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A Novel Unmanned Aerial Vehicle Charging Scheme for Wireless Rechargeable Sensor Networks in an Urban Bus System

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Abstract: Wireless sensor networks (WSNs) are implemented in many aspects of daily life, such as Internet of Things applications, industrial automation, and intelligent agriculture. Sensors are typically powered by batteries. Chargers can be used to supply power to sensor nodes and thus extend the lifetime of WSNs. This special type of network is named a wireless rechargeable sensor network (WRSN). However, due to the limited battery power and different deployment locations of the sensors, efficiently moving the chargers from the current sensor nodes to the next sensor nodes is a challenge. In this study, we propose an unmanned aerial vehicle (UAV)-based charging scheme in an urban bus system, involving the coordination between UAVs and bus schedules. The UAVs can be recharged by urban buses and then supply the power to sensor nodes. We implemented three charging strategies: naïve, shortest path, and max power. In the naïve strategy, the UAVs fly directly to sensor nodes when the sensors are lacking power. In the shortest path strategy, the minimum distance between the sensor node and bus location is calculated, and the UAVs fly the shortest path to the sensor nodes. In the maximum power charging strategy, the UAV that has the highest battery power is assigned to work. The experimental results show that the shortest path charging and max power charging strategies perform better than naïve charging in different parameter settings. To prolong the lifetime of the network system, adjusting the bus frequency according to the number of nearby sensors around the bus route is favorable.

Keywords: wireless rechargeable sensor networks; unmanned aerial vehicles; bus system

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1. Introduction

The wireless rechargeable sensor network (WRSN) [1,2], which has a mechanism for self-charging or harvesting energy from the environment [3] (such as solar and wind energy), has an important role in future smart cities. WRSN has wide applications in many fields such as long-term environmental monitoring [4] and vehicle traffic control monitoring [5].

In this regard, Eiskamp et al. [6] proposed a method for using wireless chargers embedded in unmanned aerial vehicles (UAVs) to store energy in their batteries. Liao [7] proposed the use of a dedicated charger carried to the sensor network by a drone whereby energy could be transmitted to the sensor using wireless charging technology. The drone wireless charging of WRSNs enables recharge sensors to be continuously deployed to inaccessible outdoor environments without the need to maintain a wireless charging network.

However, as the battery capacity is limited, the drone must return to the ground charging station to recharge, which reduces its charging efficiency. Similarly, a limited battery capacity hinders the charging of sensors deployed in wide areas by UAVs. Thus, the use of UAVs for efficient charging is an interesting and important problem. Trotta et al. [8] proposed a network architecture with a supporting optimization framework to allow UAVs to perform city-scale video monitoring of points of interest (POI). They defined a mathematical framework for selecting a UAV that can periodically recharge by landing on public transportation buses and then "riding" the bus to the chosen POl. The UAV scheduler can be modeled as an instance of a multicommodity flow problem and can be mathematically solved using mixed-integer linear programming (MILP) techniques. The centralized formulation identifies the UAV, the next bus, and the next POI, given the information on energy thresholds, bus routes in the city, and the next arrival time, to ensure persistent and reliable video coverage of all POIs in the city. Jin et al. [9] designed a new electric vehicle charging system that utilizes a bus network by integrating an online electric vehicle (OLEV) system [10] and a microwave power transfer system. By taking advantage of the bus network, UAVs can refuel and also extend the range of charging services. At the same time, the bus is equipped with a large-capacity battery that can sustainably draw energy from the OLEV system or its combustion engine such that there is sufficient energy to charge the UAVs. Buses offer ubiquitous charging opportunities for UAVs because of the high penetration and wide coverage of bus networks in urban areas.

Caillouet et al. [7] proposed the wireless charging of UAVs for WRSN, and Trotta et al. [8] proposed drone scheduling using buses to charge UAVs. The process requires energy to be efficiently transferred between the WRSN, UAV, and bus to form a closed wireless charging system. In this study, we propose a bus-network assisted UAV wireless charging system that uses a bus network to supplement the energy of the UAV and minimizes the flight energy consumption of the UAV in charging the WRSN.

The bus has its own fixed schedule, and the UAV can be charged while on the bus. When the bus is near the sensor, the UAV can fly to the sensor and charge it. The sensors, landing points of the bus sections and flight segments between the sensor landing points form a comprehensive network. The UAV rides the bus through the landing point closest to the charging sensor, replenishes its energy from the bus, and leaves the bus when the energy is sufficient to charge the next sensor at the landing point.

The sustainability of the WRSN largely depends on the charging efficiency and scheduling of the UAVs. The arrangement of the bus-network assisted drones for sustainable charging of WRSN is a very challenging problem. The traveling salesman path problem cannot be directly solved on a comprehensive network that integrates the WRSN and bus network to obtain the travel path of the UAV, as the goal is only to schedule the UAV to access sensors. In addition, determining the energy-constrained shortest path for a UAV to travel from one sensor to the next in a comprehensive network is difficult. This is because the UAV can undergo a hybrid process of discharging and charging between any two sensors. In addition, the scheduling of the UAV must ensure that each road segment meets the energy constraint of the UAV such that the remaining energy of the UAV at the starting point of the road segment is not less than the energy consumed on the segment. However, the remaining energy of the UAV depends on the previously selected road/ flight segment. This paper makes the following contributions:

- We proposed a UAV-based charging scheme in an urban bus system, involving the coordination between UAVs and bus schedules;
- We use real maps and bus information to design charging algorithms. The UAVs can be recharged by urban buses and then supply the power to sensor nodes;
- We implemented three charging strategies: naïve, shortest path, and max power. The proposed charging strategy can be easily applied to practical fields.

2. Related Works

Recently, studies have indicated that UAVs can be charged using wireless energy transfer and serve as mobile chargers. The adoption of wireless energy transfer to charge UAVs has been proposed in [1], showing that the wireless charging power is sufficient to restore their battery. The UAVs can also charge Internet of Things (IoT) devices using wireless power transfer [2]. Although the concept of charging UAVs and UAVs charging IoT devices has been implemented [3], the design of an efficient UAV-specific wireless charging scheme in WRSNs still poses challenges. Previous studies have proposed efficient deployment strategies of UAVs to replenish energy, maximize the coverage of the selected region, and ensure service sustainability [4]. Chen et al. presented a rechargeable UAV paradigm for WRSNs [5], which employed a scheduling heuristic for finding the shortest path using the multi-hop method.

Previously, studies on WRSN mainly focused on solving the problems of the deployment of mobile wireless chargers [6,7], energy conservation [8,9], and routing and scheduling [10]. Several studies have been conducted on the deployment of wireless chargers as the adoption of wireless energy transfer has made it an important issue. Chiu et al. designed a charger deployment strategy for mobility-aware WRSNs and used the trajectories of mobile sensors to design wireless charger placement strategies [11]. The proposed method partitioned the region into grids and assigned wireless chargers at the grid connection positions. Liao et al. proposed a sleep schedule for wireless chargers to reduce the battery power attenuation and used cones to fill the area [12]. The design approach devised by He et al. [13] is based on placing the wireless chargers in the regions of interest and using the traditional triangular approach to detect the area. Horster and Lienhart studied the arrangement of optical sensors with the constraints of the device angles [14]. They used integer linear programming (ILP) to resolve the problem of optimal coverage, with each grid intersection representing a potential placing position [14]. In [15], the arrangement of wireless chargers was expressed as a nonlinear programming problem, and the deployment problem belonged to the NP-hard set. Thus, solving the wireless charger deployment problem is challenging. Mo et al. proposed MILP to formulate the coordination problem among multiple mobile chargers and provided a decomposition approach to solve the problem [15]. Tang et al. addressed charging and routing together and suggested an optimization method to improve the network lifetime [16]. Aiming to balance the energy distribution of the network, they divided the battery charging time according to the energy consumption, thereby dynamically balancing the charging efficiency. Lin et al. proposed a power balance aware deployment (PBAD) strategy to solve the problem of unbalanced battery power distribution in WRSNs. The comparison between PBAD and random position random orientation was presented in [6]. The charger arrangement was formulated as a minimum dominating set problem, and the aim was to find the minimal number of chargers needed to overlay the WRSNs. Lin et al. leveraged a greedy heuristic to compute the coverage set [6]. They presented a two-step approach. In the beginning, the selected area was divided into several sub-regions, and each sub-region could obtain a continued source of charging power. Then, each sub-region was further checked, and the minimum dominating set was calculated. Later, an approximate optimal set was selected. A comparison between the surveyed studies is organized in Table 1.

Table 1. Related deployment literature.

Research	Charger Mobility	Bus Route and Schedule	Awareness	UAV Based	Simulation Environment	Hardware Experiment
He et al. (2012) [13]	Fixed	No	Energy Provision	No	WISP platform	Yes
Chiu et al. (2012) [11]	Fixed	No	Mobility Aware	No	Manhattan grid-based map and Random Walk Mobility Model	No
Liao et al. (2013) [12]	Fixed	No	3D beamforming	No	C++	No
Lin et al. (2016) [6]	Fixed	No	Power Balance Aware	No	C++	No
Mo et al. (2019) [15]	Mobile	No	Energy Aware	No	Matlab	No
Tang et al. (2020) [16]	Mobile	No	Routing and Energy Aware	No	Matlab	No
Chen et al. (2020) [5]	Mobile	No	Travel Distance Aware	Yes	Visual Studio C#	No
Jin et al. (2021) [3]	Mobile	Yes	Energy Aware	Yes	Google Map and Inspire 2 Parameter	Yes
Ours	Mobile	Yes	Travel Distance and Energy Bound Aware	Yes	Google Map and Python	No

Compared with previous related work, we conceived a UAV-based WRSN charging system that can operate on a city bus network. The bus route and schedule are considered in the WRSN charging system. The system is aware of the UAV flight distance limit and the influence of the upper and lower energy bound on the WRSN lifetime. The Google map is used in the simulation environment to construct the bus route. Since most research did not consider bus routes and schedules, the closest environment setting would be the research from Jin et al. [3]. However, the study by Jin et al. assumes that UAVs have fixed landing points so that UAVs take off and land buses at the fixed landing points [3]. Due to the limitation of the fixed landing points, the flight distance of the UAVs may increase and thus cause more power consumption. In particular, if there is a sensor near the bus route but not near any landing point, the UAV will take more time to fly to the sensor, thus increasing the UAV's energy consumption. This study assumes that the UAV can fly directly from the bus to the sensors, then fly back to the bus from the sensors after charging. Based on this concept, the shortest path of the UAV flight can be calculated, thereby reducing the UAV flight distance compared to the study by Jin et al. [3]. Because the landing point of the flight in this study is not fixed, it is not possible to plan the path based on the fixed landing points as in the previous study. In addition, this study decides whether to charge or not based on the current remaining battery power of the sensors. This concept is also different from the previous research, which considers the deadlines of the sensors to maximize the number of rechargeable sensors [3].

3. Method

3.1. Problem Definition

In a wireless sensor network (WSN), sensors run throughout the network lifetime. Sensors simultaneously receive and send data. Thus, the network cannot receive and send data properly if the sensors shutdown. In a WRSN, chargers can supply power to the sensors on-demand to prolong the lifetime of the network. Sensors may be deployed everywhere in the urban areas. Hence, developing an approach to move chargers to supply the demand for power of sensors in WRSN is an interesting research problem. This study proposes a novel UAV charging scheme for WRSN using the urban bus system. In this study, UAVs are used as chargers for a WRSN. The UAVs can avoid traffic congestion and fly to the charging point of sensors directly. The UAVs are charged by the buses in the urban bus system. At the same time, they are transported using the buses to supply power to the sensors that are around the urban area. The UAVs pass by the sensors every few minutes, and the sensors can be frequently charged by the UAVs. When sensors lack power, a UAV can fly to the charging point of the sensor from the bus to supply power if the UAV has sufficient power. The efficiency of charging will be influenced by the charging scheme. This study implements a UAV charging scheme based on the urban bus system to simulate three types of strategies for charging.

3.2. Algorithms

In this study, three charging schemes were analyzed: naïve charging, shortest path charging, and max power charging. The naïve charging is intuitive. In this charging scheme, a UAV checks the location of the bus every 30 s. When the bus is near the sensor that lacks power, a UAV that has sufficient power flies from the bus to the charging point of the sensor. Once the sensors are charged, the UAV flies back to the bus if the bus is within the flight distance limit and is recharged by the bus. In naïve charging, the flight path of the UAV may not be the shortest because it directly flies to the sensors lacking power. It does not consider the distance between the location of the bus and the sensor. Table 2 explains the symbols used in this study. The flow chart of the charging process is shown in Figure 1. It will be adjusted according to the charging schemes. The operation of the naïve charging strategy is presented in Algorithm 1.

Algorithm 1: Charging Strategy with Naïve Charging

Input: all the sensors S, UAVs U, and Buses B
Output: Which UAV u_i charges which sensor s_i and Which UAV u_i flies to which bus b_i
Step 1. Randomly select the sensor position around bus route within flight distance limit of UAV
Step 2. Initialize the locations of UAV to each bus
Step 3. Update locations of all buses bl_i every 30 seconds
foreach b_i **do**
 $Update\_Location(bl_i);$
End foreach

Step 4. Check the power of all sensors sp_i, if the power of sensor sp_i is not enough, search the location of UAVs ul_i, and check the UAV supplementary battery up_i, if up_i, is enough, u_i flies to sl_i
foreach s_i **do**
 if $(sp_i < lpc)$ **then**
  foreach u_i **do**
   if $(up_i > lpc$ && $distance(ul_i - sl_i) < d)$ **then**
    $UAV\_flies\_to\_sensor(s_i,\ u_i);$
   End if
  End foreach
 End if
End foreach

Step 5. If the power of sensors is enough, UAV flies to bus from the sensor
foreach s_i **do**
 if $(sp_i > upc$ && s_i *is been charging*$)$ **then**
  foreach b_i **do**
   if $(distance(bl_i - ul_i) < d$ && b_i *has enough space to deliver* $u_i)$ **then**
    $UAV\_flies\_to\_bus(b_i,\ u_i);$
   End if
  End foreach
 End if
End foreach

Step 6. Supplement and consumption of power of all sensors sp_i and UAVs up_i
foreach s_i **do**
 $consumption(sp_i);$
 if $(s_i$ *is charged*$)$ **then**
$consumption(up_i);$
  $supplement(sp_i);$
 End if
End foreach
foreach u_i **do**
 if $(u_i$ *is on bus*$)$ **then**
  $supplement(up_i);$
 End if
End foreach

Table 2. Symbols used in this research.

Parameters	The Description of Parameters
s_i, u_i, b_i	Sensor, UAV, and Bus
n	The number of sensors and UAVs
sl_i, ul_i, bl_i	The locations of sensors, UAVs, and buses
sp_i, up_i	The power of sensors and UAVs
lpc	The lower bound threshold of the power of sensors and UAVs
upc	The upper bound threshold of the power of sensors and UAVs
d	UAV flight distance range

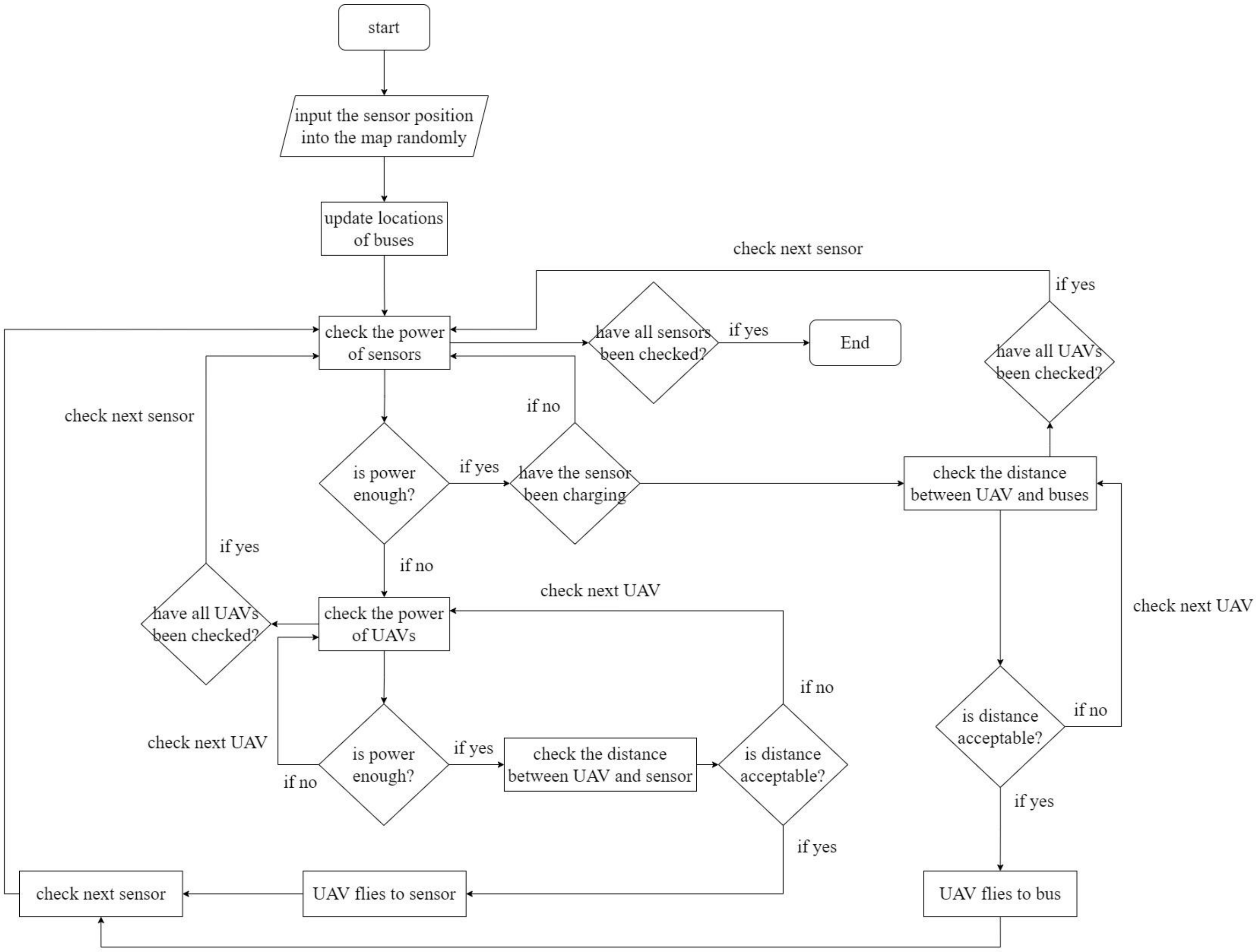

Figure 1. Flow chart of the charging process.

The strategy of shortest path charging is an extension of naïve charging. In this strategy, the distances between the sensor and all UAVs are calculated. The closest UAV that is within the flight distance limit is chosen. Then, the shortest path between the bus route in which the closest UAV is and where the sensor is obtained. The UAV is continuously charged until the bus arrives at the point of the shortest path. Therefore, the UAV has more time to be charged by the bus using the shortest path strategy, and more energy is maintained in the network. If there are no UAVs that have sufficient power to charge the sensor, the algorithm will continue the search for a suitable UAV until the sensor is charged or depleted of all charges. The steps of the shortest path charging strategy are presented in Algorithm 2.

Algorithm 2: Shortest Path Charging

Input: all the sensors S, UAVs U, and Buses B
Output: the shortest path between bus b_i route and sensor s_i
From the step 4 in Algorithm 1: find the shortest path between bus route and location of sensor s_i
foreach s_i **do**
 if $(sp_i < lpc)$ **then**
  foreach u_i **do**
   if $(distance(ul_i - sl_i) < d \text{ \&\& } up_i \textit{ is enouth})$ **then**
    $record\_the\_closest\_UAV(ul_i,\ sl_i)$;
   End if
  End foreach
  if $(found\ the\ closest\ u_i)$ **then**
   $find\_min\_distance(b_i\ route\ that\ the\ closest\ u_i\ is\ on,\ sl_i)$;
   $UAV\_flies\_to\_sensor(s_i,\ u_i)$;
  End if
 End if
End foreach

Max power charging can be combined with a different charging strategy. A bus can transport multiple UAVs on the route, and several UAVs can be assigned to a sensor simultaneously. The max power charging strategy ensures that only the UAV with the most power is assigned to the sensor. The steps of the max power charging strategy combined with the shortest path strategy are presented in Algorithm 3.

Algorithm 3: Max Power Charging (with Shortest Path Charging)

Input: all the sensors S, UAVs U, and Buses B
  Output: the max power UAV u_i
  After finding the shortest path between bus b_i and sensor s_i:
  foreach $(u_i\ is\ on\ the\ bus\ b_i)$ **do**
   $find\_max\_power(u_i)$;
  End foreach
$UAV\_flies\_to\_sensor(max\ poweru_i,\ s_i)$;

4. Experimental Results

4.1. Experimental Environment and Parameters

In this study, we used the bus routes and the bus timetables in Chiayi city and the street map from Google Maps in the simulation experiment, as shown in Figure 2. Chiayi city has three routes. We simplified the names of the routes to green, red, and orange routes. The time intervals between each bus on the three routes are 30, 40, and 60 min, and the running times are 53, 45, and 56 min, respectively. For convenience, we fixed the bus speed and did not consider the basic consumption for running of UAV. We simulated these algorithms via python. We updated the bus location and the status of sensors and UAVs every 30 s and analyzed the performance of the sensors under each algorithm.

In the experiment, the number of both sensors and UAVs was denoted by n. First, we set n equal to 30. Then, we evenly distributed the UAVs on each bus. In addition, we limited the maximum number of UAVs transported on buses to three. The flight distance limit d was set to 100 units. We randomly deployed the sensors within a distance of $d \times 0.8$ to avoid sensors that are hard to charge in the experiment. The time of flight of the UAV was calculated using a pattern: 1 min per 30 units. In this study, the maximum power of the sensor is 100%. Initially, sensors were randomly assigned powers between 30% and 100%. The power of the UAV was set to 100%. The threshold lpc of the lower bound of power was set to 30%. The threshold upc for the end of charging was set to 85%. We expected the power supplement from the bus to the UAV to be better than the power supplement from the UAV to the sensor and the power supplement from the UAV to the sensor to be more than the power consumption of the sensor. Table 3 shows the parameters used in the experiment.

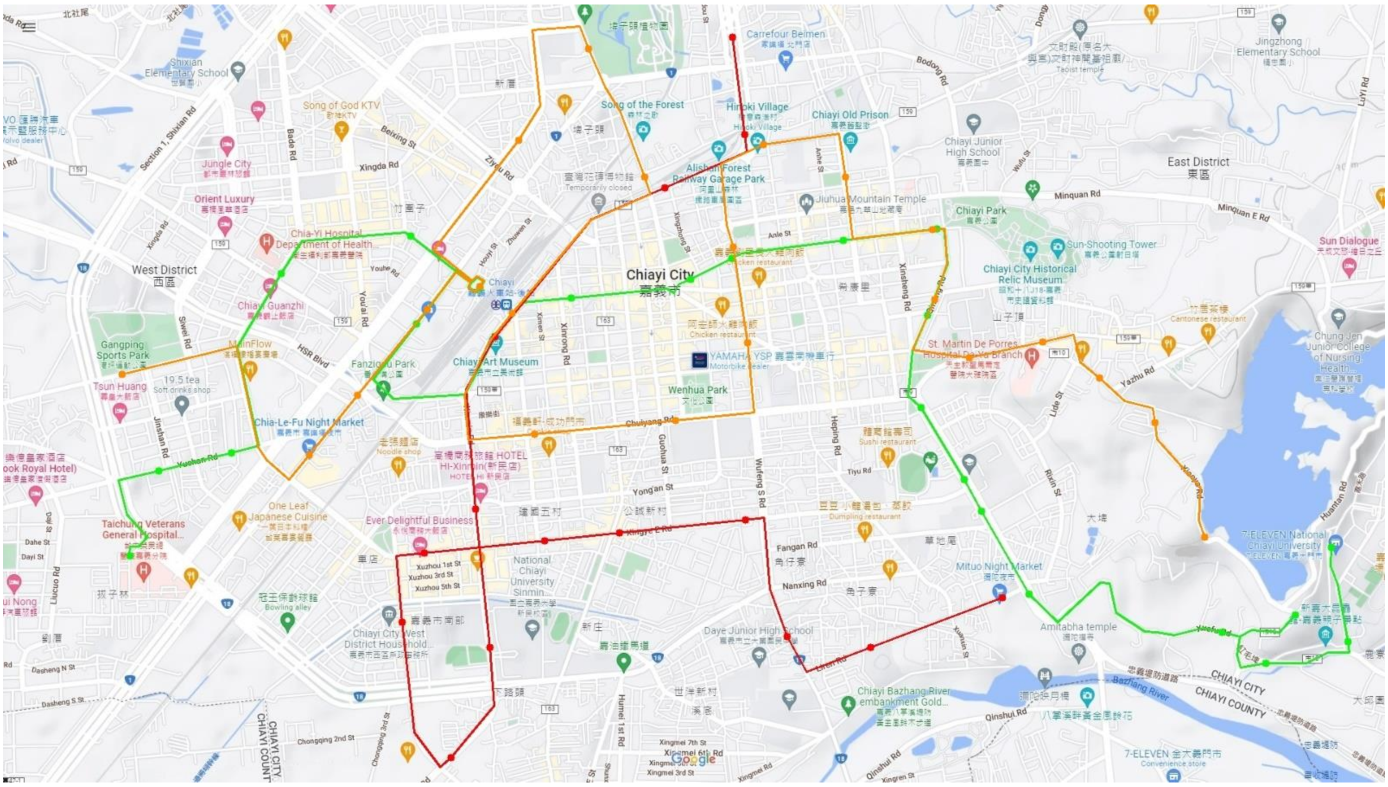

Figure 2. Bus routes in Chiayi city.

Table 3. The parameters in the experiment.

Parameters	The Description of Parameters
n	number of 30
d	100 units
Power maximum	100%
lpc	30%
upc	85%
Sensor Consumption	0.6%/min
UAV supplement Sensor	1%/min
Bus supplement UAV	2%/min

4.2. Experimental Results

In this study, we simulated the operation time of buses for 10 h in real life. We tested several times for the results. First, we compared the survival rate of sensors with the three algorithms. Figure 3 shows the impact of the different algorithms and the number of UAVs on the survival rate of sensors. We set the number of sensors to 30 and varied the number of UAVs. The results indicated that the shortest path charging and max power charging are better than the naïve charging. The survival rates of sensors with the naïve charging, shortest path charging, and max power charging were 82.33%, 87.55%, and 87.34%, respectively. The survival rate of sensors with the naïve charging strategy was 3.2% lower compared to those of the shortest path and max power charging. This could be because the UAVs with the shortest path and max power charging schemes have higher energy and lower time of flight than those with the naïve charging scheme. As the UAVs fly to the sensor directly (provided the distance between the UAV and the sensor is less than the distance limit) in the naïve charging strategy, more time is necessary for the UAVs to arrive at the charging point of the sensor. Furthermore, the supplement of energy that the buses can provide to the UAV is decreased. Compared to the naïve charging strategy, the shortest path and max power strategies provide more time to supply power for the UAVs. Hence, the UAVs have higher power and lower time of flight.

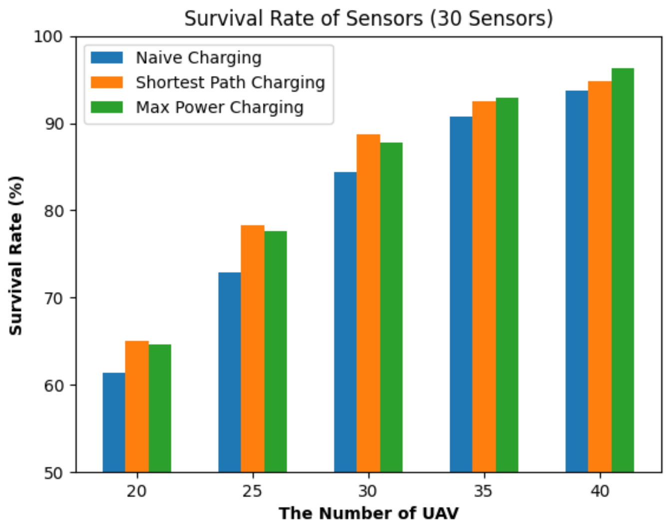

Figure 3. Impact of different algorithms and number of UAVs on the survival rate of sensors.

In addition, we changed the upper bound of the number of UAVs on the bus, which influenced the survival rate of sensors, as shown in Figure 4. We fixed the number of sensors to 30. The results indicated that compared to the upper bound of 3, the survival rate of sensors was lower by 2–4% for the upper bounds of 4 and 5. As a bus passes by many sensors, if the upper bound on a bus is higher, the buses on other routes may not have a sufficient number of UAVs, which results in some sensors on that route not being charged.

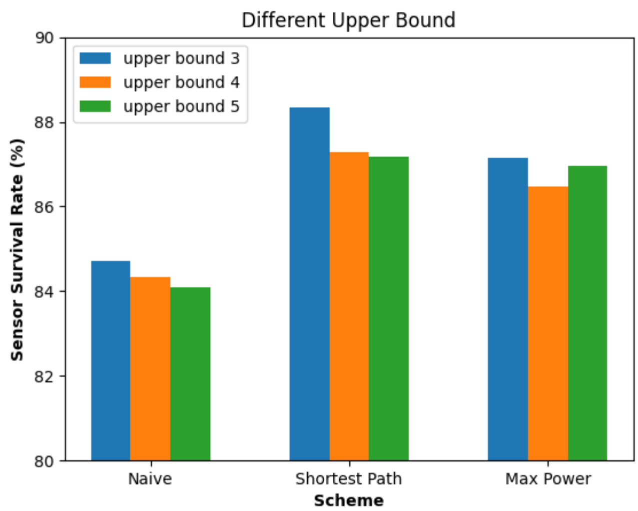

Figure 4. Impact of different upper bounds of the number of UAVs on the survival rate of sensors.

The average number of sensors on the green, red, and orange routes was 10.5, 8.0, and 11.5, respectively. We changed the interval of buses based on the average number of sensors on each route. Moreover, we exchanged the intervals of buses on routes 2 and 3 because there were more sensors on route 3. Figure 5 shows the effect of different bus intervals. The results indicate that the exchange did not affect the survival rate of sensors.

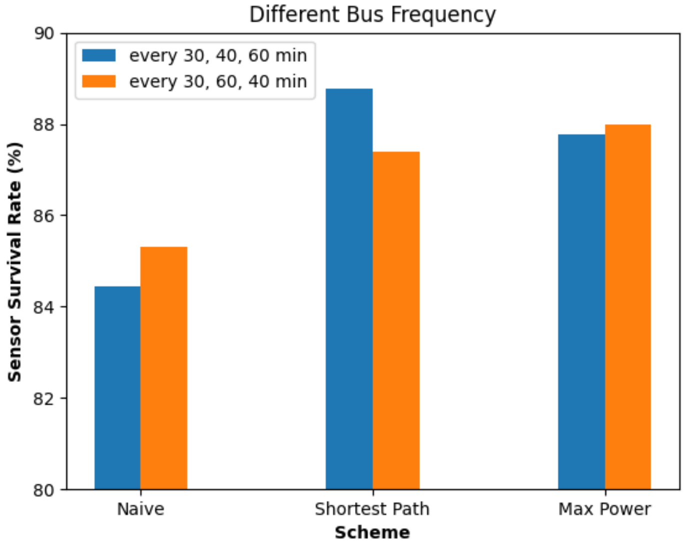

Figure 5. Impact of different bus intervals on the survival rate of sensors.

Finally, we increased the lower bound lpc of the power used by the UAV to charge the sensor and found that it would have more impact on the sensor survival rate, as shown in Figure 6. The results indicate that the survival rate of sensors with an lpc of 0.5 is higher than that with an lpc of 0.3 by 3–5%. When the lpc is lower, it can result in sensors not being charged even if buses pass by the sensor. If the arrival times of buses have wide intervals, the sensor may not be charged by the UAV in a timely manner. If only one bus route passes by the sensor, the lpc would have a higher influence on its survival rate. Therefore, increasing the lpc value can increase the fault tolerance of the WRSN networks.

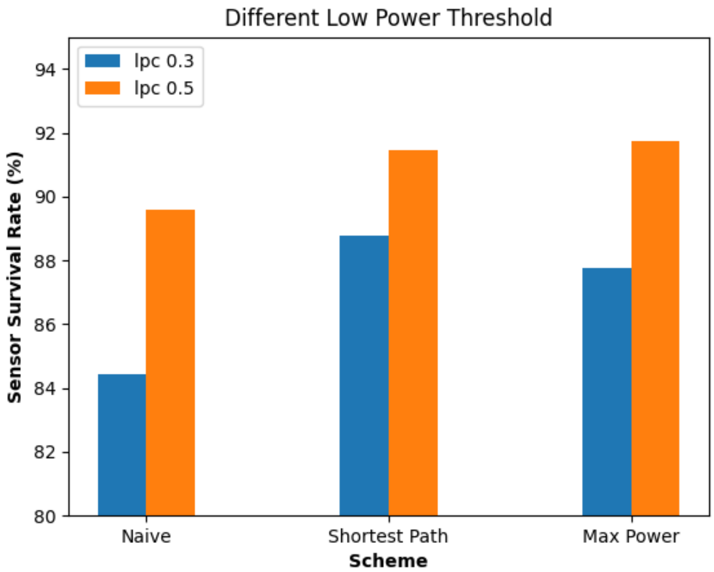

Figure 6. Impact of different lpc values on the survival rate of sensors.

5. Conclusions

In this study, we proposed a charging scheme that can operate on an urban bus system. The charging scheme is implemented to coordinate UAVs with bus schedules. The UAVs can be recharged while utilizing an urban bus system. Then, the UAV chargers supply power to sensor nodes. We also compared three different charging strategies. The first strategy is naïve charging. Under this scheme, the UAV directly flies to the sensor nodes when the sensors lack power. In the shortest path strategy, the minimum distance between the sensor node and bus location is calculated, and the UAVs choose the shortest path to the sensor nodes. In the max power charging strategy, the UAV that has the most battery power is assigned to the sensor. Finally, this scheme adjusts a suitable bus frequency based on the number of nearby sensors on the bus route to prolong the lifetime of the network system. Experimental results indicated that the strategies of shortest path charging and max power charging provide better sensor survival rates than the naïve charging strategy. The sensor survival rate for naïve charging, shortest path charging, and max power charging were 82.33%, 87.55%, and 87.34%, respectively. The survival rate of sensors in the naïve charging strategy was 3.2% lower compared to those of the other two strategies. There are regulations for the UAVs to provide a safe flight environment. In this study, we did not investigate the effect of the regulatory constraints, such as physical collision avoidance. The inter-UAV communication issue was also neglected. We also assumed fixed landing points for the UAVs, which might undermine the flexibility of the UAVs and the charging efficiency. The inter-UAV communication and mobile landing points can be explored in the future.

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