Imperial College London

Department of Earth Science and Engineering

MSc in Applied Computational Science and Engineering

Independent Research Project

Project Plan

Optimal Drone Positioning for Wireless Sensor Power Transfer and Data Collection

by

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June 2020

Section 1: Introduction

1. Literature Review

In most Internet-of-Things (IoT) projects, energy management and data gathering of sensor nodes (SNs) can be tedious, especially for dense systems. To solve this problem, much research has been carried out to prove the feasibility of interactions between Unmanned Aerial Vehicles (UAVs) and Wireless Rechargeable Sensor Networks (WRSNs). In recent years, (Mitcheson et al. 2017) implemented UAV-based wireless power transfer and data collection, adopting IEEE 802.15.4 2.4 GHz physical layer (PHY). A more promising protocol was proposed by (Qin et al. 2019), building a bespoke application layer upon augmented ContikiMAC over IEEE 802.15.4 PHY, which greatly increased reliability and network capacity .

Though their research shows great possibilities of UAV-based WRSN solution, drone positioning and flight path planning can be challenging under such scenario because of dynamic environmental factors, UAV and SN states. In 2018, (Zorbas and Douligeris 2018) introduced the Optimal Drone Positioning (ODP) problem for long-range wireless recharge process . The main objective is to find optimal Power Delivery Vehicle (PDV) positions and minimize the total energy consumption of SNs. The PDV charges a cluster of SNs as figure 1. With different altitudes of the PDV, the number of covered SNs can vary. Two solutions were proposed as (1) transform ODP to set-cover problem (2) the Drone Positioning Heuristic (DPH) solution.

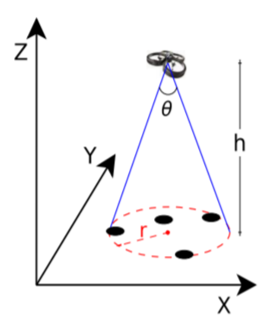

Figure 1: PDV with altitude *h* and covering radius *r* (Zorbas and Douligeris 2018)

In the context of such WRSNs, (Cheng et al. 2019) proposed a Genetic Algorithm (GA) to schedule multiple PDVs charging routes as well. They simulated the nature evolution process of chromosome with **crossover**, **mutation** and **selection** stage. To ensure the population developing towards to the desired direction (i.e. optimal solution), a fitness function was defined to mark each candidate in the whole population. Only first α % of possible solutions will be selected for the next generation. Moreover, to remain population diversity (i.e. avoid being stuck at local minimum), β % of generated chromosome instances will be added to new generation as well. Note that α and β are user-defined hyper-parameters, which means GA may obtain a trusted solution only. The simulation achieved good results with more than 99 % SNs charged in a light traffic network scenario and more than 96 % SNs charged in a heavy one. It also shows the more PDVs, the higher package delivery rate (PDR) of SNs will be (improve 2 % $\sim$ 6 % per additional PDV). However, above research adopted charging cars as PDVs and can only realize one-to-one Inductive Power Transfer (IPT) (not the one-to-multiple case, which is inefficient in the dense WRSN).

In 2019, (Boyle et al. 2019) proposed a two-stage power distribution system, which demonstrated a different clustering method of one Centre Node (CN) and several End Nodes (ENs). IPT happens on the CN firstly and then, ENs will be charged through Acoustic Power Transfer (APT) from the piezoelectric driver installed on the CN (seen as figure 2).

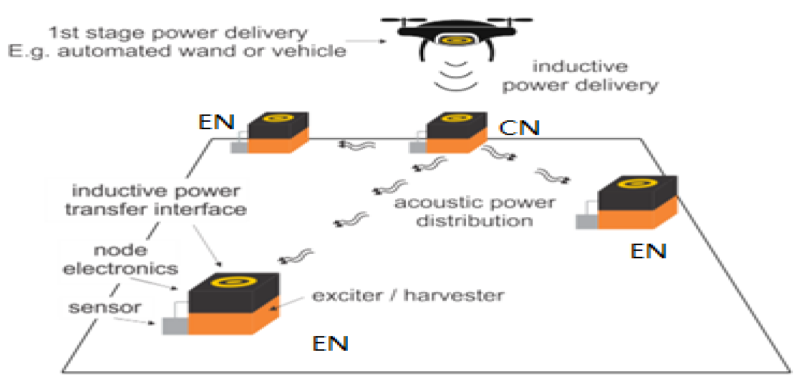

Figure 2: two-stage Power distribution system (Boyle et al. 2019)

Thanks to fixed altitude of the PDV, recharge scheduling of the two-stage power distribution system can be reduced to Travelling salesman problem (TSP). To find out trusted solution under the two-stage single-UAV power transfer scenario, (Pandiyan et al. 2019) proposed a novel algorithm based on the combination of genetic weighted clustering and nearest neighbour search. In the initialization stage, SNs with low weight factor will be placed into a CN list. Then all nearby ENs (inside the maximum acoustic transmission distance) will be assigned to one specific CN to form a SN cluster. With random permutation and combination, several possible paths will be recorded to target vectors with below form. **Crossover** (randomly swap cluster members in two 'parents' X_i and X_j, highlighted in the bolded frame), **Delete duplicates**, **Mutation** (randomly swap cluster members in V_i), **Delete duplicates** again and **Selection**, trail vector will be generated as figure 3. Different from the fitness function in (Cheng et al. 2019), the one in (Pandiyan et al. 2019) will be applied to candidates in both target and trail vectors. The one with higher metric will survive as part of the target vector in the next generation. This solution shows an average 90 % of nodes charged in the size 100 WRSN.

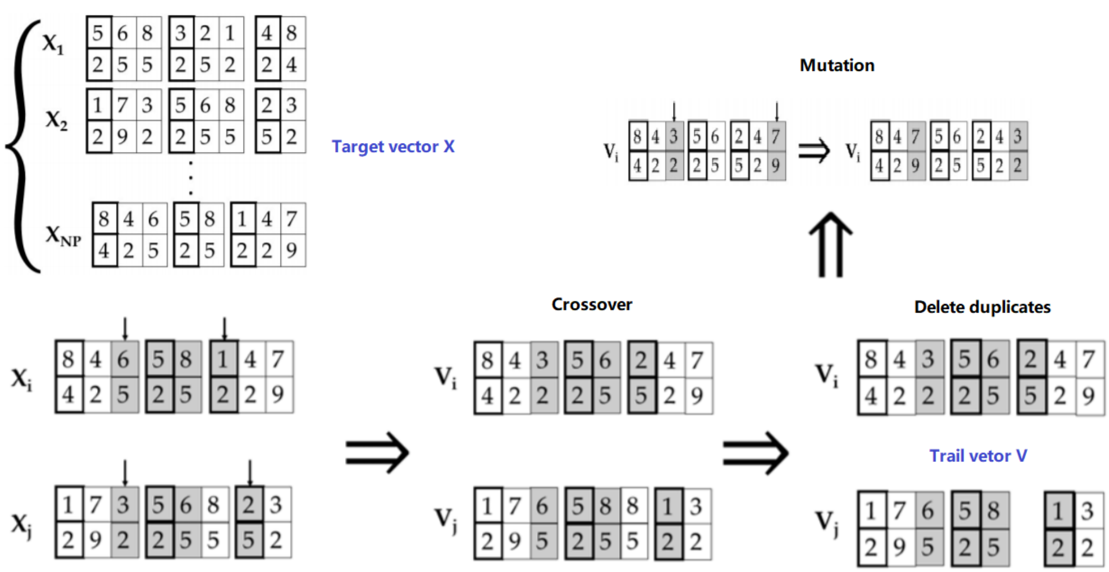

Figure 3: Stages in the process from target vector to trail vector (Pandiyan et al. 2019)

There are many other optimisation algorithms can be modified to solve TSP. For instance, (Hammouri et al. 2018) modified classic Dragonfly Algorithm (DA) , which simulates five operations (**separation**, **alignment**, **cohesion**, **food attraction** and **enemy distraction**) to find the optimal solution. Compared with GA, DA shows faster convergence speed. (Hatamlou 2018) also created fitness function to simulate the gravity of a black hole to find the optimal solution of TSP, which is known as Black Hole Algorithm (BHA). BHA can avoid precocity and cheating phenomenon existed in GA. It can improve search efficiency and reduce time complexity as well. Therefore, appropriate optimization algorithm used for solving TSP can be one of the main considerations in this project.

2. Problem Statement

This project is aimed at solving optimal recharge scheduling problem in WRSNs with UAVs. Before simulating the whole flight process, SNs will be initialized and clustered with randomly allocated attributes (i.e. sensor type, location, current energy status, etc.). A virtual simulation will be implemented to calculation the optimal path log. There are two main tasks for UAVs: (1) transfer power to SNs (2) collect data from SNs. The whole process is shown as figure 4:

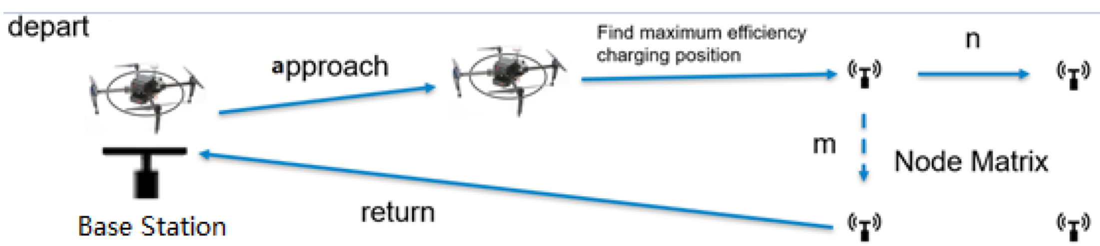

Figure 4: Flight process of the UAV

The PDV takes off from the Base Station (BS). It will check energy status before approaching to the next target coordinate. The approaching process is separated to two stages. Firstly, the PDV will fly to the target through

GPS localization, which shows around 10 meters precision. Then, it will switch to Ultra-wide band localization, which shortens the distance to less than 1 meter. Depending on different positioning method, the flight speed will be different as well, followed by data gathering. Once the PDV reaches the required position, IPT will be implemented to charge one CN and then APT to ENs. These operations will be repeated until the PDV completes the target coordinate array or the remain energy is less than 40 % of the full energy, which is reserved for returning to BS. Note that in early stage, the system is based on several basic assumptions:

a) Simulate a theoretic model environment without external influence (i.e. wind, obstacles, radio interference, etc.)
b) Set a fixed altitude of the PDV and ignore the influences on recharging efficiency with different angles
c) Energy consumption depends on defined operations (i.e. fly, recharge, gather data, etc.) only
d) Adjustable PDV flight speed when approaching to the SN
e) Communication data rate: 10 kilobytes per second
f) The PDV has full energy when taking off from the BS and return to BS when it has 40 % of full energy.
g) All sensor nodes (maximum 2000 SNs) are placed randomly inside square area with side length range between 0 and 2000 meters.

3. Main Objectives

a) Build the optimization algorithm (GA) which can calculate the optimal path planning with minimum energy consumption and maximum charging efficiency under theoretic scenario
b) For single PDV and specified number of SNs, run the simulation of the whole charging process with C++
c) Use another programming language (i.e. Python) to pre-process and post-process data
d) Visualize and analyze theoretic maximum for configuration (consider code speed and efficiency)

e) Modify the model with more complex scenarios like for multiple PDVs and specified number of SNs, high data rate transmission(10 Mbytes/sec)
f) Compare, visualize and analyse the results of different scenarios

4. Advanced objectives:

a) Improve GA with more appropriate optimization algorithms (i.e. BHA) and compare the results
b) Consider environmental influence (i.e. wind) to the model

Section 2. Project Plan

The Gantt chart of the whole project plan can be seen as below:

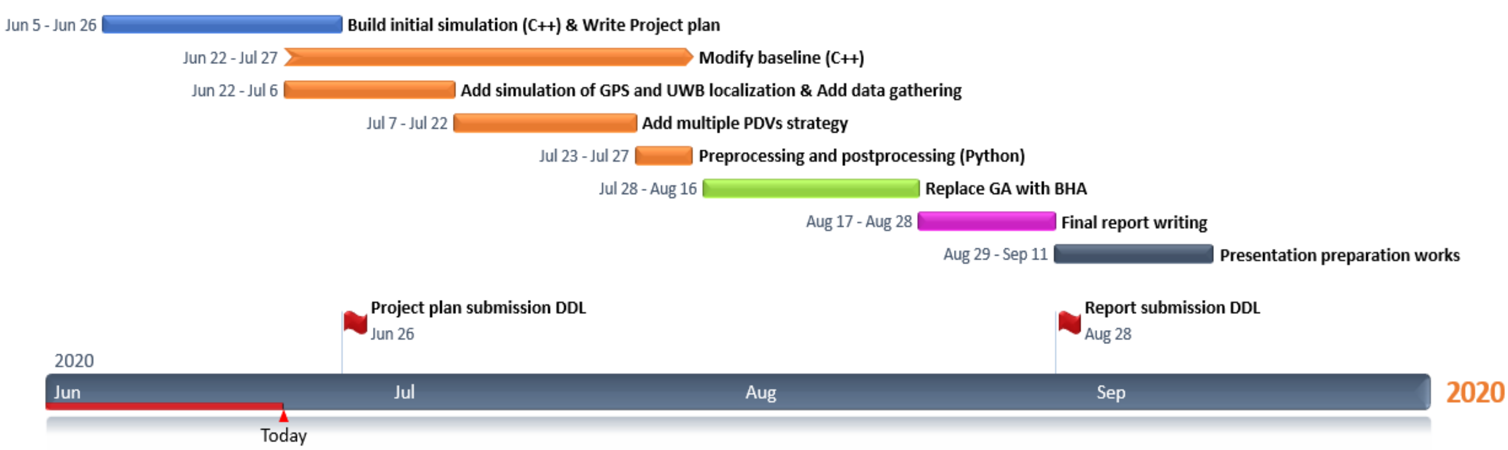

Figure 5: Gantt Chart of the individual research project

Note that for the initial simulation, it is based on the above assumptions in early stage. Considering complicated scenarios may be very time-consuming, algorithm improvement is optional. In order to prevent the project to fail, if **Modify baseline** is not finished before 5th July, **Replace GA and BHA** would not be implemented. To ensure continues progress of the project, weekly meeting with the first supervisor is arranged, using Microsoft Teams.

The following figure demonstrates the result with 250 randomly initialized sensor nodes (ran twice).

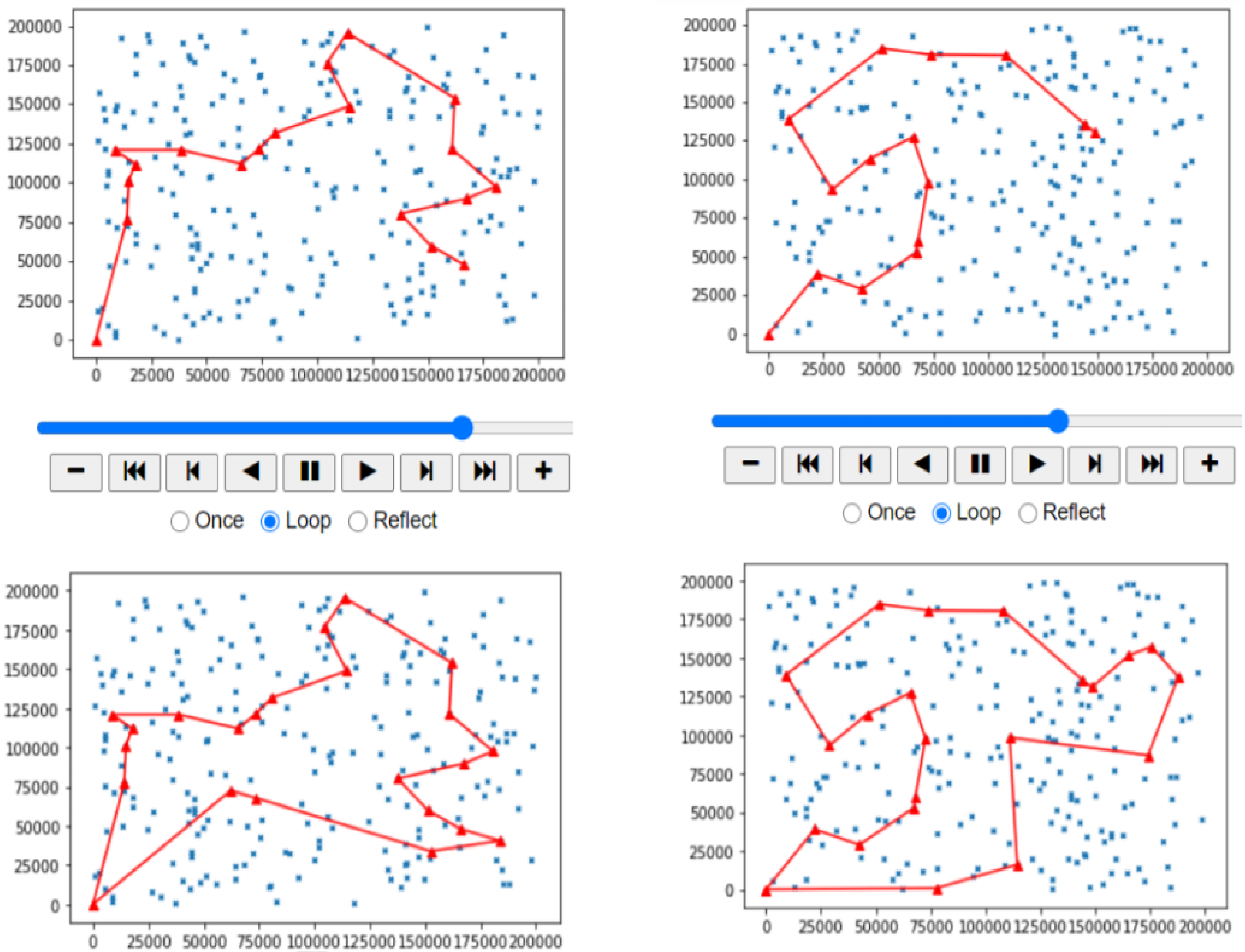

Figure 6: Flight path for 250 sensor nodes

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