Genetic Algorithm based UAV Trajectory Design in Wireless Power Transfer Systems

Tianyu Yang, Yulin Hu, Xiaopeng Yuan, and Rudolf Mathar
Institute for Theoretical Information Technology, RWTH Aachen University, D-52074 Aachen, Germany
Email: {yang, hu, yuan, mathar}@ti.rwth-aachen.de

***Abstract*—In this work, we study an unmanned aerial vehicle (UAV)-enabled wireless power transfer (WPT) system with multiple ground users. We aim at solving the non-convex UAV trajectory design problem which maximizes the minimal received energy among all users by determining the UAV's flying path under given UAV speed constraints. To solve such intractable problem, we propose a genetic algorithm (GA) based successive hover-and-fly (SHF) scheme that iteratively searches the optimal hovering points and optimizes the corresponding hovering time. Moreover, we extend the study to scenarios with no-fly zones, for which an improved GA based method with a penalizing strategy is proposed accordingly. Numerical results confirm the performance advantage of the proposed GA based algorithm in comparison to the benchmark algorithms in prior works under a wide range of system parameters.**

***Index Terms*—Unmanned aerial vehicle (UAV), wireless power transfer (WPT), trajectory optimization, genetic algorithm (GA), energy fairness, no-fly zone (NFZ).**

I. Introduction

Benefiting from their high mobility and reducing cost, unmanned aerial vehicles (UAVs) are expected to be widely applied in future wireless communication systems to realize the quick deployment for various demand. By taking the advantage of line-of-sight (LoS) aerial-to-ground wireless channels the UAV-enabled wireless systems are able to improve the system performance in terms of e.g., communication coverage [1], [2] or data throughput [3], [4], compared to the conventional terrestrial wireless systems [5]. On the other hand, UAVs can also be applied as a mobile energy transmitter in the wireless power transfer (WPT) systems to wirelessly charge the low-power ground users, e.g., the passive sensors and Internet-of-things (IoT) devices [6]–[8].

In recent years, the WPT technology has shown a significant success in wireless networks [9], [10]. Motivated by this, the UAV-enabled WPT system has been shown as a promising scheme to provide a longer lifetime of low-power ground users. Nevertheless, the trajectory design in UAV-enabled WPT systems is a intractable problem especially when the energy fairness is concerned. It is firstly studied in [6] within a one-dimensional (1D) WPT system with two users, where a Pareto boundary of the achievable energy region is characterized. A general trajectory design is then extended to a two-dimensional (2D) WPT system with multiple users in [8], where the heuristic successive hover-and-fly (SHF) trajectory and the successive convex programming (SCP) method are proposed. The heuristic SHF design is based on a relaxed problem where the maximum flying speed constraint is ignored, and thus results in sub-optimal solutions. Although the SCP method can refine the obtained heuristic SHF trajectories, it can only obtain the local optimality and normally need a huge computational cost to have an accurate quantization process.

On the other hand, genetic algorithm (GA) as a non-deterministic optimization method has been used in many works to search the quasi-optimal trajectories of the UAVs in recent years [11]–[14]. Inspired by the genetic theory of Darwin evolution, GA was developed by John Holland in the 1960s [15] to solve the optimization problem via a iterative searching process with the biology-like operations, e.g., the crossovers of the chromosomes and the mutations of genes. Therefore, GA has the low design complexity and good adaptability. Motivated by this, we intend to solve the UAV trajectory design problem in discussed WPT systems using the GA based approach, based on the fact that the optimal trajectory of the relaxed problem follows a multi-location-hovering structure [8]. It is noted that the aforementioned works only consider the cases where the UAV is not deployed as a communication node, and thus the objective of these works is to find a smooth shortest path with the given start and end points and the environment information. Therefore, a specific design of the GA based approach is needed to cope with the energy fairness concerned WPT systems.

In this work, within a UAV-enabled WPT system we intend to maximize the average received power among the ground users by designing the optimal trajectory of the mobile charger, i.e., the UAV, via the usage of the GA. The main contributions are as following:

- In contrast to the designs [6], [8], using the heuristic analytic solution based on the ignoring of the maximum speed constraints, we propose a GA based SHF design that iteratively searches the hovering points and optimizes the corresponding hovering time to achieve a quasi-optimal solution. Moreover, the proposed algorithm can solve the problems within both 1D and 2D topology.
- In addition, an extended 2D UAV-enabled WPT system with no-fly zones (NFZs) is investigated. Note that the NFZs concerned trajectory design problem in UAV-enabled WPT systems is still a open issue due to the extremely high complexity of geometry analysis. We design a penalizing strategy to adjust the fitness of the GA so that the algorithm can easily cope with the NFZs without the analytic understanding of their geometry structure.

The numerical results in Section V indicate that the proposed GA based approach outperforms the other benchmarks and can enhance the system performance significantly under a low maximum flying speed and short charging duration.

II. System Model

We consider a WPT system with a single UAV as charger and N users that are randomly and uniformly located on the ground inside the charging area with width W. Note that the charging area could be a 1D line, e.g., users are deployed along a road or river, or a 2D square, e.g., users are located in the

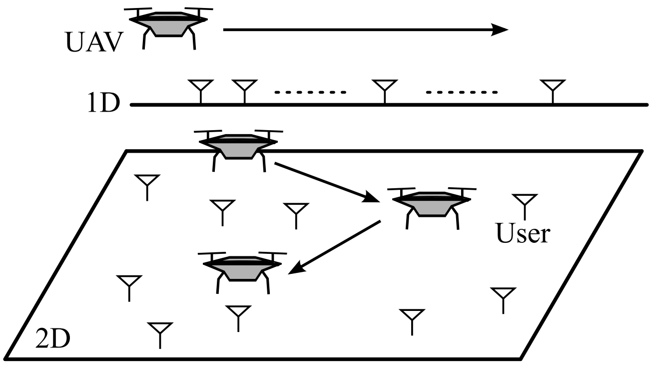


Figure 1. Illustration of the studied UAV-enabled WPT system in both 1D and 2D scenarios.

field or plain, as shown in Fig. 1. The UAV flies at a fixed altitude H with a maximum flying speed V and has a charging period $\mathcal{T}$, where $|\mathcal{T}| = T$ and T is the maximum charging time. We intend to investigate the WPT system both in 1D and 2D scenarios. For the simplicity of the presentation, we formulate the system in a general form with the coordinates presented as a vector in the Euclidean space $\mathcal{A}$. Thus, the coordinate of the n-th user and the UAV at time t are expressed as $\mathbf{c}_{\mathrm{U},n} \in \mathcal{A}$ and $\mathbf{c}(t) \in \mathcal{A}$, respectively, where $n \in \mathcal{N} = \{1, \ldots, N\}$ and $\mathcal{N}$ is the index set of all users. Considering the maximum flying speed V we have $||\dot{\mathbf{c}}(t)||_2 \leq V, \forall t \in \mathcal{T}$, where $\dot{\mathbf{c}}(t)$ denotes the first-order derivative of $\mathbf{c}(t)$. We assume that the channel between the UAV and each ground node is LoS-dominated. Therefore, we apply the free-space path loss model [3] in this work. Specifically, at time $t \in \mathcal{T}$ the power gain of the channel between the UAV and the n-th user is denoted as

$$h_n(\mathbf{c}(t)) = \beta_0 d_n^{-2}(\mathbf{c}(t)) \tag{1}$$

$$= \frac{\beta_0}{||\mathbf{c}(t) - \mathbf{c}_{\mathrm{U},n}||_2^2 + H^2}, \tag{2}$$

where $d_n(t)$ is the distance between the UAV and n-th user at the time t and β_0 presents the power gain of the channel at a reference distance of unit meter. Considering a constant transmit power P of the UAV, the received radio frequency (RF) power of n-th user at time t is thus expressed as

$$Q_n(\mathbf{c}(t)) = h_n(\mathbf{c}(t))P. \tag{3}$$

We consider that the UAV is equipped with a omnidirectional antenna. Consequently, each user receives the power continuously during the whole charging period. Thus, the total received energy of n-th user is written as

$$E_n = \int_0^T Q_n(\mathbf{c}(t))dt. \tag{4}$$

Note that in practice the received RF signals are firstly converted into direct current (DC) signals in order to charge the batteries of users. This RF-to-DC conversion is normally non-linear and the conversion efficiency depends on the power and waveform of the received RF signals [16]. For simplicity, in this work we consider the expressions in (3) and (4) to present the received power and energy by ignoring the RF-to-DC conversion process, as in [6], [8].

For the fairness concern of the studied WPT system with multiple users, we intend to maximize the minimal received energy among all users. Hence, the optimization problem of the system is written as

$$\max_{\mathbb{C}} \quad \min_{n \in \mathcal{N}} \; E_n \tag{5a}$$

$$\text{s.t.} \quad ||\dot{\mathbf{c}}(t)||_2 \leq V, \; \forall t \in \mathcal{T}, \tag{5b}$$

where $\mathbb{C}$ represents the set of $\mathbf{c}(t) \in \mathcal{A}, \forall t \in \mathcal{T}$. Due to the objective form of minimum value in (5a), the problem in (5) is intractable. Nevertheless, by introducing a auxiliary variable E the problem in (5) can be reformulated as

$$\max_{\mathbb{C}, E} \quad E \tag{6a}$$

$$\text{s.t.} \quad E \leq E_n, \; \forall n \in \mathcal{N}, \tag{6b}$$

$$||\dot{\mathbf{c}}(t)||_2 \leq V, \; \forall t \in \mathcal{T}. \tag{6c}$$

Note that the optimization problem in (6) is still intractable due to the non-convex constraints. It has been shown in [6], [8], the SHF trajectory with a multi-location-hovering structure is an effective solution of the problem. Specifically, the trajectory consists of a sequence of finite hovering points and corresponding hovering time. The UAV sequentially hovers at each hovering point for the corresponding hovering time and flies at the maximum speed between two neighbouring hovering points. Then, the problem is transformed to find the optimal hovering points and corresponding hovering time. Nevertheless, the problem is still intractable due to the non-convex nature. In [6], [8] a heuristic SHF design is proposed, which is initially based on an extreme case where the maximum flying speed constraint is ignored. Then, the obtained trajectory is adjusted to a solution with the consideration of maximum speed constraint. Thus, the obtained solution is not a global optimum. Moreover, because of this extreme case basement the algorithm separately discusses the situations with large and small total charging time T, which leads to a low performance under the scenarios with low maximum flying speed. Furthermore, an SCP method is also proposed in [8] to refine the obtained trajectory of the heuristic SHF design via the quantization of the path or time. Nevertheless, this SCP based trajectory design can only achieve a local optimality with a extremely accurate quantization, and thus leads a high computational cost. An efficient low-complexity solution to the trajectory design problem is missing. Note that the optimal trajectory follows the SHF structure. The trajectory design can be fully determined as long as the hovering points the corresponding hovering time are obtained. This motivates us to propose a GA based approach with significant low-complexity to address such SHF trajectory design problem.

III. GA based SHF trajectory design

In this section, we aim at solving the optimization problem in (6) via a GA based SHF trajectory design. The proposed algorithm searches the coordinates of the hovering points following the GA and optimizes the corresponding hovering time via solving a linear problem (LP).

A. GA based adaptive searching algorithm

We consider a SHF trajectory with K hovering points. The coordinate vector and hovering time of the k-th hovering point are denoted as $\mathbf{c}_{\mathrm{H},k}$ and $t_{\mathrm{H},k}$ respectively, where $k \in \mathcal{K} = \{1, \ldots, K\}$ and $\mathcal{K}$ is the index set of all hovering points and hovering time. The GA based searching algorithm searches the optimal hovering points iteratively. In GA we call each iteration as a generation. In each generation, the environment contains a fixed population of M entities which are the expression of the corresponding chromosomes. Let $l > 0$ denote the generation number. Then, the sequence of hovering points of the m-th entity in the l-th generation is encoded into a chromosome in a phenotype way, denoted as $\mathcal{Z}^{(m,l)} = \{\mathbf{c}_{\mathrm{H},1}^{(m,l)}, \ldots, \mathbf{c}_{\mathrm{H},K}^{(m,l)}\}$, where $m \in \mathcal{M} = \{1, \ldots, M\}$ and $\mathcal{M}$ is the index set of all entities. Moreover, the set of all entities in l-th generation, i.e., $\mathcal{Z}^{(m,l)}, \forall m \in \mathcal{M}$, is denoted as $\mathbb{Z}^{(l)}$. The evolution of each generation includes 4 processes, which are fitness update, selection, crossover and mutation. The details of each process are explained in the following.

1) Fitness update: In each generation we firstly update the fitness scores of all entities. The fitness indicates how good the performance of the entity is. Therefore, the fitness should reflect the objective of original problem in (5). The calculation of the fitness function for each entity includes 5 steps as shown in the following.

- *Find shortest path*: For a given set of hovering points we firstly arrange a sequence of points so that the total flying distance is shortest. This shortest path can be found via solving a traveling salesman problem (TSP), as in [8]. Specifically, by introducing a dummy hovering point that has zero distance to any other hovering point, we formulate a TSP over these $K + 1$ points. After solving the TSP we remove the two paths connected to the dummy point and obtain the desired sequence of the m-th entity in the l-th generation, which is denoted as $\hat{\mathcal{Z}}^{(m,l)} = \{\hat{\mathbf{c}}_{\mathrm{H},1}^{(m,l)}, \ldots, \hat{\mathbf{c}}_{\mathrm{H},K}^{(m,l)}\}$. Let $D_{\mathrm{F}}^{(m,l)}$ be the obtained shortest flying distance of the m-th entity in the l-th generation. Then, the corresponding total flying time $T_{\mathrm{F}}^{(m,l)}$ is calculated as $T_{\mathrm{F}}^{(m,l)} = D_{\mathrm{F}}^{(m,l)}/V$.
- *Revise invalid trajectory*: Note that if the obtained $T_{\mathrm{F}}^{(m,l)} > T$ the trajectory of the m-th entity is invalid. In this case we revise the invalid trajectory in the following way. First, we find the single optimal hovering point $\mathbf{c}_{\mathrm{S}}^{\star} \in \mathcal{A}$, obtained as
$$\mathbf{c}_{\mathrm{S}}^{\star} = \arg\max_{\mathbf{c}} \left(\min_{n \in \mathcal{N}} Q_n(\mathbf{c}) \right), \tag{7}$$
by applying an exhaust search over $\tilde{\mathcal{A}}$, where $\tilde{\mathcal{A}}$ is the convex hull of the coordinate set of $\mathbf{c}_{\mathrm{U},n}, \forall n \in \mathcal{N}$. Then, the coordinates in $\mathcal{Z}^{(m,l)}$ and $\hat{\mathcal{Z}}^{(m,l)}$ are downscaled to obtain a valid trajectory. This update is obtained as
$$\mathbf{c}' = \alpha \mathbf{c} + (1-\alpha)\mathbf{c}_{\mathrm{S}}^{\star}, \;\; \forall \mathbf{c} \in \mathcal{Z}^{(m,l)} \cup \hat{\mathcal{Z}}^{(m,l)}, \tag{8}$$
where $\alpha = \frac{T}{T_{\mathrm{F}}^{(m,l)}}$ is the scaling factor, $\mathbf{c}$ and $\mathbf{c}'$ represent the coordinates before and after the scaling, respectively.
- *Calculate received energy during flying*: After the flying sequence is fixed, we can calculate the received energy for each user during flying. Since the trajectory is a combination of piece-wise lines (a straight line in 1D and a polyline in 2D), the received energy in the l-th generation by the n-th user during flying is written as
$$E_{\mathrm{F},n}^{(m,l)} = \sum_{k=1}^{K-1} \int_{\hat{\mathbf{c}}_{\mathrm{H},k}^{(m,l)}}^{\hat{\mathbf{c}}_{\mathrm{H},k+1}^{(m,l)}} \frac{\beta_0 P}{||\mathbf{c} - \mathbf{c}_{\mathrm{U},n}||_2^2 + H^2} d\mathbf{c}. \tag{9}$$
- *Optimize the hovering time*: In this step we optimize the hovering time of all hovering points in order to maximize the minimal received energy among all users. With the obtained ordered hovering points and received energy during flying the optimization problem for hovering time is a linear problem (LP), which is expressed as
$$\max_{\mathbf{t}_{\mathrm{H}}^{(m,l)}, E^{(m,l)}} \quad E^{(m,l)} \tag{10a}$$
$$\text{s.t.} \quad t_{\mathrm{H},k}^{(m,l)} \geq 0, \quad \forall k \in \mathcal{K}, \tag{10b}$$
$$\sum_{k \in \mathcal{K}} t_{\mathrm{H},k}^{(m,l)} = T - T_{\mathrm{F}}^{(m,l)}, \tag{10c}$$
$$\sum_{k \in \mathcal{K}} t_{\mathrm{H},k}^{(m,l)} Q_{k,n}^{(m,l)} + E_{\mathrm{F},n}^{(m,l)} \geq E^{(m,l)}, \forall n \in \mathcal{N}, \tag{10d}$$
where for the m-th entity in l-th generation $\mathbf{t}_{\mathrm{H}}^{(m,l)} = [t_{\mathrm{H},1}^{(m,l)}, \ldots, t_{\mathrm{H},K}^{(m,l)}]$ and $E^{(m,l)}$ are the hovering time vector of all ordered hovering points and the auxiliary variable, respectively, and
$$Q_{k,n}^{(m,l)} = \frac{\beta_0 P}{||\hat{\mathbf{c}}_{\mathrm{H},k}^{(m,l)} - \mathbf{c}_{\mathrm{U},n}||_2^2 + H^2} \tag{11}$$
is the RF power between the n-th user and the k-th hovering point of the m-th entity.
- *Calculate fitness*: Note that the obtained optimum $E^{(m,l)\star}$ via solving the LP in (10) is the optimal minimal received energy among all users. Then, we set the fitness as minimal average received power among all users, which is obtained for m-th entity in l-th generation as $S^{(m,l)} = E^{(m,l)\star}/T$.

2) Selection: In each generation the best γ of entities in terms of their fitness are chosen to reproduce next generation, where $\gamma \in [0\%, 100\%]$ is a percentage number. We denote the set of chosen entities in l-th generation as $\tilde{\mathbb{Z}}^{(l)}$. Note that the selection with a larger γ can keep the diversity of the population but may incur slow convergence or even the divergence of the algorithm. Conversely, the selection with a small γ may lack of the diversity and thus the algorithm converges to a local point.

3) Crossover: The entities of $\tilde{\mathbb{Z}}^{(l)}$ reproduce the $(l+1)$-th generation via crossover process. Specifically, during each crossover process two entities are chosen from $\tilde{\mathbb{Z}}^{(l)}$ according to the ratio between their fitness and the total fitness, i.e., the probability of m-th entity in the l-th generation to be chosen is calculated as $P^{(m,l)} = \frac{S^{(m,l)}}{\sum_{m \in \tilde{\mathbb{Z}}^{(l)}} S^{(m,l)}}$. Then, a new chromosome is generated via the crossover of the chromosomes of two chosen entities. Each fragment of the child chromosome comes from one of the parent corresponding chromosome fragments with a probability of 0.5. This crossover process happens M times in each generation and thus the next generation, i.e., $\mathbb{Z}^{(l+1)}$, is created with the population of M.

4) Mutation: It is noted that in the crossover process all genes of the child generation are directly inherited from the parent generation, which limits the searching domain. In order to ensure the diversity of the genes and the adequate exploration of unknown genes, the mutation process is applied during the reproduction of each generation. In l-th generation with a given mutation rate $\mu \in [0, 1]$ the k-th segment of the m-th chromosome, i.e., $\mathbf{c}_{\mathrm{H},k}^{(m,l)}$, has a possibility of μ to mutate to a random vector $\tilde{\mathbf{c}}_{\mathrm{H},k}^{(m,l)} \in \mathcal{A}$. We define a mutation range denoted as d_{r} and set $||\tilde{\mathbf{c}}_{\mathrm{H},k}^{(m,l)} - \mathbf{c}_{\mathrm{H},k}^{(m,l)}||_2 \leq d_{\mathrm{r}}$. Note that at the first few of generations the mutation range should be large to enable a wide exploration of unknown genes. Nevertheless, with the increment of generations the mutation range should gradually decrease to reduce the searching area and avoid the divergence. Therefore, we set a adaptive mutation range for the l-th generation, denoted as $d_{\rm r}^{(l)} = \max\{\frac{W}{2l}, d_{\min}\}$, where $d_{\min}$ is the minimal mutation range.

B. Combined LP for optimization of hovering time

Note that the LP in (10) should be solved for all entities in a population, which incurs a long running time when M is large. Fortunately, the LPs for different entities are independent. Therefore, we can form them as one LP and thus in each generation the algorithm only needs to solve one LP. The combined LP is expressed as

$$\max_{\mathbb{T}_{\rm H}^{(l)},\mathbb{E}^{(l)}} \quad \sum_{m\in\mathcal{M}} E^{(m,l)} \tag{12a}$$

$$\text{s.t.} \quad t_{{\rm H},k}^{(m,l)} \geq 0,\ \forall k \in \mathcal{K},\ \forall m \in \mathcal{M}, \tag{12b}$$

$$\sum_{k\in\mathcal{K}} t_{{\rm H},k}^{(m,l)} = T - T_{\rm F}^{(m,l)},\ \forall m \in \mathcal{M}, \tag{12c}$$

$$\sum_{k\in\mathcal{K}} t_{{\rm H},k}^{(m,l)} Q_{k,n}^{(m,l)} + E_{{\rm F},n}^{(m,l)} \geq E^{(m,l)}, \quad \forall n \in \mathcal{N},\ \forall m \in \mathcal{M}, \tag{12d}$$

where $\mathbb{T}_{\rm H}^{(l)}$ $(\mathbb{E}^{(l)})$ represents the set of $\mathbf{t}_{\rm H}^{(m,l)}$ $(E^{(m,l)}), \forall m \in \mathcal{M}$ in the l-th generation. The full GA based adaptive searching algorithm is shown in Algorithm 1.

Algorithm 1 GA based adaptive searching algorithm for SHF trajectory design. L denotes the generation number when the algorithm converges.

Find single optimal hovering point $\mathbf{c}_{\rm S}^{\star}$ via (7)
Randomly create initial generation $\mathbb{Z}^{(1)}$ in $\tilde{\mathcal{A}}$
for $l = 1, \ldots, L$ **do**
  for $m = 1, \ldots, M$ **do**
    Find shortest path $\hat{\mathcal{Z}}^{(m,l)}$ and corresponding $T_{\rm F}^{(m,l)}$
    if $T_{\rm F}^{(m,l)} > T$ **then**
      Revise trajectory according to $\mathbf{c}_{\rm S}^{\star}$ via (8)
    end if
    Calculate $E_{{\rm F},n}^{(m,l)}, \forall n \in \mathcal{N}$ via (9)
  end for
  $\mathbb{E}^{(l)\star}, \mathbb{T}_{\rm H}^{(l)\star} \leftarrow$ solve (12)
  Update $S^{(m,l)}, \forall m \in \mathcal{M}$
  Select the best γ to obtain $\tilde{\mathbb{Z}}^{(l)}$ according to $S^{(m,l)}$
  Crossover to reproduce $\mathbb{Z}^{(l+1)}$
  Mutation with rate μ and range $d_{\rm r}^{(l)}$
end for
return $\left\{\hat{\mathcal{Z}}^{(L)\star}, \mathbf{t}_{\rm H}^{(L)\star}\right\}$

IV. 2D WPT SYSTEMS WITH NO-FLY ZONES

In this part we extend the 2D WPT system with the consideration of NFZs. In the practice the WPT system may contain the NFZs, e.g., military restricted area or danger area for flight, such that the UAV is forbidden to fly through them. In this respect, the designed UAV trajectory should not cross through the NFZs. We consider Q number of circular NFZs with all equal radius $R_{\rm NFZ}$ that are randomly located in our system area $\mathcal{A}$. Let $\mathcal{D}$ be the coordinate set of NFZs. Then the coordinate set of the feasible area for the trajectory is thereby $\mathcal{F} = \mathcal{A} \setminus \mathcal{D}$.

The trajectory design with the consideration of NFZs makes the problem much more complex to obtain a analytic solution.

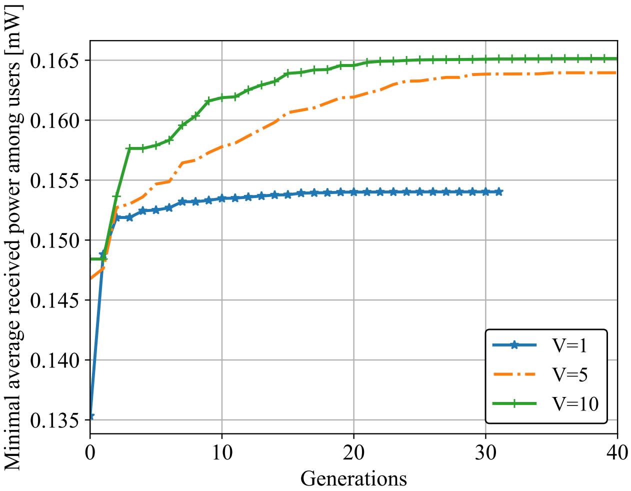


Figure 2. Convergence behavior of the proposed iterative algorithm for various maximum flying speed V.

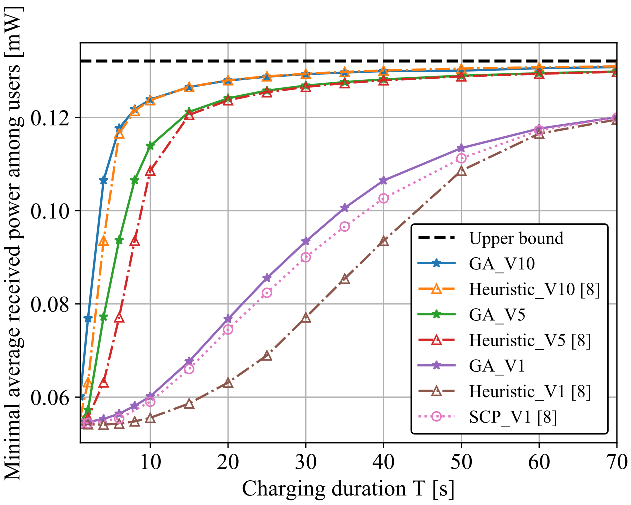


Figure 3. Performance vs. various charging duration T and maximum flying speed V.

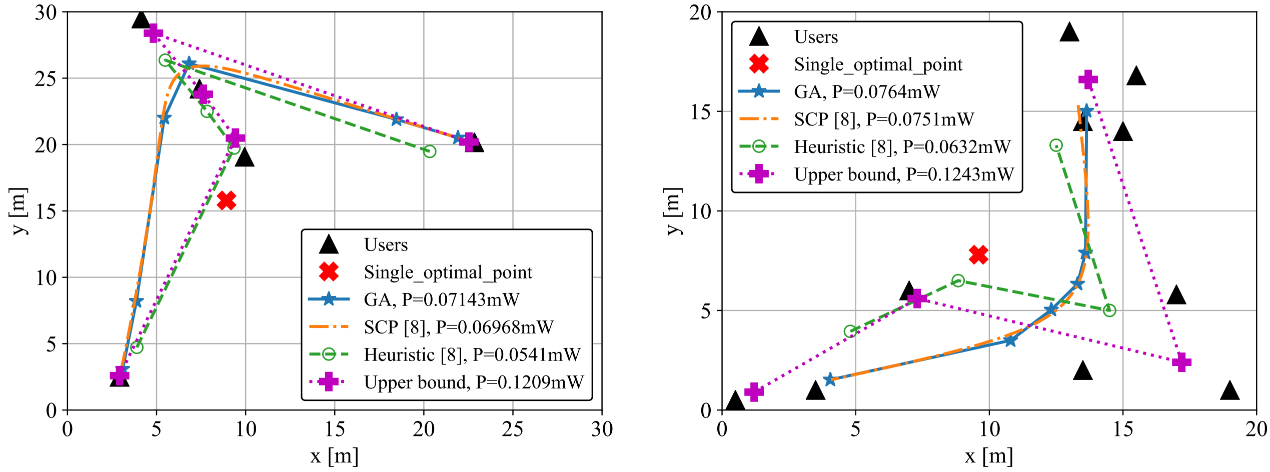
Nevertheless, our proposed GA based algorithm can easily solve it with a small update of fitness calculation. Firstly the initial generation is created within $\mathcal{F}$. Then, for the m-th entity in l-th generation, let $D_{\rm NFZ}^{(m,l)}$ be the total length of the intersect segments between its trajectory and the NFZs, the corresponding fitness is updated as

$$S' = S\left(1 - \frac{D_{\rm NFZ}^{(m,l)}}{D_{\rm F}^{(m,l)}}\right), \tag{13}$$

where S and S' are the corresponding fitness before and after the update, respectively. Note that instead of setting the fitness of trajectory that passes through the NFZs directly as zero, the proposed update penalizes the fitness according to the ratio of the length between the invalid segments and the total flight path, which ensures that the algorithm can adjust the trajectory that only passes through the NFZs slightly. The rest of the algorithm is the same as Algorithm 1.

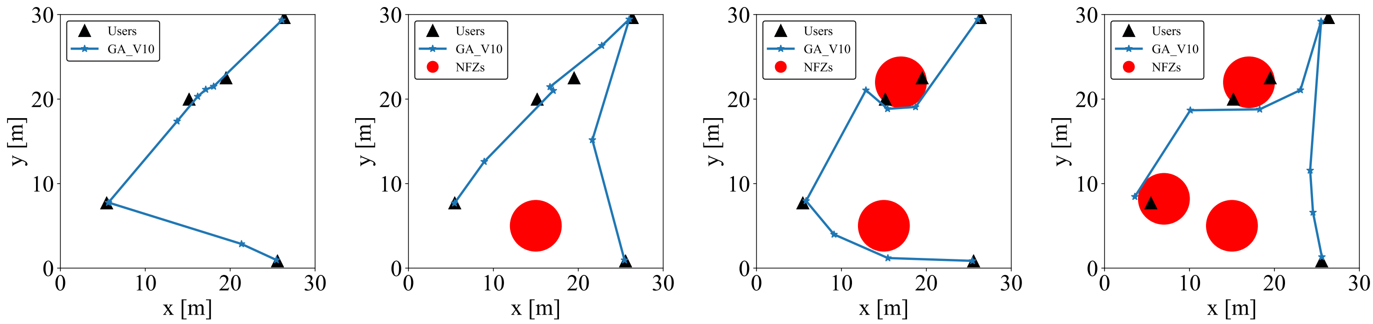
V. SIMULATION RESULTS

In this section, the proposed GA based SHF trajectory design for the considered WPT system is numerically evaluated in terms of the minimal average received power among all users.

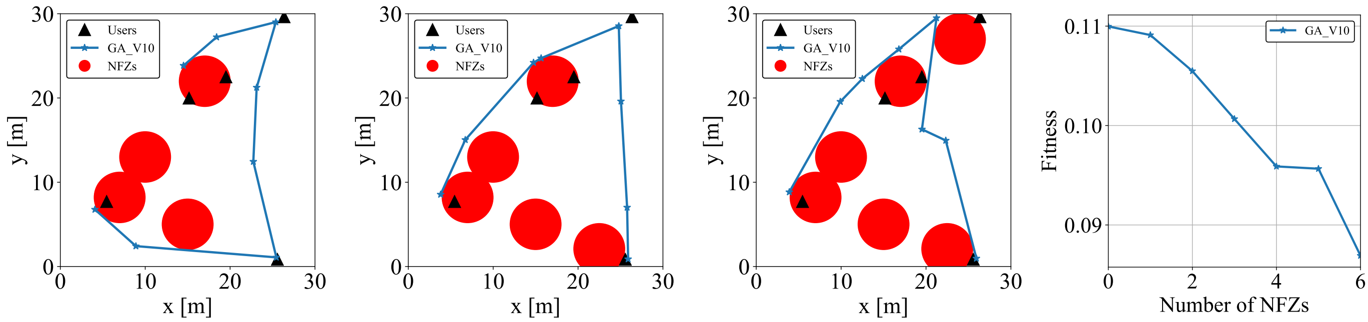


(a) A 2D scenario with $N = 5$, $T = 40$s, $V = 1$m/s (b) A 2D scenario with $N = 10$, $T = 20$s, $V = 1$m/s

Figure 4. Trajectory examples of the proposed algorithm and solutions in [8].



(a) No NFZ (b) 1 NFZ (c) 2 NFZ (d) 3 NFZ



(e) 4 NFZ (f) 5 NFZ (g) 6 NFZ (h) Fitness vs. Q

Figure 5. GA based trajectory design for various number of NFZs.

The resulting system performance is averaged over 20 realizations. Unless otherwise is stated the default values of simulation parameters are as following: $\beta_0 = -30$dB, $P = 40$dBm, $H = 5$m, $T = 40$s, $W = 30$m, $N = 5$, $K = 6$, $M = 100$, $\gamma = 20\%$, $\mu = 0.1$ and $d_{\text{min}} = 0.05W$.

A. Algorithm convergence

As the proposed GA based approach is a iterative searching solution, we firstly present the convergence behavior. In Fig. 2 the convergence behavior is depicted for the cases with different maximum flying speed V. The curves show the minimal average received power among users, i.e., the best fitness by the definition, of each generation. It is observed that the proposed GA based algorithm has significant improvements in the first few of generations and converges in 20-40 generations. It is also shown that the algorithm with small maximum flying speed needs less generations to converge. This is since under small maximum flying speed limit the optimal trajectory is simpler so that the searching complexity is lower. Based on the observed various convergence behavior in different scenarios we set a checking of convergence threshold as the stop condition of the algorithm.

B. Algorithm comparison

In this part we evaluate the proposed GA based algorithm with the comparison to the heuristic SHF solution and SCP solution that are proposed in [8]. It is worth to mention that the SCP method requires a time quantization as the accurate of the searching algorithm. We set the quantization of distance for the exhaustive search as $d_{\text{s,min}} = 0.01$m and the corresponding time quantization as $t_{\text{s,min}} = d_{\text{s,min}}/V$. Note that this quantization process results in a very large computational complexity. Therefore, we only perform this SCP method in the cases with maximum flying speed $V = 1$m/s.

1) Performance comparison: In Fig. 3 the system performance in terms of the minimal average received power among all users related to the charging duration T and maximum flying speed V is depicted. The upper bound is achieved with the UAV's maximum speed constraints ignored. It is firstly observed that the proposed GA based algorithm outperforms the heuristic SHF solution and SCP solution within all range of charging duration and maximum flying speed. A significant gain is observed for the case with $V = 1$m/s and the range of T between 10s and 50s. This is since the heuristic SHF solution and SCP solution are based on the trajectory with the maximum flying speed constraints ignored. When the maximum flying speed is low, e.g., 1m/s, and the charging duration is short, the optimal trajectories are no longer similar as the trajectories without flying speed limit. This will be further explained in next part. On the other hand, the performance of the proposed algorithm and the heuristic SHF solution get close with large maximum flying speed and converge to the upper bound when T becomes large.

2) Trajectory comparison: In Figs 4(a) and 4(b) the trajectory examples obtained from the proposed GA based approach, the heuristic SHF and SCP solutions with low maximum flying speed ($V = 1$m/s) are depicted. The corresponding performance are also given in the legend. It is observed that in both scenarios the heuristic SHF trajectories and the proposed GA based SHF trajectories are quiet different, which leads the gain of the performance as observed in Fig. 3. It is clear that the heuristic SHF trajectories are adjusted from the upper bound, i.e., trajectories without flying speed constraints, according to the single optimal point, which only gives local optimal solutions. Although the trajectories of the SCP method and the the proposed algorithm are very close to each other, our algorithm's performance is still better than the SCP. Note that the hovering points number in the heuristic SHF trajectories is automatically searched. Therefore, the heuristic SHF trajectory in Fig 4(b) with only 4 hovering points is clearly a bad design due to the flaw of the algorithm.

C. Trajectory design with NFZs

In this part we study a NFZ contained 2D WPT system with $N = 5$ users. The UAV is with maximum flying speed $V = 10$m/s and charging duration $T = 40$s. The radius of NFZs are all equal to $R_{\text{NFZ}} = 3$m. We gradually increase the NFZ number Q and set the location of any new NFZ on the current best trajectory in order to enforce the algorithm to find a new valid trajectory. As the existence of NFZs makes the optimal trajectory more complex, we set $K = 8$ hovering points to ensure a adequate flexibility of trajectory design. In Figs 5(a)-5(g) the obtained trajectories under various number of NFZs Q using proposed GA based approach are depicted. Moreover, the corresponding fitness, i.e., the minimal average received power among users, of these trajectories are shown in Fig 5(h). It is observed that the best trajectory in the scenario without any NFZ is a direct path passing through all users. As the number of NFZs is increasing, the algorithm effectively finds new valid trajectories. The fitness decreases with the increment of the NFZs as expected. Nevertheless, in the scenarios with less NFZs the performance still keep a relatively good level, e.g., in the case with 3 NFZs the fitness only drops 9.1%. It is also shown that the obtained trajectories are in many case along the boundaries of the NFZs to achieve a optimal path around the NFZs. Note that the proposed algorithm does not contain any analytic understanding of the geometry structure in the NFZs contained space. This indicates the success of the proposed fitness update method in (13).

VI. Conclusion

In this paper, we studied a trajectory design problem in a UAV-enabled WPT system with multiple ground users. We intend to maximize the minimal received energy among all users. We proposed a GA based solution to the trajectory design problems in both 1D and 2D scenarios. The numerical results show that the proposed algorithm outperforms the heuristic and SCP that are proposed in the previous works in all range of charging duration. Under a short charging duration and a low maximum flying speed, the results also indicate a significant gain of the proposed GA based method compared to the heuristic and SCP solutions. Furthermore, a NFZs contained 2D WPT system is extended and a revised GA based method is proposed. The numerical results show that the proposed GA based method can effectively search the quasi-optimal trajectories without analyzing the location and the geometry structure of the NFZs.

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