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Using a UAV to Effectively Prolong Wireless Sensor Network Lifetime with Wireless Power Transfer

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USING A UAV TO EFFECTIVELY PROLONG WIRELESS SENSOR NETWORK LIFETIME WITH WIRELESS POWER TRANSFER

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USING A UAV TO EFFECTIVELY PROLONG WIRELESS SENSOR NETWORK LIFETIME WITH WIRELESS POWER TRANSFER

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Wireless sensor networks are widely used for everything from border security to monitoring waterway pollution. Supplying energy for long term deployment is a main challenge in the applications of wireless sensor networks, as batteries are the primary energy source. Current wireless sensor networks deployed for long periods either require additional infrastructure, such as solar panels, or periodic maintenance. Our research lab has proposed a novel solution that uses a micro unmanned aerial vehicle (UAV) to wirelessly charge the sensor nodes and prolong the sensor network lifetime. Recent studies have shown that significant power can be transferred wirelessly over medium distances. As the UAV itself has a limited energy capacity, the challenge is how to charge the sensor nodes so that the sensor network lifetime can be maximized. We prove that the optimization problem is NP-Complete and propose a series of algorithms. The results show that the current UAV wireless power transfer system can prolong the sensor network lifetime by more than 50%. The algorithms are divided into three categories: complete knowledge, some knowledge and no knowledge of sensor network energy. As expected, the results indicate that the more information the algorithm can use, the better performance it can achieve. In addition, we identify the bottlenecks of the current system, such as the high energy consumption rate of hovering while charging, and provide guidance for future improvements.

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DEDICATION

To my family.

ACKNOWLEDGMENTS

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Chapter 1

Introduction

A wireless sensor network is a collection of sensor nodes organized into a cooperative network [13]. Now wireless sensor networks are widely used in many fields, from habit monitoring to healthcare [2], [6], [32] and [3]. Batteries are currently the main energy source for the wireless sensor networks. Roundy *et al.* indicated that effective energy supplies become the challenge of the applications of wireless sensor networks, although a few very low power wireless sensor platforms have entered the marketplace [26]. Current wireless sensor networks deployed for long periods either require additional infrastructure, such as solar panels, or periodic maintenance.

In our lab, Griffin and Detweiler proposed a novel solution, using a micro unmanned aerial vehicle (UAV) to wirelessly charge the sensor nodes and then prolong the lifetime of the wireless sensor network [11]. UAV has been adopted in the military world over the last decade and achieved great success [8]. Now there are a wide range of non-military UAV applications, from autonomous aerial water sampling [24] to UAV-based remote sensing [22]. Tesla developed the original idea of wireless power transfer over a century ago [33]. Then recently, researchers have shown that they can significantly and effectively transfer power over medium distance. For instance, Kurs *et al.* were able to transfer several tens of watts to fully light up a 60 W light bulb from distances more than 2 m away [17].

UAV based wireless power transfer system is a very promising solution for prolonging the sensor network lifetime. First, the sensor nodes are usually distributed over a large area, and the UAV is able to cover a large area because of its fast moving speed. At the same time, the UAV is even able to charge sensor nodes at locations which are normally inaccessible to humans. Second, the wireless power transfer method makes the charging process easy since no complicated mechanical mechanism is required to operate the sensor node. Fig 1.1 shows a motivating example of using a UAV to charge sensor nodes. Recently we have experienced several bridge collapses, such as Minneapolis I35 bridge in 2007 [12]. These disasters would be avoided by deploying wireless sensor nodes on the bridge to monitor the health of the bridge. The UAV-based wireless power transfer system is able to maintain the wireless sensor network as a long-term monitoring system by regularly charge these sensor nodes. In addition, these sensor nodes even can be embedded into the bridge as some wireless power transfer methods can work through many materials [28].

If there are many sensor nodes and they are distributed widely, it is a challenge to decide which nodes should be charged and how much energy should be transfered. In this thesis, we answer the question: Given the UAV and the sensor network, what is the most optimal strategy for the UAV so it can prolong the lifetime of the sensor network as much as possible with a single flight?

There are many possible strategies. For example, one simple strategy is to let the UAV always fly to next random sensor node and then transfer a random amount of energy to this sensor node until the UAV has to fly back to the base

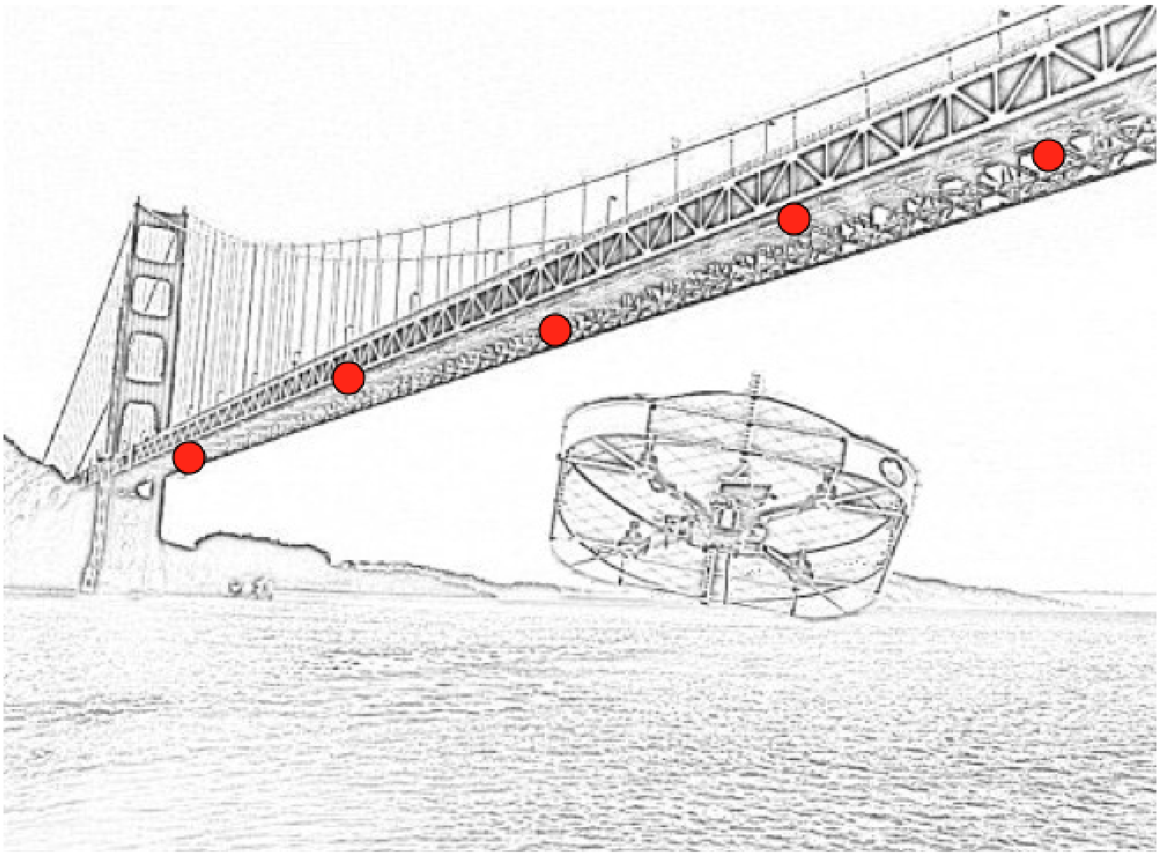


Figure 1.1: A motivating example of using a UAV to charge sensor nodes

station because of insufficient energy. However, there are a few obvious problems with this simple strategy. First, the UAV may need to fly back and forth to visit all these sensor nodes and waste its energy on extra flight. Second, the UAV may transfer not enough energy to sensor nodes with low energy level but too much energy to sensor nodes with high energy level, while the sensor network lifetime is determined by the sensor node with the least energy level. As a result, the sensor network lifetime is not the optimal, or not even close to the optimal. There are some other intuitive strategies, including fully charging each sensor node, transferring a fixed amount of energy to each sensor node, and flying in the shortest cycle. Also, the UAV is able to use more advanced algorithms if it has more information about the sensor network, such as the average energy level of all sensor nodes or the exact energy level of each sensor node. However, there is energy overhead on collecting and maintaining this type of information since sensor nodes are widely located.

1.1 Contributions

In this thesis, we address the challenge of how to use a UAV to effectively charge a sensor network. This work partially contributes to a submitted paper [20]. Specially, we

- Give a formal definition of the problem and prove its NP-Completeness. To the best of our knowledge, this is the first complete NP-Completeness proof for this problem.

- Propose a series of heuristic algorithms and develop a simulation system to test them. Since the UAV-based wireless power transfer system is a novel platform, there is not too much existing research providing related algorithms. The sensor network energy information can help the UAV to make decisions, but the sensor network consumes extra resource to provide this information. Based on this fact, three types of algorithms are discussed.

- Identify the bottleneck of the current system and then guide future development. There are many trade-offs while building the UAV-based wireless power transfer system. It is not straightforward to always make the correct decision, and it is expensive to build and test different designs. The simulation system can offer insights about these trade-offs and reduce the cost of the experiments.

The rest of this paper is organized as follows. In Chapter 2, we review the related work, including different approaches to prolong the sensor network lifetime, main methods of wireless power transfer, and several existing charging algorithms. In Chapter 3, we then introduce the background, the design of our UAV-based wireless power transfer system. Next, Chapter 4 gives a formal definition of the problem and its NP-Completeness proof. Chapter 5 proposes three categories of algorithms based on their knowledge level of the sensor node energy. In Chapter 6, we describe a simulation system which is used to evaluate the performance of different algorithms later. Chapter 7 shows the simulation results and discusses their implications. We conclude in Chapter 8.

Chapter 2

Related Work

The UAV-based wireless power transfer system is a novel platform for prolonging sensor network lifetime. Many other methods have been proposed to increase the sensor network lifetime. In section 2.1, we review the existing methods to prolong the lifetime of sensor networks and discuss their advantages and limitations. Next, Section 2.2 discusses recent research in wireless power transfer and its combination with aerial vehicles. Lastly, many researchers focus their efforts on creating algorithms to allow robots to efficiently traverse the network and charge the nodes. Section 2.3 introduces current work on optimizing algorithms to improve the overall charging efficiency.

2.1 Prolonging Wireless Sensor Network Lifetime

Wireless sensor networks consist of sensor nodes mainly powered by small batteries. After deployment, the small sensor nodes are usually inaccessible to the users, and thus replacement of the energy source is not feasible [21]. As a result, a critical limitation of wireless sensor networks applications is the sensor network lifetime. This section briefly reviews the main methods used to prolong the lifetime of the wireless sensor network. These methods can be divided into three types, improving energy capacity, reducing energy consumption, and harvesting environmental energy.

Electrochemical energy, stored in the battery, is the predominant means of providing power to wireless devices today [26]. Both academia and industry have been working on improving the energy density of the batteries for decades. For example, Sim *et al.* fabricated a micro power source using a micro direct methanol fuel cell [30]. However, the size of batteries has only decreased mildly while the size of electronic circuits has decreased by orders of magnitude. Although the energy density of hydrocarbon fuels used in micro heat engines is very high, they are not applicable to the wireless sensor nodes because the output power of these devices is too high and they are not easily to be turned off once started [18].

Sensing and communications consume significant amount of energy in wireless sensor network. Many researchers have been working on optimizing the data collecting and data transmission to reduce the energy consumption. Chang and Tassiulas proposed to adjust the transmitter power level to use the minimum energy required to reach the intended next hop receiver [7]. Cardei *et al.* considered adjusting the sensing range of each sensor node to maximize the sensor network lifetime for the scenario where a large number of sensors are randomly deployed to monitor a number of targets [5]. Wang *et al.* investigated the benefits of adding a few resource rich mobile nodes to a large number of simple static nodes, where these resource rich mobile nodes can either act as mobile relays or mobile sinks [34]. Ye *et al.* developed an energy-efficient medium-access control (MAC) protocol for wireless sensor networks [36].

There are some other potential energy sources for wireless sensor network.

On a bright day, the incident light on the earth surface has a power density of roughly 100 mW/cm^2, and Zhao *et al.* showed that single crystal silicon solar cells can achieve efficiency as much as 24.4% [27, 39]. However, in areas or in times when there is little or no light, the energy density of solar is inadequate. Stordeur and Stark built a low power thermoelectric generator, which converts thermal energy directly in electrical energy, so the micro systems have self-sufficient energy supply [31]. The problem is that it is difficult to get greater than a $10°C$ thermal gradient in a volume of 1 cm^3 [27].

Improving battery capacity and optimizing sensing and communications can slow down the energy consumption of the wireless sensor network, but the sensor network lifetime is still limited. For harvesting environmental energy, its continuous work is subject to the environment.

2.2 Wireless Power Transfer

In this section, we briefly introduce the research on the intersections between aerial vehicles and wireless power transfer.

The vast majority of the previous research focused on supplying power to the aerial vehicles from ground to improve their flight time. In 1964, a microwave-powered helicopter was demonstrated to fly 60 ft above a transmitting antenna [4]. In 2011, Achtelik *et al.* designed a quadcopter platform which broke the micro aerial vehicle endurance record with laser power beaming [1]. Their work is based on a powerful infrared laser system. They used complex optics to direct the laser beam to a special optimized solar cell array equipped on the quadcopter. In this solar cell array, the laser beam is transformed back to electric energy. In fact, according to Achtelik *et al.*, this 1 kg quadcopter can achieve unlimited flight time. On the contrary, we are interested in prolonging the lifetime of the sensor network by using the UAV to supply energy to sensor nodes. The high flexibility of movement makes the UAV an excellent mobile power station for wireless devices which are located away from regular energy sources. In our lab, Griffin and Detweiler built a UAV based wireless power transfer system, which is based on magnetic resonant power transfer [11]. Kurs *et al.* experimentally demonstrated efficient nonradiative power transfer over medium-range distances through magnetic resonant power transfer [17]. Another advantage of magnetic resonant power transfer is that it has low interference with any surrounding objects and can work around and through objects, thus it is useful for charging sensors that are underground or underwater.

The UAV-based wireless power transfer system is the fundamentals of our work. However, the contribution of our work is not how to build this UAV-based wireless power transfer system, but how to effectively use it.

2.3 Charging Algorithms

This section reviews the current work on optimizing the charging strategies in wireless sensor networks, and it is highly related to our work. Because of different assumption of the conditions, such as number of chargers, energy consumption of sensor nodes, charger's knowledge of the wireless sensor network, there are many types of scenarios.

Peng *et al.* [25] studied the problem in a scenario where the sensor nodes periodically report their energy information to the sink, and the aggregated report contains the energy information about the k shortest-lifetime nodes. They formulated the problem and provided a sketch of the NP-Completeness proof, a reduction from the TSP problem. They proposed two algorithms, and the time complexity of both are superpolynomial. The core idea of the two algorithms is to test each permutation of the charging sequence. The difference is that the preliminary one select the target energy from the current sensor node energy levels and the more advanced one used a binary search to look for the target energy. They built a proof-of-concept prototype of the system, and used simulation to study the proposed algorithms. We believe that their proof is not accurate because the TSP problem requires that each node to be visited *exactly* once while the transformed problem requires that each node to be visited *at least* once. We provide a more precise proof based on our definition of problem in Chapter 4. In addition, because the time complexity of their algorithms are superpolynomial, they are not feasible for the case where there are a large number of sensor nodes. Also, they studied the case where the k shortest-lifetime nodes are known, but they did not consider other cases, such as no energy information at all.

Yoon *et al.* [37] examined a scenario where the sensor nodes are moving and that the charging events rely on a fortuitous encounter. Within this scenario, it is very hard to keep all the sensor nodes alive all the time. The authors used the time ratio of a node being alive to evaluate the performance of each charging algorithms. The alive time is assumed to be proportional to the energy consumed by the node. In addition, they assumed there is a mobile charger with very large energy capacity. They proposed three basic algorithms: *Passive Energy Charging*, only charge nodes with dead battery; *Active Energy Charging*, charge any encountered nodes; *Restricted Energy Charging*, only charge nodes with energy level under a certain threshold. Through simulation, they found that the performance rank of algorithms were highly related to the encounter rate. As a result, they proposed the fourth algorithm, *Trend-based Energy Charging*, an algorithm like *Restricted Energy Charging* but adjusting the value of the threshold according to current encounter rate.

Shi *et al.* [29] discussed a scenario where a mobile charging vehicle periodically visits sensor nodes and charges them with wireless power transfer, thus the sensor network can have unlimited lifetime. They assumed that the charger knows the energy level of all the sensor nodes and has enough energy to visit and charge all sensor nodes in a single trip. They studied the problem, given that guaranteeing unlimited sensor network lifetime is the prerequisite, how to minimize the cost? Here they defined the cost as working time of the mobile charging vehicle. They proposed the concept of Renewable Energy Cycle, where the energy level of each sensor node exhibits periodicity within cycles. A full cycle includes working period and resting period, based on the status of the mobile charging vehicle, and their goal is to minimize the percent of working period. First, they offered the necessary and sufficient conditions for the existence of Renewable Energy Cycle. Second, they proved that the shortest Hamiltonian cycle is the optimal traveling path by contradiction. Third, they developed a provable near-optimal algorithm. This work considers the problem of how to minimize the cost if the mobile charging vehicle can work multiple times, while we consider the problem of how to maximize the sensor network lifetime if the mobile charging vehicle only has one working opportunity.

Zhang *et al.* [38] defined an interesting scenario, collaborative mobile charging, where multiple mobile charging vehicles are used to charge sensor nodes and these charging vehicles are allowed to charge each other. They considered to maximize the ratio of payload energy (the energy eventually obtained by sensors) to the overhead energy (energy consumed by chargers' movements). They had two significant assumptions. First, the energy transfer efficiencies (base station to charger, charger to charger, and charger to sensor node) are 1.0. Second, the charging time is negligible compared to the traveling time. Moreover, they restricted their work on 1-D wireless sensor networks to reduce the complexity. For homogeneous case where all sensors consume energy at the same rate, they indicated that the payload energy is fixed in a charging cycle and the goal is equivalent to minimizing the overhead energy (i.e., the total moving distance of chargers). They proposed to let these chargers meet at some rendezvous points and concentrate their residual energy to a few chargers to reduce the total moving distance. For heterogeneous case where sensors have various energy consumption rate, they presented a heuristic algorithm. The main idea of this algorithm is to cluster the sensor nodes into groups and then employs the previous algorithm (the algorithm for homogeneous case) to these groups. We consider that their proposed algorithms are not applicable to our UAV-based wireless power transfer system because their two assumptions, 1.0 transfer efficiency and negligible charging time, are not practical for our system, or even any existing wireless power transfer system.

Johnson *et al.* [15] already studied using the UAV-based wireless power transfer system, built by Griffin and Detweiler [11], to prolong the sensor network lifetime. Their work focused on the scenario where the UAV can have multiple flights but it can only charge a single node in every single flight. Regarding the wireless sensor network, they explored five different sink positioning algorithms and found that Greedy Heuristic and LP sink selection algorithms performed well. Regarding charging, they found that charging the sensor node with the least energy level is the best sensor node selection strategy. In our work, we removed the restriction that the UAV can only charge a single sensor node during a flight.

Chapter 3

Background

3.1 System Overview

Fig. 3.1 shows an overview of the hardware of the UAV-based wireless power transfer system. The three main components are the UAV, the wireless power transfer system and the sensor node localization system.

Our basic UAV platform is an Ascending Technologies Hummingbird quadcopter. The UAV is light weight and agile. We give more details of the UAV in section 3.2.

The wireless power transfer system consists of the power transmission part and power receiver part. The power transmission part is deployed on the UAV and it consists of a plastic frame, a drive board and coils. The plastic frame holds the transmitting coils and the drive board on the UAV. The power receiver part consists of a receiver board, coils, and a sensor node that is specific to the application, such as vibration, temperature, soil moisture, or pressure sensing. In this paper we omit any application specific sensing system and instead focus on the wireless power transfer and the sensor node localization. We give more details of the wireless

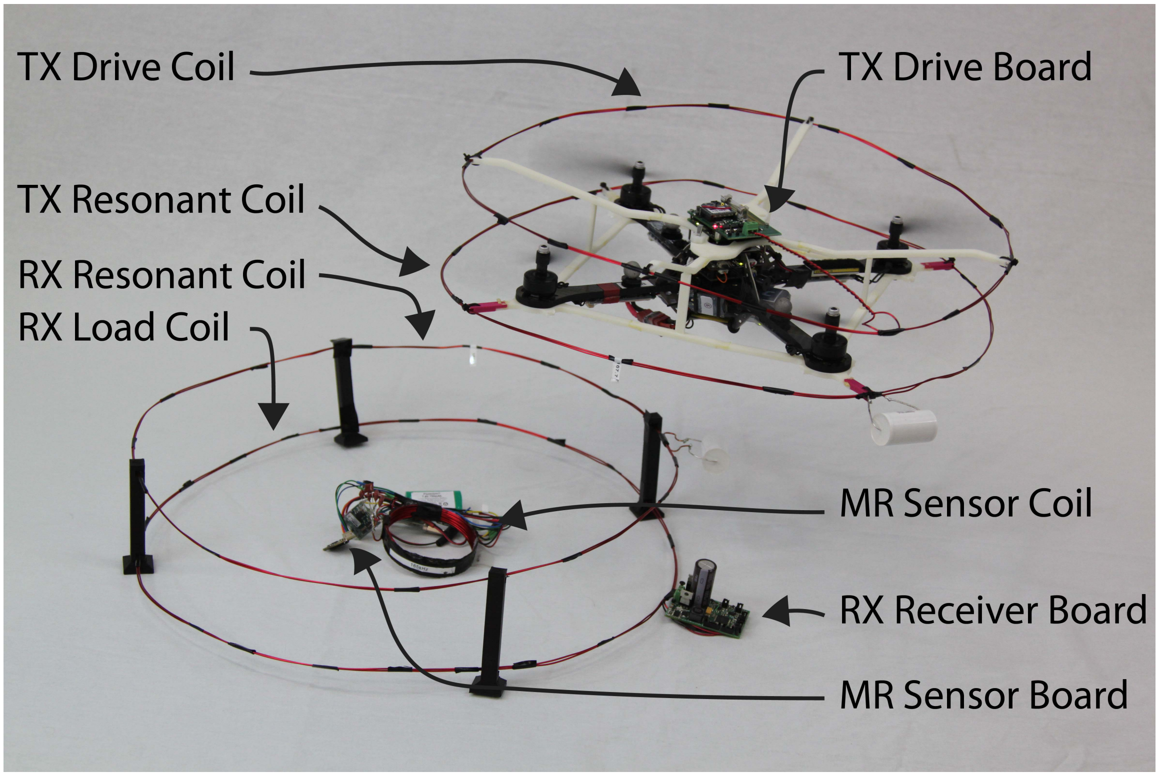


Figure 3.1: The UAV-based wireless power transfer system (Andrew Mittleider).

power transfer system in section 3.3.

The sensor node localization system can guide the UAV to achieve more accurate localization than only using GPS data. It consists of a magnetic resonant sensor and an optical flow camera. The magnetic resonant sensor is supposed to be deployed with the the power receiver part. The magnetic resonant sensor can be used to estimate the distance between the UAV and itself by measuring the voltage. The optical flow camera, mounted on the bottom of the UAV, can provide accurate relative motion estimates. Combining the estimated distance and the estimated relative motion, the UAV is able to localize the magnetic resonant sensor with decent error. More details can be found in section 3.4.

The UAV power transfer system is controlled by a computer station. The computer station runs Robot Operating System (ROS), which provides a collection

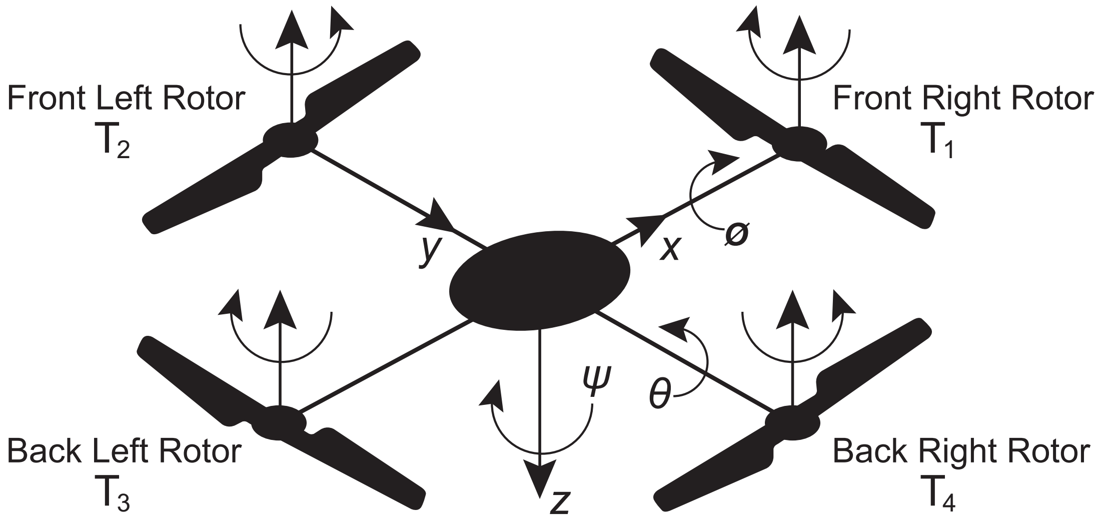


Figure 3.2: The schematic of the UAV (Andrew Mittleider). Rotors 1 and 3 spin in one direction, while rotors 2 and 4 spin in the opposite direction, yielding opposing torques for control.

of libraries and tools for developing robot applications [10]. We use ROS to control the overall system and operate the communication. The computer station has two separate 802.15.4 (Zigbee) radio links operating at 2.4GHz. One of the Zigbee links is used for the flight of the UAV and the other is dedicated to the power transfer and localization.

3.2 UAV

Fig. 3.2 shows the schematic of the UAV. It has four rotors. Different spinning speed of the rotor will produce different thrust and torque about the center of the rotor. If the thrust and torque from all sides are equal, the vehicle will produce force only in the z-axis direction. Unequal thrust and torque will cause rotational moments around ψ, θ, or ϕ and force moments in the x-axis or y-axis direction.

The UAV is 368 g without battery and 543 with the battery. It has a recommended maximum payload of 200 g, and our experiment results show that the UAV is capable to carry object up to 400 g. We are interested finding an optimal UAV velocity so that the UAV can minimize the energy cost for reaching the sensor nodes. Andrew Mittleider did comprehensive experiments and determined that the optimal speed for the UAV we are using is 7.3 m/s. In fact, results show that with a single battery by flying at the speed of 7.3 m/s the UAV can fly for 2.7 km more than flying at 9.5 m/s and 3.5 km more than flying at 3 m/s.

3.3 Wireless Power Transfer

In our lab, Brent Griffin designed and built the wireless power transfer system as discussed below.

An AD9833 programmable waveform generator is the main component of the TX Drive Board. In our system, we use the waveform generator to generate a signal at 165 KH. The frequency of the generated wave can be tuned online to increase power transfer or utilize different coils. This signal is input into an H-Bridge that generates a high-power alternating current that is driven through the TX Drive Coil. A processor is integrated into the TX Drive Board to control the frequency, enable or disable power transfer, monitor voltage and current, and communicate with the ground sensors and the computer station. The Drive Board sends an alternating current through the TX Drive Coil causing an alternating magnetic field that drives the neighboring TX Resonant Coil. The TX Resonant Coil focuses the magnetic field to the RX Resonant Coil for transmission. The RX Resonant Coil, which is placed near the sensor node, receives power from the magnetic field, then the power is inductively transferred to the RX load coil. The Rx Receiver Board is connected to the RX Load Coil to draw energy from the RX Resonant Coil and then provide to the sensor node. For additional details see [11].

3.4 Sensor Node Localization

To charge a sensor node, the UAV need to localize this sensor node at first. GPS data is good to lead the UAV to the rough location of the sensor node, but GPS data has up to 7.8 *m* error in a 95% confidence range [9]. As a result, sole GPS data is insufficient for sensor node localization in our application, since the UAV must be within 30 *cm* for efficient wireless power transfer. Andrew Mittleider designed and built the sensor node localization system to achieve more accurate localization as discussed below.

A MR Sensor Node, including a MR Sensor Board and a MR Sensor Coil, is used to assist more accurate localization. The MR Sensor Node measures the voltage through the a MR Sensor Coil. The voltage measurements are then be sent to the computer station over a short-range radio. We are able to estimate the distance between the UAV and the MR Sensor Node through the measured voltage. At the same time, the equipped optical flow camera can provide accurate relative motion estimates over short periods of time [16, 35]. The UAV starts by going to points in a square surrounding the initially estimated position while simultaneously calculating the position of the sensor node based on the voltage and relative motion measurements. After the last waypoint is reached, the UAV flies to the estimated position of the sensor node.

The experiment results show an average error of 27 *cm*, with a maximum of 48 *cm*, and an average localization time of 36 seconds. At 27 *cm*, the wireless power transfer rate is at 98.6% of the maximum [20].

Chapter 4

Problem Definition and NP-Completeness Proof

We begin by talking about the intuition of the problem. Then we formally describe the problem and give the decision version of the problem. At the end, we show that the problem is NP-Complete by reduction from *Metric-TSP* [19]. *Metric-TSP* is a special case of Traveling Salesman Problem (*TSP*) where the intercity distances satisfy the triangle inequality thus the direct connection between two cities is never farther than a route via intermediate cities.

4.1 Problem Intuition

Usually a group of wireless sensor nodes is distributed on a field with a pre-designed scheme. The number of sensor nodes and the size of the field may vary depending on the application. We assume that all the sensor nodes have a constant energy consumption rate for simplicity. For our system, we assume the UAV starts at a fixed or mobile base station near the sensor network field. The UAV starts with full energy capacity from the base station and returns to the base station for further maintenance and recharging after it finishes its work. During the working time, the UAV is either flying from one location to another location, or it is hovering to charge a sensor node. To reduce the complexity of the proof we assume that the energy consumption rate of hovering is 0 in the formal problem definition. In addition, the UAV needs a process to localize the sensor node before charging. This is because that the GPS data is not accurate enough to lead the UAV to a satisfied position to achieve good transfer efficiency. For the sake of simplicity, we do not include the localization process in our formal definition of the problem. However, we do consider this process in our simulation experiments, as discussed in Chapter 6 and Chapter 7. We also assume that the UAV transfers power at a constant rate to the sensor node with a constant transfer efficiency. The goal of our work is to use a system like this to prolong the sensor network lifetime as much as possible.

4.2 Problem Definition

We now present a formal definition of this problem, and we call it *UAVWS* (UAV Wireless Power Transfer for Sensor Network). Fig. 4.1 shows a visual representation of the problem. We begin by defining the problem in a graph $G = (V, E)$, $V = \{v_{base}\} \cup V_{nodes}$, where v_{base} is the base station and each vertex of the V_{nodes} is a sensor node that may need to be charged. Base station and sensor nodes are connected through edges of possible UAV flight paths, E. The UAV is able to travel along edges in E and stop at nodes in V_{nodes} to charge the sensors. The UAV also consumes energy at a rate of e_{cf} while flying and e_{ct} while transferring energy. The total energy consumed by the UAV cannot exceed energy capacity,

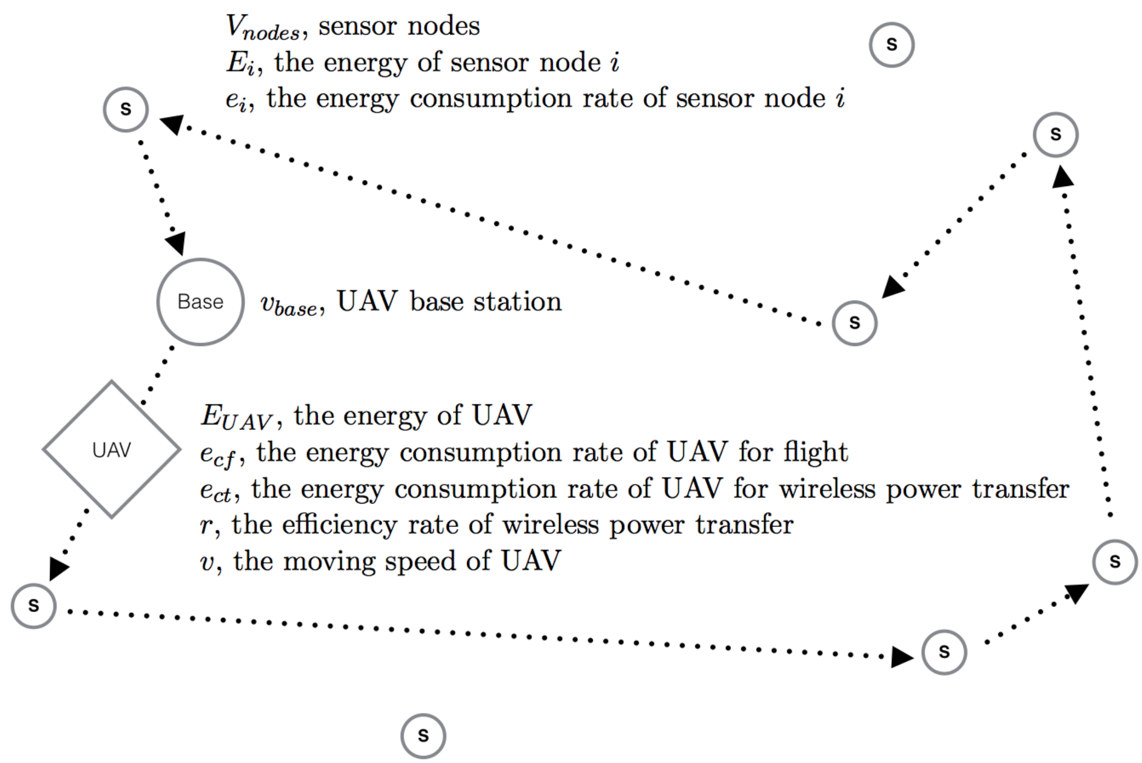


Figure 4.1: A representation of the UAV, UAV base station, and sensor nodes along with the different variables used in the algorithm.

E_{UAV} of the UAV. These variables and notations are summarized in Table 4.1.

The system is said to be *dead* when the energy of any of the sensor nodes is 0. It is constrained such that the initial location of the UAV is at v_{base} and the UAV must return to v_{base} before it consumes all of its energy. When the UAV is at vertex A, where $A \in V$, it has two types of valid actions. It can move to vertex B, where $B \in V$ and edge $(A, B) \in E$, or it can stay at A and charge A, if $A \in V_{nodes}$, for a time of t, where $t \in \mathbb{R}^+$. The optimization version of the problem is stated as: What is the longest lifetime the system can achieve? The decision version of the problem is stated as: Given the values of the variables (G, v_{base}, V_{nodes}, E_{UAV}, e_{cf}, e_{ct}, r, v, E_i, e_i), is there a finite sequence of valid UAV actions that can keep the system alive until time T?

Variables	Description
$G = (V, E)$	the graph of the sensor nodes and UAV base station
$v_{base} \in V$	UAV base station
$V_{nodes} = V - \{v_{base}\}$	sensor nodes
$E_{UAV} \in \mathbb{R}_{>0}$	the energy of UAV
$e_{cf} \in \mathbb{R}_{>0}$	the energy consumption rate of UAV for flight
$e_{ct} \in \mathbb{R}_{>0}$	the energy consumption rate of UAV for wireless power transfer
$r \in \mathbb{R}$ and $r \in [0.0, 1.0]$	the efficiency rate of wireless power transfer
$v \in \mathbb{R}_{\geq 0}$	the moving speed of UAV
$E_i \in \mathbb{R}_{>0}$	the energy of sensor node i
$e_i \in \mathbb{R}_{>0}$	the energy consumption rate of sensor node i
$T \in \mathbb{R}_{\geq 0}$	the lifetime of the system

Table 4.1: Variables in *UAVWS* problem

4.3 NP-Completeness Proof

To prove a problem is NP-complete, we need to do two things. First, we need to show that the problem is in NP. Second, we need to prove that the problem is NP-Hard, and we will do so by reducing from a known NP-Complete problem to this problem.

Proof: First, *UAVWS* is in NP, since given a finite sequence of UAV actions, we can successively simulate these UAV actions and update the state of the UAV and the sensor nodes after each action, and at the end we can efficiently check if the system is alive at time T.

Next, we will reduce from the NP-Complete problem *Metric-TSP* to our problem *UAVWS*. The decision version of *Metric-TSP* is: Given a graph $G' = (V', E')$, where G' satisfies triangle inequality, is there a route that visits each vertex exactly once and returns to the origin and has a length of at most $L \in \mathbb{R}^+$?

Given any instance of *Metric-TSP*, we can construct an instance of *UAVWS* by setting the parameters in *UAVWS* to those specified in Table 4.2. It is clear that this

Variables	Values
$G = (V, E)$	$G' = (V', E')$
v_{base}	a random vertex from V'
V_{nodes}	$V' - \{v_{base}\}$
E_{UAV}	$L + \lvert V_{nodes} \rvert$
e_{cf}	1.0
e_{ct}	1.0
r	1.0
v	1.0
E_i	$L + \lvert V_{nodes} \rvert - 1.0$
e_i	1.0
T	$L + \lvert V_{nodes} \rvert$

Table 4.2: Reduction from *Metric-TSP* instance to *UAVWS* instance

transformation can be finished in polynomial time. The core idea of the reduction is to construct an instance of *UAVWS* such that the UAV has to visit and charge all the sensor nodes. At the same time, we limit the initial energy of the UAV so that the UAV can only fly for a distance of at most L besides charging.

Now, we need to show that the original instance of *Metric-TSP* is a yes instance if and only if the instance of *UAVWS* we constructed is also a yes instance.

Suppose that G' has a route that visits each vertex exactly once and returns to the origin and has a length of at most L. By our construction, the UAV can use L unit of energy for flight to follow this route and visit all the sensor nodes, considering the energy consumption rate of flight (e_{cf}) is 1.0 and the moving speed (v) is 1.0. As a result, the UAV has $|V_{nodes}|$ unit of energy left for charging, as the initial UAV energy (E_{UAV}) is $L + |V_{nodes}|$. Because the transfer efficiency rate (r) is 1.0, the UAV is able to transfer $|V_{nodes}|$ unit of energy to the sensor nodes. If the UAV transfers 1.0 unit of energy to each of these $|V_{nodes}|$ sensor nodes, the energy of each sensor node can be increased to $L + |V_{nodes}|$, considering the initial energy of each sensor node (E_i) is $L + |V_{nodes}| - 1.0$. In this case, the sensor network lifetime can be prolonged to the desired time (T), $L + |V_{nodes}|$, considering the energy consumption rate of each sensor node (e_i) is 1.0. Therefore, our constructed instance is a yes instance if the instance of *Metric-TSP* is a yes instance.

Now suppose that our constructed instance of *UAVWS* is a yes instance, where the UAV can follow a sequence of UAV actions and then no sensor node is dead before the desired time (T), $L + |V_{nodes}|$. Because each sensor node needs to be charged at least 1.0 unit of energy to be alive until time T, $|V_{nodes}|$ unit of energy is required for charging in total. As a result, the UAV has at most L unit of energy for flight and thus it can fly a distance of at most L. Therefore, G must have a route that covers all these $|V_{nodes}|$ sensor nodes and returns to the origin and the distance is at most L. Consequently, G' must have a route that visits each vertex exactly once and returns to the origin and has a length of at most L. This is because that if a vertex is previously visited we can simply remove it from the route and directly connect the previous vertex and the next vertex to guarantee that no vertex will be visited more than once. At the same time, the triangle inequality of the edges can warrant that the distance of the updated route will never be farther then the origin one. Therefore, the instance of *Metric-TSP* is a yes instance if our constructed instance is a yes instance.

We have shown that *UAVWS* is in NP, and proved that the original instance of *Metric-TSP* is a yes instance if and only if the constructed instance of *UAVWS* is a yes instance. Therefore, *UAVWS* is NP-Complete.

Chapter 5

Algorithms

In this chapter, we develop a set of heuristic algorithms for selecting the nodes to charge. We evaluate their performance in the Chapter 7.

The UAV is assumed to be able to know the energy level of a node when it is nearby. When the UAV just starts from the base station, it may have no knowledge, some knowledge, or complete knowledge of the sensor node energy level. We separate the algorithms based on knowledge levels because that the UAV is able to use more advanced algorithms with more available information but in practical applications there is overhead on maintaining this information.

For the three categories, there are nine total algorithms. Fig. 5.1 summarizes all the nine algorithms. For *No Knowledge* category, there are six algorithms, combining two path planning algorithms (*SHORTEST* and *CLOSEST*) and three charging algorithms (*FULL*, *RND* and *FIX*). For *Some Knowledge* category, there are two algorithms, combining two path planning algorithms (*SHORTEST* and *CLOSEST*) and one charging algorithm (*AVG*). There is one specific algorithm for *Complete Knowledge* category. The details of these algorithms are discussed in the following sections.

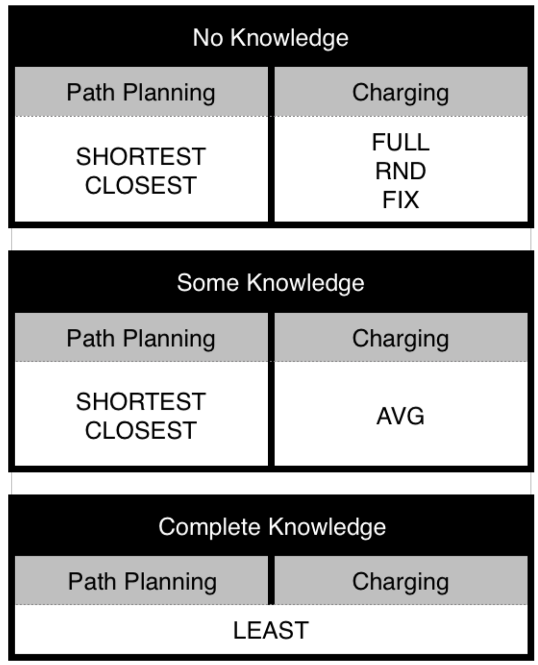


Figure 5.1: A summary of algorithms.

5.1 Algorithms with No Knowledge of Sensor Node Energy Level

We break the problem into two parts. First, we examine two different approaches for planning the path of the UAV. The second part of the problem is determining how much should be charged for each node.

The path planning algorithm schedules the order of nodes to visit. If the UAV has to fly back to base station before finishing visiting all the scheduled sensor nodes, it gives up charging those unvisited sensor nodes. If the UAV still has energy after visiting all the scheduled sensor nodes, the same path planning algorithm is used again. We evaluate two separate path planning algorithms as follows:

- *SHORTEST*: Since we want to minimize the energy cost of flight, one obvious path planning algorithm is to find the shortest tour to cover each node at least once and returns to the origin at the end. This path is similar to Traveling Salesman Path, except that the our path is not required to visit each place exactly once. Alg. 1 shows the pseudo code of the algorithm. The algorithm enumerates all the possible paths and find out the shortest one. Theoretically, *SHORTEST* is the most efficient route and it can reduce the energy consumption of flight. In the case where the flight uses a large portion of the total energy, this path planning algorithm is supposed to greatly improve the overall performance of the system. However, finding the shortest tour is computational expensive and thus this algorithm is not flexible for sensor network of a large number of sensor nodes. Also, because the sensor network lifetime is determined by the sensor node with the least energy, sometimes the sensor network might die quickly if the UAV strictly follow the energy-efficient path and schedule to charge those low energy level sensor nodes at the end.

Algorithm 1 SHORTEST Algorithm

```
Require: nodes                                          ▷ Sensor nodes
Require: UAV                                            ▷ UAV
procedure ComputeSHORTESTpath(nodes, UAV)
    sd ← INF                                            ▷ Shortest distance
    sp ← NULL                                           ▷ Shortest path
    nn ← len(nodes)                                     ▷ Node number
    ep ← Permutation(nn)                                ▷ Enumeration of paths
    for all path ∈ ep do
        if TourDistance(path, nodes, UAV) < sd then
            sd ← Distance(path)
            sp ← path
        end if
    end for
    return sp
end procedure
```

- *CLOSEST*: It is a greedy algorithm to always move to the closest unvisited sensor node until all the nodes are visited. Alg. 2 shows the pseudo code of the algorithm. The status of all the nodes are initiated as *unvisited*. Then the algorithm uses loops to find the next closest unvisited node, add it to the path, and set its status to *visited*, until all the nodes are added to the path. The time complexity of the algorithm is polynomial, so it is applicable to the sensor network of a large number of sensor nodes. At the same time, the implementation of the algorithm is straightforward and easy. The problem is that the UAV may need to move back and forth several times and then waste its energy on flight. Also, the sensor nodes with low energy level might be located far away and then be ignored at the beginning. As a result, these sensor nodes may use up their energy before the UAV starts charging them.

The charging algorithm determines the amount of energy to transfer from the UAV to the node. We evaluate three different charging algorithms as follows:

- *FULL*: It charges each candidate node to its full capacity. *FULL* can reduce the ratio of overhead (flight and localization), regarding energy consumption. However, charging each node to its full capacity means that the UAV may be unable to visit every node in the network due to its own energy limitations.

- *RND*: It charges each candidate node with a random amount of energy. The random value is generated in the range from 0 to the amount of used energy. *RND* decreases the possibility of the case where the UAV charges a few sensor nodes and leave most sensor nodes uncharged. However, this algorithm may have the problem of charging too much energy to sensor nodes with high energy level and charging too few energy to sensor nodes with low energy level. As a result, the energy is not distributed effectively to sensor nodes.

Algorithm 2 CLOSEST Algorithm

```
Require: nodes                                              ▷ Sensor nodes
Require: UAV                                                ▷ UAV
procedure ComputeSHORTESTPath(nodes, UAV)
    cl ← UAV['location']                                    ▷ Current location
    cp ← []                                                 ▷ CLOSEST Path
    nn ← len(nodes)                                         ▷ Node number
    for i = 0 to nn − 1 do
        nodes[i]['visited'] ← False
    end for
    for i = 1 to nn do
        cd ← INF                                            ▷ Closest distance
        cn ← −1                                             ▷ Closest node
        for j = 0 to nn − 1 do
            if nodes[j]['visited'] == False and Distance(cl, nodes[j]['location']) < cd then
                cd ← Distance(cl, nodes[j]['location'])
                cn ← j
            end if
        end for
        cl ← nodes[cn]['location']
        nodes[cn]['visited'] ← True
        cp.append(cn)
    end for
    return cp
end procedure
```

- *FIX*: It charges each candidate node with a fixed amount of energy. Although *FIX* is not optimal as sensor nodes with lower energy level should be charged with more energy, it guarantees that each sensor node gets a roughly equal amount of energy. It is supposed to work well for the case where the initial energy levels of sensor nodes are close, but work poorly for the case where the initial energy levels of sensor nodes are very different. Also, another problem is that it is hard to determine the value of the fixed amount. A small value may increase the ratio of energy consumption overhead, and a large value may lead to that the UAV does not have enough energy to charge the sensor nodes which are scheduled to visit at the end.

Combining two path planning algorithms and three charging algorithms there are six total algorithms in this category.

5.2 Algorithms with Some Knowledge of Sensor Node Energy Level

Because the lifetime of the whole system is determined by the node with the least energy level, an intuitive idea is to firstly charge nodes whose energy levels are below the average. Olfati-Saber and Shamma introduced a distributed filter that allows the nodes to track the average of multiple measurements using an average consensus based distributed filter [23]. We consider the case where the UAV knows the initial average energy level of all the sensor nodes, and then uses this knowledge to guide its behavior. We call this charging algorithm *AVG*, and the UAV charges each candidate node to the initial average energy level of the sensor network. However, the potential problem is that the UAV may fly around and do nothing when all the sensor nodes are already charged to the initial average energy level. This is likely to occur when all the sensor nodes have similar initial energy or the UAV has a very large energy capacity.

We still evaluate two separate path planning algorithms *SHORTEST* and *CLOSEST*, as described in last section 5.1.

Combining two path planning algorithms and one charging algorithm there are two total algorithms in this category.

5.3 Algorithms with Complete Knowledge of Sensor Node Energy Level

We have one more algorithm, *LEAST*, which requires the knowledge of the exact energy level of each sensor node at the beginning. The *LEAST* algorithm schedules its path based on the energy level of sensor nodes. It starts from the sensor node with the least power, then move to sensor node with second least power, and so forth. Although this path is not the most energy-efficient, it makes sure that sensor nodes with low energy level can be charged at the beginning. Because the energy level of each sensor node and the scheduled path is known, the UAV is able to compute how much energy is required for flying, localization and hovering, and then the UAV knows how much energy can be effectively transfered to sensor nodes. At the end, it computes a value as target energy, and charges all the candidate nodes to this target energy.

The algorithm used to compute this target energy is demonstrated in Alg. 3. It uses a loop to enumerate the number of sensor nodes to be charged, computes their corresponding optimal values of target energy, and finds out the overall best. Given the number of sensor nodes to be charged, it firstly computes the amount of energy which can be effectively received by sensor nodes. Next, the corresponding optimal target energy is computed by a helper function *BINARYSEARCHTARGET*, which uses binary search to narrow the range of the optimal target energy until the result satisfies the accuracy requirement.

The *LEAST* algorithm in practice performs extremely well (details discussed in the Chapter 7), even though it is not optimal theoretically. We can improve *LEAST* in the path planning part by finding the shortest cycle to cover all the candidate nodes and thus more energy can be used for charging sensor nodes. The problem

Algorithm 3 Compute Target Energy for LEAST Algorithm

```
Require: nodes                                              ▷ Sensor nodes
Require: UAV                                                ▷ UAV
procedure ComputeTargetEnergy(nodes, UAV)
    sn ← SortByEnergy(nodes)                                ▷ Sorted nodes
    te ← 0                                                  ▷ Target energy
    nn ← len(sn)                                            ▷ Node number
    for i = 1 to nn do
        cn ← sn[0 : i]   ▷ Candidate nodes, the first i nodes of the sorted nodes
        te ← UAV['energy']                                  ▷ Total energy
        te ← te − FlyingCost(cn, UAV)
        te ← te − LocalizationCost(cn, UAV)
        te ← te − HoveringCost(cn, UAV)
        ee ← te * transferRate                ▷ Efficient energy for sensor nodes
        cte ← BinarySearchTarget(ee, cn)                    ▷ Current target energy
        if i < nn then
            cte ← min(cte, nodes[i]['energy'])
        end if
        te ← max(te, cte)
    end for
    return te
end procedure
Require: ee                                                 ▷ Efficient energy
Require: cn                                                 ▷ Candidate nodes
procedure BinarySearchTarget(ee, cn)
    lb ← cn[0]['energy']                                    ▷ Left bound
    rb ← lb + ee                                            ▷ Right bound
    while (rb − lb) > AccurancyRequirement do
        m ← (rb + lb)/2
        re ← 0                                              ▷ Required energy
        for i = 0 to len(cn) − 1 do
            if cn[i]['energy'] < m then
                re ← re + m − cn[i]['energy']
            end if
        end for
        if re < ee then
            lb ← m
        else
            rb ← m
        end if
    end while
    return lb
end procedure
```

is that finding the shortest cycle is computationally expensive and thus it is not feasible for sensor networks with a large number of sensor nodes. In some extreme cases, the charging part of *LEAST* may fail. For example, the second sensor node may die before the UAV finishes charging the first sensor node. However, in practice, this is very unlikely to happen. This is because the chance that several sensor nodes are dying while the UAV is charging another sensor node is very low considering that the charging only takes a few minutes and the full lifetime of a sensor node is tens of days. Also, the path planning algorithm of starting from the sensor nodes with lower energy even further reduces the probability.

We should note that the *LEAST* algorithm assumes that the UAV has complete knowledge of sensor node energy level, and there is overhead to maintain this knowledge in real life. At this point, the information of sensor nodes' energy consumption rates is not assumed to be available to the UAV. If this information is available, *LEAST* can be improved by computing individual target energy for each sensor node. For example, if a sensor node has a higher energy consumption rate, *LEAST* could be modified to charge it to a higher target energy.

Chapter 6

Simulation System

We developed a simulation system to test the performance of the nine algorithms discussed in Chapter 5 and explore the impacts of a series of system parameters.

Fig. 6.1 shows the framework of the simulation system. It consists of four main components, *System State Generator*, *UAV AI*, *System State Simulator*, and *Validator and Recorder*. *System State Generator* takes the system parameters as the input and then generates the initial system state. *UAV AI* takes the current system state as input and returns the UAV action as output. *System State Simulator* takes the current system state and UAV action as input and returns the next system state as output. *Validator and Recorder* connects the other components, validates the data, and records the simulation results.

The simulation system gets the values of all system parameters by reading a configuration file. Every system parameter can have a list of possible values, and then the simulation system will test all the combinations of these values. The simulation system writes the simulation results (system parameters, algorithm name, and sensor network lifetime) to specified output files, which are then used by other scripts to generate figures. The simulation system is implemented in

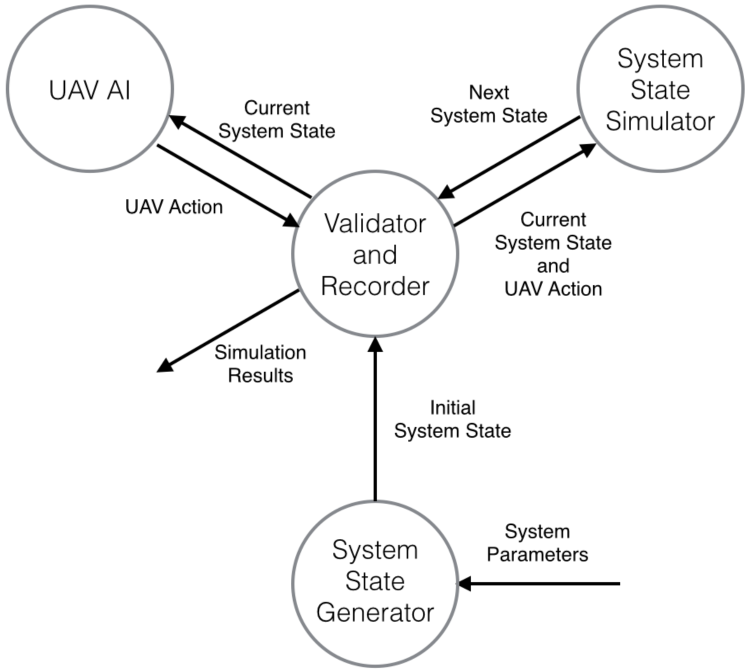


Figure 6.1: The framework of the simulation system

Python and has about 700 lines of code. The simulation system does not rely on any external libraries, but the scripts for figure generating does rely on an external plotting library *matplotlib* [14]. Fig. 6.2 shows a sample configuration file. Users can configure all the system parameters in this file, and then specify its path on the simulation system. Fig. 6.3 shows a sample output file. It is a *CSV* file, and it has three fields, *system*, *algorithm* and *lifetime*. The *system* field indicates the values of the system parameters which are separated by underline, the *algorithm* field indicates the tested algorithm, and the *lifetime* field indicates the corresponding sensor network lifetime.

In the simulation, we randomly (uniform distribution) generate the topology of the graph. We assume that there is a virtual field, where the center of the field is the UAV base station and a set of sensor nodes were randomly deployed within this field. Based on other work in our lab, we determined that the UAV consumes sample_config.py

```
# sample configuration file
param_number_nodes = 8
param_ground_width = 200.0
param_ground_height = 200.0

param_node_power_capacity = 2.34 * 3600
param_node_power_consumption_rate = 0.001625

param_UAV_power_capacity = 25.0 * 3600
param_UAV_flight_power_consumption_rate = 121.91
param_UAV_hovering_power_consumption_rate = 92.28
param_UAV_initial_power = param_UAV_power_capacity
param_UAV_charging_power_consumption_rate = 20.0
param_UAV_charging_power_transfer_rate = 0.2
param_UAV_localization_time = 36.0
param_UAV_moving_speed = 7.33
param_UAV_base_distance = 0
param_UAV_initial_x = param_ground_width / 2 + param_UAV_base_distance
param_UAV_initial_y = param_ground_height / 2
```

Figure 6.2: A sample configuration file

system	algorithm	lifetime
8_200_200_36_0.2_92.28_20_0_90000.0	no_charge	1112842
8_200_200_36_0.2_92.28_20_0_90000.0	closest_with_random	1161319
8_200_200_36_0.2_92.28_20_0_90000.0	shortest_with_random	1112841
8_200_200_36_0.2_92.28_20_0_90000.0	closest_to_full	1161319
8_200_200_36_0.2_92.28_20_0_90000.0	shortest_to_full	1112841
8_200_200_36_0.2_92.28_20_0_90000.0	closest_to_initial_average	1336088
8_200_200_36_0.2_92.28_20_0_90000.0	shortest_to_initial_average	1112841
8_200_200_36_0.2_92.28_20_0_90000.0	closest_with_fix	1257319
8_200_200_36_0.2_92.28_20_0_90000.0	shortest_with_fix	1208841
8_200_200_36_0.2_92.28_20_0_90000.0	least	1961264
8_200_200_36_0.2_92.28_20_0_90000.0	no_charge	1070890
8_200_200_36_0.2_92.28_20_0_90000.0	closest_with_random	1149200
8_200_200_36_0.2_92.28_20_0_90000.0	shortest_with_random	1070889
8_200_200_36_0.2_92.28_20_0_90000.0	closest_to_full	1070889
8_200_200_36_0.2_92.28_20_0_90000.0	shortest_to_full	1070889
8_200_200_36_0.2_92.28_20_0_90000.0	closest_to_initial_average	1383046
8_200_200_36_0.2_92.28_20_0_90000.0	shortest_to_initial_average	1390431
8_200_200_36_0.2_92.28_20_0_90000.0	closest_with_fix	1166889
8_200_200_36_0.2_92.28_20_0_90000.0	shortest_with_fix	1166889
8_200_200_36_0.2_92.28_20_0_90000.0	least	1636089

Figure 6.3: A sample output file

92.28 W to hover and 121.91 W to fly at the optimal velocity. At the same time, we found that it takes the UAV an average of 36 seconds to localize over a node. In addition, for the sensor network, we assume an energy capacity of 2.34 WH,

Variables	Default Value
Field size	200m * 200m
Number of sensor nodes	8
Energy of UAV: E_{UAV}	25WH
Energy consumption rate of UAV for flight: e_{cf}	121.91W
Energy consumption rate of UAV for hovering: e_{cf}	92.28W
Energy consumption rate of UAV for wireless power transfer: e_{ct}	20W
Efficiency rate of wireless power transfer r	0.2
Moving speed of UAV: v	7.33m/s
Sensor localization time	36s
Energy capacity of sensor node	2.34WH
Energy of sensor node i: E_i	20% to 60% of 2.34WH
Energy consumption rate of sensor node i: e_i	1.625mW

Table 6.1: Simulation system parameters

about the capacity of a pair of AAA batteries. We assume an average energy consumption rate of 1.625 mW, which is reasonable for low power WSN nodes sleeping much of the time and would allow operation for 60 days. At the same time, we assume that the sensor nodes have energy of 20% to 60% of their capacity when the UAV begins its mission. Table 6.1 lists the default values of all system parameters used for the base simulation runs.

The simulation system has a visualization mode, which is helpful for validating the system and debugging the algorithms. Fig. 6.4 shows the visualization of one sample simulation experiment. This sample simulation uses *CLOSEST* path planning algorithm and *FIX* charging algorithm with default values of the system parameters. The blue circle is the current location of the UAV, the blue line is the moving path of the UAV, and the black texts indicate the locations, IDs and energy level of the sensor nodes. Fig. 6.4(a) shows that the initial state of the system. The UAV is located on the center of the field, and 8 sensor nodes with initial energy are randomly distributed on the field. In Fig. 6.4(b), the UAV firstly moves to the

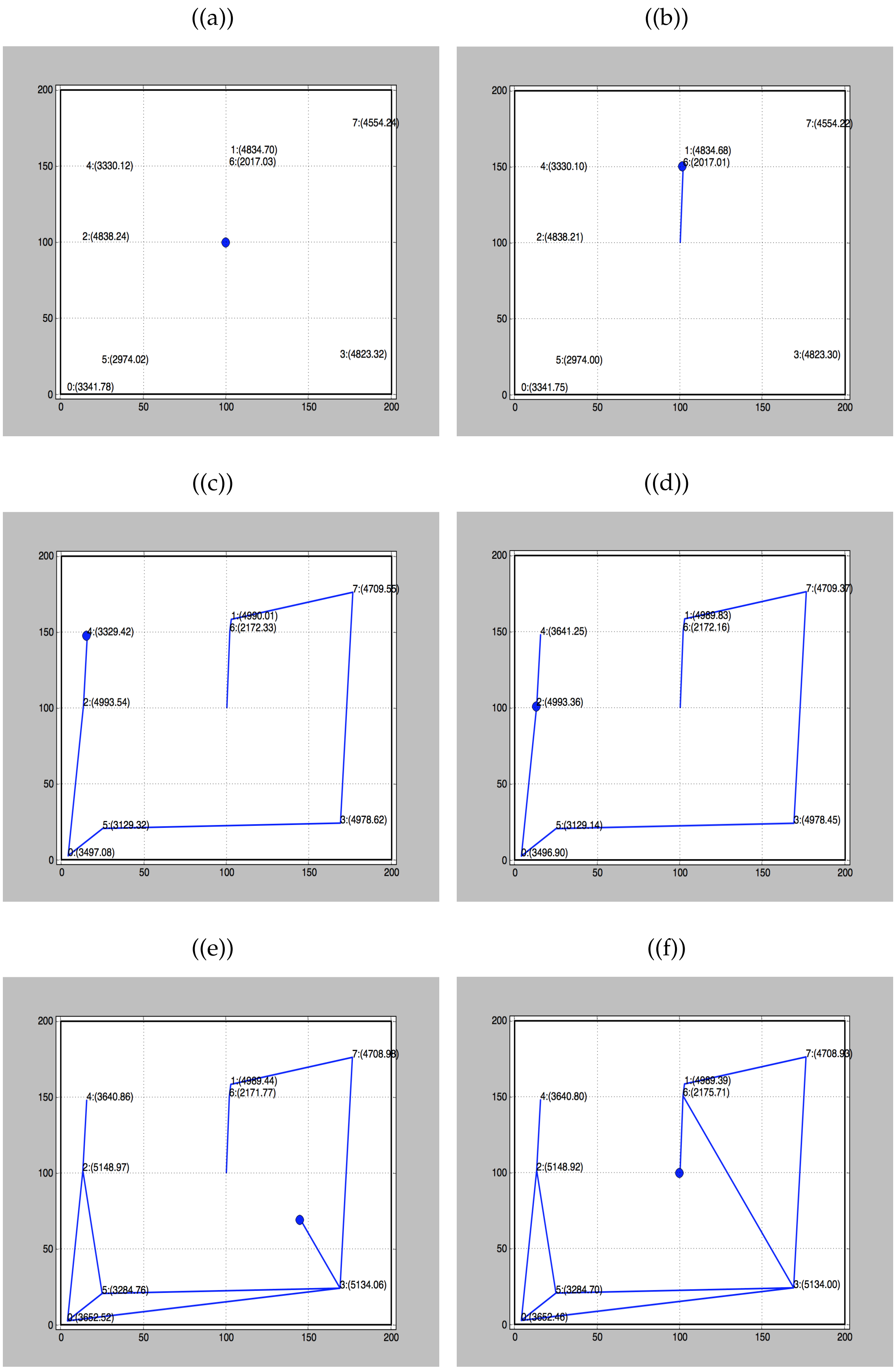


Figure 6.4: Visualization of one sample simulation experiment

sensor node 6 since this is the closest sensor node to the UAV. Fig. 6.4(c) shows that the UAV successively charges sensor node 6, 1, 7, 3, 5, 0, 2 and 4. At this point, the UAV has visited all the sensor nodes. In Fig. 6.4(d), the UAV begins a new round of charging and starts from sensor node 4 and 2. Fig. 6.4(e) shows that in the second round of charging the UAV has visited sensor node 4, 2, 5, 0, 3 and is moving to sensor node 6. Fig. 6.4(f) shows the final state of the system. We can notice that the UAV has to fly back to the base station before complete its charging at sensor node 6.

In next section, we use the average sensor network lifetime to compare the performance of the nine algorithms. For each configuration of the system parameters, we run all the algorithms 100 times. The running time of the simulation depends on the values of the system parameters. It takes about 30 minutes for the simulation system to test all the algorithms 100 times with default values of the system parameters.

Chapter 7

Results

7.1 Introduction

In this chapter, we test the algorithms with different system configurations. On the one hand, we are interested in comparing and summarizing these algorithms' performance in different situations. On the other hand, we want to explore the influence of these system parameters and then guide the development of the UAV-based wireless power transfer system.

Based on the requirements of real world applications, the field size of sensor network and the number of sensor nodes may change. In Section 7.2 and Section 7.3, we evaluate simulation results to determine the performance of the algorithms with varying size of sensor network field or varying number of sensor nodes.

Also, the UAV base station may not be able to be located in the center of every sensor network field in consideration of the operation cost. For example, several sensor networks may need to share a centralized UAV base station. We have an experiment in Section 7.4 to explore the impact of the distance from the UAV base station to the sensor network.

In addition, at this point, it requires 36 seconds for the UAV to locate a sensor node before charging. The localization time might be greatly reduced with a better localization algorithm and thus the overhead of charging a sensor node can be reduced. Section 7.5 explores the impact of an improved localization time.

The UAV itself has a very limited energy capacity now. For example, the UAV energy capacity is 25 WH and the energy consumption rate of flight is 121.91 W. This means the UAV can merely fly about 12 minutes. With the increasing cargo ability, the UAV will be able to carry larger battery with large energy capacity. Section 7.6 shows the simulation results of larger UAV energy capacity.

At this point, the UAV-based wireless power transfer system is still in rapid progress stage, and we believe that the system has the potential to be improved in many aspects. For example, the UAV might be able to land on the ground while charging the sensor node to reduce the energy consumption of hovering, and the potential influence is discussed in Section 7.7. Also, currently the wireless power transfer energy consumption rate is only 20 WH and the efficiency rate is only 0.2. In Section 7.8, we discuss the impact of stronger wireless power transfer, and in Section 7.9 we discuss the benefit of higher charging efficiency.

In Section 7.10, we compare all these changes of system parameters to each other and discuss what changes are more achievable in reality. In addition, we show the simulation results assuming we can combine all these changes.

For every experiment, we run the simulation 100 times and use the average value in the figures. Also, to make the figures clearer, we use a shorter symbol to represent each algorithm, as showed in Table 7.1. Through all these experiments, we:

- Identify the characters of each algorithm and its applicable scenarios. For

Symbol	Description
NO	No charge
FULL	Path algorithm *CLOSEST* with charging algorithm *FULL*
FULL*	Path algorithm *SHORTEST* with charging algorithm *FULL*
RND	Path algorithm *CLOSEST* with charging algorithm *RND*
RND*	Path algorithm *SHORTEST* with charging algorithm *RND*
FIX	Path algorithm *CLOSEST* with charging algorithm *FIX*
FIX*	Path algorithm *SHORTEST* with charging algorithm *FIX*
AVG	Path algorithm *CLOSEST* with charging algorithm *AVG*
AVG*	Path algorithm *SHORTEST* with charging algorithm *AVG*
LEAST	Algorithm *LEAST*

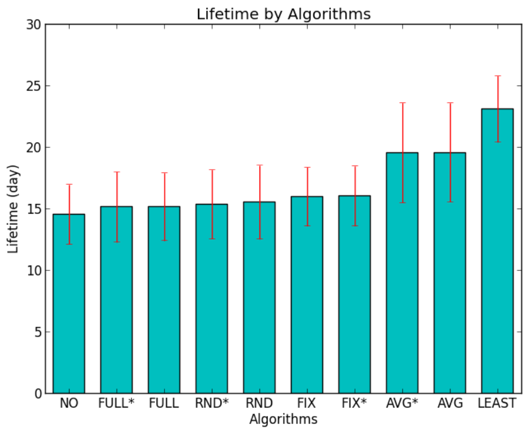
Table 7.1: Symbols and descriptions

example, we note that in some cases the naive algorithms have very poor performance and it may be worthwhile to spend extra energy on gathering more sensor network information to improve the overall performance.

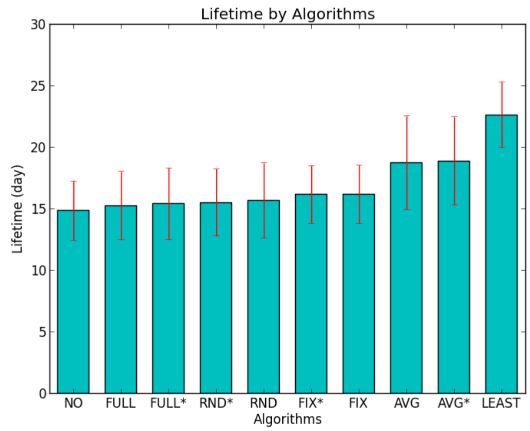
- Find the bottleneck of the current system. For instance, we find out that the current localization time is acceptable, but the huge hovering energy consumption significantly degrades the system performance.
- Conclude suggestions for future work. An example is that we suggest to land the UAV on the ground while charing to reduce the vast energy consumption of hovering.

7.2 Varying Field Size of Sensor Network

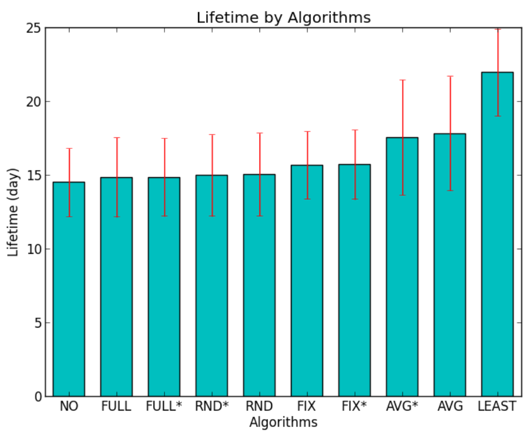
Depending on the requirements of real life applications, the field size of the sensor network are different. For instance, structural monitoring may requires the sensor network to cover a building, and soil composition monitoring may require the sensor network to cover a few square kilometers. Fig. 7.1 shows the performance



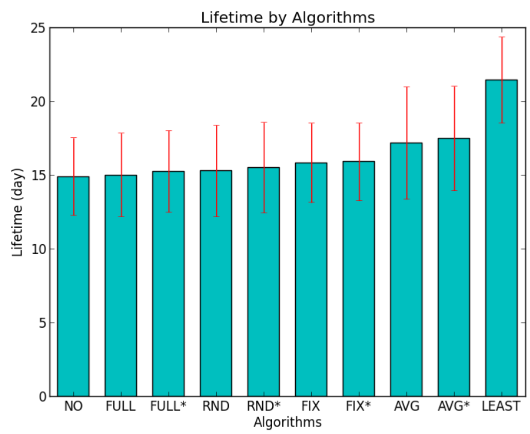
((a)) 100 m × 100 m field



((b)) 200 m × 200 m field



((c)) 400 m × 400 m field



((d)) 800 m × 800 m field

Figure 7.1: The performance of algorithms with different field size of sensor network. Error bar is for the standard error.

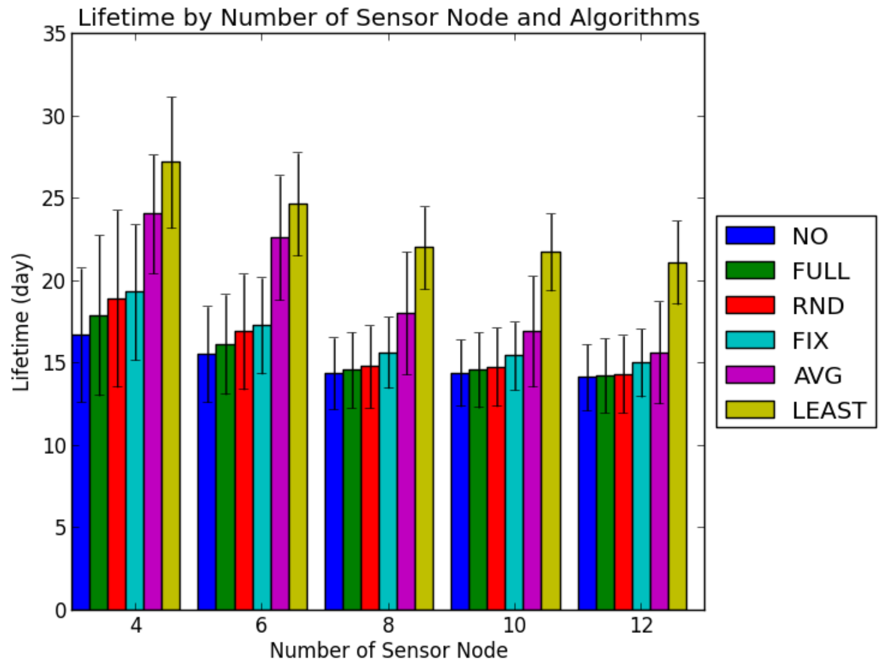
of algorithms on sensor network of 8 sensor nodes deployed over a variety of areas: 100 m × 100 m, 200 m × 200 m, 400 m × 400 m and 800 m × 800 m. We choose to test with 8 sensor nodes, because the computation of the *SHORTEST* path planning algorithm is NP-Complete and it is too computational expensive with more than 8 sensor nodes.

For all sizes of fields, the performance difference between the two path planning algorithms is very limited. This is because UAV has a relatively fast movement speed in relation to the size of the field. As a result, significantly more energy is used to localize, hover and charge than is used to move between nodes. The difference among charging algorithms is more significant. For the *FULL* charging algorithm, the improvement of the lifetime is negligible over the basic case, no charge. This is because the lifetime of the network is determined by the node with the least energy, but by charging each node fully, the UAV may leave too many nodes uncharged, or else the UAV may not be able to return to the base station. Overall, the *RND* charging algorithm works slightly better than the *FULL* charging algorithm, but the improvement is still negligible. This is because the UAV charges a random amount of energy to nodes, thus it may charge too few energy to nodes with insufficient energy or waste energy on nodes with enough energy. The *FIX* charging algorithm gives better results. This method alleviates the problems of the *FULL* and the *RND* algorithms by more evenly distributing the energy from the UAV into the sensor network. The problem with this method is that this fixed value may not be optimal. In the simulations, we determine that 156 j is nearly optimal and is used in the simulations, however this number depends on the area of the sensor network, the number of nodes in the network, the current power level of each node, and other factors. The *AVG* charging algorithm is significantly better than the *FULL*, *RND* and *FIX* charging algorithms. In the *FIX* charging algorithm, we have to guess a value which evenly distributes the energy of the UAV. In contrast, the *AVG* charging algorithm essentially has an estimate of the state of the network. While the initial average may not be the optimal value for which to charge the network, it is a relatively good estimation. The *LEAST* algorithm is remarkably, even better than the *AVG* charging algorithm. Because the energy level of each sensor node is known, the UAV is able to travel along the nodes with least energy. Even though this path may not be the most energy-efficient path, it is guaranteed that the nodes urgently need energy can be charged firstly. As we discussed above, the energy cost for flight is only a very small portion of the total cost. For the charging part, the *LEAST* algorithm computes an optimal target energy level based the energy level of each sensor nodes, instead of using initial average energy as an estimation. The performance ranking of the charging algorithms holds regardless of the change of the size of the network and number of nodes in the network. From the best to the worst, they are *LEAST*, *AVG*, *FIX*, *RND* and *FULL*. Simply put: the more information the UAV has about the network, the longer the network will survive.

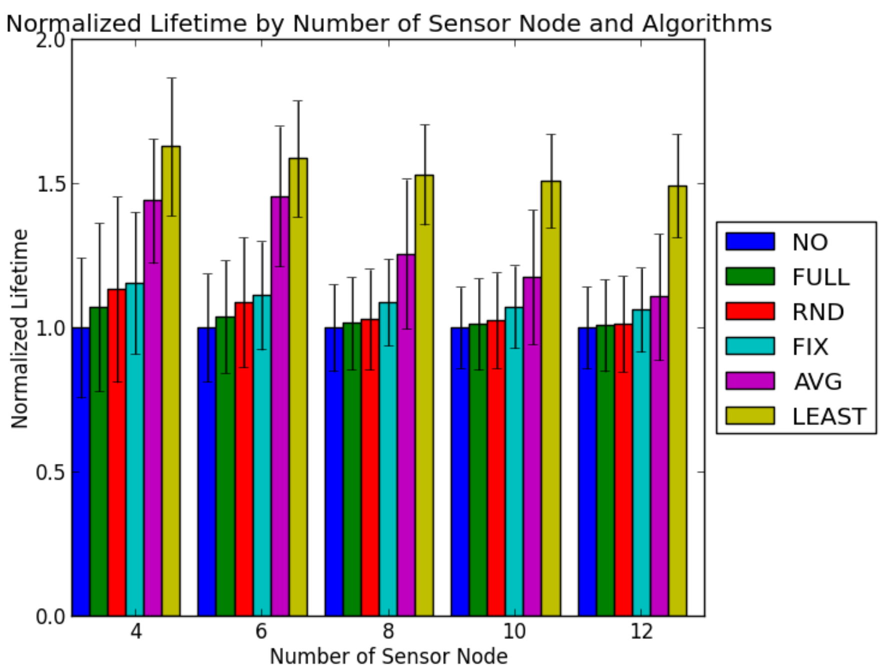
7.3 Varying Number of Sensor Nodes

Based on the requirements of real life applications, the number of the sensor nodes may change. We are interested in exploring the influence of the number of the sensor nodes, and thus we can decide the appropriate strategy of using the UAV-based wireless power transfer system given an application. For this experiment, *CLOSEST* is used as the path planning algorithm with charging algorithms, *FULL*, *RND*, *FIX* and *AVG*. We do not use the path planning algorithm *SHORTEST* because it is too computationally expensive for more than 8 nodes. In addition, the previous results indicate that the difference between *SHORTEST* and *CLOSEST* is very small for sensor network of this size. If there is no specific explanation, *CLOSEST* is used as the default path planning algorithm for all later experiments.

Fig. 7.2 shows lifetime of five algorithms on sensor network of different number of sensor nodes. The performance of five algorithms remains the same order with varying number of sensor nodes. Fig. 7.2(a) shows that, as expected, the lifetime decreases with the increasing of number of sensor nodes for all algorithms.



((a)) Lifetime



((b)) Normalized lifetime

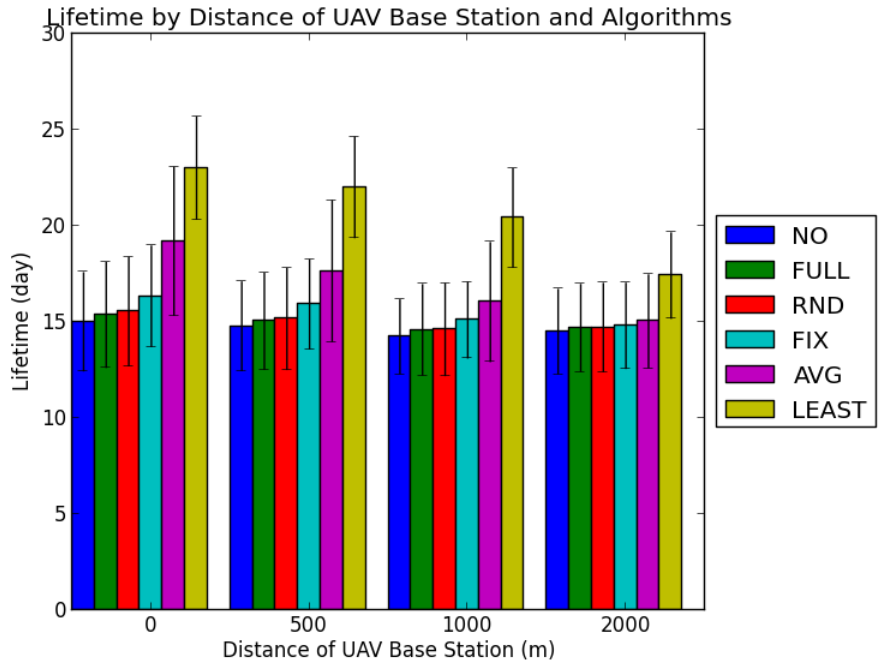
Figure 7.2: The performance of algorithms with different number of sensor nodes. Error bar is for the standard error.

Fig. 7.2(b) shows the lifetime of each algorithm normalized around base case, no charge. The *LEAST* algorithm works well from sensor network of 4 nodes to sensor network of 12 sensor nodes, and the improvement is between 45% to 60%. However, the performance of the *AVG* algorithm decreases dramatically when there are more than 8 sensor nodes. One possible reason is that the initial average is not a good indicator if there are too many sensor nodes. This is because too much energy is required to charge all the sensor nodes to their initial average energy. The *FIX* algorithm, which has no knowledge of the energy level of sensor nodes, can prolong the sensor network lifetime by 7% to 15%.

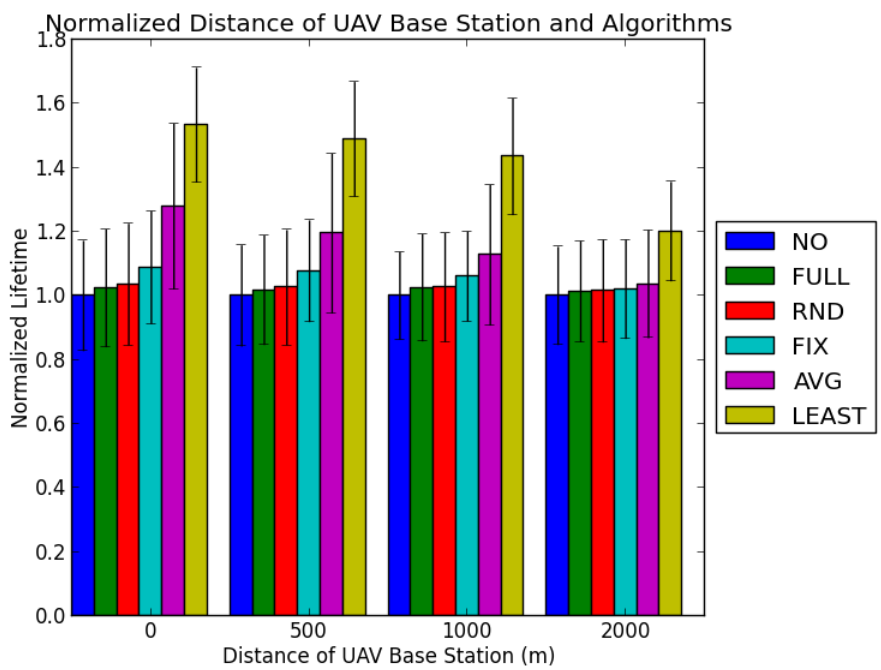
7.4 Varying Distance of UAV Base Station

By default, we assume that the UAV base station is in the center of the sensor network. However, in some cases, there might be a centralized base station which covers multiple sensor networks, and then the UAV base station can not be located in the center of every sensor network. In this section, we explore the impact of the distance of UAV base station.

Fig. 7.3 shows that the lifetime of the sensor network decreases with the increasing of the distance of the UAV base station. For algorithms with no knowledge of the sensor node energy level, *FULL*, *RND* and *FIX*, the impact is slight when the distance increases from 0 m to 500 m. However, when the distance increases to 1000 m, the sensor network can rarely benefit from this type of algorithms. For the algorithm with some knowledge of sensor node energy level, *AVG*, the gained sensor network lifetime drops from about 25% to almost nothing while the distance increases from 0 m to 2000 m, but it still outperforms all the algorithms with no knowledge. For the algorithm with complete knowledge of



((a)) Lifetime



((b)) Normalized lifetime

Figure 7.3: The performance of algorithms with different distance of UAV base station. Error bar is for the standard error.

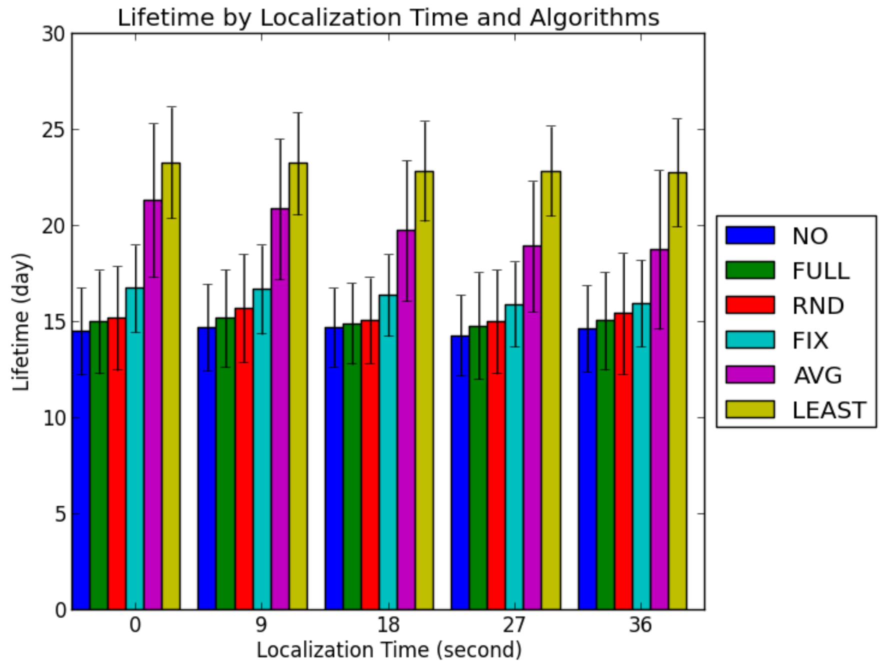
sensor node energy level, *LEAST*, the prolonged lifetime remains above 40% when the distance is within 1000 m, but it drops to about 20% for the distance of 2000 m. Increased distance to the sensor network is equivalent to reduced UAV energy capacity. For the UAV, farther distance means that the UAV has to spend more energy on flight, and thus it has less energy before charging the sensor nodes.

7.5 Varying Length of Localization Time

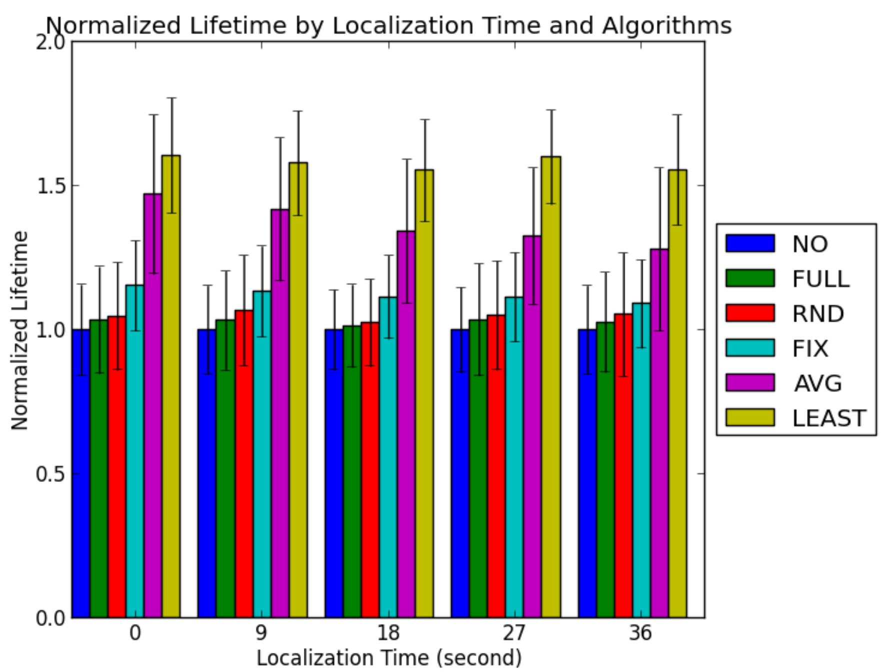
Currently, our average localization time is about 36 seconds. We believe that in the future the localization time can be reduced with a better algorithm or other methods, such as visual object detection. We are curious how much improvement we can gain by reducing the localization time. In this section, we explore the impact of the localization time on the system.

Fig. 7.4(a) shows lifetime of five charging algorithms on sensor network of different localization time. The sensor network lifetime is supposed to be increased as the localization time decreases, since the localization process consumes extra energy. Fig. 7.4(b) shows the lifetime of each algorithm normalized around the base case, no charge. For the *LEAST* algorithm, the improvement fluctuates between 50% and 60% for all lengths of localization time. For the *AVG* algorithm, its improvement increases from about 30% to about 45% if no localization time is required. For all the algorithms with no knowledge of the sensor node energy level, we can see the trend that the sensor network life decreases with the increasing of the localization time. However, the difference is insignificant except that the *FIX* algorithm's improvement increase from about 10% to about 15%.

Overall, the longer the localization time, the shorter the sensor network lifetime. For algorithms, *FULL*, *RND* and *LEAST*, the impact of reduced localization time is



((a)) Lifetime



((b)) Normalized lifetime

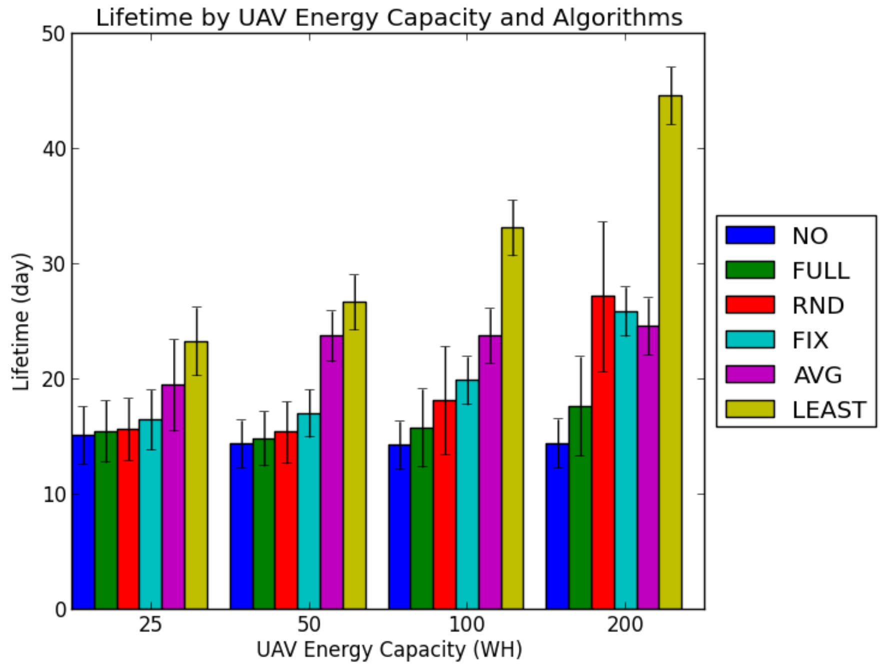
Figure 7.4: The performance of algorithms with different localization time. Error bar is for the standard error.

slight. This is because the *FULL* and *RND* algorithms spend all the energy on a very few number of sensor nodes the UAV meets at the beginning, and the *LEAST* algorithm is sophisticatedly designed to charge each sensor node at most once. All these algorithm only require a few times of localization process. The *FIX* and *AVG* algorithms are supposed to gain more benefit from the reduced localization time, because these two algorithms require the UAV to visit and then localize each sensor node multiple times.

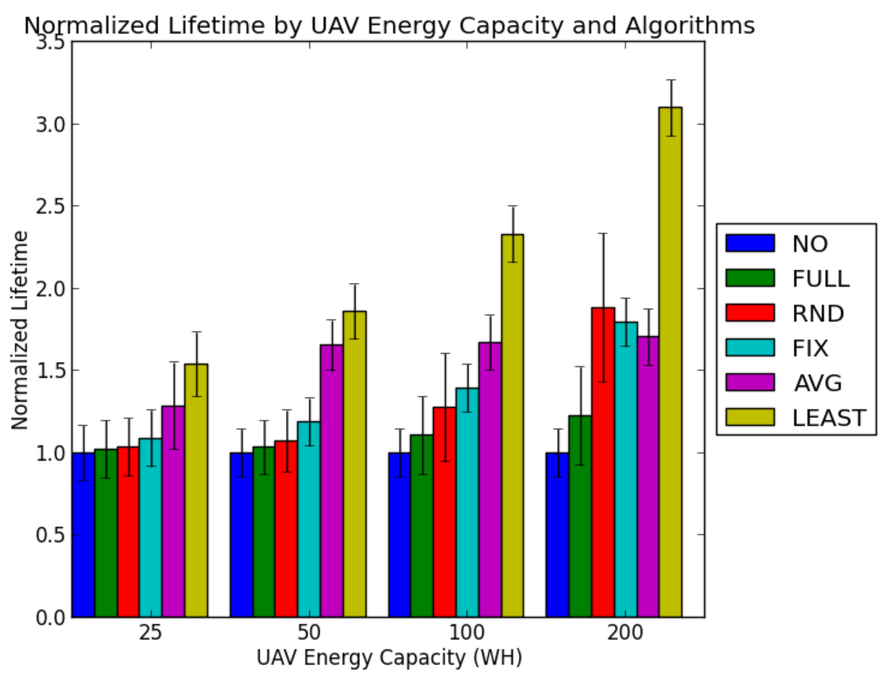
7.6 Varying Energy Capacity of UAV

Energy capacity of UAV is one of the main constraints of the UAV power transfer system. As the development of the UAV, the cargo capacity of UAV is increasing. So, in the future, the UAV might be able to carry larger size battery, which has larger energy capacity.

Currently, the UAV is using a battery of 25 WH energy, and we test what if the UAV can have batteries of 50 WH, 100 WH and 200 WH energy. Fig. 7.5 shows the results. The larger the UAV energy capacity, the longer the sensor network lifetime, for most of the algorithms. The *AVG* algorithm is an exception. This is reasonable because when the UAV energy capacity is large enough for the UAV to charge every sensor node to the initial average energy level of the sensor network, the *AVG* algorithm can barely benefit from a larger UAV energy capacity. For the *FIX* and *LEAST* algorithms, the sensor network lifetime is constantly improved when the UAV energy capacity increases from 25 WH to 200 WH. For the *FULL* algorithm, the improvement is slight even if the battery energy capacity is 200 WH. This is because the sensor network lifetime is determined by the sensor node with the least power, and algorithm *FULL* may fully charge a few sensor nodes and then



((a)) Lifetime



((b)) Normalized lifetime

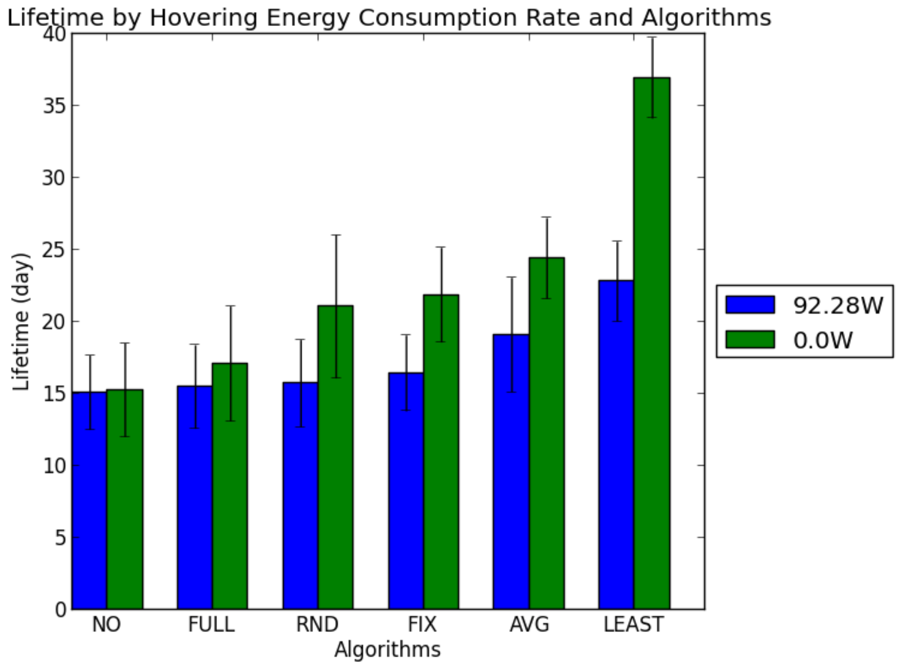
Figure 7.5: The performance of algorithms with different UAV energy capacity. Error bar is for the standard error.

leave others completely uncharged. When the UAV energy capacity is 200 WH, the *RND* algorithm becomes the second best. We guess that statistically the *RND* algorithm transfers more energy to sensor nodes with less energy compared with the *FIX* algorithm, and at the same time it covers more sensor nodes compared with the *FULL* algorithm.

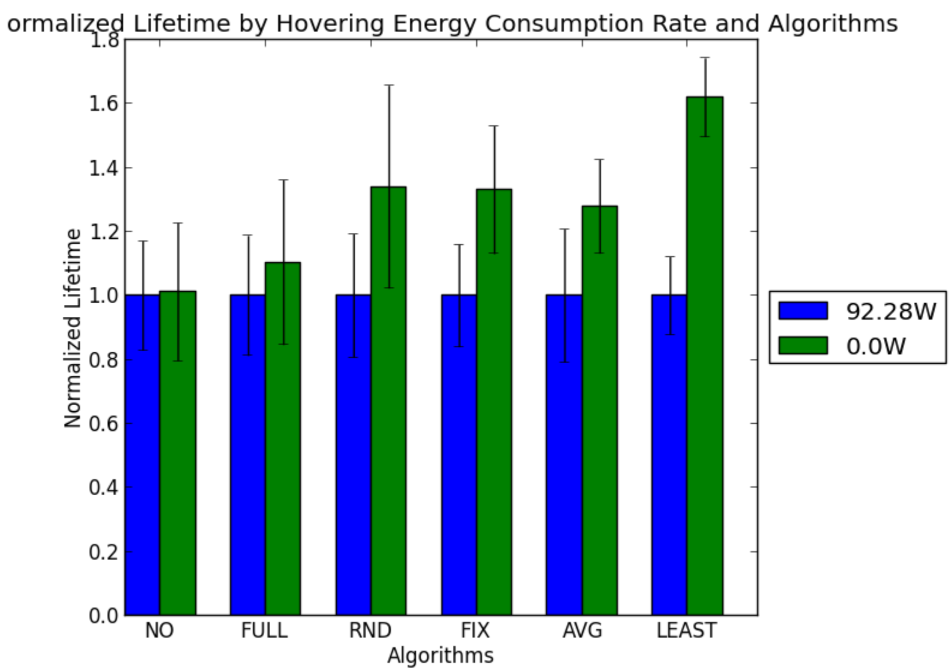
7.7 Varying Energy Consumption Rate of UAV Hovering

Because the UAV consumes a significant amount of energy for hovering while charging a sensor node, we are interested in reducing the energy used for hovering and exploring its influence. For example, in the case where a sensor node is placed on the ground, the UAV can land on it and then turn off its motors.

Fig. 7.6 demonstrates the influence of zero hovering energy consumption rate. As expected, the performance of all the algorithms are improved. The previous experiments shows that the naive charging algorithms, *FULL* and *RND*, can rarely prolong the lifetime of the sensor network. However, Fig. 7.6(a) shows that their performance are significantly improved with zero hovering energy consumption rate. The *FULL* algorithm can prolong the lifetime by about two days, and the *RND* algorithm can prolong the lifetime by more than five days. To easily see the lifetime percent gained, Fig. 7.6(b) shows the lifetime with no cost to hover normalized around the lifetime with the standard energy consumption rate for each algorithm. The *LEAST* algorithm gains largest percent, 60%, of improvement. After that, charging algorithm *RND* gains about 40 percent improvement. Algorithms *FIX* and *AVG* are both improved more than 30 percent as well.



((a)) Lifetime



((b)) Normalized lifetime

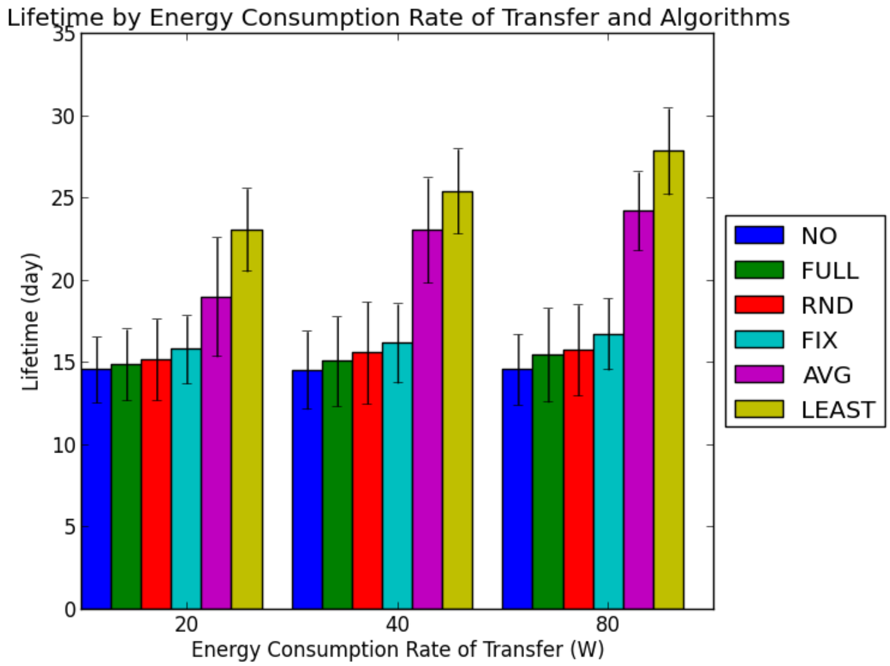
Figure 7.6: The performance of algorithms with different hovering energy consumption rate. Error bar is for the standard error.

It is obvious that all the charging algorithms can greatly benefit from the reduced energy consumption for hovering. This result suggest that, when charging the sensor nodes, the UAV should land, when it is possible.

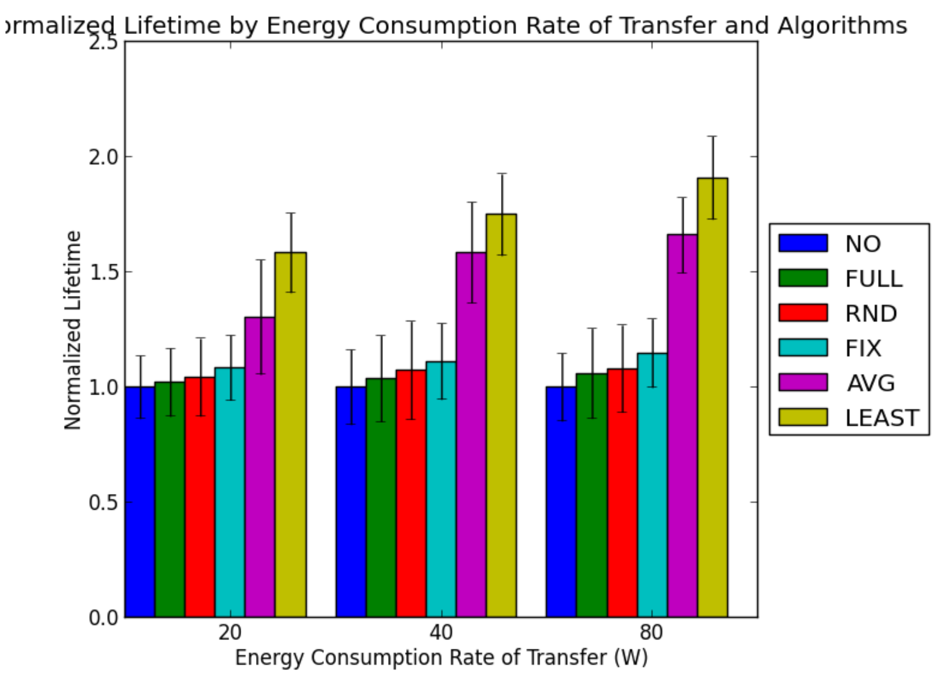
7.8 Varying Energy Consumption Rate of Wireless Power Transfer

To charge a specific amount of energy to a sensor node, with a fixed charging efficiency rate, the higher the transfer energy consumption rate, the shorter the required time. Because the UAV consumes extra energy for hovering while charging a sensor node, shorter charging time can reduce the extra energy for hovering. We guess that the performance of the algorithms can be improved with a higher transfer energy consumption rate.

Fig. 7.7 shows the performance of algorithms with different transfer energy consumption rate. For algorithms with no knowledge of sensor node energy level, *FULL*, *RND* and *FIX*, the gained benefit is very limited. For the algorithm with some knowledge of sensor node energy level, *AVG*, the improvement is more significant. For example, when the transfer energy consumption rate is 20 W, the *AVG* algorithm prolongs the lifetime of the sensor network by about 25%, and when the transfer energy consumption rate is 80 W, the *AVG* algorithm prolongs the lifetime of the sensor network by about 60%. For the algorithm with complete knowledge of sensor node energy level, *LEAST*, the improvement is also obvious. The prolonging of lifetime increases from about 60% to almost 90% when the transfer energy consumption rate changes from 20 W to 80 W.



((a)) Lifetime



((b)) Normalized lifetime

Figure 7.7: The performance of algorithms with different transfer energy consumption rate. Error bar is for the standard error.

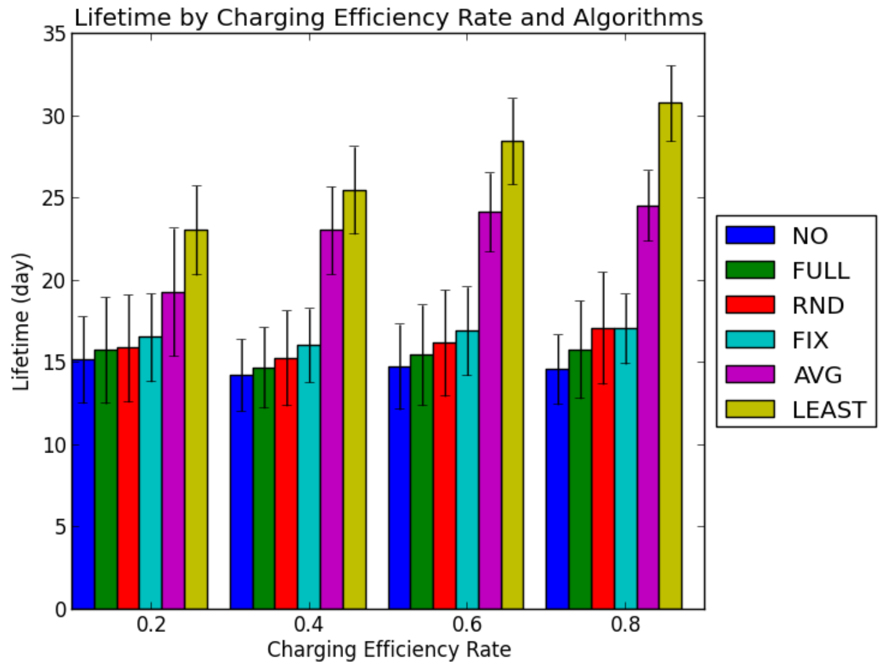
7.9 Varying Charging Efficiency Rate of Wireless Power Transfer

Higher charging efficiency rate implies that same energy can be charged to the sensor nodes with less time and energy consumption. We expect that the increment of lifetime can be positively and significantly improved when doubling the efficiency. However, our expectation is not true. Fig. 7.8 shows that the benefit of higher charging efficiency is not obvious for algorithms, *FULL*, *RND* and *FIX*. The *AVG* algorithm improves its performance when the charging efficiency rate increases from 0.2 to 0.4, but the its performance almost does not change when the charging efficiency rate increases from 0.4 to 0.6. We guess that it is because that the UAV mainly spends the gained time (by reducing charging time) on looking for and localizing more sensor nodes, instead of transferring more energy to visited sensor nodes. This indicates that the algorithms should adjust their parameters based on the state of the sensor network. For instance, with default system parameters 156 J is nearly optimal for *FIX* algorithm, but with increased transfer efficiency 312 J might be closer to the optimal value. Indeed, the *LEAST* algorithm, which is able to adjust its charging schedule based on the available full knowledge, has the most stable improvement with the increasing charging efficiency rate.

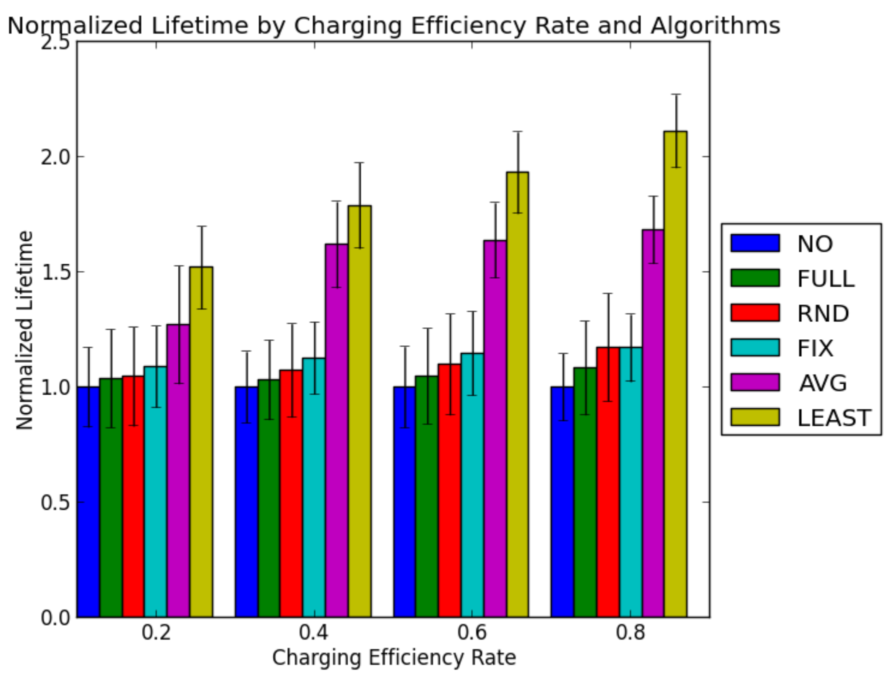
7.10 Comparison of System Parameters

In the previous sections, we have individually discussed the impacts of a series of system parameters. In this section, we want to compare the impacts of these system parameters to each other.

Fig. 7.9 shows the sensor network lifetime by system parameter changes for

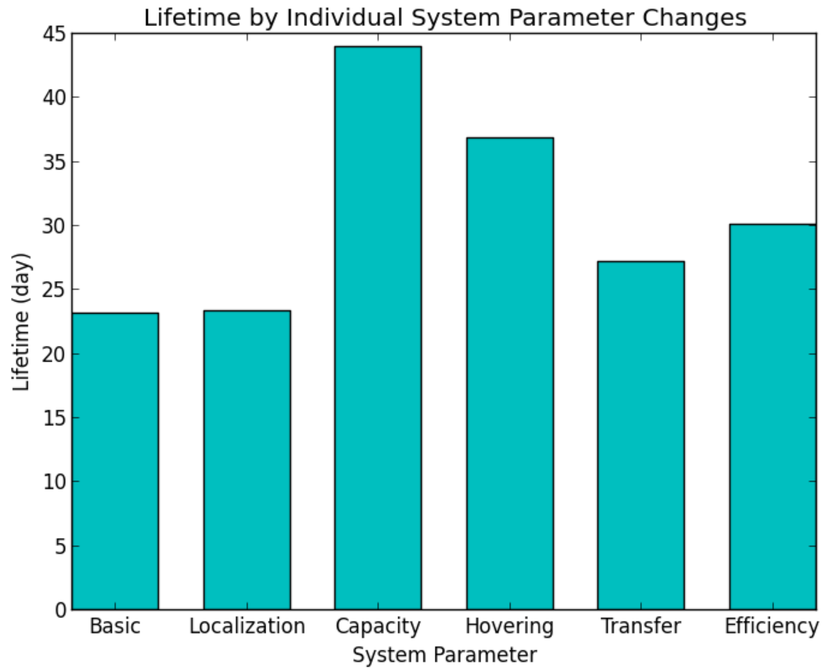


((a)) Lifetime

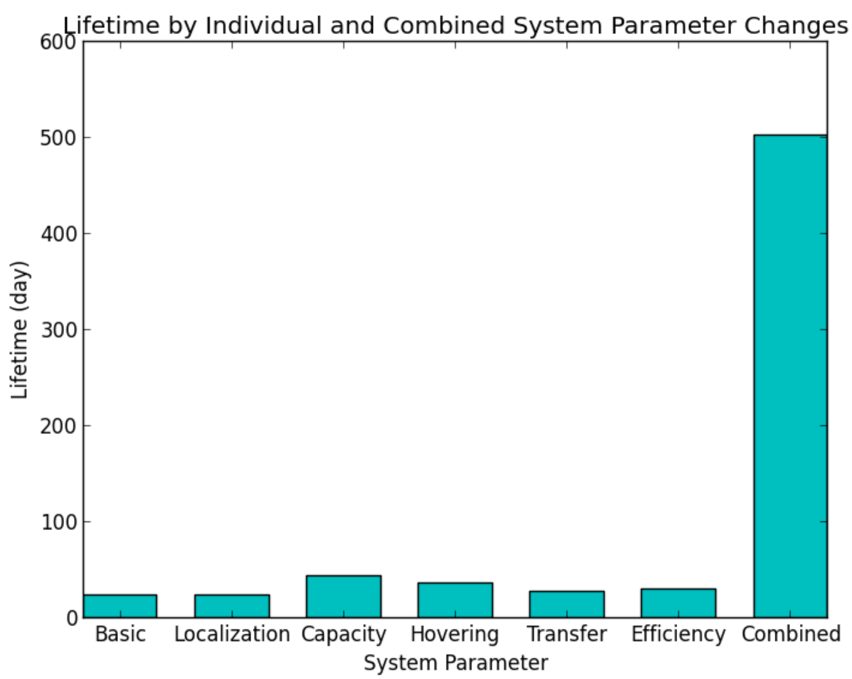


((b)) Normalized lifetime

Figure 7.8: The performance of algorithms with different charging efficiency rate. Error bar is for the standard error.



((a)) Individual system parameter changes



((b)) Individual and combined system parameters changes

Figure 7.9: The performance of *LEAST* algorithm with different system parameter changes.

LEAST algorithm. In this figure, label *Basic* means that default system parameters are used, label *Localization* means that the localization time is changed to 0 second, label *Capacity* means that the UAV energy capacity is changed to 200 WH, label *Hovering* means that the UAV hovering energy consumption rate is changed 0 WH, label *Transfer* means that the wireless power transfer energy consumption rate is changed to 80 WH, label *Efficiency* means that the charging efficiency rate is changed to 0.8, and label *Combined* means the combination all all these changes. In Fig. 7.9(a), all the data match the data we presented in the previous sections. The plot shows that decreasing the localization time from 36 seconds to 0 seconds has little effect. The sensor network lifetime can be prolonged to almost 45 days if the UAV can have 200 WH energy capacity. Even though the improvement is significant, it is not likely to occur soon since 200 WH is 8 times larger than the current 25 WH. Reducing hovering energy consumption rate can also greatly improve the performance. In addition, it is more achievable since landing the UAV while charging can reduce energy consumption of hovering. Both larger wireless power transfer energy consumption rate and better charging efficiency can mildly improve the performance. Larger energy transfer is likely since it is obtainable with current system by using higher voltage batteries. Better charging efficiency is also possible because Kurs *et al.* already experimentally measured about 0.8 charging efficiency at a distance of $1m$ [17]. In fact, based on these comparisons, we see that the UAV energy capacity is the most important (but hard to achieve), and removing the hovering while charging is nearly as important but much easier to achieve simply by landing while charging. Fig. 7.9(b) adds the data of the combined changes. To demonstrate the idea we set the sensor node energy capacity to unlimited otherwise the sensor network lifetime is bounded by the sensor node energy capacity. Obviously we are still faraway from this, but it shows us that the UAV only need to charge the sensor nodes once and then the sensor network can work for more than one year.

7.11 Summary

These results show that the energy status of the sensor network can effectively guide the behavior of UAV. We consider this, 8 sensor nodes distribute on a 200 m $\times$ 200 m field, as the basic case. With no information of the energy level of sensor nodes, the best charging algorithm can achieve about 15% improvement. With information of the initial average energy of sensor nodes, the charging algorithm can achieve about 40% improvement. With information of the energy level of each sensor node, the algorithm can achieve about 60% improvement. In fact, for all the system parameters we tested, the results show that the algorithm with complete information always beats all the other algorithms, and the algorithm with some information mostly beats all the algorithms with no information. Even more, in some cases, the algorithm with complete information is the only algorithm which can effectively prolong the lifetime the sensor network. For instance, when the distance between UAV base station and the sensor network increases to 2000 m, the *LEAST* algorithm can improve the sensor network lifetime by about 20%, and the improvement by all the other algorithms can barely achieve 5%.

These results also imply that the majority of UAV's energy is being spent charging the nodes and hovering. Assuming as we do that the energy capacity of a sensor node is 2.34 WH, and knowing that the UAV consumes 20 W to transfer power with an efficiency rate of 0.2, the energy transferred to the node is 4 W. At this rate, it would take 35 minutes to charge a fully discharged node. The energy required to fully charge just one completely discharged node exceeds the energy capacity of the UAV. If the UAV has a larger energy capacity, like 200 WH, the sensor network lifetime can be improved to more than 40 days in the best case. One experiment shows that a higher charging efficiency rate can improve all the algorithms' performance. For instance, the the sensor network lifetime is improved to about 25 days by the *AVG* algorithm and to about 30 days by the *LEAST* algorithm, when the charging efficiency rate is 0.8. Another experiment shows that for the *LEAST* algorithm the prolonging of lifetime increases from about 60% to nearly 90% when the energy consumption rate of transfer changes from 20 W to 80 W. Additionally, the cost to hover is very expensive. The energy consumption rate of hovering is 92.28 W and the efficient energy transfer is 4 W. By that it means the UAV consumes 23.07 unit of energy for hovering to transfer 1 unit of energy to the sensor nodes. According to one experiment, if the UAV does not have to hover while charging the sensor nodes, the *LEAST* algorithm can prolong the sensor network lifetime from about 15 days to more than 35 days. In addition, even the most naive algorithm, *FULL*, can prolong the sensor network lifetime by 2 days in this case. The localization process is the overhead for the UAV before charging a sensor node. An experiment shows that most algorithms can only slightly benefit from a reduced localization time, even when the localization time is 0 second. For instance, the *AVG* can prolong the sensor network lifetime to about 19 days for a localization time of 36 seconds and to about 21 days for a localization time of 0 second.

To summarize, we believe that reducing the energy consumption of UAV hovering by landing the UAV while charging a sensor node is the most efficient method to improve the performance of the UAV-based wireless power transfer system. Also, the system can benefit from larger UAV energy capacity, more efficient wireless power transfer and reduced localization time as well.

Chapter 8

Conclusions

In this work, we study the problem of how to use a UAV to effectively charge a sensor network with wireless power transfer.

8.1 Contributions

The contributions of this work are as follows.

NP-Completeness Proof: The problem is based on a novel UAV-based wireless power transfer system. We introduce the background of the problem, give a formal definition of the problem, and also prove its NP-Completeness by reduction from the problem *Metric-TSP*.

Heuristic Algorithms: As the problem is NP-Complete, we propose three categories of heuristic algorithms based on different information types, *No Knowledge*, *Some Knowledge* and *Complete Knowledge*, of sensor node energy level. Experiment results show that these algorithms can effectively prolong the lifetime of a basic sensor network by 50%, and some advanced algorithms can significantly outperform some naive algorithms.

Bottlenecks Identification: The experiment results indicate that the biggest bottleneck of the current UAV-based wireless power transfer system is the huge energy consumption of hovering while the UAV is charging sensor nodes. This finding suggests us to make the UAV being able to land while charging in our next generation of UAV-based wireless power transfer system. Also, we identify that limited UAV energy capacity and inefficient wireless power transfer also notably restrict the overall performance.

8.2 Future Work

The work presented is only a first step in investigating UAV-based wireless power transfer system. There are several directions in which this work will proceed.

More Accurate Simulation: In the future, we can build a more accurate simulation system. For example, the current simulation system does not consider the acceleration of moving. We just assume that the UAV can have immediate stop and immediate optimal speed. Also, in real life the energy consumption rate of then sensor nodes is changing since the sensor nodes work for a little while and then rest for a while. However, the current simulation system consider the sensor nodes have a constant energy consumption rate. In our next generation of simulation system, we can remove all this type of assumptions and make the simulation results more accurate.

Multiple UAVs: As we discussed, the UAV has a limited energy capacity, so it is hard for a UAV to cover more than tens of sensor nodes in a single flight. As the cost of the UAV is decreasing, more and more UAVs will be affordable. Then, how to arrange multiple UAVs to work together and effectively charge tens or hundreds of sensor nodes is a challenge. A naive solution is to assign a group of sensor nodes to a UAV, and then every UAV only charge its assigned sensor nodes. More advanced algorithms should make the UAV dynamically select sensor nodes based on the status, such as location and energy level, of UAVs and sensor nodes to optimize the performance.

Multiple Flights: In our work, we only consider the scenario where the UAV can charge the sensor nodes with a single flight. In fact, the UAV might be able to be recharged at the base station, and then the UAV can fly out and charge the sensor nodes periodically. For charging with a single flight, the best strategy is to charge those sensor nodes with low energy level because the UAV can only have a single flight and the sensor network lifetime is determined by the sensor node with lowest energy level. However, if the UAV is able to repeatably charge these sensor nodes, the UAV might want to charge one single node as much as possible for every flight to reduce the overhead of charging and then improve the overall efficiency. We are interested in exploring this scenario in our future work.

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