Dynamics of Laser-Charged UAVs: A Battery Perspective

Wael Jaafar, Senior Member, IEEE, and Halim Yanikomeroglu, Fellow, IEEE

Abstract—In this paper, we investigate the dynamics of a laser-charged unmanned aerial vehicle (UAV) aiming to achieve a mission under energy constraints. We study the UAV’s battery dynamics by leveraging the electrical models for motors and battery. Subsequently, using these models, the path planning problem in a particular Internet-of-Things based use-case is revisited from the battery perspective. By leveraging a graph theory approach, the problem is solved optimally, and compared to benchmark trajectory approaches. Through numerical results, we show the efficiency of this novel perspective for all path planning approaches. In contrast to the battery perspective, we show the efficiency of this novel perspective for all path planning approaches. In contrast to the battery perspective, we found that the energy perspective is very conservative and does not exploit optimally the available energy resources. However, it can be adjusted by carefully evaluating the energy as a function of the UAV motion regime. Finally, the impact of some parameters, such as turbulence and distance to charging source, is studied.

Index Terms—Unmanned aerial vehicle, kinetic battery model, distributed laser charging.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) have been experiencing a boom in interest lately from industry and research. Indeed, several new applications that rely on UAVs have emerged in recent years in connection with the evolution of wireless networks into 5G and beyond [1]. UAVs have been deployed for aerial based applications such as security inspection [2], precision agriculture [3], traffic control [4], and package delivery [5]. They can also act as cellular base-stations to provide connectivity to rural and disaster-hit areas. For instance, authors in [6] proposed a three-layer architecture, in which an edge-cloud layer is formed temporarily by UAVs to provide edge computing and connectivity during disaster instances, while in [7], the authors investigated the joint UAV access selection and base station (BS) bandwidth allocation problem of a UAV-assisted Internet-of-Things (IoT) communication network. Hence, UAVs are seen as a promising technology to profit businesses and help society.

Despite all their promise, most battery-powered UAVs have a major drawback: their flight duration is significantly limited and thus are unable to satisfy the requirements of all these emerging applications. This limitation is mainly due to the limited on-board lithium-ion polymer (LiPo) battery capacity. To overcome this limitation, several works focused on reducing on-board energy consumption through UAV or battery hot-swapping [8], battery capacity increase [9], UAV placement or path optimization [10], [11]. Unfortunately, these approaches are unable to deliver a significant flight time increase and satisfy the requirements of UAV-based applications. Recently, powering through laser beaming has been proposed to enable longer UAV flight times [12]–[16]. Its potential has encouraged several companies to develop this technology [17], [18]. Laser beaming can be implemented using a laser array oriented through an optical system (e.g., set of mirrors or diamonds) towards the collecting lens of a targeted UAV. Alternatively, distributed laser charging (DLC) advocates the use of photovoltaic cells instead of the collecting lens at the receiver, which is cost-effective and practical in small UAVs [14]. For efficient charging, a line-of-sight (LoS) link between the charging source and UAV is required. It is to be noted that due to current technology limitations, UAVs cannot rely solely on laser charging; besides, LoS (which is necessary for laser charging) cannot be guaranteed all the time. Also, equipping the UAV with more battery cells would make the UAV heavier, which is counterproductive as the target is to extend the UAVs operating time. Complementing a lighter UAV (having a small battery) with laser charging can be seen as a hybrid approach, as it would allow operating the UAVs for extended times.

On the other hand, the importance of energy consumption and harvesting have received a limited consideration from the battery perspective. Indeed, almost all works investigating UAV-based issues, such as 3D trajectory optimization and resource allocation, focused on the energy perspective of consumed/harvested average or instantaneous power when flying, hovering, data processing, or communicating, without taking into account the relation to the initial available energy, and impact of turbulence forces. In [11], the authors derived a theoretical model for propulsion energy consumption of fixed-wing UAVs, expressed as a function of the UAVs flying speed and acceleration. Then, they studied the energy-efficiency (EE) maximization problem subject to the UAVs trajectory constraints, including departure and arrival locations, minimum and maximum speeds, and maximum acceleration. The EE was defined as the ratio of the total amount of information that can be transmitted from the UAV to the consumed propulsion energy, during an observation time period. The obtained results show a significant EE gain over baseline approaches. A similar problem is investigated by Zeng et al. in [19] for a rotary-wing UAV, where the latter was deployed to serve IoT ground nodes. The objective was to minimize the total UAV consumed propulsion and communication energy while satisfying a predefined data rate requirement. The energy minimization problem is formulated, where the UAV trajectory and communication time allocation among IoT nodes are jointly optimized, as well as the...
mission completion time. First, by following the fly-hover-communicate design, the problem is solved by leveraging the traveling salesman problem with neighborhood and convex optimization approaches. Then, the general case, where the UAV communicates while flying, is solved sub-optimally through successive convex optimization. Numerical results illustrate the superiority of the proposed solutions compared to benchmark schemes. In contrast, authors of [20] studied the downlink transmission of a multi-band heterogeneous network, where UAVs can be deployed as small BSs. They formulated a two-layer optimization problem to maximize the EE of the system, where both the coverage radius of UAVs and radio resource allocation are optimized subject to minimum quality-of-service (QoS) and maximum transmit power constraints. EE was defined as the ratio of the aggregate user data rate delivered by the system to its aggregate energy consumption, which is limited to downlink transmission power and circuitry power. Presented results demonstrate the potential of a UAV tier in the heterogeneous network, which can nearly double the system’s EE for particular QoS requirements. Also, the authors of [21] optimized jointly the trajectory, speed, and acceleration of a UAV user, aiming to minimize its propulsion power while travelling between two locations. Although non-convex, the authors reformulated this problem to a more tractable form, and solved it using an iterative successive convex approximation technique. In a green energy context, Sun et al. studied in [22] joint trajectory and wireless resource allocation for solar-powered UAVs, aiming to maximize ground users’ sum throughput over a given time period. The aerodynamic power consumption, solar energy harvesting, a finite energy storage capacity, and the QoS requirements of ground users were taken into account in the problem formulation. Optimal UAV trajectory, power, and subcarrier allocation are obtained through monotonic optimization in the offline case. Then, the online problem, where only real-time and statistical knowledge of the channel gains are available, is solved using a low-complexity iterative sub-optimal scheme, which is based on successive convex approximation. The results revealed the near-optimality of the proposed online schemes. Also, a tradeoff between solar energy harvesting and power-efficient communication is identified, where solar energy harvesting is preferred at high altitudes, before moving to lower altitudes to reliably serve ground users. Finally, Sekander et al. presented in [23] novel models of energy harvesting from renewable energy sources, namely solar, wind, and hybrid solar and wind. They derived closed-form expressions of energy-outage probability at harvesting UAVs and SNR outage at ground users for both solar and wind harvesting scenarios. Analytical results were validated through simulations, exhibiting insights on the optimal UAV flight time and transmit power as functions of the harvested energy.

Although interesting, the aforementioned works did not establish a clear link between the UAV motion model, its energy consumption/harvesting, and battery capacity. For instance, [11, 19–23] considered a motion model that ignored the turbulence’s effect, while [23] simply neglected the propulsion power. Moreover, [22–23] assumed quasi-static flight equilibrium conditions, hence nulling the UAV speed and acceleration effects. Finally, the few works that have discussed the battery capacity [19, 21–22] were limited to a conventional energy perspective, where the effect of the UAV rotor’s operating voltage on the real amount of consumed energy is ignored. Indeed, a battery perspective is of capital importance since battery-powered UAVs suffer from uncertain estimation of charge level, and hence most mission plans are highly-conservative. In fact, UAV batteries may be affected by the storage state-of-charge (SOC), imposed discharge or load profile, and the variable requirements of flight regimes (take-off/landing/travelling/hovering). These factors might degrade the terminal voltage that defines the battery shut-off criteria, as the battery SOC nears empty [9]. Hence, we establish here the energy-battery relationship, and show its relevance when investigating a UAV-based challenge such as path planning. To the best of our knowledge, this is the first work that revisits a UAV-based issue from the battery perspective, while taking into account on-the-mission laser-charging. The main contributions of this paper may be summarized as follows:

1) First, we expose the energy model of an on-the-mission laser-charged UAV, and establish its relation to the battery dynamics.
2) To prove the relevance of the battery perspective in mission design, a UAV path planning problem is revisited, solved optimally, and compared to different benchmark trajectory approaches. It is found that the battery perspective outperforms the energy perspective, and the latter is very conservative for mission design. Nevertheless, we show that the energy perspective can be corrected by carefully evaluating the consumed energy for different motion regimes, i.e., hovering, flying, etc.
3) Finally, the impact of parameters, e.g., turbulence and distance to charging source, is investigated, showing the different influence of lateral and vertical turbulence, as well as the importance of the distance between the UAV and laser source for efficient recharging.

The remaining of the paper is organized as follows. In Section II, the UAV energy model is presented. Section III details the associated battery dynamics, while Section IV formulates the revisited path planning problem and exposes the solution approach. Section V presents the numerical results. Finally, Section VI concludes the paper.

II. UAV Energy Model

In this section, we provide the expressions of consumed/harvested energy by a quadrotor UAV. Consumed energy is defined by $E_c = E_{\text{trav}} + E_{\text{hov}} + E_{\text{comm}}$, where $E_{\text{trav}}$ is the energy to travel between locations, $E_{\text{hov}}$ is the hovering energy, and $E_{\text{comm}}$ is the communication energy.

For motion control, we consider the model of [24], where by adequately adjusting the rotors velocities $v_r$ ($r = 1, \ldots, 4$), the UAV can hover or travel vertically or horizontally. This model assumes that a path from location $[0, 0, 0]$ to 3D-destination $w_D$ (assuming no obstacles along the path) can be broken into six stages, as detailed in (eqs. (44)–(49), [24]). In contrast to the simplified motion model presented in [11] and [19], the model of [24] captures both the instantaneous 3D UAV movement...
flexibility and impact of turbulence. Consequently, the motion control energy consumed by the UAV between times $t_0$ and $t_f$ can be given by [23]

$$E = \int_{t_0}^{t_f} \sum_{r=1}^{4} e_r(t) i_r(t) \, dt,$$

(1)

where $e_r(t)$ and $i_r(t)$ are the voltage and current across motor $r$ respectively. In steady-state conditions, they are written [20]

$$e_r(t) = R_i(t) + \kappa_E i_r(t),$$

(2)

and

$$i_r(t) = \frac{1}{\kappa_T} \left[ T_f + \kappa_0 v_r^2(t) + D_f v_r(t) + J \frac{dv_r(t)}{dt} \right].$$

(3)

where $R$ is the resistance, $\kappa_E$ is the motor’s voltage constant, $\kappa_T$ is the torque constant, $T_f$ is the motor friction torque, $\kappa_0$ is the drag coefficient, $D_f$ is the motor viscous damping coefficient, and $J$ is the rotor inertia. By combining (2)-(3) into (1), the latter can be written

$$E = \int_{t_0}^{t_f} \sum_{r=1}^{4} \left( \sum_{s=0}^{4} c_{1+s} v_r(t)^s \frac{dv_r(t)}{dt} + c_8 v_r(t) + c_9 v_r(t)^2 \right) \, dt,$$

(4)

where $c_1, \ldots, c_9$ are expressed as

$$c_1 = \frac{R_T^2}{\kappa_T^2}, \quad c_2 = \frac{T_f}{\kappa_T} \left( \kappa_E + \frac{2RD_f}{\kappa_T} \right), \quad c_4 = \frac{\kappa_0}{T_f} c_2,$$

$$c_3 = \frac{D_f}{\kappa_T} \left( \frac{RD_f}{\kappa_T} + \kappa_E \right) + \frac{2RT_f\kappa_0}{\kappa_T^2}, \quad c_5 = \frac{\kappa_0}{T_f} c_1,$$

$$c_6 = \frac{2J}{T_f} c_1, \quad c_7 = \frac{J^2}{T_f^2} c_1, \quad c_8 = \frac{J}{T_f} c_2, \quad c_9 = \frac{\kappa_T}{T_f} c_6.$$

Consequently, travelling energy $E_{trav}$ can be written as

$$E_{trav} = \sum_{s=1}^{5} E_s,$$

(5)

where $E_s$ is the consumed energy in stage $s$ ($s = 1, \ldots, 5$), where $s = 1, 3, 5$ correspond to orientation change, and $s = 2, 4$ to displacement stages. Since $v_r$ are constant (eqs. (44)-(48), [24]), the consumed energy can be given by

$$E_s = \left( \tau_{(2.5s+1.5)} - \tau_{(2.5s-2.5)} \right) \left( 3c_1 + \left( 1 + \frac{1}{\sqrt{2}} \right) c_2 v_{\max}^2 \right.

\left. + 2c_3 v_{\max}^2 + \left( 1 + \frac{1}{\sqrt{2}} \right) c_4 v_{\max}^3 + \frac{3}{2} c_5 v_{\max}^4 \right), \quad s = 1, 3, 5,$$

$$E_s = \left( \tau_{2.5s} - \tau_{2.5s-1} \right) \cdot 4 \sum_{i=1}^{5} c_i v_{i-1}^{\max}, \quad s = 2, 4, 6$$

(6)

where $v_{\max}$ is the maximal velocity and $\tau_j$ ($\tau_1 < \ldots < \tau_{14}$) are the switching times at which UAV control inputs change, given in (Appendix D, [24]).

In the presence of an external force, e.g., gravity and turbulence, the UAV’s hovering energy can be written as

$$E_{hov} = \Delta \cdot 4 \sum_{i=1}^{5} c_i \left( \frac{F_e}{\bar{g}} \right)^{\frac{s-1}{2}},$$

where $\Delta$ is the hovering duration, $|F_e|$ is the external force amplitude, and $\bar{g}$ is the lift coefficient, whereas, the communication energy of the UAV is expressed by

$$E_{comm} = \int_{t_0}^{t_f} \sum_{u=1}^{U} P_u(t) \, dt,$$

(7)

where $P_u(t)$ is the communication power to node $u$ in time $t$, and $U$ is the total number of nodes. Finally, the received charging energy from a DLC source is given by [14]

$$E_{harv} = \int_{t_0}^{t_f} P_0(t) \, dt = a_1 \alpha_2 \int_{t_0}^{t_f} \nu(t) P_s(t) \, dt$$

$$+ a_2 b_1 \int_{t_0}^{t_f} \nu(t) dt + b_2 (t_f - t_0),$$

(8)

where $P_0(t)$ (resp. $P_s$) is the received (emitted) power, $a_i$ and $b_i$ are curve fitting parameters, $\nu(t) = e^{-\alpha d}$ is the average transmission efficiency, $d$ is the distance between the UAV and DLC source at time $t$, and $\alpha$ is the laser attenuation coefficient [14]. It is to be noted that laser charging and communication operations occur on different frequency bands (e.g., above 1 THz for laser charging [16] and below 6 GHz for communication [10]), hence the UAV-user wireless link does not experience interference from laser charging.

III. KINETIC BATTERY MODEL AND DYNAMICS

A. Background

Due to the different flight regimes of UAVs, and variable load and discharge profiles, it is important to present an accurate relationship between energy and battery dynamics. In the literature, besides the theoretical Peukert’s law that describes the discharge profile of a battery [27], several battery models have been proposed for different applications. For instance, authors of [28] characterized the battery electro-chemically using six differential equations, while the authors in [29] proposed an electrical circuit-based model. Despite their accurate battery characterization, these models are complex to manage in a performance-oriented setup. Later, preference has been shifted towards the Kinetic Battery Model (KiBaM) [30] and the diffusion-based model [31]. With only two differential equations to fully describe the battery behavior, they are seen as low-complex and practical models [32].

B. UAV Battery Model and Dynamics

Since most UAVs use LiPo batteries and this type of batteries can be well modeled using KiBaM, we opt here for this model [30], [32] and [33]. In KiBaM, the battery charge is divided into two wells: an available-charge well ($y_1$) and a bound-charge well ($y_2$). Given $t \in [t_0, t_f]$, and the initial battery conditions $y_1(t_0) = \omega B$ and $y_2(t_0) = (1 - \omega)B$, where $B$ is the battery capacity and $\omega \in [0,1]$ is the splitting factor of well levels, the change in charge of both wells is described by [33]:

$$\frac{\partial y_1(t)}{\partial t} = i(t) + k_F (h_2(t) - h_1(t))$$

(9)

$$\frac{\partial y_2(t)}{\partial t} = -k_F (h_2(t) - h_1(t)),$$

(10)
where $k_F$ controls the flow rate between the wells, $h_1(t) = y_1(t)/\omega$ and $h_2(t) = y_2(t)/(1 - \omega)$ are the heights of the wells, and

$$\tilde{i}(t) = \begin{cases} \bar{i}_{ch}(t) & \text{in the charge state} \\ -\bar{i}_{dis}(t) & \text{in the discharge state} \end{cases}$$

(11)

where $\bar{i}_{ch}(t)$ and $\bar{i}_{dis}(t)$ are the recharge and discharge currents of the UAV’s battery respectively. On one hand, we assume KibiA constant current charging, where $\bar{i}_{ch}(t) = I_{ch}$. To extend the battery life, it is recommended that $I_{ch}$ should not exceed $1C \times B$, where $1C$ is a measure of the charge current, known as C-rating, and $B$ value in Ah. Given the nominal voltage of the LiPo battery $e_{nom}$, we have the constraint $P_0 \leq I_{ch}e_{nom}$, i.e., the DLC source power should respect $P_s(t) \leq \frac{I_{ch}e_{nom}}{a_1a_2v(t-a_2b_2)}$. On the other hand, $\bar{i}_{dis}(t) = i_{cont}(t) + i_{comm}(t)$, where $i_{cont}(t) = \sum_{r=1}^4 i_r(t)$ is the UAV’s control current, obtained using (3), and $i_{comm}(t) = \frac{P_0}{\gamma_0}$ is the communication current, where $\gamma_0$ is the UAV transceiver’s voltage. By solving (9)–(10) for constant $\tilde{i}(t) = I$, we obtain the battery levels at $t_f$ [32]

$$y_1(t_f) = \frac{y_1(t_0)e^{-k'\delta} + \left(y(t_0)k'\omega + \frac{\bar{I}}{k'}\right)(1 - e^{-k'\delta})}{k'} + \frac{\bar{I}\omega(k'\delta - 1 + e^{-k'\delta})}{k'},$$

(12)

$$y_2(t_f) = \frac{y_2(t_0)e^{-k'\delta} + y(t_0)(1 - \omega)(1 - e^{-k'\delta})}{k'} + \frac{\bar{I}(1 - \omega)(k'\delta - 1 + e^{-k'\delta})}{k'},$$

(13)

where $k' = k_F/\omega(1 - \omega)$, $\delta = t_f - t_0$ and $y = y_1 + y_2$.

Fig. 1: System model and UAV trajectories.

IV. REVISITED PATH PLANNING PROBLEM

We consider a downlink communication system, consisting of a UAV, a ground device (e.g., a remote server, IoT sink/gateway, etc.), a DLC source, and $B = 10$ buildings, placed in the 3D space, where the device is outside the suburban environment, as shown in Fig. 1. The UAV flies from an origin location to a destination during $T < T_{max}$ time slots, with $T_{max}$ is the maximal tolerated flight duration. Among these $T$ time slots, the UAV has to hover and successfully communicate with the ground device for a maximized number of $\Delta$ time slots, where the communication outage probability $P_{out}$ has to be kept below a threshold $\varepsilon$. Given a Rician communication channel[32] $P_{out}$ can be obtained as [36]

$$P_{out} = 1 - Q_1\left(\sqrt{2K}, \sqrt{\frac{2\gamma_{th}(1 + K)N_0}{P_d\delta^{-\beta}}}\right) \leq \varepsilon,$$

(14)

where $\gamma_{th}$ is the signal-to-noise-ratio (SNR) threshold, $N_0$ is the noise power, $d$ is the distance between the UAV and the ground device, $\beta$ is the path-loss exponent, $K \geq 0$ is the Rice factor, and $Q_1(\cdot, \cdot)$ is the 1st-order Marcum Q-function [37, eq. 4.33]. Also, the UAV can receive power from the DLC source either when hovering or resting on a building. Thus, we formulate the following problem (P1):

$$\max_{\Delta} \Delta$$

s.t. $P_{out} \leq \varepsilon, \forall t \in \Delta$, (P1.a)

$\eta(T) \geq \eta_0$ (P1.b)

$w(1) = w_0, w(T) = w_F$, (P1.c)

$0 \leq \Delta \leq T_{max}$, (P1.d)

$z_{min} \leq z \leq z_{max}$, (P1.e)

where $\eta(T)$ is the state-of-charge (SOC) by the end of the mission time $T (T \leq T_{max})$. It can be expressed either as

$$\eta(T) = \eta_1(T) = \frac{y_1(t) + y_2(T)}{B}$$

(Battery perspective), (16)

where $y_1(T)$ and $y_2(T)$ are the wells levels at the end of time slot $T$, respectively, or as

$$\eta(T) = \eta_2(T) = 1 - \frac{E_{fl,ov} + E_{lv,ov} - E_{harv}}{E_0}$$

(Energy perspective), (17)

where $E_{fl,ov}$, $E_{lv,ov}$, and $E_{harv}$ are the consumed overall flying energy, hovering+communication energy, and harvested energy during times $T_{fl,ov}$, $\Delta$, and $T_{harv}$, respectively, such that $T = T_{fl,ov} + T_{harv} \leq T_{max}$. The energy expressions can be obtained using [5–8]. Also, $E_0$ is the nominal initial battery energy, $\varepsilon \in [0, 1]$ is the outage probability threshold, $\eta_0$ is the desired SOC level at the end of $T$, $w(t) = [x(t), y(t), z(t)], t = 1, \ldots, T$ is the UAV 3D trajectory, such that $\mathbf{W} = [w(t)]_{t=1,\ldots,T}$, $w_0$ and $w_F$ are the origin and destination 3D-locations respectively, and $z_{min}$ and $z_{max}$ are the minimum and maximum flying altitudes. Constraint

1Usually, charging has two phases, the first at constant maximum current until maximum voltage is reached, and the second at constant maximum voltage to keep the level of the available charge well at its maximum [33]. Since current wireless recharging technologies cannot recharge a flying UAV fully, only the first phase can be achieved.

2The Rician channel is an accurate air-to-ground channel model [33]. Other models can be considered, such as the probabilistic model discussed in [35].

3To be noted that $T_{harv}$ includes the time spent for hovering, $\Delta$, and the time spent resting on one or several buildings $T_{harv} = T_{harv} - \Delta$. 


Algorithm 1 Hovering and Resting Times Optimization Algorithm, given building $b$

1: Initialize $\Delta_{\text{ov}} = 0$, $T_{\text{harv,ov}} = 0$.

2: Initialize $T_{\text{harv,ov}} = 0$.

3: for $T_{\text{harv}} = 1$ to $T_{\text{max}} - T_{\text{harv}}$ do

4: for $\Delta = 1$ to $T_{\text{max}} - T_{\text{harv}}$ do

5: Calculate $\eta = \eta(T_{\text{harv,ov}} + \Delta + T_{\text{harv}})$.

6: if $\eta \geq \eta_0$ then

7: $\Delta_{\text{ov}}(T'_{\text{harv}}, \Delta) = \Delta$.

8: $T'_{\text{harv,ov}}(T'_{\text{harv}}, \Delta) = T'_{\text{harv}}$.

9: end if

10: end for

11: end for

12: Return $\Delta_{\text{opt}} = \max(\Delta_{\text{ov}})$.

13: Return $T'_{\text{opt}} = T'_{\text{harv,ov}}(\arg \max \Delta_{\text{ov}})$.

Algorithm 2 Global Optimization Algorithm

1: Solve (P3) and return the solution $\Delta_1$.

2: Initialize $\Delta_B = \theta_{|B|}$ and $T_B = 0_{|B|}$.

3: for $b = 1$ to $B$ do

4: Execute Algorithm 1.

5: $\Delta_B(b) = \Delta_{\text{opt}}$.

6: $T_B(b) = T'_{\text{opt}}$.

7: end for

8: $\Delta_2 = \max(\Delta_B)$ and $T_2 = T_B(\arg \max \Delta_B)$.

9: if $\Delta_1 > \Delta_2$ then

10: Return $\Delta = \Delta_1$.

11: else

12: Return $\Delta = \Delta_2$.

13: end if

V. SIMULATION RESULTS

The simulation parameters are set as follows: $w_0 = [0, 0, 50]$ m, $w_F = [2000, 0, 50]$ m, DLC source location $w_s = [1000, 0, 50]$ m, and ground device location $w_a = [1000, 3000, 0]$ m, whereas the buildings have heights in $\{60, 80, 100\}$ m, ordered such that buildings with lowest heights are the closest to x-axis edges. When hovering, the UAV communicates with the ground device during $\Delta$ seconds, where the duration of a time slot is one second. For the sake of simplicity, the UAV experiences only gravity, i.e., external force $F_e = [0, 0, -12.74]$ N, unless stated otherwise. For the quadrotor UAV characteristics, we rely on the model of [26], where the UAV is powered by two 3-cell (3S) LiPo 11.1 V batteries with capacities $B_1=B_2=36000$ As (10Ah) [38], corresponding to $E_0 = 2 \times (36000 \times 11.1) = 799200$ J. The use of two independent batteries allows to extend the battery life by alternatively using one for motion and the other for recharging, and vice versa. Moreover, we assume that communication channel path-loss $\beta = 2$, K-factor $K = 20$ (i.e., strong LoS), $N_0 = 10^{-4}$, $\gamma_{th} = -11$ dB, $\varepsilon = 10^{-2}$, $z_{\text{min}} = 50$ m, and $z_{\text{max}} = 100$ m. Also, we assume that the duration of 1 time slot is equal to 1 second. The remaining UAV parameters are summarized in Table I.

First, we evaluate in Table II the solutions to (P3) given the direct path ($w_0 \rightarrow w_U \rightarrow w_F$), and for different $T_{\text{max}}$ and per-
The division of $E_{\text{cap}}$ calculated using (36000 × 15.4) = 1108800 J and $E_2 = 2 \times (36000 \times 14.33) = 1032036$ J are the initial battery capacities calculated using $e_{\text{nom}}$ in (2), which correspond to $e_{\text{t}}(t) = 15.4$ V for flying and $e_{\text{r}}(t) = 14.33$ V for hovering. The division of $E_{\text{fl}}$, $E_{\text{hv}}$, and $E_{\text{harv}}$ by $E_1$ and $E_2$ respectively is justified by the different flight regime/battery usage compared to resting/harvesting. As it can be seen, the adjusted energy perspective, denoted “Adj. Ener. Persp.”, achieves the same $\Delta$ as for “Battery Persp.”. For $T_{\text{max}}=1200$ s, similar results are obtained, where both “Battery Persp.” and “Adj. Ener. Persp.” achieve the best performance, with a mission time $T=1009.35$ s, which is below $T_{\text{max}}$.

In Figs. 2–3, we solve (P1) with different trajectory approaches and illustrate the resulting maximum hovering time, $\Delta$, and the SOC from the battery perspective, $\eta_1(T)$, given that $T_{\text{max}}=800$ s. (P1) is solved from the “Battery Persp.”, “Ener. Persp.”, and “Adj. Ener. Persp.” as defined in the previous paragraph. We define “Direct path”, “Traj. 1”, “Traj. 2” and “Optimal” trajectory approaches, where “Direct path” is described in the previous paragraph, “Traj. 1” corresponds to a modified nearest neighbor approach with the UAV passing by or resting over the closest building to the ground device, “Traj. 2” is defined as the shortest trajectory with the UAV passing by or resting over one building, and “Optimal” is obtained using Algorithm 2. These trajectories are depicted in Fig. 1. In Fig. 2 “Direct path” provides the maximal hovering time $\Delta$ for all solution perspectives as it follows the shortest path. Also, both “Battery Persp.” and “Adj. Ener. Persp.” achieve better performances than “Ener. Persp.”. According to Fig. 3 the SOC measured from the battery perspective, $\eta_1(T)$, respects the constraint $\eta_0$ with “Ener. Persp.” saving a lot of the battery’s capacity due to its low hovering time. Therefore, the “Ener. Persp.” has a conservative approach to the problem.

In Figs. 4 and 5 the same performances are depicted, but for $T_{\text{max}}=1200$. In Fig. 4 “Traj. 2” slightly outperforms the other approaches, which is also the optimal solution. Indeed, since $T_{\text{max}}$ is high, the UAV is capable of hovering for a longer time and compensates for the extra consumed
energy by resting over one building and recharging its battery. Moreover, both “Battery Persp.” and “Adj. Ener. Persp.” have the same best performance. Although these perspectives are similar, the “Battery Persp.” is recommended when designing energy-efficient UAV-based missions, as it simplifies the SOC expression in contrast to “Adj. Ener. Persp.”, which requires different initial battery calculations, depending on the UAV’s motion regimes.

Let $\vec{F}_w = \vec{F}_e - mg$ be the turbulence (e.g., wind) force that hits the UAV when hovering during $\Delta = 100$ s to serve the ground device, where $mg$ is the gravity. The impact of $F_w$ is investigated in Fig. 6. For $\vec{F}_w = F_w \hat{e}$ (resp. $F_w \hat{y}$), $E_{hv, ov}$ has a parabolic shape, where the lowest consumed energy is for $F_w = 0$N. Also, the curves are bounded by minimum and maximum $F_w$ values $-11.57$ N and $11.57$ N, corresponding to the maximum wind force that can be handled by the UAV without losing its balance. Going beyond these values requires a higher $v_{\text{max}}$ and hence higher power. Along $\hat{z}$, $F_w \in [-4.45, 12.74]$N counters gravity, hence the UAV can hover using less angular velocity $v_r$ ($r = 1, \ldots, 4$) and power, which decreases $E_{hv, ov}$. However, for $F_w \in [12.74, 29.9]$N, the wind pushes the UAV to provide more power in order to stay aloft. Beyond these values, the UAV would lose its vertical balance.

Fig. 7 evaluates $E_{\text{harv}}$ (eq. (8)) and the harvesting efficiency $\zeta = \frac{P_s}{P_s}$ when the UAV is hovering for 100 s, as functions of the distance between the DLC source and the UAV, and for different $P_s$. As the distance increases, both $E_{\text{harv}}$ and $\zeta$ degrade due to path-loss. For distances below 1 km, $\zeta$ is around 17.5%. $E_{\text{harv}}$ can be significantly improved by increasing $P_s$.

VI. CONCLUSION

In this paper, we established the relationship between power, energy, and battery dynamics for a laser-charged quadrotor UAV. Based on the obtained expressions, we revisited a path planning problem and solved it optimally. The obtained results emphasize the importance of the battery perspective when investigating UAV-based challenges, such as path planning, UAV placement, and resource optimization. Indeed, it is shown that the conventional energy perspective is very conservative and does not exploit optimally the available energy. Nevertheless, it can be adjusted by adequately evaluating the energy as a function of the UAV motion regime. Finally, the impact of
turbulence and distance to recharging source on the UAV’s consumed/harvested energy is studied, which highlights the influence of the lateral and vertical turbulence, as well as the importance of the distance between the UAV and laser source for an efficient recharging.

REFERENCES

[1] I. Bor-Yaliniz and H. Yanikomeroglu, “The new frontier in RAN heterogeneity: Multi-tier drone-cells,” IEEE Commun. Mag., vol. 54, no. 11, pp. 48–55, Nov. 2016.

[2] Z. Liu, X. Wang, and Y. Liu, “Application of unmanned aerial vehicle hangar in transmission tower inspection considering the risk probabilities of steel towers,” IEEE Access, vol. 7, pp. 159048–159057, Oct. 2019.

[3] P. Tokekar, J. V. Hook, D. Mulla, and V. Isler, “Sensor planning for a symbiotic uav and ugv system for precision agriculture,” IEEE Trans. Robot., vol. 32, no. 6, pp. 1498–1511, Oct. 2016.

[4] J. Zhu, K. Sun, S. Jia, Q. Li, X. Hou, W. Lin, B. Liu, and G. Qiu, “Urban traffic density estimation based on ultra-high resolution UAV video and deep neural network,” IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens., vol. 11, no. 12, pp. 4968–4981, Nov. 2018.

[5] S. Sawadsitang, D. Niyato, P. Pan, and P. Wang, “Joint ground and aerial package delivery services: A stochastic optimization approach,” IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 6, pp. 2241–2254, Oct. 2019.

[6] Z. Kaleem, M. Yousaf, A. Qamar, A. Ahmad, T. Q. Duong, W. Choi, and A. Jamalipour, “UAV-empowered disaster-resilient edge architecture for delay-sensitive communication,” IEEE Network, vol. 33, no. 6, pp. 124–132, Nov. 2019.

[7] S. Yan, M. Peng, and X. Cao, “A game theory approach for joint access selection and resource allocation in uav assisted iot communication networks,” IEEE Internet of Things Journal, vol. 6, no. 2, pp. 1663–1674, Apr. 2019.

[8] B. Galkin, J. Kibilda, and L. A. DaSilva, “UAVs as mobile infrastructure: addressing battery lifetime,” IEEE Commun. Mag., vol. 57, no. 6, pp. 132–137, Jun. 2019.

[9] B. Saha, E. Koshimoto, C. C. Quach, E. F. Hogge, T. H. Strom, B. L. Hill, S. L. Vazquez, and K. Goebel, “Battery health management system for electric UAVs,” in Proc. Aerospace Conf., Mar. 2011, pp. 1–9.

[10] M. Alzenad, A. El-Keyi, and H. Yanikomeroglu, “3-D placement of an unmanned aerial vehicle base station for maximum coverage of users with different QoS requirements,” IEEE Wireless Commun. Letters, vol. 7, no. 1, pp. 38–41, Feb. 2018.

[11] Y. Zeng and R. Zhang, “Energy-efficient UAV communication with trajectory optimization,” IEEE Trans. Wireless Commun., vol. 16, no. 6, pp. 3747–3760, Jun. 2017.

[12] P. D. Diamantoulakis, K. N. Pappi, Z. Ma, X. Lei, P. C. Sofotasios, and G. K. Karagiannidis, “Airborne radio access networks with simultaneous lightweight information and power transfer (SLIFT),” in Proc. IEEE Global Commun. Conf., Dec. 2018, pp. 1–6.

[13] J. Ouyang, Y. Che, J. Xu, and K. Wu, “Throughput maximization for laser-powered uav wireless communication systems,” Proc. IEEE Int. Conf. Comm. Workshps., pp. 1–6, 2018.

[14] Q. Zhang, W. Fang, Q. Liu, J. Wu, P. Xia, and L. Yang, “Distributed laser charging: A wireless power transfer approach,” IEEE IoT J., vol. 5, no. 5, pp. 3853–3864, Oct. 2018.

[15] G. Pan, P. D. Diamantoulakis, Z. Ma, Z. Ding, and G. K. Karagiannidis, “Simultaneous lightweight information and power transfer: Policies, techniques, and future directions,” IEEE Access, vol. 7, pp. 28250–28257, Feb. 2019.

[16] M. Lahmeri, M. A. Kishk, and M. Alouini, “Stochastic geometry-based analysis of airborne base stations with laser-powered UAVs,” IEEE Commun. Lett., vol. 24, no. 1, pp. 173–177, Oct. 2019.

[17] T. J. Nugent and J. T. Kure, “Laser power for UAVs,” White-Paper-Power Beaming for UAVs, vol. 1, pp. 1–1, 2010.

[18] Free-Space Power Beaming. [Online]. Available: https://powerlighttech.com/free-space-power-beaming-2/

[19] Y. Zeng, J. Xu, and R. Zhang, “Energy minimization for wireless communication with rotary-wing UAV,” IEEE Trans. Wireless Commun., vol. 18, no. 4, pp. 2329–2345, Apr. 2019.

[20] J. Ouyang, S. Naqvi, N. Mastronarde, J. Xu, F. Afgah, and A. Razi, “An energy efficient framework for UAV-assisted millimeter wave 5G heterogeneous cellular networks,” IEEE Trans. Green Commun. and Netw., vol. 3, no. 1, pp. 37–44, Mar. 2019.

[21] B. Khamideh and E. S. Sousa, “Power efficient trajectory optimization for the cellular-connected aerial vehicles,” in Proc. IEEE Int. Symp. Pers., Indoor and Mob. Radio Commun. (PIMRC), Sep. 2019, pp. 1–6.

[22] Y. Sun, D. Xu, D. W. K. Ng, L. Dai, and R. Schober, “Optimal 3D-trajectory design and resource allocation for solar-powered UAV communication systems,” IEEE Trans. Commun., vol. 67, no. 6, pp. 4281–4298, Jun. 2019.

[23] S. Sekander, H. Tabassum, and E. Hossain, “On the performance of renewable energy-powered UAV-assisted wireless communications,” ArXiv, vol. abs/1907.07158, 2019.

[24] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, “Communications and control for wireless drone-based antenna array,” IEEE Trans. Commun., vol. 67, no. 1, pp. 820–834, Jan. 2019.

[25] E.-C. Corp., DC Motors, Speed Controls, Servo Systems: An Engineering Handbook, 3rd ed. Pergamon Press, 1977.

[26] F. Morbidi, R. Cano, and D. Lara, “Minimum-energy path generation for a quadrotor UAV,” in Proc. IEEE Int. Conf. Robot. and Automat., May 2016, pp. 1492–1498.

[27] D. Linden, Handbook of Batteries. McGraw-Hill, 1985.

[28] M. Doyle, T. Fuller, and J. Newman, “Modeling of galvanostatic charge and discharge of the lithium/polymer/insertion cell,” J. Electrochemical Society, vol. 140, no. 6, pp. 1526–1533, Jan. 1993.

[29] S. Hageman, “Simple PSpice models let you simulate common battery types,” Electronic Design News, vol. 38, no. 22, pp. 117–129, Oct. 1993.

[30] J. F. Manwell and J. G. McGowan, “Lead acid battery storage model for hybrid energy systems,” Solar Energy, vol. 50, no. 5, pp. 399–405, May 1993.

[31] D. N. Rakhmatov and S. B. K. Vrudhula, “An analytical high-level battery model for use in energy management of portable electronic systems,” in Proc. IET/ACM Int. Conf. Comp. Aided Design, 2001, pp. 488–493.

[32] M. R. Jongeren and B. R. Haverkort, “Which battery model to use?” IET Software, vol. 3, no. 6, pp. 445–457, Dec. 2009.

[33] M. R. Jongeren and B. R. Haverkort, “Battery aging, battery charging and the kinetic battery model: a first exploration,” in Quant. Eval. of Syst., N. Bertrand and L. Bortolussi, Eds. Springer, 2017, pp. 88–103.

[34] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, “Communications and control for wireless drone-based antenna array,” IEEE Trans. Commun., vol. 54, no. 5, pp. 26–34, May 2016.

[35] J. Zhong and J. Thompson, “Single-antenna selection for MISO cognitive radio,” in Proc. IET Sem. Cogn. Radio Soft. Def. Radios: Tech. and Res., Sept. 2008, pp. 1–5.

[36] M. K. Simon and M.-S. Alouini, Digital Communication Over Fading Channels: A Unified Approach to Performance Analysis. Wiley, 2004.

[37] D.-K. E. Editors, “Build a redundant power bus for reliable UAV operation,” Digi-Key’s, https://www.digikey.ca/en/articles/techzone/2016/nov/ build-a-redundant-power-bus-for-reliable-uav-operation, 2016.