# Laser-Empowered UAVs for Aerial Data Aggregation in Passive IoT Networks

<table>
<thead>
<tr>
<th>Item Type</th>
<th>Article</th>
</tr>
</thead>
<tbody>
<tr>
<td>Authors</td>
<td>Abdelhady, Amr Mohamed Abdelaziz; Celik, Abdulkadir; Diaz-Vilor, Carles; Jafarkhani, Hamid; Eltawil, Ahmed Mohamed</td>
</tr>
<tr>
<td>Eprint version</td>
<td>Publisher's Version/PDF</td>
</tr>
<tr>
<td>DOI</td>
<td>10.1109/ojcoms.2024.3372881</td>
</tr>
<tr>
<td>Publisher</td>
<td>Institute of Electrical and Electronics Engineers (IEEE)</td>
</tr>
<tr>
<td>Journal</td>
<td>IEEE Open Journal of the Communications Society</td>
</tr>
<tr>
<td>Rights</td>
<td>Archived with thanks to IEEE Open Journal of the Communications Society under a Creative Commons license, details at: <a href="https://creativecommons.org/licenses/by/4.0/legalcode">https://creativecommons.org/licenses/by/4.0/legalcode</a></td>
</tr>
<tr>
<td>Download date</td>
<td>2024-03-15 02:26:58</td>
</tr>
<tr>
<td>Item License</td>
<td><a href="https://creativecommons.org/licenses/by/4.0/legalcode">https://creativecommons.org/licenses/by/4.0/legalcode</a></td>
</tr>
<tr>
<td>Link to Item</td>
<td><a href="https://repository.kaust.edu.sa/handle/10754/697606">https://repository.kaust.edu.sa/handle/10754/697606</a></td>
</tr>
</tbody>
</table>
Laser-Empowered UAVs for Aerial Data Aggregation in Passive IoT Networks

Amr M. Abdelhady1, Member, IEEE, Abdulkadir Çelik1, Senior Member, IEEE, Carles Diaz-Vilor2, Student Member, IEEE, Hamid Jafarkhani2, Fellow, IEEE, Ahmed M. Eltawil1, Senior Member, IEEE

1Computer Electrical, and Mathematical Science and Engineering (CEMSE) Division, King Abdullah University of Science and Technology (KAUST), Thuwal, Makkah Province, Kingdom of Saudi Arabia
2Center for Pervasive Communications and Computing, Department of Electrical Engineering and Computer Science, University of California, Irvine, CA, 92697 USA

CORRESPONDING AUTHOR: Amr M. Abdelhady (e-mail: amr.abdelhady@kaust.edu.sa).

The authors gratefully acknowledge funding from NEOM under grant number 4849 and from KAUST under the OFP2023 program grant number URF/1/5532-01-01.

ABSTRACT This paper investigates the maximization of data harvested by an uncrewed aerial vehicle (UAV) that supports Internet of Things (IoT) deployment scenarios. The novelty of the paper is that we study the feasibility of battery-free UAV and IoT device deployment where the UAV is powered by a ground laser source, and the IoT devices are powered by a power beacon via bistatic backscattering. We aim to optimize the UAV trajectory while minimizing the laser energy consumption throughout the entire flight by tuning the laser power and the power beacon radiated temporal power profiles. Upon considering an unspecified flying time, we adopt path discretization and resort to the single-block successive convex approximation (SCA) to solve the data collection maximization problem. In addition to considering the UAV dynamics and power budget, two novel SCA-compatible bounds are introduced for the product of positive mixed convex/concave functions. Finally, the simulation results show that the proposed algorithm increases the data collected under different operation conditions by approximately 90%.

INDEX TERMS Laser-powered UAVs, Trajectory optimization, Backscatter communications, Resource allocation

I. Introduction

ENERGY provisioning and management of airborne-aided IoT networks has garnered significant research interest due to the power-limited nature of both uncrewed aerial vehicles (UAVs) and Internet of Things (IoT) devices, as evidenced in [1]–[4] and the references therein. Moreover, recent advances in acquisition, pointing, and tracking (APT) technologies have increased the affordability of ground-to-air laser links [5], [6]. Consequently, numerous recent works have emphasized laser-based UAV charging [7]–[12] due to its \((i)\) relatively high power transfer efficiency compared to other schemes, \((ii)\) miniature transmission and reception apertures, and \((iii)\) capability of supporting longer ranges and prolonged missions. In particular, different UAV charging technologies were compared to laser-based charging in [7], where simulations confirmed the superiority of laser charging. Additionally, PowerLight Technologies and Ericsson managed to power a 5G base station through safe laser beaming\(^1\).

Exploiting free space optical (FSO) links to provide airborne simultaneous lightwave information and power transfer (SLIPT) was introduced in [8], where the inherent energy-information transfer tradeoff was highlighted. In [13], the authors provided coverage analysis for large-scale deployments, which served as guidelines for the density of deployment of laser stations. In fact, operation optimization has taken a significant share of research contributions in this area [10]–[12], [14]–[20]. Among the aforementioned works, optimal UAV positioning was studied in [10] and [11], where the drone placement/trajectory and resource allocation were jointly optimized for a laser-powered drone acting as a flying base station (BS) serving a multitude of users with the aim of total flight time and communication data rate maximization.

The main contributions of this work include:

- exploiting the merits of both static and moving aerial platforms to provide a flexible remotely powered and operated data collection system that serves a field of passive IoT devices,
- presenting the minimum required laser output optical power needed to empower UAVs over different ranges and weather conditions while accounting for pointing error losses,
- deriving novel SCA-compatible upper bounds for the product of two positive convex/concave functions, that were heavily exploited to solve both the unspecified time horizon i) aggregate data maximization, and ii) overall laser energy consumption minimization problems,
- the derived bounds enabled us to solve the previously mentioned problems using single-block SCA, despite the intricacies associated with the probabilistic LoS channel model and path discretization formulation, which guarantees coverage to a Karush-Kuhn-Tucker
providing a novel asymptotically tight approximation for the UAV acceleration magnitude under path discretization and account for the acceleration magnitude effect on propulsion energy consumption, in addition to proposing a low-complexity solution for the aggregate data maximization problem,
• conducting a comprehensive set of simulations to show the optimization gains behavior against different critical system parameters such as the power beacon height, minimum data requirement, PDs locations, and laser source locations.

B. Paper Notations and Organization

Notations: In this paper, we represent vectors by small bold letters as $\mathbf{a}$, where $\mathbf{a} = [a_x \ a_y \ a_z]^T$, with $a_x$, $a_y$, and $a_z$ representing its $x$, $y$, and $z$ coordinates, respectively, and $(\cdot)^T$ represents the transpose operator. Furthermore, we use $||.||_2$ to denote the $\ell_2$-norm, while we use $|.|$ to represent the absolute value of a scalar, or the Lebesgue measure of a set. $\mathbb{I}(\cdot)$ represents an indicator function where $\mathbb{I}(\cdot) = 1$ if the condition $\cdot$ is satisfied and $\mathbb{I}(\cdot) = 0$, otherwise. We use calligraphic fonts to represent symbols for sets. The rest of this paper is organized as follows: first, we detail the adopted system and channel models in Section II. We then provide a mathematical formulation for joint trajectory optimization and resource allocation in Section III. Next, we propose a detailed SCA-based solution of the data maximization problem in Section IV and discuss the problem feasibility requirements in Section V. Then, we present the SCA-based solution of the laser energy minimization SCA solution, and then we propose a low-complexity solution for the collected data maximization problem in Section VI, followed by a set of extensive simulations to highlight the system dynamics and assess its performance in Section VII. Finally, the paper is concluded in Section VIII.

II. System model

In this work, we consider a laser-powered fixed-wing UAV traveling from a departure point ‘A’ towards a destination point ‘B’ at a fixed altitude $H$. Contrary to most of the existing literature, the flying time is not predetermined and therefore we adopt the path discretization approach [41]. Accordingly, we assume that the UAV path consists of $N_W$ way points, excluding ‘A’ and ‘B’, with a maximum distance between consecutive way points of $\Delta_M$. Specifically, $\Delta_M$ is set to guarantee negligible parameter variations between successive trajectory points. Hence, $N_W$ is selected as $[L_{UB}/\Delta_M] - 1$ to maintain the accuracy of the path discretization approximation, where $L_{UB}$ represents the maximum allowed total flight distance. To this end, the UAV’s location at the $n$-th way point is given by $q^{(n)} = [q^{(n)}_x \ q^{(n)}_y \ q^{(n)}_z]^T$ m with the origin assumed to be located right below ‘A’ on the ground plane. In addition, we denote by $\mathbf{v}[n] = [v_x[n] \ v_y[n] \ 0]^T$ m/sec, and $\mathbf{a}[n] = [a_x[n] \ a_y[n] \ 0]^T$ m/sec$^2$ the velocity and acceleration vectors at the $n$-th way point, respectively, where $v_- \leq ||\mathbf{v}||_2 \leq v_+$, and $||\mathbf{a}||_2 \leq a_M$.

The network features $K$ terrestrial PDs whose data is continuously collected by the UAV via backscatter communications in a time division multiple access (TDMA) fashion. Specifically, the location of the $i$-th PD is given by $q_i = [q^x_i \ q^y_i \ 0]^T$ m. In addition, a power beacon source is placed at ‘PB’ with coordinates $q_{PB} = [x_{PB} \ y_{PB} \ z_{PB}]^T$, generating an unmodulated carrier signal at a carrier frequency of $f_c$ Hz with an instantaneous radiated power of $p_B[n]$, that should not exceed a maximum limit $p_B^{\max}$. Without loss of generality, we assumed that such a source could be a tethered aerostat or a helikite, although other possibilities include, for example, mobile deployable towers. Such a helikite/aerostat could be fixed with three tension wires that are controlled by motors to counteract wind effects and keep its position relatively stable as studied in [42]. The PDs scatter the impinging waves from the power beacon source while modulating them with their generated data, where the modulation bandwidth is denoted by $B_s$ as depicted in Fig. 1. The power beacon transmitter is electrically powered via a battery having a capacity of $E_B$ Joules.

The laser station, assumed to be located at point ‘L’ defined by $q_L = [x_L \ y_L \ z_L]^T$ m, radiates $p_L[t]$ W of optical power with a maximum value of $p_L^{\max}$. In addition, the UAV carries a photoelectric converter, of area $A_{PD}$ m$^2$ and photodetector responsivity $R_{PD}$ A/W. The photodetector aperture is assumed to be perfectly oriented orthogonal to the line joining the laser source and the photoelectric converter center throughout the whole flight duration to ensure maximum power transfer. Moreover, we assume that the laser source is attached to an APT system that supports wide angular range and fast switching response to handle the potential laser narrow beam interruptions and agile UAV dynamics. Such features can be best supported by hybrid gimbal and fast switching mirror or a hybrid radio frequency (RF)-FSO APT system [5].
A. Laser beam imperfections

It is evident that the laser beam’s total radiated power experiences many forms of losses along its path of propagation to the photovoltaic converter onboard the UAV. First, a portion of the emitted optical power is scattered and absorbed by atmospheric particles, e.g., rain, fog or smoke to mention a few. Second, the temperature variations along the beam propagation path result in a variable refractive index and consequently beam scintillation, a.k.a turbulence, which reduces the power captured by the receiving aperture. In addition, due to the imperfect estimation of the UAV’s location, mechanical friction, and vibration of the used pointing and tracking system, pointing losses need to be accounted for. Finally, the laser-emitted power is distributed over a larger area as the beam propagates away from the laser aperture. This beam spreading leads to a decrease in the power being absorbed by the photoelectric converter, denoted by geometric losses. This loss is totally determined by the aperture size, the beam divergence angle, and the separation distance between the laser and the photoelectric converter apertures.

The extinction coefficients associated with absorption and scattering losses can be quantified for rain, snow [43], fog, and smoke [44], respectively, as

\[
\alpha_{\text{Rain}} = 0.1076 \times 10^{-3} \ln(10) \frac{\lambda}{R_v^{2/3}},
\]

\[
\alpha_{\text{Snow}} = 0.1 \times 10^{-3} \ln(10) \frac{\lambda}{a S_b^b},
\]

\[
\alpha_{\text{Fog}} = \frac{0.17 \times 10^{-3} \ln(10)}{V} \left( \frac{\lambda}{\lambda_0} \right)^{-q_{\text{fog}}(\lambda)}.
\]

\[
\alpha_{\text{Smoke}} = \frac{0.17 \times 10^{-3} \ln(10)}{V} \left( \frac{\lambda}{\lambda_0} \right)^{-q_{\text{smoke}}(\lambda)},
\]

where \( R_v \) is the rain rate in mm/h, \( S_b \) is the snow rate in mm/h, \( \lambda \) represents the laser wavelength in m, \( V \) is the laser beam visibility in km, and \( \lambda_0 \) is the visibility reference wavelength in m. In addition, the turbulence losses can be expressed as

\[
L_{\text{Turb}} = 10^{-\alpha_{\text{scin}} ||q^b||^2 - q_L||z||^2/4},
\]

where

\[
\alpha_{\text{scin}} = 2 \sqrt{23.17 \left( \frac{2 \pi}{\lambda} \right)^{7/6} C_n^2 \frac{||q^b||^2}{||q^0||^2} ||q^b||^2 z^{11/6}},
\]

\( C_n^2 \) is 10^{-16} for weak turbulence, 10^{-14} for moderate turbulence, and 10^{-13} for strong turbulence. Finally, the pointing losses can be expressed as [45, Eq. 2.21]

\[
L_p = e^{-s(t_{\text{max}} + t_{\text{ave}})^2},
\]

where \( t_{\text{ave}} \) represents the total angular misalignment error between the laser beam axis and the line joining the centers of the laser source and the photodetector apertures.

III. Problem Formulation

With the aim of increasing the UAV’s data collection capability, we now focus on maximizing the harvested data by the UAV from the PDs throughout its flight, having a maximum length \( L_{\text{UB}} \). Hence, we are interested in finding the optimal values for (i) the UAV waypoint locations \( \{q^u[n]\}_{n=1}^{N_w} \), (ii) the time intervals between two successive trajectory points \( \{\Delta t^u[n]\}_{n=1}^{N_w} \), and (iii) the radiated power profiles of the power beacon and the laser sources \( \{p_b[n]\}_{n=1}^{N_w+1} \) and \( \{p_L[n]\}_{n=1}^{N_w+1} \), respectively.

We adopt the probabilistic LoS channel model to account for potential blocking effects in different environments [46], while small scale fading effects are ignored. Consequently, the average collected data, to be maximized, can be expressed as

\[
D = \sum_{i=1}^{K} D_i,
\]

\[
D_i = \sum_{n=1}^{N_w+1} \frac{B_n}{K} \Delta t^u[n] \log_2 \left( 1 + \frac{p_b[n] \delta_{\text{L},i} \delta_{\text{R},i} \frac{\rho_{\text{L},i}}{\rho_{\text{R},i}}}{\mu_{\text{L},i}} \right),
\]

where \( P \) is the transmit power, \( \delta_{\text{L},i} \) and \( \delta_{\text{R},i} \) represent the channel path loss exponents for LoS and Non-LoS cases, respectively. Finally, \( \zeta_{\text{L},i} \) and \( \zeta_{\text{R},i} \) are the path loss exponents for the LoS and Non-LoS power beacon, respectively, and can be expressed as [39]

\[
\zeta_{\text{L},i} = \frac{1}{\rho_{\text{L},i}} \frac{1}{\rho_{\text{R},i}} \frac{1}{\zeta_{\text{L},i}},
\]

where \( \rho_{\text{L},i} \) and \( \rho_{\text{R},i} \) are the power beacon and the laser sources, respectively.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/
In addition, we adopt the non-linear model given by [48, Eq. 2.21] to represent the harvested power by the UAV:

\[
P_H[n] = 0.75 V_i x[n] \ln (1 + x[n]/I_o),
\]

where \( V_i \) represents the thermal voltage, \( x[n] \) is the photocurrent generated at the photodiode by the impinging laser beam, and \( I_o \) is the dark saturation current with \( x[n] \) given by [49]

\[
x[n] = A_{PD} \cdot P_{PD} \cdot P_L[n] e^{-\alpha d_B[n]} r_{LUM} L_{TM} L_P,
\]

where \( \alpha \) is the extinction coefficient, \( D_o \) is the laser beam diameter at the aperture, \( \Delta \theta \) is the laser angular beam deviation, \( d_B[n] = ||q[n] - q_L||_2 \), and \( r_{LUM} = ||D_o + \Delta \theta d_B[n]||_2 \). In terms of the UAV’s propulsion power at the \( n \)-th way point, the following approximation is adopted, by replacing \( ||a||_2 \) in [50, Eq. 12] with \( a_M \)

\[
\hat{p}_R[n] = c_1 ||| \vec{v}[n] ||_2^2 + \frac{c_2}{||| \vec{v}[n] ||_2^2} \left( 1 + \frac{a_M^2}{g^2} \right),
\]

where \( c_1 \) and \( c_2 \) are constants that depend on the UAV’s characteristics and the experienced wind properties. Consequently, the harvested data maximization problem can be expressed as

\[
(P1) \quad \max_{Q, \Delta t, \hat{p}_R} \hat{D}
\]

s.t.

\[
C_1: ||q'[n] - q''[n - 1]||_2 \leq \Delta t, \quad \forall n \in N_1, \\
C_2: v \leq ||\vec{v}[n]||_2 \leq \bar{v}, \quad \forall n \in N_1, \\
C_3: ||\vec{a}[n]||_2 \leq a_M, \quad \forall n \in N_2, \\
C_4: \hat{p}_R[n] \leq \bar{p}_B[n], \quad \forall n \in N_1, \\
C_5: \sum_{n=1}^{N_W+1} \Delta t[n] p_B[n] \leq \bar{E}_B, \\
C_6: p_B[n] \leq \bar{p}_B = \bar{p}_B^\text{max}, \quad \forall n \in N_1, \\
C_7: p_B[n] \geq 0, \quad \forall n \in N_1, \\
C_8: D_i \geq D_{\text{min}}^\text{ind} \quad \forall i \in \{1, \ldots, K\},
\]

where (i) \( Q \) represents the set of way-point locations \( \{q'[n]\}_{n=1}^{N_W+1} \), (ii) \( \Delta t \) represents the set of interval durations between the UAV successive transitions \( \{\Delta t[n]\}_{n=1}^{N_W+1} \), (iii) \( p_B \) is the set of radiated power variables by the power beacon source at the trajectory points \( \{p_B[n]\}_{n=1}^{N_W+1} \), and (iv) \( \hat{p}_B \) represents the radiated laser power variables \( \{\hat{p}_B[n]\}_{n=1}^{N_W+1} \). Moreover, \( N_1 = \{1, \ldots, N_W + 1\} \), \( N_2 = \{2, \ldots, N_W + 1\} \), and we enforce initial and final UAV positions through \( q[0] = q_A \) and \( q[N_W + 1] = q_F \), respectively. Finally, \( E_B = \bar{E}_B/\eta_\text{rad} \), with \( \eta_\text{rad} \) being the ratio between the radiated power from the beacon transmitter to the supplied power.

In the previous formulation, \( C_1 \) ensures a minimum path discretization accuracy while \( C_2 \) imposes the minimum and maximum speed constraints of the UAV. In addition, \( C_3 \) enforces the maximum acceleration magnitude whereas \( C_4 \) ensures that the propulsion power needed by the UAV is supplied by the harvested power. Moreover, \( C_5 \) embodies the limited battery capacity of the power beacon source, where the total radiated energy throughout the UAV’s flight cannot exceed a certain threshold. Furthermore, the box constraints in C6 and C7 enforce a maximum power restriction for both radiation sources and positiveness of the radiated powers and the UAV’s inter-way-points durations, respectively. Finally, \( C_8 \) guarantees that each PD transfers at least \( D_{\text{min}}^\text{ind} \) bits throughout the UAV’s flight.

Following an approach similar to that of [46], we lower bound \( D \) by neglecting the NLoS contribution terms in (11), due to the huge channel magnitude gap with respect to the pure LoS term, to get \( D_{\text{LB}} \) given by

\[
\hat{D}_{\text{LB}} = B_\infty/(K \ln(2)) \sum_{i=1}^K \sum_{n=1}^{N_W+1} \Delta t[n] \bar{p}_B[i][n] \ln \left( 1 + p_B[n] \xi_1 d_{C1}^{-\alpha_1}[n] \right).
\]

To tackle the non-convexity of \((P1)\), we first adopt the following change of variables \( \hat{p}_B[n] = \Delta t[n] p_B[n] \forall n \). Moreover, \( \hat{\vec{a}}[n] \) in \((C3)\) is replaced by \( \hat{\vec{a}}[n] \) in \((C3)\) with \( \bar{a}_M \)

\[
\hat{p}_B[n] \leq \bar{p}_B = \bar{p}_B^\text{max}, \quad \forall n \in N_1, \\
C_7': \bar{p}_B[n] \geq 0, \quad \forall n \in N_1, \\
C_8': D_i \geq D_{\text{min}}^\text{ind} \quad \forall i \in \{1, \ldots, K\},
\]

where \( \hat{P}_H[n] = P_H[n] \bar{p}_B[n] = p_B^\text{max} \forall n \), widens the feasibility space. Hence, we solve the optimization problem \((P1)\), which is an approximation of \((P1)\):

\[
(P1) \quad \max_{Q, \Delta t, \hat{p}_B} \hat{D}_{\text{LB}}
\]

s.t.

\[
C_1, C_2, C_3', \|\hat{\vec{a}}[n]\|_2 \leq a_M, \quad \forall n \in N_2, \\
C_4', \hat{p}_R[n] \leq \bar{P}_H[n], \quad \forall n \in N_1, \\
C_5', \sum_{n=1}^{N_W+1} \hat{p}_B[n] \leq \bar{E}_B, \\
C_7': \bar{p}_B[n] \geq 0, \quad \forall n \in N_1, \\
C_8': D_i \geq D_{\text{min}}^\text{ind} \quad \forall i \in \{1, \ldots, K\},
\]

where \( \bar{P}_H[n] = P_H[n] \bar{p}_B[n] = p_B^\text{max} \).

### A. UAV Laser Charging Feasibility

Before delving into the solution details, the feasibility of laser power beaming for fixed-wing UAVs under different weather conditions is worth discussion. To keep the UAV aloft, the laser beam has to deliver the least propulsion power needed for the desired coverage range, which can be well approximated by [51]

\[
p_{\text{min}}^\text{Pr} = a_1 v_{\text{em}}^3 + \frac{a_2}{v_{\text{em}}} (1 + a_3 g / g^2),
\]

where \( v_{\text{em}} = \frac{(a_2 (1 + a_3 g / g^2)^2)^{1/3}}{3a_1} \).

Towards this end, we study the minimum required laser output optical power to keep the UAV flying for different mission range requirements as shown in Fig. 2. Specifically, the results presented in such a figure show that 1 KW of output laser power is sufficient to cover more than 2 Km under clear weather conditions. However, in the presence of haze the range decreases to 1.5 Km, 1.2 Km with light rain, and
800 m under light snow conditions. Although those ranges are much larger than what tethered drones can offer, under severe weather conditions, e.g., heavy fog and smoke, laser power beaming may not be a viable solution.

IV. Aggregate Data Maximization via SCA

To reach a KKT solution for (P1), certain manipulations are needed for the non-convex terms. Particularly, we first derive locally tight, gradient matching, concave lower and convex upper bounds for the non-convex terms of (P1), which are provided in Appendix B, to construct the convex problem (P2) expressed as

\[
(P2) \quad \max_{\Delta t, p_B} \quad \sum_{i=1}^{K} \sum_{n=1}^{N_W+1} \tilde{D}_{LB,i}[n] \\
\text{s.t.} \quad C1, C2a, C5', C6', C7', \quad C4'' : \tilde{P}_R[n] \leq \tilde{P}_H[n], \forall n \in N_1, \\
C2a' : \tilde{s}[n] \geq v_+ \Delta t[n], \forall n \in N_1, \quad C2b : \|q[n] - q[n - 1]\|_2 \leq v_+ \Delta t[n], \forall n \in N_1, \quad C3' : \|q[n] - 2q[n - 1] + q[n - 2]\|_2 \leq a_M \Delta t[n], \forall n \in N_2, \quad C8' : \sum_{n=1}^{N_W+1} \tilde{D}_{LB,i}[n] \geq D_{\text{ind}}^{\text{min}}, \forall i \in \{1, \ldots, K\}.
\]

Then, we employ the SCA algorithm to solve (P1) by solving a different (P2) instance at each SCA iteration, until convergence is reached as shown in Algorithm I. It is worth mentioning that Algorithm I incurs an iteration complexity of \(O(I_{\text{SCA}}(4N_W + 2)^3.5)\), where \(I_{\text{SCA}}\) represents the number of outer iterations needed by the SCA approach to converge.

Algorithm I: Aggregate Data Maximization via SCA

1: Initialize \(Q^o, \Delta t^o, p_B^o\), Relative Error
2: while Relative Error \(\geq \epsilon_{\text{ener}}\) do
3: Solve (P2) for \(Q, \Delta t, p_B\) via interior point method.
4: Relative Error \(\leftarrow |D_{LB} - D_{LB}^o| / D_{LB}^o\)
5: \(Q^o \leftarrow Q, \Delta t^o \leftarrow \Delta t, p_B^o \leftarrow p_B\)
6: end while

V. Laser Energy Minimization

On the other performance end, energy expenditure is of utmost importance. Hence, the minimization of the laser energy expenditure over the flight that governs a minimum amount of collected data set by the mission goals is formulated as

\[
(P3) \quad \min_{Q, \Delta t, p_B, p_L} \quad \sum_{i=1}^{K} \sum_{n=1}^{N_W+1} p_L[n] \Delta t[n] \\
\text{s.t.} \quad C1 - C8, \quad C9 : \tilde{D} \geq \tilde{D}_{\text{min}}.
\]

The non-convexity of the previous problem is evident as it shares all the constraints of (P1) along with the non-convex objective function formed by the sum of bilinear terms. To guarantee a KKT point solution, we iteratively solve (P3) using the single-block SCA approach, and, in particular by solving the convex problem (P3) at each iteration.

\[
(P3) \quad \min_{Q, \Delta t, p_B, p_L} \quad \sum_{i=1}^{K} \sum_{n=1}^{N_W+1} \left( (p_L[n] + \Delta t[n])^2 + (p_{L,o}[n] - \Delta t_o[n])^2 - 2(p_{L,o}[n] - \Delta t_o[n])(p_L[n] - \Delta t[n]) \right) \\
\text{s.t.} \quad C1, C2a', C2b', C5', C6', C7', C8', \\
C4'' : \tilde{P}_R[n] \leq \tilde{P}_{H,2}[n], \forall n \in N_1, \\
C9' : \sum_{i=1}^{K} \sum_{n=1}^{N_W+1} \tilde{D}_{LB,i}[n] \geq D_{\text{min}},
\]

where \(p_{L,o}[n]\) represents the value of \(p_L[n]\) in the previous SCA iteration, and \(\tilde{P}_{H,2}[n]\) represents an SCA-compatible lower bound for the instantaneous harvested energy when the instantaneous laser power is considered as a variable parameter, unlike \(\tilde{P}_H[n]\).

\[
\tilde{P}_{H,2}[n] = a_o[n] + b_o[n] c_o[n] p_L[n] - b_o[n] d_o[n] f_{n UB}[n], \quad (21)
\]

where \(a_o[n], b_o[n], c_o[n]\), and \(d_o[n]\) are constants, and \(f_{n UB}[n]\) is a convex function of all the optimization parameters\(^2\).

It is worth mentioning that the feasibility of (P3) can be determined by solving (P1) optimally, and checking if the optimal amount of the collected data surpasses \(D_{\text{min}}\).

Finally, the solution of (P3) proceeds as depicted in Algorithm II, where \(E_L\) represents the laser energy expenditure throughout the whole flight evaluated using the

Algorithm II: Laser Energy Minimization

1: Initialize \(Q^o, \Delta t^o, p_B^o, p_L^o\), Relative Error
2: while Relative Error \(\geq \epsilon_{\text{ener}}\) do
3: Solve (P3) for \(Q, \Delta t, p_B, p_L\) via interior point method.
4: Relative Error \(\leftarrow |E_L - E_{L}^o| / E_{L}^o\)
5: \(Q^o \leftarrow Q, \Delta t^o \leftarrow \Delta t, p_B^o \leftarrow p_B, p_L^o \leftarrow p_L\)
6: end while

\(^2\)The definitions of the constants and \(f_{n UB}[n]\) are all provided in Appendix B
updated values of \( Q, \Delta t, p_B, \rho_L \) whilst \( E_{\text{I}}^{\text{eq}} \) is its previous iteration counterpart. In addition, Algorithm II incurs an iteration complexity of \( O(I_{\text{SCA,2}}(5N_W + 3)^3) \), where \( I_{\text{SCA,2}} \) represents the number of outer SCA iterations the algorithm takes to converge.

VI. Low Complexity Aggregate Data Maximization

In this section, we provide a simpler way to find a feasible trajectory and power beacon radiated power profile aiming at maximizing the aggregate collected data by the UAV throughout its flight. It is clear that the aggregate data increases by lengthening the overall flight duration and by improving the channel gains between the UAV and the PDs. The former can be realized by slowing down the UAV as much as possible and the latter can be attained by keeping the UAV in close vicinity of the PDs.

In our simplified approach, we assume the UAV path is restricted to straight lines and circular arcs while moving at a constant speed \( v_c \). To maintain the velocity vector continuity as a function of time, we enforce that the UAV transition from a linear path to a circular path is performed at a point where both path portions are tangential. Based on the previously mentioned preferences for the UAV trajectory with respect to aggregate data maximization, we propose the UAV path depicted in Fig. 3. In such a trajectory, the UAV moves in a straight line till it reaches the point right above the centroid of the sensors ‘\( \bar{S} \)’ in the UAV flight plane. Then, it initiates a circular turn and concludes the turn at ‘\( X \)’ in a tangential straight line heading towards ‘\( B \)’ after completing the maximum possible number of cycles \( n_c \) over the PDs’ region. To fully specify the trajectory, we need to determine the radius of turn \( r_t \) and the UAV’s speed throughout the trajectory.

From an objective maximization perspective, it is favorable to reduce the UAV’s speed and reduce the turn radius to keep close to the sensors and be able to complete larger number of cycles. Nonetheless, both actions might result in violating the power budget and acceleration magnitude requirements of the problem. Consequently, we first introduce a more restrictive version of the power budget constraint that simplifies the turn radius and speed search as

\[
\nu = \frac{p_{\text{L}}^{\text{max}}L_D}{\left(\frac{\sqrt{d_{SL}^2+2r_t^2}}{d_{SL}}+\sqrt{d_{AL}^2+d_{BL}^2}\right)^2} + \left(1 + \frac{a_{\text{max}}^2}{g^2}\right)
\]

We propose that the UAV takes the maximum number of turns before it heads towards ‘\( B \)’. Accordingly, \( n_c \) is expressed as

\[
n_c = \left\lfloor \frac{L_{UB} - |A\bar{S}| - |XB|}{2\pi r_t} \right\rfloor.
\]

Now, the minimal UAV trajectory is fully specified by \( r_t \) and \( v_c \). We propose that the UAV takes the maximum number of turns before it heads towards ‘\( B \)’. Accordingly, \( n_c \) is expressed as

\[
n_c = \left\lfloor \frac{L_{UB} - |A\bar{S}| - |XB|}{2\pi r_t} \right\rfloor.
\]

At this point, the trajectory path is discretized by dividing it into equal length segments, where the number of segments is determined by \( L_{UB} \) and \( N_W \), as indicated in the previous sections. By plugging the derived trajectory into (P1), the power beacon radiated power profile is determined by

\[
(P4) \max_{\bar{p}_B} P_B \sum_{i=1}^{K} \sum_{n=1}^{N_W+1} \Delta t[n]P_{L,i}[n]P_{L,i}[n] \ln \left(1 + \frac{\zeta_{i,i}L_{UB}^2}{\Delta t[n]d_{SL}^2[n]} \right)
\]

\[
C6', 0 \leq \bar{p}_B [n] \leq p_{\text{B}}^{\text{max}}, \forall n \in \{1, \ldots, N_W + 1\}
\]

which is a convex problem that can be solved by solving its KKT system at a quadratic iteration complexity. 

\[3\] The KKT solution is omitted for brevity.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/
VII. Simulation Results

In this section, we assume default initial and final UAV locations defined by \( q_A = [0 0 80]^T \) m and \( q_B = [1000 1000 80]^T \) m, respectively, while the default laser source and the power beacon locations are \( q_L = [1000 0 20]^T \) m and \( q_{PB} = [200 600 60]^T \) m, respectively, although other locations would work as well. In addition, we assume that the PDs are placed evenly on 6 concentric circles on the ground around the power beacon, where the largest circle has a radius of 500 m. Moreover, the system parameters, summarized in Table 1, are set based on [10], [11], [39] with \( f_c = 900 \text{ MHz} \), \( D_{\text{ind}} = 0 \) and \( g = 9.8 \text{ m/sec}^2 \). With the aim of providing a fair comparison, we also include different benchmark algorithms. Particularly, the five different solutions are: (i) the data maximization solution using SCA (DMSCA), (ii) the energy minimization solution using SCA (EMSCA), (iii) the low-complexity linear-circular-linear (LCL) solution (as explained in Section VI), (iv) the energy minimization solution using SCA with a constant speed constraint (EMCS), (v) the data maximization solution using SCA with a constant speed constraint (DMCS), and (vi) the straight path solution where the UAV directly flies from ‘A’ to ‘B’ and power allocation is done similar to ‘LCL’ while the UAV moves at the power minimizing speed. In the following simulations, the LCL solution is used to initialize the DMSCA, EMSCA, DMCS, and the EMCS solutions. Finally, the pointing errors due to the angular localization uncertainty and the pointing devices aiming errors are both assumed to be submicroradian contributing to a total angular pointing uncertainty \( \theta_{\text{err}} = 2 \mu \text{rad} \).

A. System Dynamics

To gain insights into the dynamic behavior of the considered aerial data collection system, we fix all system parameters and observe the UAV’s path and instantaneous speed pro-

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( D_{\alpha} )</td>
<td>10 cm</td>
</tr>
<tr>
<td>( v_- )</td>
<td>3 m/sec</td>
</tr>
<tr>
<td>( R_{PD} )</td>
<td>1 A/W</td>
</tr>
<tr>
<td>( n_b )</td>
<td>0.043</td>
</tr>
<tr>
<td>( \Delta \theta )</td>
<td>( 2 \times 10^{-5} )</td>
</tr>
<tr>
<td>( v_T )</td>
<td>0.025 V</td>
</tr>
<tr>
<td>( K )</td>
<td>54</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>( 10^{-6} )</td>
</tr>
<tr>
<td>( \beta_0 )</td>
<td>( 7 \times 10^{-4} )</td>
</tr>
<tr>
<td>( \sigma^2 )</td>
<td>-174 dB</td>
</tr>
<tr>
<td>( C_1 )</td>
<td>-0.63</td>
</tr>
<tr>
<td>( C_2 )</td>
<td>1.63</td>
</tr>
<tr>
<td>( \alpha_N )</td>
<td>3.5</td>
</tr>
<tr>
<td>( \beta_0 )</td>
<td>7 \times 10^{-4}</td>
</tr>
<tr>
<td>( \sigma^2 )</td>
<td>-174 dB</td>
</tr>
<tr>
<td>( C_1 )</td>
<td>-0.63</td>
</tr>
<tr>
<td>( C_2 )</td>
<td>1.63</td>
</tr>
<tr>
<td>( \alpha_N )</td>
<td>3.5</td>
</tr>
</tbody>
</table>
constant velocity, i.e., $v_c$, is higher than the speed profile of the DMSCA solution within the data transmission window owing to the fact that $v_c$ is set according to the furthest UAV way-point from the laser source.

Fig. 6 shows that DMSCA and DMCS solutions tend to increase the power of the beacon source power transmission until it reaches the maximum value and maintains it within the data transmission window, then decreases to zero. This owes to the progression of the UAV’s path where the initial way-points and the final way-points are far from the PDs, hence experiencing weak channels. EMSCA and EMCS solutions use the maximum beacon source power throughout the whole flight to shorten the flight as much as possible.

It is evident that the DMSCA and DMCS solutions push the laser source to use the maximum power throughout the whole flight duration, as shown in Fig. 7 and highlighted in the transition from $(P3)$ to $(P3)$. On the other hand, EMSCA and EMCS push the solution towards achieving the power budget constraint with equality by using the minimum feasible laser power. Hence, the laser radiated power profile is shaped by the UAV’s distance from the laser source for the EMCS solution, while it is shaped by both the UAV-laser separation distance and the UAV’s velocity for the EMSCA solution.

B. Performance Evaluation

In the simulations presented in this section, we vary one of the system parameters and monitor its impact on the performance in terms of laser energy consumption and the total collected data for the proposed solutions. As changing the simulation parameters generally affects the collected data performance of the LCL solution (initial point for EMSCA and EMCS), we set $D_{\text{min}}$ for each of the following simulations to 90% of the minimum value achieved by the LCL solutions associated with the study to ensure a fair comparison and feasibility of the problem.

By varying the laser location as shown in Fig. 8, it is observed that the collected data of the DMSCA solution exhibit unimodal behavior. The local maximum of this trend occurs around the laser source alignment with the center of the PDs’ deployment region. The DMCS and the initial solution show a similar collected data trend, albeit, at a different maximum location owing to constant speed restriction, which makes the optimal laser location different from the DMSCA case. On the other hand, the laser energy consumption of the EMSCA solution exhibits a unimodal behavior with a local minimum that mimics the UAV-laser source separation distance behavior. The EMCS solution follows a different trend in energy consumption compared to the EMSCA solution. This is due to the reduced impact of the relative PDs’ deployment-laser location attributed to fixing the UAV’s speed, which reduces the UAV maneuverability. Simulation results of changing the laser source y-coordinate while keeping the x-coordinate fixed produce similar conclusions and are not included for brevity.

In Fig. 9, the effect of the PD deployment is studied by altering the radius of the deployment circle. The performance...
of the collected data of all proposed solutions deteriorates as $R_e$ increases. This is due to the deterioration of the wireless power links between the beacon source and the PDs as a result of increased pathloss. Similarly, the energy consumption increases with $R_e$ as satisfying the same data collection requirement requires longer flight intervals.

In Fig. 10, we monitor the effect of the battery capacity of the power beacon source on the proposed solutions. It is observed that since the power beacon source is supplied with a larger-capacity battery, both the data maximization and the energy minimization solutions perform better. This is because of the system capability to support high-power transmission for longer intervals. Nevertheless, the performance enhancement saturates at a certain point when the system becomes able to offer the maximum radiated power for the entire flight duration. In this case, the maximum allowed radiated power by the power beacon source limits the system performance.

In Fig. 11 and Fig. 14, the minimum aggregate and individual data requirements are increased, respectively, and the laser energy consumption is observed. It can be seen clearly that increasing $D_{\text{min}}$ or $D_{\text{min}}^{\text{ind}}$ increases the laser energy consumption, as it requires the UAV’s flight duration to be extended to collect the excess amount of data. In addition, it can be seen that the laser energy savings offered by optimization decreases as the data requirement increases and approaches the data amount provided by the initial solution.

Finally, the impact of the power beacon height on the system performance is studied and presented in Fig. 12. It can be seen that the average harvested data experiences a unimodal behavior that features a local maximum. The likelihood of line-of-sight (LoS) outweighs the increased propagation losses caused by greater distances when the beacon source is at a low altitude, resulting in this result. However, at higher altitudes, the LoS probability approaches saturation as the elevation angle approaches $90^\circ$ while the propagation losses increase at the same pace. The energy performance exhibits a unimodal behavior as well, with a local minimum due to deterioration of channel gains between the power beacon source and the PD’s for low and high heights due to low LoS probability and large path loss, respectively. Furthermore, it is clear that the optimal height power beacon deployment altitude depends on the altitude of the UAV as observed in Fig. 13. The performance gap between the DMSCA solution and the LCL solution stems from the constant speed and inconsideration of PDs layout features of the LCL solution. The straight path performs even worse due to the inconsideration of the power beacon source location.

In all simulations, the DMSCA solution showed superiority over the DMCS, which performs better than the initial solution, and all of them outperformed the straight-path solution. Similarly, the EMSCA solution outperforms all other solutions, while the EMCS solution outperforms the initial solution. In addition, the trade-off between laser energy consumption and the collected data throughout the flight is clearly seen in the energy consumption gap between the DMSCA and the EMSCA solutions. Moreover, it is observed that the data collection performance improvement offered by DMSCA over DMCS fluctuates between 8% and 48% depending on the laser location, while DMSCA outperforms the LCL solution by 80% - 100%. On the energy consumption frontier, EMCS provides 29% laser energy reduction compared with the LCL solution, while the EMSCA solution provides 100% energy reduction for the majority of the simulation points.

VIII. Conclusion

In this paper, we considered a laser-powered fixed-wing UAV-aided data collection system serving an IoT field of passive devices via bistatic backscatter wireless links. We aimed at minimizing the laser source’s overall energy consumption whilst guaranteeing a minimum amount of collected data from the passive devices. Towards this aim, we studied the UAV trajectory, and the radiated power profile of both the laser source and the power beacon source. Adopting path discretization, we solved the energy minimization problem and its associated feasibility problem via SCA over the joint set of variables. The conducted simulations highlighted the dependencies between the UAV path, dynamics and the system energy delivery behavior at both the laser station and the power beacon source. In particular, it was found that relaxing the UAV power budget enables the UAV to
FIGURE 9: PDs deployment simulation

FIGURE 10: Power beacon battery capacity simulation

FIGURE 11: Minimum aggregate data requirement simulation

FIGURE 12: Average harvested data vs power beacon height

FIGURE 13: Average harvested data for different UAV heights

FIGURE 14: Minimum individual data requirement simulation.
slow down over the IoT devices field and take sharper turns without violating the maximum acceleration magnitude constraint. Hence, the UAV can loop around the passive devices in tighter circles and collect the required amount of data in a shorter time.

Appendix A: Asymptotic approximation of path discretized time intervals proof
It can be noticed that for efficient sampling (guaranteeing that any two successive points are not more than $\Delta_M$ apart with the least number of points), we need

$$N_W = \left\lfloor \frac{L}{\Delta_M} \right\rfloor$$ (26)

Hence,

$$\frac{L}{\Delta_M} \leq N_W < \frac{L}{\Delta_M} + 1,$$ (27)

which is equivalent to

$$\frac{L}{N_W} \leq \Delta < \frac{L}{N_W - 1}.$$ (28)

Consequently, for fixed $L$, as $N_W$ increases, the upper bound on $\Delta$ decreases. Now by adding the UAV’s speed bounds $v_{\text{min}} \leq v \leq v_{\text{max}}$ and after some straightforward manipulations, we obtain

$$\frac{\|q[n] - q[n-1]\|}{v_{\text{max}}} \leq \Delta t[n] \leq \frac{\|q[n] - q[n-1]\|}{v_{\text{min}}} \leq \frac{\Delta}{v_{\text{min}}} < \frac{L}{(N_W - 1) v_{\text{min}}},$$ (29)

which leads to a decreasing bound on $|\Delta t[n] - \Delta t[n-1]|$ w.r.t. $N_W$ as

$$|\Delta t[n] - \Delta t[m]| < \frac{L}{(N_W - 1) v_{\text{min}}}.\quad (30)$$

The previous inequality implies that $\Delta t[n]$ and $\Delta t[m]$ get closer as $N_W$ increases.

Appendix B: SCA bounds Derivations of (P1) and (P3)
The subsequent theorems propose generic SCA-compatible bounds for the product of two positive convex functions and the product of a positive convex and a positive concave function, and are used heavily in the following SCA bound derivations.

Theorem 1. If $f(x) \geq 0$, $\forall x \in D_1$, and $g(y) \geq 0$, $\forall y \in D_2$, $f(.),$ $g(.)$ are both convex over $D_1$, $D_2$, respectively, then

$$f(x)g(y) \leq F(f,g) = \frac{1}{4}(f_2^2 + f_{d,o}^2 - 2f_{d,o}f_2) \times$$

$$(I_1(f_2 - f_2) + f(x) - \tilde{g}(y)), \forall (x,y) \in \hat{D}, (x_o,y_o) \in \hat{D},$ s.t. $f_2 = f(x) + g(y), f_{d,o} = f(x_o) - g(y_o), I_1 = 1$ if $f_{d,o} \geq 0,$

$I_1 = 0$ o.w., $\tilde{g}(z) = \chi(z_o) + \nabla \chi(z_o)(z-z_o), \hat{D} = D_1 \times D_2.$

Proof:

$$4f(x)g(y) = f_2^2 - f_{d,o}^2 \leq f_2^2 + f_{d,o}^2 - 2f_{d,o}f_2 \leq f_2^2 + f_{d,o}^2 - f_{d,o}(f_1(\bar{f}(x) - g(y)) + (1 - I_1)(f(x) - \tilde{g}(y))),$$

where the convexity of $f_2$ holds as $(.)^2$ is a convex increasing function for positive argument. Hence, its composition with the convex $f_2$ is convex. Particularly, (a) follows from lower bounding the $(.)^2$ function of the second term by its first order Taylor series (F.O.T) approximation. Similarly, (b) follows by decomposing $f_{d,o}$ into $f_{d,o}I_1$ and $f_{d,o}(1 - I_1)$. Then, lower bounding the $f(x)$ term within the former and the $g(y)$ term the latter with their F.O.T approximations completes the proof.

$$f(x)g(y) \leq G(f,g) = \frac{1}{4}(f(x) + \tilde{g}(y))^2 + f_{d,o}^2 - 2f_{d,o}(I_1f - f_{d,o} + f_{d,o})),$$

$$\forall (x,y) \in \hat{D}, (x_o,y_o) \in \hat{D}, f_d = f(x) - g(y).$$

Proof:

$$4f(x)g(y) \leq (f(x) + \tilde{g}(y))^2 + f_{d,o}^2 - 2f_{d,o}f_d \leq (f(x) + \tilde{g}(y))^2 + f_{d,o}^2 - 2f_{d,o}(I_1f + (1 - I_1)f_{d,o}),$$

where (a) follows from upper bounding $g(y)$ by its F.O.T. The convexity of $(f(x) + \tilde{g}(y))^2$ follows from the convexity function $g(.)$ in the argument. Likewise, (b) follows by decomposing $f_{d,o}$ as in the proof of Theorem 1, and lower bounding the convex $f_{d,o}$ associated with $I_1$ by its F.O.T approximation.

A. Aggregate data SCA-compatible lower bound derivation
We first derive a lower bound for $\hat{D}_{LB,i}[n]$, presented in (18), by applying [46, Lemma 2] to get $(\hat{D}_{LB,i}[n])$. Next, through [46, Lemma 3], a lower bound on the latter term is obtained. Therefore, it follows: $\hat{D}_{LB,i}[n] \geq \hat{D}_{LB,i}[n] \geq \hat{D}_{LB,i}[n]$, with $\hat{D}_{LB,i}[n]$ expressed as

$$\hat{D}_{LB,i}[n] = P_{LB}^{1}(T_i[n] - \hat{\Psi}_i[n] \Delta q_{\alpha_i}^n[n]^2 - \hat{\Psi}_i[n] \Delta \hat{q}_{\alpha_i}^n[n]),$$ (31)

$$T_i[n] = \hat{D}_{LB,i}[n] + \hat{\phi}_i[n](X_i[n] - 1) + \Psi_i[n] \Delta q_{\alpha_i}^n[n]^2,$$ (32)

$$\hat{D}_{LB,i}[n] = \Delta t[n] P_{LB}(\hat{\theta}_i[n]) \ln \left(1 + \frac{\zeta_i L \hat{p}_B[n]}{d_{i,u,o}^n[n] \Delta t[n]}\right),$$ (33)

$$\hat{\phi}_i[n] = \Delta t[n] \frac{C_2}{X_i[n]} \ln \left(1 + \frac{\zeta_i L \hat{p}_B[n]}{d_{i,u,o}^n[n] \Delta t[n]}\right),$$ (34)

$$\hat{\Psi}_i[n] = \Delta t[n] P_{LB}(\hat{\theta}_i[n]) \zeta_i L \hat{p}_B[n] \alpha L / 2 d_{i,u,o}^n[n] \Delta t[n] + \zeta_i L \hat{p}_B[n]),$$ (35)
\[
\dot{X}_i[n] = 1 + \exp\left(-\left(B_1 + B_2\hat{\theta}_i[n]\right)\right),
\]
\[
d_i[n,o] = \sqrt{\Delta q_i^{u, o}_n[a_i] + H^2},
\]
\[
\tau_i[n] = B_1 + \frac{180}{\pi} B_2 \left(\tan^{-1}\left(\frac{H}{\Delta q_i^{u, o}_n[a_i]}\right) + \frac{H\Delta q_i^{u, o}_n[a_i]}{d_i^{u, o}_n}\right),
\]
\[
\Delta q_i^{u, o}_n[a_i] = -\tau_i[n] + 180/\pi B_2 H d_i^{u, o}_n\Delta q_i^{u, o}_n[a_i],
\]
\[
\hat{\theta}_i[n] = \frac{180}{\pi} \tan^{-1}\left(H/\Delta q_i^{u, o}_n[a_i]\right),
\]
\[
\Delta q_i^{u, o}_n[a_i] = \sqrt{(q_i^{u, o}_n[a_i] - q_i^{o, o}_n)^2 + (q_i^{u, o}_n[a_i] - q_i^{o, o}_n)^2}, \chi \in \{1, o\}.
\]

By inspecting \(\dot{D}_{LB,i}^{(2)}[n]\), the concavity of \(V_t[n]\) can be deduced from its composition of positive sum of three terms that are the perspective transform of concave functions in the joint set of variables. The remaining two terms, \(\phi_i[n]\) and \(\hat{\phi}_i[n]\), are concave in the optimization parameters as they are the perspective transform of concave functions, which can be easily shown. In addition, \(\exp(\beta ||z||^2)\) is a convex function for \(\beta \geq 0\) as it is the composition of a convex increasing function with another convex function. Hence, by upper bounding the remaining two products of a positive convex function and a positive concave function, the SCA-compatible lower bound for \(D_{LB,i}^{(2)}[n]\) is given by
\[
D_{LB,i}^{(2)}[n] = P_{B,i}(T_i[n] - G(\Delta q_i^{u, o}_n[a_i], \hat{\phi}_i[n]) - G(e^{-D q_i^{u, o}_n[a_i]}, \hat{\phi}_i[n])).
\]

### B. Propulsion power SCA-compatible upper bound derivation

In terms of constraints, the SCA-compatible version of the minimum speed constraint can be obtained by lower bounding \(\|q_i^{u} - q_i^{1}-1\|_2\) with its F.O.T approximation, \(\bar{s}[n]\), expressed as
\[
\bar{s}[n] = \|\Delta q_i^{u, o}_n[a_i]\|_2 + \Delta q_i^{u, o}_n[a_i]T(\Delta q_i^{u, o}_n[a_i] - \|\Delta q_i^{u, o}_n[a_i]\|_2),
\]
where \(\Delta q_i^{u, o}_n[a_i] = q_i^{u, o}_n[a_i] - q_i^{u, o}_n[a_i] - 1\) and \(\Delta q_i^{u, o}_n[a_i] = q_i^{o, o}_n[a_i] - q_i^{o, o}_n[a_i] - 1\). Similarly, \(\Delta t[n]\) can be lower bounded by \(\Delta t[n]\) as follows:
\[
\Delta t[n] = \Delta t_0^2 + 2\Delta t_0[(\Delta t[n] - \Delta t_0[n)].
\]

Note that the propulsion power, denoted by \(p_{P,i}[n]\), introduces a non-convex constraint as well. However, such a term can be upper bounded by applying Theorem 1 to (a) its first term and (b) to the upper bound of the second term obtained by lower bounding the denominator with \(\bar{s}[n]\) to get \(p_{P,i}[n] \leq \bar{p}_{P,i}[n]\) expressed as
\[
\bar{p}_{P,i}[n] = F\left(\|\Delta q_i^{u, o}_n[a_i]\|_2^3, \Delta t_3^{-3}[n]\right) + F\left(\Delta t[n], \bar{s}[n]^{-1}\right).
\]

### C. Harvested power SCA-compatible lower bound derivation

For the harvested power presuming maximum radiated laser power, \(P_{H}[n]\), by inspecting (15) and (16), it can be deduced that \(P_{H}[n]\) is a convex decreasing function in \(d_i^{u, o}[n]\). This owes to its composition of a convex increasing function in the generated photocurrent, which is convex and decreasing in \(d_i^{u, o}[n]\). Accordingly, \(P_{H}[n]\) can be lower bounded as
\[
P_{H}[n] \geq E_1[n] - E_2[n] (d_i^{u, o}[n] - d_i^{u, o}[n]) \leq \hat{P}_H[n],
\]
\[
E_1[n] = 0.75V_i x_o[n] \ln(1 + x_o[n]/I_o),
\]
\[
x_o[n] = A_{PD} R_{PD} p_{L, o}^{max}[n] e^{-\alpha d_i^{u, o}[n]} I_{L, o}^{-3}[n],
\]
\[
E_2[n] = 0.75V_i \Delta \theta A_{PD} R_{PD} \left(1 + x_o[n]/I_o\right)
\]
\[
- \left(\frac{x_o[n]}{I_o + x_o[n]}\right) \left(\frac{\alpha d_i^{u, o}[n]}{L_o}\right) I_{L, o}^{-3}[n] (r_{L, o}[n] + 2),
\]
where \(d_i^{u, o} = \|q_i^{u, o}_n[a_i] - q_i^{u, o}_n\|_2\), and \(r_{L, o} = D_o + \Delta \theta d_i^{u, o}\).

Now we derive the SCA-compatible lower bound on the harvested power, \(P_{H}[n]\), when \(p_{L, o}[n]\) is a variable. Exploiting the convexity of \(P_{H}[n]\) with respect to \(x\) and its positive monotonicity for positive arguments, \(P_{H}[n]\) can be lower bounded as
\[
P_{H}[n] \geq a_o[n] + b_o[n] p_{L, o}[n] L_D[n],
\]
\[
L_D[n] = \left(\frac{D_o + \Delta \theta |q_i^{u, o}_n[a_i] - q_i^{u, o}_n|_2^2}{L_o}\right),
\]
\[
a_o[n] = 0.75V_i A_{PD} R_{PD} p_{L, o}^{max}[n] e^{-\alpha d_i^{u, o}[n]} I_{L, o}^{-3}[n] (r_{L, o}[n] + 2),
\]
\[
b_o[n] = 0.75V_i \left(1 + \frac{A_{PD} R_{PD} p_{L, o}^{max}[n] e^{-\alpha d_i^{u, o}[n]} |q_i^{u, o}_n[a_i] - q_i^{u, o}_n|_2^2}{L_o (D_o + \Delta \theta |q_i^{u, o}_n[a_i] - q_i^{u, o}_n|_2^2)}\right).
\]

Since \(L_D[n]\) is convex in \(\|q_i^{u, o}_n[a_i] - q_i^{u, o}_n\|_2\), we lower bound it using its F.O.T approximation as
\[
L_D[n] \geq c_o[n] - d_o[n] |q_i^{u, o}_n[a_i] - q_i^{u, o}_n|_2^2,
\]
\[
c_o[n] = \alpha (D_o + \Delta \theta |q_i^{u, o}_n[a_i] - q_i^{u, o}_n|_2^2) + d_o[n] |q_i^{u, o}_n[a_i] - q_i^{u, o}_n|_2^2 + 2\Delta \theta
\]
\[
\times A_{PD} R_{PD} p_{L, o}^{max}[n] e^{-\alpha d_i^{u, o}[n]} I_{L, o}^{-3}[n].
\]

Hence, \(P_{H}[n]\) can be further lower bounded as
\[
P_{H}[n] \geq a_o[n] + b_o[n] p_{L, o}[n] (c_o[n] - d_o[n] |q_i^{u, o}_n[a_i] - q_i^{u, o}_n|_2^2).
\]
The scalar source of non-convexity in the previous SCA compatible lower bound is the product term \( p_{L[n]} |q^{|n}| - q_L|2\), hence, we upper bound it using Theorem 1 as

\[
p_{L[n]} |q^{|n}| - q_L|2 \leq \frac{1}{4} \left( (p_{L[n]} + |q^{|n}| - q_L|2)^2 + (p_{L[n]} - |q^{|n}| - q_L|2)^2 - 2(p_{L[n]} - |q^{|n}| - q_L|2)(p_{L[n]} - I_5|q^{|n}| - q_L|2 + I_6 \right. \\
\times \left( |q^{|n}| - q_L|2 + (q^{|n}| - q_L|2)^T(q^{|n}| - q_L|2) \right) ) \right),
\]

(52)

where \( I_5 = I (p_{L[n]} |q^{|n}| - q_L|2) \) and \( I_6 = 1 - I_5\). Finally, an SCA compatible lower bound for \( P_H[n] \) is given as

\[
P_H[n] \geq \bar{P}_H[n] = a_{m[n]} + b_{m[n]}c_{m[n]}p_{L[n]} - b_{m[n]}d_{m[n]}f_{mUB[n]}.
\]

(53)

REFERENCES


Amr M. Abdelhady (S’16, M’21) received the B.Sc. degree with honors in Communications and Computer Engineering from Cairo University, Giza, Egypt, in 2012, M.Sc. and Ph.D. degree in Electrical Engineering from King Abdullah University of Science and Technology (KAUST), Thuwal, Makkah, Kingdom of Saudi Arabia in 2016, and 2021, respectively. Currently, he is a postdoctoral fellow with King Abdullah University of Science and Technology. His research interests lie in communications theory, signal processing for communications with special emphasis on Non-terrestrial networks and optical wireless communications systems. Specific research areas include UAV communications, visible light communications, green communications, energy harvesting, and reconfigurable intelligent surfaces.

Abdulkadir Celik (Senior Member, IEEE) received the first M.S. degree in electrical engineering in 2013, the second M.S. degree in computer engineering in 2015, and the Ph.D. degree in co-majors of electrical engineering and computer engineering from Iowa State University, Ames, IA, USA, in 2016. He was a Postdoctoral Fellow with the King Abdullah University of Science and Technology, Thuwal, KSA, from 2016 to 2020, where he is currently a Senior Research Scientist with the Communications and Computing Systems Laboratory. His research interests are in the broad areas of next-generation wireless communication systems and networks. Dr. Celik currently serves as an editor for IEEE COMMUNICATIONS LETTERS, IEEE WIRELESS COMMUNICATION LETTERS, and FRONTIERS IN COMMUNICATIONS AND NETWORKS.

Carles Diaz-Vilor received the B.S. and M.S. degrees from the Polytechnic University of Catalo- nia (UPC), Barcelona, Spain, in 2017 and 2019, respectively. He is currently pursuing the Ph.D. in electrical engineering with the University of California, Irvine, Irvine, CA, USA. His current research interests are wireless communications and signal processing with an emphasis on UAV and sensor networks.

Hamid Jafarkhani (Fellow, IEEE) is a Chancel- lor’s Professor at the Department of Electrical Engineering and Computer Science, University of California, Irvine, where he is also the Direc- tor of Center for Pervasive Communications and Computing, , the former Director of Networked Systems Program, and the Conexant-Broadcom Endowed Chair. He was a Visiting Scholar at Har- vard University in 2015 and a Visiting Professor at California Institute of Technology in 2018. He was the 2020-2022 elected Faculty Chair of the UCI School of Engineering.

Among his awards are the NSF Career Award, the UCI Distinguished Mid-Career Faculty Award for Research, the School of Engineering Excel- lence in Research Senior Career Award, the IEEE Marconi Prize Paper Award in Wireless Communications, the IEEE Communications Society Award for Advances in Communication, the IEEE Wireless Communications Technical Committee Recognition Award, the IEEE Signal Processing and Computing for Communications Technical Recognition Award, couple of conference best paper awards, and the IEEE Eric E. Sumner Award. He is the 2017 Innovation Hall of Fame Inductee at the University of Maryland’s School of Engineering.

He was an Associate Editor for the IEEE Communications Letters from 2001-2005, an editor for the IEEE Transactions on Wireless Communications from 2002-2007, an editor for the IEEE Transactions on Communications from 2005-2007, an area editor for the IEEE Transactions on Wireless Communications from 2007-2012, and a Steering Committee Member of the IEEE Transactions on Wireless Communications from 2013-2016. He was the general chair of the 2015 IEEE Communication Theory Workshop and the general co-chair of the 2018 IEEE Global Conference on Signal and Information Processing (GlobalSIP). He was an IEEE ComSoc Distinguished Lecturer.

Dr. Jafarkhani is listed as an ISI highly cited researcher. According to the Thomson Scientific, he is one of the top 10 most-cited researchers in the field of “computer science” during 1997-2007. He is a Fellow of AAAS, an IEEE Fellow, and the author of the book “Space-Time Coding: Theory and Practice.”

Ahmed M. Eltawil (Senior Member, IEEE) re- ceived the B.Sc. and M.Sc. degrees (Hons.) from Cairo University, Giza, Egypt, in 1997 and 1999, respectively, and the Ph.D. degree from the Univer- sity of California, Los Angeles, in 2003. He is currently a Professor of electrical and computer engineering with the King Abdullah University of Science and Technology (KAUST), where he joined the Computer, Electrical and Mathematical Science and Engineering Division (CEMSE), in 2019. Prior to that, he has been with the Electrical Engineering and Computer Science Department, University of California, Irvine (UCI), since 2005. At KAUST, he is the Founder and the Director of the Communication and Computing Systems Laboratory (CCSL). His current research interests include the general area of smart and connected systems with an emphasis on mobile systems. He has been on the technical program committees and steering committees for numerous workshops.
symposia, and conferences in the areas of low power computing and wireless communication system design. He is a Senior Member of the National Academy of Inventors, USA. He received several awards, including the NSF CAREER grant supporting his research in low power computing and communication systems. He received two United States Congressional certificates recognizing his contributions to research and innovation. In 2021, he was selected as the “Innovator of the Year” by the Henry Samueli School of Engineering, University of California, Irvine.