging vehicles (WCVs), sometimes called mobile charging robots (MCRs), are often relied upon to replenish energies of all rechargeable sensor nodes [7]. Hence, it is very imperative for these WCVs to charge depleting energy nodes before their battery energy gets exhausted. Else, sensor nodes with depleted energies would not be able to replenish their energies with the aid of WCV, thereby reducing the lifespan of the network. This problem can, however, be resolved by establishing suitable scheduling algorithms to charge sensor nodes [8,9]. However, which suitable scheduling procedure to use at different times becomes a major problem. This, however, was behind our motivation for this paper in delivering efficient and suitable scheduling and charging algorithms so as to effectively replenish depleting energies in sensor nodes of a WRSN. Various works in literature have distinguished these scheduling strategies into two different classes: deterministic and non-deterministic approaches [10–13]. In the deterministic approach, charging individual sensor nodes in the WRSN is done periodically and this method does require explicit network information such as energy status and exact node location for its workability. However, this information can be very difficult or almost impossible to obtain, making it unfit for practical applications and large-scale deployment [3,14–16].

On the contrary, non-deterministic approaches are usually available whenever required as long as individual sensors forward their charging request to the WCV when they are running extremely low on energy levels or when the level of energy is lower than a certain threshold [17]. When energy-charging requests are received, WCV will automatically reorganize the order of received charging tasks, choose the optimal sensor to charge, and then proceed. However, the non-deterministic approaches come in various forms but the core difference is the number of WCVs available for charging. In as much as various solutions have been proposed to curb issues relating to non-deterministic methods, proposed multiple WCVs' models have, however, seemed to be quite expensive, while singular WCVs' models may have induced lengthy delay in practical charging.

These above detailed proposals in practicality may address only a fraction of WRSNs' energy issues and might be unable to fulfil the frequent charging demands of the sensor nodes in the network, which may eventually lead to a shorter lifetime of the network.

In as much as the non-deterministic approach is more feasible and advantageous, there are still some key shortcomings that cannot be ignored. These are:

(1) Deciding on which sensor nodes to charge if all the sensor nodes cannot be charged at that particular moment is a key problem that requires a solution so as to fulfil the charging demands of sensors in a WRSN of a cyber-physical system.
(2) The best stopping point for a WCV to charge a sensor node to a certain level and move to the next priority node in order to avoid the charging of one node over the other, thereby ensuring there is enough energy left in the WCV to charge the next node so as not to encounter a short lifetime of the WRSN.
(3) Existing disturbances in the system due to finding the ideal path for charging and the ability for WCVs to reach locations that are difficult to access and the use of high energy while in motion or flight.
(4) Previous approaches make use of a charging request, which is primarily tied to spatial priority. This, however, creates a severe weight on the spatial relations, consequently leaving some distant sensor nodes running out of battery energy.

In a typical WRSN, it is very imperative to detect which sensor nodes have low energies and the optimal charge stopping point for the best charging approach as this will lead to an increase in the life span of the network. This, however, strengthens the necessity to detect the sensor nodes with the lowest energies swiftly and at a very low cost, and this was the main motivation for this work. The key contributions of this paper are highlighted as follows.

- We present efficient algorithms that are capable of boosting the life span of a typical WRSN without any previous knowledge of sensor nodes' energy levels.

- We also developed an algorithm to ensure sensor nodes are prioritized and served based on their importance and contribution to the inspection tasks.
- To determine the suitable sensor nodes for optimal charging by introducing a sensor node selection algorithm that assists in reducing the running out of battery energy.
- To carry out experimental simulations of the proposed scheme and compare it with other scheduling schemes to ascertain its performance.

It is very essential to determine the exact energy levels of sensor nodes in a WRSN so as to effectively charge the network nodes. One of the major strengths of this paper is the ability to swiftly detect the energy levels of nodes in the network and then charge afterwards. Inspecting and charging sensor nodes in a WRSN based on the original energy information collected during the time of inspection facilitates the preservation of energy and robustness of efficient WRSN charging. This paper also takes into account that there might exist some low-energy sensor nodes in the network that were not previously charged or overlooked by the WCV; hence, a further inspection was carried out to identify the lowest-energy nodes that need charging.

The structure of the paper is outlined thus: Section 2 reviews the relevant literature related to this work; Section 3 describes the network and system models; Section 4 narrates the energy consumption, the problem to be solved in the WRSN; and our approach in detail; Section 5 presents the simulation analysis and discussion of our results, while Section 6 concludes the paper and suggests future works.

2. Related Work

In a bid to increase the lifetime of a WRSN, various innovative technologies have been steadily introduced to wirelessly charge sensor nodes in the network even though these technologies are still in their initial stages. Some of these previous efforts can be split into several categories based on the kind of wireless deployment techniques being used and the charging method that was adopted.

2.1. Energy Replenishment

There have been different approaches proposed in replenishing the energy levels of sensor nodes in WRSN. As an example, the works proposed in [18–22] employed energy harvesting strategies to charge sensor nodes in the WRSN either by solar cells, vibration, temperature difference, or wind sources. It was, however, noticed that energy harvesting techniques can become quite hard to control and unpredictable [23]. Wireless energy transfer strategies from a battery-based energy source, which is more predictable and controllable, was further researched. Among those approaches is the employment of a wireless charging method using radio frequencies to harvest energies from dedicated transmitters and ambient RF energies [24,25].

Employing immobile charging stations possessing partial coverage can also play a huge role in extending the life span of WRSNs, as demonstrated in [26]. Single or multiple base stations or charge stations can also be employed to boost the lifespan of a movable WRSN, as outlined in [27,28], but the challenge of maximizing energy becomes a daunting task. A single WCV can also be used in an immobile, based WRSN to periodically navigate through the network and recharge sensor nodes in the WRSN or multiple WCVs can be employed depending on the size of the network, as in [29]. To further replenish energy in the network, a scheme was proposed in [30] that only needs to examine a portion of the sensor nodes in the network, which, consequently, led to a significant decrease in energy consumed in the network.

Several charging solutions that can collaboratively be achieved by the utilization of WCVs for charging sensor nodes were analyzed in [13,16,31–33]. It was, however, shown that it is imperative to opt for a cooperative charging scheme so as to fulfil the varying demands for topology and node properties. In as much as these cooperative charging approaches seem to efficiently tackle the effects of uncertainty factors in WRSNs, however, it still overlooks the authenticity of demands regarding charging information and demands due to real-time transmission [34].

In terms of scalability in WRSNs, the employment of multiple WCVs for recharging by determining their recharging and coordination activities was carried out in [35]. Additionally, in the work by Ye et al. in [36], an approximation algorithm and scalable heuristic solution were proposed to reduce the energy consumption in a WRSN. As a WRSN continues to scale and grow larger, the cost of propagating data also rises; hence, the works in [37,38] made efforts to propose algorithms to decrease the energy of sensor nodes on reporting data to the sink. Similarly, an efficient energy exploration approach was proposed in [39] to mitigate the problem associated to the cost of collecting energy information in a WRSN. Unfortunately, while several WCVs were used in this approach, it was under the assumption that every WCV in the network would require a full information and knowledge of the sensor nodes and communication protocols in the network.

2.2. Optimizations

The optimization of energies in a WRSN is also an area of active research. In [40], an optimization framework was proposed by cooperatively optimizing entities such as the charging time, traveling path, and flow routing, while the same authors, in [10], subsequently developed an optimization problem that included stopping points. However, charging time of the WCV is considered as zero. A practical optimization problem with flow rate was formulated in [30] so as to determine the rate of energy consumed in a WRSN. The system was further designed to combine the period used for charging each sensor node and the traveling path of each cycle. In [41], an optimization problem was created in which the WCV departure time and the overall cycle time were maximized in order to address the charging problem in a WRSN. To address the problem associated with sensor selection and energy allocation, the authors in [42] proposed an algorithm that maximized a monotonous submodular function, which was subjected to a general routing constraint while achieving a higher approximation ratio in WRSNs.

In a bid to optimize the charging scheduling algorithm of a WRSN, a K-covering redundant nodes' inactive scheduling algorithm was proposed by utilizing numerous WCVs to replenish energies so as to prevent exhaustion from nodes in the network [43]. A WRSN optimizing scheduling problem was also studied based on the condition of random events. The system's performance was also optimized using the quantities of data transfer protocol, WCV's behavior, coordination control, and the likes [44,45]. In [46], the authors developed a K-means cluster algorithm to calculate the energy core set while an optimizing algorithm was proposed to convert the energy charging stage into a task splitting model so as to increase its energy efficiency. Additionally, in [47], another K-means clustering algorithm was introduced to balance the energy consumption among sensor nodes, while a dynamic selection algorithm was proposed to charge sensor nodes in order to reduce the charging time spent in the network. There are quite some issues in most of the models, as mentioned above, and to solve these problems to an extent, we proposed a set of algorithms that can inspect the network and make decisions on the best possible sensor nodes to charge. The symbols and their interpretations as used in this article are documented in Table 1.

Table 1. Symbols and definition.

Nomenclature	
N	set of all the sensor nodes
N_{re}	set of all residual energy levels
N_d	Distance between sensor nodes
BS	Base station
E_C	Sensor node's battery capacity
E_t	MCV's battery capacity

Table 1. *Cont.*

Nomenclature	
τ	Cost of centrally localizing the WCV on a sensor node
μ	Target energy of a sensor node to charge
C_e	Total energy consumed during charging
λ	Inspection termination point
C_r	Energy required to return to BS
Z	Energy level of the currently inspected sensor node
Ω	Optimal WRSN time increase
$\mathcal{R}$	Total energy consumed during moving
ψ_r	WCV's moving energy consumption per move
s	Discharge rate for sensor node
$v(n)$	Sensor node's discharge function
δ	Set of sensor nodes that requires charging
h	Number of bits sent or received
Φ	Optimal inspection terminal point
F_e	Sensor node at full energy

3. Network and System Models

We considered a WRSN, which is made up of rechargeable sensors, a base station (BS), and a wireless charging vehicle. The base station was in charge of gathering data from sensor nodes and could also act as a charging center for the WCV. The BS employed a Wireless Power Transfer (WPT) technology to replenish exhausted WCVs that had serviced the sensor nodes with their energies, and these nodes were also equipped with energy-receiving coils for receiving energy from the WCVs. We also considered a line network topology, as illustrated in Figure 1 and also as adopted in [48], with the assumption that when a path plan was already designed, a network topology of any kind can simply be reformulated to a line network topology according to its path plan. We also adopted an Unmanned Aerial Vehicle (UAV) as our WCV to charge the sensor nodes in the network. This was more effective since our UAV could seamlessly and quickly navigate the area. This kind of setup will also be suitable and a lot more practical when operated in line-based, cyber-physical systems such as railways, oil lines, border protection, bridges, and power lines. We also took into consideration the term WRSN lifespan to be the percentage of time in which the network is in existence [49].

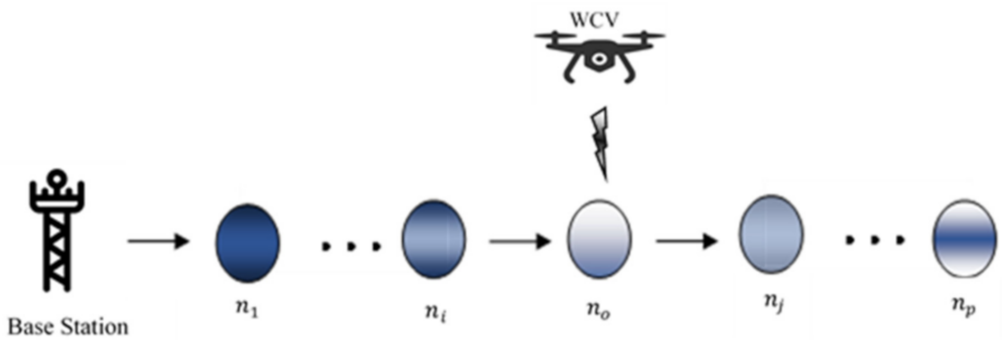

Figure 1. A typical WRSN with a WCV charging a low-energy sensor node.

In this section, the framework for the WRSN is presented while the proper definition of our problem is analyzed. In the network, there existed a BS and a set of sensor nodes up to the number p.

$$N = \{n_1,\ n_2,\ n_3 \ldots n_p\} \tag{1}$$

where the nodes are independent and each of the nodes n_i have a residual energy level re_i and with the assumption that each of the sensor nodes in the network possesses the same battery capacity E_c. Then, the set of sensor nodes with residual energy levels is then represented as

$$N_{re} = \{re_1,\ re_2, re_3 \ldots\ re_p\} \tag{2}$$

The set representing the distance from a sensor node n_{n-1} to n_n with each of the nodes positioned at a distance d_i from the preceding sensor node is given as

$$N_d = \{d_1,\ d_{2,}\ d_3 \ldots\ d_p\} \tag{3}$$

In the system, a single WCV with a total energy of E_t was employed to charge a subset of sensor nodes. The energy required to position the WCV charging coils centrally to the sensor node's receiver coil is given as τ, which localizes the WCV and the sensor node concentrically. While the target energy level of each sensor node that needs to be recharged is given as μ_i, the total number of sensor nodes to be charged is W and the total localization and charge energy is $C_{e,}$ which is given as

$$C_e = W \times \tau + \sum_{i=0}^{W} \mu_i - re_i \tag{4}$$

The maximum possible subset of sensor nodes that the WCV can charge to accomplish the maximum possible extension of life is defined as Z, while the point allowing the WCV to get to the farthest sensor node in Z is given as Φ. Hence,

$W = |Z|$, while,

$$Z = \{n_{t1},\ \ldots,\ n_{tW}\} \subset N \tag{5}$$

Then,

$$\Phi = \sum_{i=1}^{t_W} d_i \tag{6}$$

When Z is fully charged, it leads to the maximum life extension of the WRSN, given as Ω. Hence, the total moving energy consumed by the WCV is regarded as $\mathcal{R}$ and this is inclusive of the energy required to reach the farthest sensor node and return to BS, with the assumption that the unit moving cost is ψ_r. Then

$$\mathcal{R} = \psi_r \times \Phi \tag{7}$$

While the energy constraint formula is given as

$$E_t \geq C_e + \mathcal{R} \tag{8}$$

Each of the sensor nodes n_i, discharges its energy at a rate denoted as s or possibly zero, depending on the discharge probability p and discharge function v. A fixed discharge probability was, however, used in each run, also as used in [50].

$$v(n) = \begin{cases} s, & if\ node\ is\ activated \\ 0, & otherwise. \end{cases} \tag{9}$$

We can now express the lifetime of the network as the possible amount of time until b sensor nodes finally reach a residual energy of zero:

$$b = \sum_{i=1}^{p} f(n_i), \tag{10}$$

where

$$f(n_i) = \begin{cases} 1, & if\ re_i = 0 \\ 0, & otherwise. \end{cases} \tag{11}$$

The objective, however, was to create an increment in the network's life while finding the best possible point to cease inspecting and return to BS, λ and the best possible set of nodes that needs to be charged δ.

4. WRSN Energy Consumption and Probability Model

In a typical WRSN model, a significant amount of energy is consumed during communication activities. In this work, we implemented a simple WRSN energy consumption model of a sensor node, as also used in [51]. When data with h number of bits are sent or received, the energy consumption $E_{con,}$ which is dissipated at a discharge rate of s, can be given as

$$E_{con} = E_{tx}(h,\ d_i) + E_{tx}(h) = 2 \times E_{dip} \times h + E_{amp} \times d_{ij} \tag{12}$$

where E_{dip} denotes the energy consumed in sending and receiving each bit and d_{ij} indicates the distance between sender and receiver. E_{amp} indicates the transmitting amplifier's energy consumption while the radio dissipates $50\frac{nJ}{bits}$ to run the transmitter and receiver circuitry.

Considering a discharge function $v(n)$ in which the sensor nodes are not active (nodes are asleep) or active (nodes are awake) with a consuming energy E_{con}, the sensor nodes' energy levels are always decreasing. We can assume that the sensor nodes discharge randomly and independently of each other, in which random events and usage can trigger the discharge. We can then define T_t as the amount of time that has elapsed since the sensor node was at full energy F_e.

With the assumptions that

(1) Every sensor node in the network starts on the same energy level F_e,
(2) Every sensor node possesses the same maximum energy capacity E_c,
(3) The energy capacity of the WCV will always be more than the total energy requested by the sensor nodes,
(4) Every sensor node has the same discharge rate s,
(5) There is a probability p that each sensor node discharges at a unit time,
(6) The energy level of the presently inspected sensor node is at Z,

and with the discrete nature of v, we can then compute the probability that a node exists at a different energy level in the network, the expected energy levels, and the probability bounds.

The discrete levels l that are required by a sensor node to reach an energy level Z is given as

$$l = \frac{(F_e - Z)}{v} \tag{13}$$

The probability that exactly l is discharged in a sensor node can then be represented as

$$\binom{T_t}{l} p^l (1-p)^{(T_t - l)} \tag{14}$$

Bernoulli trials' formula is employed, with success labelled as p and failure as $1-p$. The probability that a sensor node with energy lesser than or equal to Z can be expressed as

$$\chi = \sum_{j=l}^{T_t} \binom{T_t}{j} p^j (1-p)^{(T_t - j)} \tag{15}$$

In order to ensure that the probabilistic value gives us an accurate prediction and to also avoid mistakes in calculating each computed probability component as zero, we define an upper probabilistic bound, which will assist in determining the maximum permissible values without necessarily considering the exact probability and variance. Putting the probability discharge function into consideration, each node's expected level of charge $E(C)$ can be modeled as

$$E(C) = F_e - \sum_{l=1}^{T_t} p(l)v(l) = F_e - \sum_{l=1}^{T_t} (p \times s + (1-p) \times 0) \tag{16}$$

$$E(C) = F_e - psT_t \tag{17}$$

In a bid to identify that the sensor node's probability is at a particular level of energy, or below a particular level of energy Z, a tail probability estimation method used in [52] can be employed. The ideal method that can be employed in this scenario is the Chernoff Bound [53,54] since it possesses a tighter bound when compared to Markov inequality. The conditions for Chernoff Bound are, however, satisfied, and employing the multiplicative form of the bound, the upper bound probability can be expressed as

$$P_r[C \leq (1-\varepsilon)E(C)] \leq re^{-\frac{\varepsilon^2}{2}E(C)} \tag{18}$$

where ε can be represented as

$$\varepsilon = \frac{E(C) - Z}{E(C)} \tag{19}$$

where Z is always less than $E(C)$. The upper bound probability of a sensor node at a particular level of energy $\leq Z$ is represented as

$$P_r[C \leq Z] \leq e^{\frac{(F_e - psT_t - Z)^2}{2(psT_t - F_e)}} \tag{20}$$

Inspection, Greedy Charge, and Energy for Nodes' Algorithms

We developed suitable algorithms with the objectives of identifying the quickest distance the WCV had to travel λ and the ideal set of sensor nodes that were to be charged δ when travelling in order to ensure that the life span Ω of the WRSN was increased. We first proposed the Inspection Algorithm 1, which can successfully inspect the nodes in a sequential manner and makes certain decisions after exploring each sensor node in the network. After the examination of each sensor node, the algorithm determines the subset of the examined nodes to charge, decides when and if to examine sensor nodes in the network or return to the BS, and subsequently charge nodes on its way back to the BS.

This Inspection algorithm also assists in directing the WCV to find suitable sensor nodes to charge and also when to leave and return to the BS and calculate the energy C_r required to return to the BS at all times. The algorithm can successfully create a charging list, the energy that is needed to charge, and the new energy level. The subsets of visited nodes to charge δ is calculated by introducing another algorithm (Greedy charge algorithm). In line 8, if the WCV still has enough energy to inspect another node, then the WCV automatically examines the next node and so on until no energy is left and it returns to the BS with a constantly updated C_r. The inspection is then terminated at λ while the WCV returns to the base station and charges the sensor nodes in δ.

Algorithm 1: Inspection Algorithm

Input: Input parameters: Node set N and WCV
Output: λ; δ and C_r
1. **procedure**: INSPECT(N)
2. Listing nodes visited $\delta Nodes \leftarrow empty$
3. Subset of nodes to charge $\delta \leftarrow empty$
4. Charging energy $C_e \leftarrow zero$
5. **for** $i \leftarrow 1 : size\ of\ N\ do$
6. energy $\leftarrow calculate\ WCV\ energy\ level$
7. $C_r \leftarrow calculate\ energy\ to\ return\ to\ base$
8. $\delta, C_e, \mu \leftarrow charge(\delta Nodes, energy - C_r)$
9. $energy \leftarrow energy - C_e - C_r$
10. **if** ENERGYFORNODES $(energy, i)$ **then**
11. inspect next $node$ i and examine $node$ energy
12. add $node$ to $\delta Nodes$
13. ***else***
14. Break
15. ***end*** **if**
16. ***end*** **for**
17. go to BS and charge $nodes$ in δ
18. ***end*** **process**

To determine δ, we introduced another algorithm (Greedy Charge Algorithm), which is our Algorithm 2. This algorithm is somewhat similar to the Greedy algorithm applied in [55], which also used a line topology. The difference between both algorithms is in the localization cost, discharge behavior, and knowledge requirements. In our greedy charge algorithm, it was assumed that the WCV moves in a fast pace across the network from and to the BS before there is a discharge between two sensor nodes. The primary aim of the algorithm was to sort out the sensor nodes in the network, using their energy levels (line 2) and including the lower energy nodes into the set of nodes that is needed to be charged (line 13–15). This is carried out until the WCV runs out of energy to obtain the set of nodes that is expected to be charged $\ddot{\delta}$ to the next energy level.

Algorithm 3, Energy for Nodes, was implemented to determine whether further inspection should be carried out or terminated and to also determine a stopping point λ in which the algorithm returns *False*. The decision to implement Algorithm 3 in line 10 of Algorithm 1 was a function of the amount of energy left in the WCV. The energy left in the WCV can be determined by subtracting the energy for charging C_e and the energy C_r required to return to the BS from the energy of the WCV.

Algorithm 2: Greedy Charge Algorithm

Input: Input parameters: Node set N, WCV and τ
Output: δ
1. **procedure** $GREEDYCHARGE(\delta Nodes, energy)$
2. sort nodes base on energy level $sNodes \leftarrow sort\ (\delta Nodes)$
3. list of $nodes$ to charge $\delta \leftarrow empty$
4. list of intended $nodes$ to charge $\ddot{\delta} \leftarrow empty$
5. Charging energy $C_e \leftarrow zero$
6. Target energy level to charge $nodes$ $\mu_i \leftarrow zero$
7. **for** $i \leftarrow 1$: $size\ of\ sNodes - 1$ **do**
8. $sEnergy \leftarrow energy\ level\ of\ i^{th}\ node\ in\ sNodes$
9. $tEnergy \leftarrow energy\ level\ of\ i^{th} + 1\ node\ in\ sNodes$
10. Add not to intended charging list $\ddot{\delta} \leftarrow \delta + i^{th}\ node\ in\ sNodes$
11. $Compute\ Energyrequired = \tau + ((tEnergy - sEnergy) \times (1 + size\ of\ \ddot{\delta}))$;
12. **if** $energy \geq Energy\ required$ **then**
13. Intended list is feasible $\delta \leftarrow \ddot{\delta}$
14. Update Charging energy $C_e = C_e + Energy\ required$
15. Update Target energy level $\mu_i = tEnergy$
16. **else**
17. **return** δ, C_e, μ_i
18. **end if**
19. **end for**
20. **return** δ, C_e, μ_i
21. **end process**

This algorithm builds on the perception that there might still be low-energy sensor nodes in the network; hence, further inspection needs to be done to identify the lowest-energy nodes that need charging in δ. The Energy for Nodes' Algorithm employs the probabilistic bound equation in Equations (18) and (20) to compute the probability *prLow* of a sensor node currently at an energy level that is equal to or lower than the lowest energy level examined in δ. Hence, the main function of the *prLow* is to ascertain if further inspection should be carried out or otherwise terminated.

A minimum threshold *mthreshold* is also created by the algorithm. This threshold must be exceeded so as to ensure that inspection continues and to make sure that low-energy nodes are found with a guarantee that at least a sensor node is charged. In the algorithm process, it is ensured that the total energy for charging C_e is not lesser than the energy required to recharge at least the lowest energy sensor node in δ, as expressed in lines 5–6. Should the energy utilized in charging be only used in charging a single sensor node, then the inspection process is terminated since that might not necessarily lead to an increase in the life of the network.

Algorithm 3: Energy for Nodes' Algorithm

```
Output: N, N_d and mthreshold
procedure EnergyforNodes(Energy, δ, C_e, μ,, δNodes, i)
    if Energy ≥ (d_i . ψ_r) then
        return True
    else
        Energy to charge lowest energy node C_l ← τ + 1 − min (δ)
        if C_e > C_l then
            prLow ← findProbLess(min(δ))
            if prLow > mthreshold then
                return True
            else
                return False
            end if
        end if
    end if
end process
```

5. Simulation Analysis and Discussion

We undertook simulation experiments so as to evaluate and analyze the performance of our proposed scheme. We performed a comparability study of our scheme with two other different state-of-the-art charging models in literature, which were the HCCA-TP charging model in [46] and the DBCS charging model in [47]. These models adopted clear and well-defined network topologies instead of complex topologies that are often initiated by network dynamics requiring collaborative charging mechanisms and large re-computational cost. The simulation was run on MATLAB (R2014a 64-bit) employing real-life WRSN parameters obtained from the work in [56], and this is shown in Table 2.

Table 2. Simulation Parameters.

Parameters	Values
Set of working nodes	5
Total Energy of WCV (E_t)	25 WH
Sensor node Energy capacity (F_e)	2.34 WH
Sensor node energy discharge rate (s)	1.625 mWH
Energy consumption rate for WCV hovering	92.28 W
Energy consumption rate for WCV flight	121.91 W
Travelling Speed of WCV	6 m/s
Centralizing WCV with a node (τ)	92.28 W × 36 s
mThreshold	0.17

From Table 2, the size of the set of nodes was set at 5, while the moving speed of the WCV with a total energy of 25 WH was set at 7.33 m/s. The travelling speed was set at 6 m/s since it proved to be the optimal speed to attain an increase in the life of the network, i.e., the optimal speed that was not too fast to quickly deplete the energy of the WCV and not too slow to get to the sensor node to be charged. The WCV charged one node at a time and charged several nodes on a single round trip.

Firstly, we analyzed the performance of the network using the network's surviving rate as an indicator and compared it with the HCCA-TP and DBCS schemes, as shown in Figure 2. From the figure, it can be seen that, as the network stayed in operation, the nodes' survival rates of the HCCA-TP scheme continued to fluctuate and they were a bit unstable, while the DBCS scheme's were mostly on the decline. This was obviously due to the fact that, at a specific period of time, factors such as travelling distance and charging time brought about an increase in the energy consumed by the WCV, thereby making it unable to charge more nodes in the network. Our scheme, however, went further down the network to discover low-energy sensor nodes that required charging, thereby increasing the survival rate of the sensor nodes in the network. In our scheme, no energy was, however, wasted in charging high-energy nodes. Additionally, from the figure, it can be observed that, at a certain point in time, the survival rate attained 100%, which indicated that low-energy sensor nodes were charged effectively.

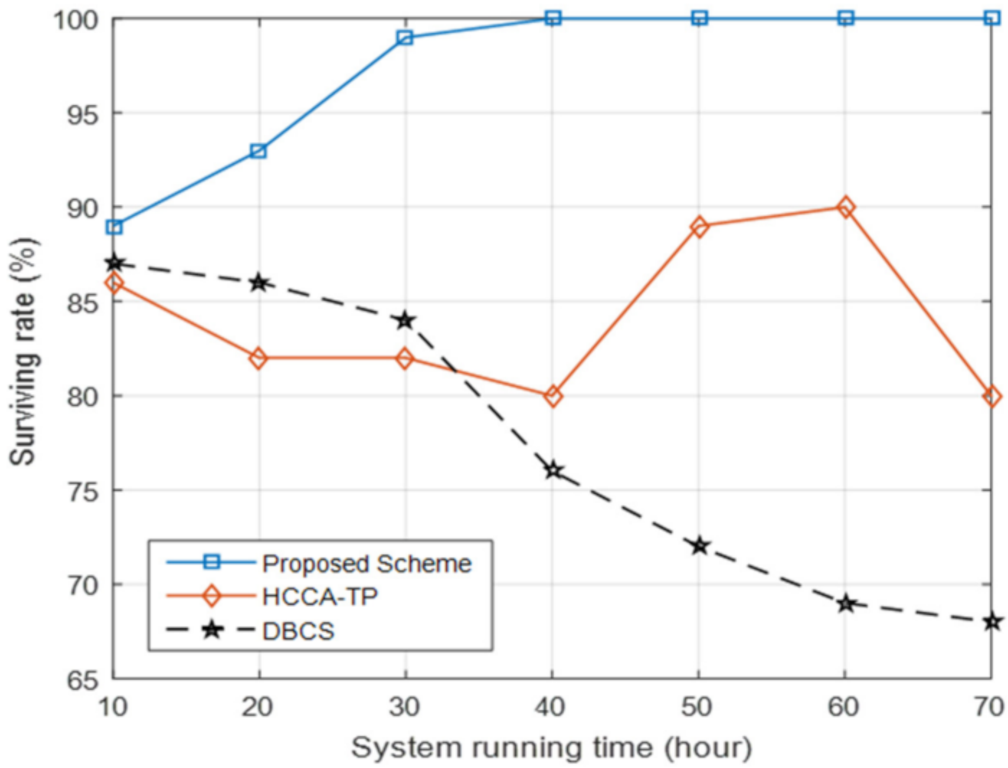

Figure 2. Survival rates of sensor nodes in the network.

In a bid to assess the efficiency of the network, the charging throughput was employed as it was seen as a key and major indicator for the efficiency and schedulability of the algorithms used. In this instance, the charging throughput was defined as the number of sensor nodes that the WCV charged successfully per a unit time. A lower throughput indicated a higher charging loss and a lower charging efficiency, while a higher throughput indicated otherwise. Figure 3 shows the charging throughput of three different schemes. It is seen that there was a gradual and steady improvement in the charging throughput of our proposed scheme when the network was in operation. There was also a slight improvement for both the HCCA-TP and DBCS schemes but with a lower throughput when compared to our proposed scheme. Generally, it was also noticed that there was a lower throughput at the start of the network; however, as the energies of sensor nodes were replenished, the network gradually began to maintain stability.

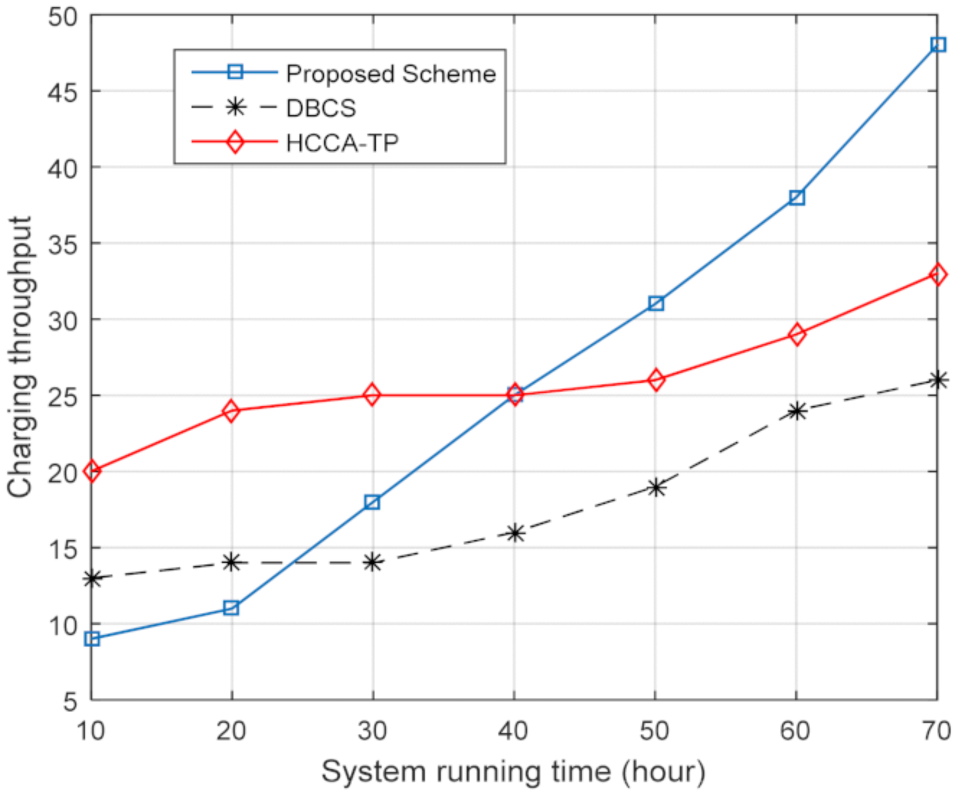

Figure 3. Comparing the charging throughputs of the various schemes.

In Figure 4, the average servicing time for the various schemes is shown. The average servicing time was defined as the time taken by the WCV to complete a successful charging task. This also encompassed the time spent to charge a current sensor node and the time it took the WCV to travel from the previous sensor node to the current node. It can be deduced from the figure that the average service time of our proposed scheme was lower than that of the HCCA-TP and DBCS schemes and tended to be a lot more stable after a certain period of time. That is to say that, while our proposed scheme got to low-energy sensor nodes on time, it also spent less time in completing the charging task, hence greatly improving the energy efficiency of the network.

The impact on the performance of the network when the travelling speed of the WCV was varied and adjusted is shown in Figure 5. The travelling speed of the WCV was a function of how many numbers of nodes it can serve within a certain period of time. Hence, we deduced that, at a relatively fast travelling speed, there were more sensor nodes that could be charged, which would eventually lead to an improved surviving rate of the nodes. From Figure 5, as expected, it is seen that, as the travelling speed increased, the surviving rates of all the schemes also increased. When the schemes were compared, it was noticed that our proposed scheme still performed a lot better than the other two schemes. The proposed scheme and the two other schemes initially did not get to an optimal level at lower travelling speeds but, however, stabilized at a certain speed, of 6 m/s. That means the speed of 6 m/s is the optimal speed in which all the schemes can flourish and perform a lot better. The HCCA-TP and DBCS schemes were noticed to be quite sensitive to a change in travelling speeds and this is due to the fact that, at low travelling speeds, there was a lot of time consumed in the network, which cannot be recovered. With the employment of our scheme, the death rate of the sensor nodes in the WRSN can be minimized, providing an ample time for the replenishment of energy.

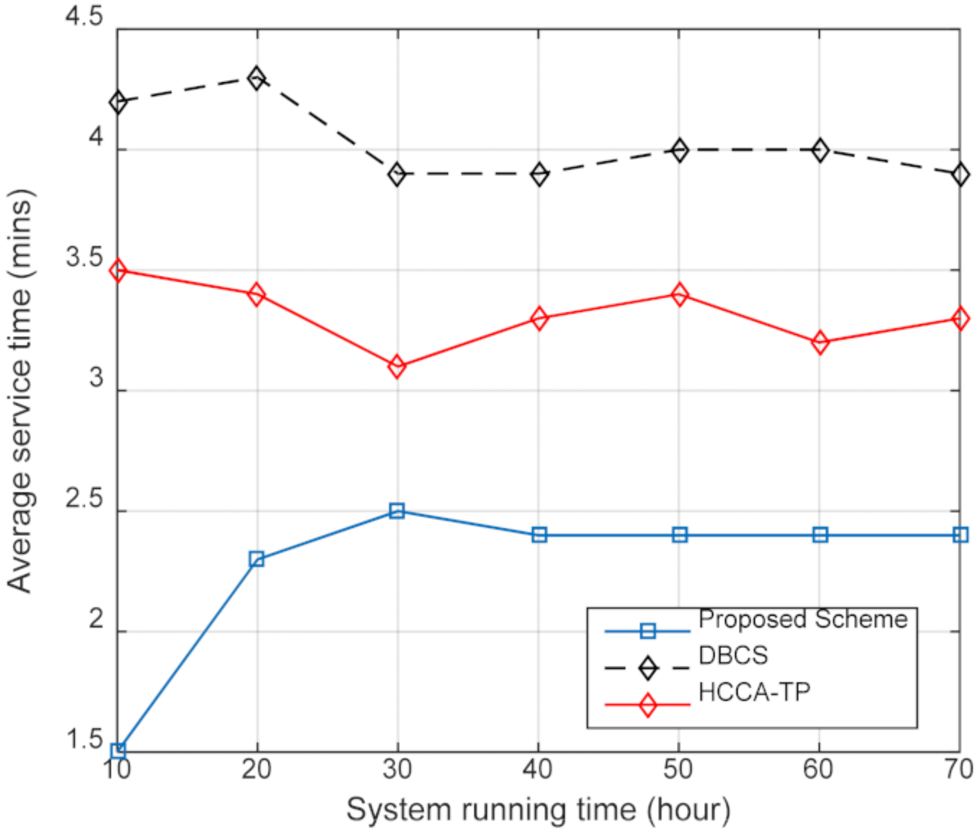

Figure 4. Comparing the average servicing times of the various schemes.

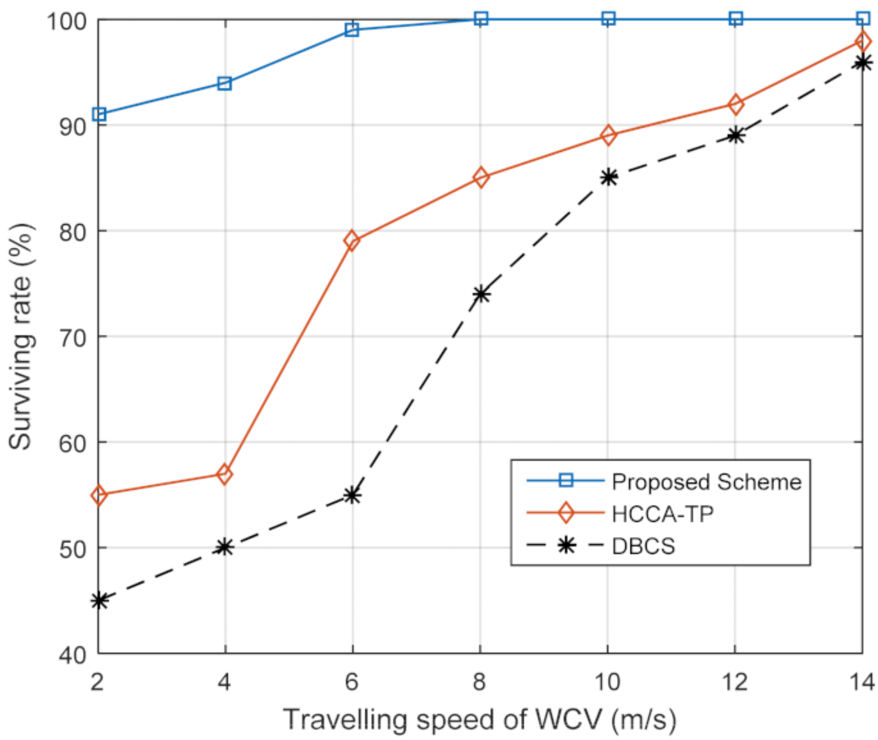

Figure 5. The surviving rate at different travelling speeds of WCV.

6. Conclusions and Future Works

Increasing the lifetime of typical Wireless Rechargeable Sensor Networks (WRSNs) has been a daunting task in recent times since they continue to grow larger. Overcoming this challenge, however, will not only render WRSNs a lot more practicable but extremely adaptable and flexible to growth in the real world. In this work, a set of algorithms was proposed to inspect which set of nodes to charge, then conveniently and effectively charge them with the aid of an unmanned aerial vehicle (UAV), which, in this case, was a wireless charging vehicle (WCV), in order to extend the overall lifetime of the network. We analyzed the network model, the energy consumption, and probability models and proposed efficient algorithms to determine and identify the quickest distance the WCV can travel and the set of sensor nodes that requires charging. The inspection algorithm was introduced to inspect the sensor nodes in the network and make certain decisions on when to visit and examine sensor nodes, which subset of sensor nodes to charge, and, lastly, when to return to the base station. The greedy charge algorithm was proposed to determine the shortest distance the WCV had to travel and to sort out the sensor nodes based on their energy levels. To determine whether further inspection is needed and to also determine the algorithm's stopping and returning points, an energy for nodes' algorithm was also proposed. Finally, simulations' experiments were carried out to ascertain the performance of our scheme. It was noticed that our scheme outperformed other schemes with respect to the survival rate, charging output, average service time, and varying travelling speed. Our proposed scheme is adaptable and can effectively operate under various network parameters and will be very practicable in large-scale WRSNs employing a single WCV.

For future works, we will be evaluating our proposed algorithm on a physical wireless charging vehicle system, implement multiple wireless charging systems with multiple vehicles on the existing network, and determining their performance. We will also extend this work into incoporating a larger and richer set of parameters for the sensor nodes' energy consumption model with respect to the WRSN primary protocols.

Author Contributions: Conceptualization, E.F.O. and K.A.-A.-E.; methodology, E.F.O.; software, E.F.O.; validation, E.F.O. and K.A.-A.-E.; formal analysis, K.A.-A.-E.; investigation, E.F.O.; resources, K.A.-A.-E.; data curation, E.F.O. and K.A.-A.-E.; writing—original draft preparation, E.F.O.; writing—review and editing, K.A.-A.-E.; and E.F.O.; supervision, K.A.-A.-E.; project administration, K.A.-A.-E.; funding acquisition, E.F.O. and K.A.-A.-E. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the 2021 funds of the Centre for Postgraduate Studies (CPS), Cape Peninsula University of Technology.

Data Availability Statement: Not applicable.

Acknowledgments: The authors would like to thank MTE Khan for all his assistance and efforts.

Conflicts of Interest: The authors declare no conflict of interest.

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