Optimizing Energy Usage for an Electric Drone

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Abstract. Unmanned Aerial Vehicles (UAVs) are rapidly gaining popularity in a wide variety of applications, e.g., agriculture, health care, environmental management, supply chains, law enforcement, surveillance, and photography. Dones are often powered by batteries, making energy a critical resource that must be optimised during the mission of the drone. The duration of a done's mission depends on the amount of energy required to perform some manoeuvering actions (takeoff, level flight, hovering, and landing), the energy required to power the ICT modules in the drone, the drone's speed, payload, and the wind. In this paper, we present a model that minimizes the energy consumption of a low power drone and maximizes the time required to completely drain the drone's battery and ensure the safe landing of the drone.

Keywords: Drones · Battery capacity · Diffusion approximation · Mission optimization · Energy

1 Introduction

The recent advances in Unmanned Arial Vehicle (UAV) technologies (e.g., data collection, data storage, data processing, data transmission, data security, delivery of loads) [32] have increased their adoption rate for military and commercial applications. The fast adoption rate is partly driven by the decrease in the cost of drones and granting licenses to commercial service providers and hobbyists. Some of the industries that are being transformed through the application of drones include agriculture, environmental management, supply chains, law enforcement, surveillance, and photography [27–29]. At the beginning of the COVID-19 pandemic, drones were used for deliveries [11] and to enforce restriction rules (social distancing, no mass gatherings in open public spaces) designed to slow down the transmission of the virus.

Most drones are powered by batteries, making energy a critical resource that must be optimised during the mission of the drone. One of the responsibility

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of a drone pilot is to ensure that the drone returns with enough energy in the battery that is sufficient for safe landing after its mission. If the drone's battery is completely depleted during its mission, it will crash to the ground and could damage the drone or result in a lawsuit if it damages properties or causes harm to human life. Even the most experienced drone "ground pilots" sometimes encounter drone crashes due to battery depletion. It is difficult to estimate how much time is required to completely deplete the energy stored in the battery during flight because a complex interaction of multiple factors influences the battery energy depletion process in drones. These factors include weather (e.g., wind, temperature), drone speed, the ICT-related functionalities performed by the drone, and the weight of the drone and the load carried by the drone (if any). The energy stored in the battery could also be rapidly depleted due to cyber attacks, which are designed to induce the ICT systems of the drone to draw more energy from the drone unnecessarily. Some drones are configured to return to the operator at predefined battery levels and to land at 15% battery level automatically. Therefore, the drone operator should ensure the safe landing of the drone while preventing any harm to human lives.

To adapt a UAV to perform its functionalities for a given application, advanced on-board information and communication technology significantly increase its energy needs during a mission [6] because of the computationally intensive visual information processing before transmission or storage [9]. Using multiple cooperating UAVs to conduct a mission [23] also increases the computational burden and energy consumption of each UAV, in order to coordinate movements and create a consistent view of the events or scenes that are monitored [21], also leading to additional on-board energy consumption from communications [22], and more on-board software [31]. On-board computing and communication equipment cannot easily be put to sleep to save energy, to avoid compromising the real-time needs which would be impaired by "wake-up" delays [17].

Since careful usage of the UAVs energy budget is needed to achieve the best possible mission output from the battery storage and possible other on-board energy sources such as phtovoltaic and fuel cells, the optimization of the power consumption of an UAV via its speed was studied in [5,7,34]. More broadly, energy consumption is also a major concern in information processing systems [31] and it has been analyzed via a variety of models with the purpose of understanding and minimizing the energy consumption in this area in general [16,22].

However, the energy used to perform functions such as encryption, compression of multimedia data, and communications is significant. In addition, the interplay of multiple factors influencing energy consumption implies that the energy drawn from the battery is not deterministic. Any energy harvesting mechanism that is used on-board is also influenced by the environment. Therefore, both the energy generation and consumption processes on-board a UAV need to be modelled as stochastic processes.

Markovian stochastic models have been applied to model the changes in the energy content of a battery [4,10,18,19,24–26,33]. However, the Poisson assumption in the arrival of energy packets into the battery [15] may deviate from reality. This is why we apply a diffusion model [12,14,20,30] where the interarrival times of energy and the depletion times of the energy follow any distribution, as proposed in earlier work on energy consumption and battery models [1,2,13].

In this paper, we present an optimization model to minimize the energy consumption of a low power drone, and hence maximize the time required to completely drain the drone's battery and ensure the safe landing of the drone. The rest of the paper is organised as follows: Sect. 2 contains a diffusion model of a drone's battery, Sect. 3 contains the proposed optimization model, we present some numerical examples in Sect. 4 and then conclude in Sect. 5.

2 Diffusion Process for the Energy Depletion Process of the Drone

The amount of energy present in the battery at time t may be represented by a diffusion process. This process is frequently used to approximate more complex and analytically intractable stochastic process. It is a strong Markov process with continuous time and continuous space (continuous sample path). We demonstrate how it may be used to evaluate the time after which a device consumes a fixed amount of energy if the consumption per time unit is random.

Consider a Wiener (diffusion) process $X(t)$, corresponding to the energy stored at a battery at the time t. Its changes at unit time have mean β and variance α. For simplicity, we assume that β, α are constant. They can be interpreted as instantaneous mean and variance of the change of $X(t)$

$$\beta = \lim_{\Delta t \to 0} \frac{E[X(t+\Delta t) - X(t)]}{\Delta t}$$
$$\alpha = \lim_{\Delta t \to 0} \frac{Var[X(t+\Delta t) - X(t)]}{\Delta t}.$$

The process' probability density function (pdf) $f(x,t;x_0)$

$$f(x,t;x_0)dx = P[x \le X(t) < x + dx \mid X(0) = x_0]$$

is defined by the diffusion equation (parabolic partial differential equation), e.g. [8]

$$\frac{\partial f(x,t;x_0)}{\partial t} = \frac{\alpha}{2}\frac{\partial^2 f(x,t;x_0)}{\partial x^2} - \beta\frac{\partial f(x,t;x_0)}{\partial x}. \tag{1}$$

For the unrestricted process starting from the point x_0

$$f(x,t;x_0) = \frac{1}{\sqrt{2\Pi\alpha t}}\exp(\frac{(x-x_0-\beta t)^2}{2\alpha t}) \tag{2}$$

and the incremental changes of $X(t)$ at interval dt

$$dX(t) = X(t + dt) - X(t)$$

are normally distributed with the mean βdt and variance αdt.

If the value of the diffusion process represents the energy content of the battery, then the life time the battery is corresponds to the time the diffusion process needs to pass from the initial point $x_0 = B > 0$, where B is the maximum volume of the battery to $x = 0$. If we refer it to the UAV mission, it corresponds to its maximal duration.

The distribution of the amount of energy present in the battery at time t is given by the Eq. (1) with the absorbing barrier at $x = 0$, i.e. the process is ended when it comes to zero. It corresponds to the condition

$$\lim_{x \to 0} f(x, t; x_0) = 0.$$

The problem of diffusion with absorbing barrier was studied e.g. in [8] and the solution in Eq. (3) was obtained with the use of the method of images: on may treat the barrier as a mirror, and the solution is a superposition of two unrestricted processes, one of unit strength, starting at the origin, and the other of strength $-\exp(\frac{2\beta x_0}{\alpha})$ starting at $x = 2x_0$. It yields

$$\begin{aligned} f(x, t; x_0) = \frac{1}{\sqrt{2\Pi\alpha t}} \Bigg[& \exp(-\frac{(x - \beta t)^2}{2\alpha t}) \\ & - \exp(\frac{2\beta x_0}{\alpha} - \frac{(x - 2x_0 - \beta t)^2}{2\alpha t}) \Bigg] \end{aligned} \tag{3}$$

The pdf of the first passage time distribution for a diffusion process that starts from the point $x = x_0$ and is absorbed at $x = 0$ is

$$\begin{aligned} \gamma_{x_0,0}(t) &= \int_{0+}^{\infty} \frac{\partial f(x, t; x_0)}{\partial t} dx \\ &= \int_{0+}^{\infty} [\frac{\alpha}{2} \frac{\partial^2 f(x, t; x_0)}{\partial x^2} - \beta \frac{\partial f(x, t; x_0)}{\partial x}] dx \\ &= \lim_{x \to 0} [\frac{\alpha}{2} \frac{\partial f(x, t; x_0)}{\partial x} - \beta f(x, t; x_0] \\ &= \frac{x_0}{\sqrt{2\Pi\alpha t^3}} e^{-\frac{(x_0 - \beta t)^2}{2\alpha t}} \ , \end{aligned} \tag{4}$$

with the Laplace transform

$$\bar{\gamma}_{x_0,0}(s) = e^{-x_0 \frac{\beta + \sqrt{\beta^2 + 2\alpha s}}{\alpha}} \ . \tag{5}$$

Equation (4) presents a probability density function in case of $\beta < 0$, when probability that the process will reach the barrier equals 1, and $\int_0^\infty \gamma_{x_0,0}(t) dt = 1$. Otherwise, for $\beta > 1$, the probability that the process ends at the barrier is $e^{-2\beta x_0/\alpha}$ and the conditional pdf is $\gamma'_{x_0,0}(t) = \gamma_{x_0,0}(t) e^{2\beta x_0/\alpha}$ and $\bar{\gamma}'_{x_0,0}(s) =$

$\bar{\gamma}_{x_0,0}(s)e^{2\beta x_0/\alpha}$. The same refers to the case $\beta < 0$ with the initial point x_0 placed left to the absorbing barrier.

From (4) or (5) we compute the moments of the time the battery is active

$$E[\gamma_{x_0,0}] = \frac{x_0}{|\beta|}, \qquad E[\gamma^2_{x_0,0}] = \frac{|\beta|x_0^2 + \alpha x_0}{|\beta|^3}.$$

In battery model, assuming $x_0 = B$, the pdf given by Eq. (3) determines the distribution of the energy still in the battery, and Eq. (4) the battery life time distribution. Let us imagine that the units of energy are consumed with the mean rate μ units and σ_B^2 is the variance of time intervals between consumption of energy units. It means that the number of consumed energy units in time Δ has the distribution close to normal with mean $\mu\Delta$ and variance $\sigma_B^2\mu^3\Delta$ and the parameters of the diffusion process are $\beta = -\mu$ and $\alpha = \sigma_B^2\mu^3 = C_B^2\mu$, where $C_B^2 = \sigma_B^2\mu^2$ is the squared coefficient of variation (variance/mean^2) of this distribution. A numerical example illustrating the pdf of the first passage time distribution is given in Fig. 1.

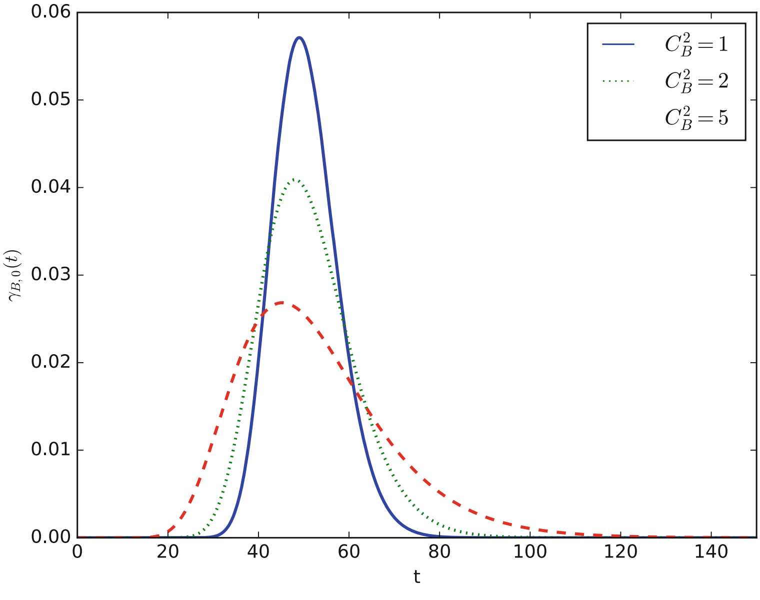

Fig. 1. Probability density function $\gamma_{B,0}(t)$ of the first passage time from a full battery at $B = 50$ to an empty battery at $x = 0$, i.e. the pdf of the battery life time distribution, when the mean power consumption (energy consumption per time unit) is $\mu = 1$. The curves show the influence of the squared coefficient of variation of energy consumption per time unit $C_B^2 = \sigma_B^2\mu^2$ on the life time. We see how the increase of C_B^2 increases the variance of the battery life time distribution

3 Energy Optimization for an UAV During Its Mission

We investigate a problem of UAV control where the energy is limited by the volume of the battery supplying energy to the UAV. The control should maximise a chosen reward function.

There are two phases of the UAV mission. During the first one, the UAV uses all its functions, including the transmission of the collected images. When the energy goes below a certain level of b, the UAV passes to the second, energy-saving phase before landing. During this phase, it is still collecting images, but they are not transmitted. The diffusion parameters, corresponding to energy consumption, are different in both phases, see Fig. 2.

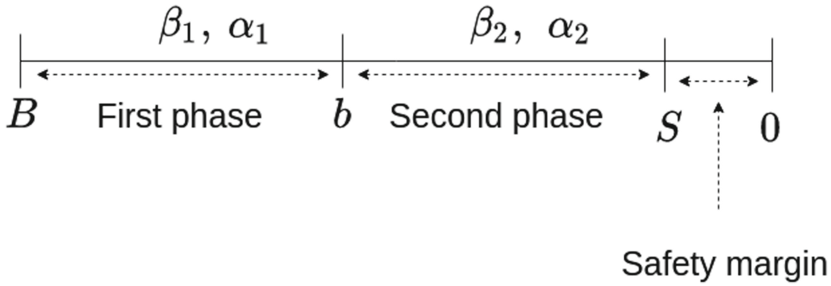

Fig. 2. The two phases of the UAV mission: in the first phase we assume that energy is used for flying, for ground communications and data acquisition. The second phase focuses on the landing phase, including any indispensable data acquisition and communications for the return to the landing base.

The data recorded during the second phase may be accessed only after landing when their validity has partially deteriorated. We assume in the reward function (7) that the value (relevance) of these data is decreasing following a certain function $\Theta(\cdot)$ with the time elapsed between their acquisition and availability.

The formal description of the problem is as follows.

Let $B > 0$ denotes the battery capacity before the UAV platform starts its mission, and S be a minimum value of energy that the UAV battery must contain when it lands after ending the mission, with $B > S \geq 0$.

Let $u,\ v$ be non-negative real numbers such that $B \geq u > v \geq S$.

Define the non-negative random variables τ_u and $Y_{\tau_u}[u, v]$ such that the diffusion process $D \equiv \{X_t, t \geq 0\}$ with $X_0 = B$ has the values

$$\tau_u = \{\inf t : X_t = u\}, \tau_u + Y_{\tau_u}[u, v]\} = \{\inf t > u : X_t = v\}. \tag{6}$$

Thus τ_u is the first passage time of the diffusion D to level u. Also $\tau_u + Y_{\tau_u}[u, v]$ is the first passage time of D to level v at time $\tau_u + Y_{\tau_u}[u, v]$ after its first passage time to u at time τ_u.

Then our problem is to choose a decision point represented by an "energy switching level" b, $B \geq b \geq S$ for the battery, from "normal energy consumption" to "reduced energy consumption", which maximises the useful duration of the mission.

Thus we must solve the following maximization problem:

$$\max_{b\in[S,B]}\{C = \ E[\tau_b] + E[\int_0^{Y_\tau[b,S]} dt\Theta(Y_\tau[b,S]-t]\} \ . \tag{7}$$

The first phase's duration corresponds to the first passage time from B to b, and the second phase is the first passage time from b to S.

Denote by μ_i the mean intensity of the power consumption per time unit at phase i, $i = 1, 2$ (i.e. $1/\mu_i$ is the mean consumption per time unit) and α_i its variance, representing diffusion parameters.

The densities of the duration of the phases are

$$f_1(t) = \gamma_{B,b}(t) = \frac{B-b}{\sqrt{2\Pi\alpha_1 t^3}} \exp(-\frac{(B-b-\mu_1 t)^2}{2\alpha_1 t})$$

$$f_2(t) = \gamma_{b,S}(t) = \frac{b-S}{\sqrt{2\Pi\alpha_2 t^3}} \exp(-\frac{(b-S-\mu_2 t)^2}{2\alpha_2 t})$$

and the mean time of the first phase is

$$E_1 = \int_0^\infty t f_1(t)dt = \frac{(B-b)}{\mu_1}.$$

The reward function C becomes

$$C = E_1 + \int_0^\infty y f_2(y) \int_0^y \Theta(y-t)dt\, dy \tag{8}$$

and we are looking for b, which maximises

$$C = \frac{(B-b)}{\mu_1} + \int_0^\infty y \frac{b-S}{\sqrt{2\Pi\alpha_2 y^3}} \exp(-\frac{(B-S-\mu_2 y)^2}{2\alpha_2 y}) \int_0^y \Theta(y-t)dt\, dy. \tag{9}$$

In the numerical examples below we assume exponential and linear Θ function

$$\Theta(y-t) = e^{-a(y-t)}, \tag{10}$$

$$\text{or} \qquad \Theta(y-t) = \begin{cases} 1-a(y-t) & \text{for} \quad y \leq 1/a - t \\ 0 & \text{for} \quad y \geq 1/a - t; \end{cases} \tag{11}$$

$\Theta(y-t) = 0$ means that information older than $1/a$ is useless.

4 Numerical Example

We assume that the battery capacity is $B = 50$ energy units, safety margin is $S = 5$ energy units, and $\mu_1 = 0.2$, μ_2 takes several values $\mu_2 = 0.05, 0.1, 0.12, 0.15$, and $\alpha_1 = \alpha_2 = 1$.

A few numerical results giving $C(b)$ for various parameters are displayed in Figs. 3, 4, 5, 6, 7, 8 and 9. In general, they demonstrate the sensibility of $C(b)$ on its parameters and demonstrate the important differences introduced by the deterioration function type. In some cases, the maximum of $C(b)$ is inside the interval $[0, B - S]$, sometimes the function is monotonic, and the maximum is on the edge of the interval. Maximum of $C(b)$ at $b = 50$ means that only the second phase is recommended; maximum at $b = 5$ means we should have only the first phase. It depends on the ratio of the speed of energy consumption in both phases and the function lowering the value of delayed results. A few numerical results giving $C(b)$ for various parameters are displayed in Figs. 3–9. In general, they demonstrate the sensibility of $C(b)$ on its parameters and demonstrate the notable differences introduced by the deterioration function type. In some cases, the maximum of $C(b)$ is inside the interval $[0, B - S]$, sometimes the function is monotonic, and the maximum is on the edge of the interval. Maximum of C(b) at $b = 50$ means that only the second phase is recommended; maximum at $b = 5$ means we should have only the first phase. It depends on the ratio of the speed of energy consumption in both phases and the function lowering the value of

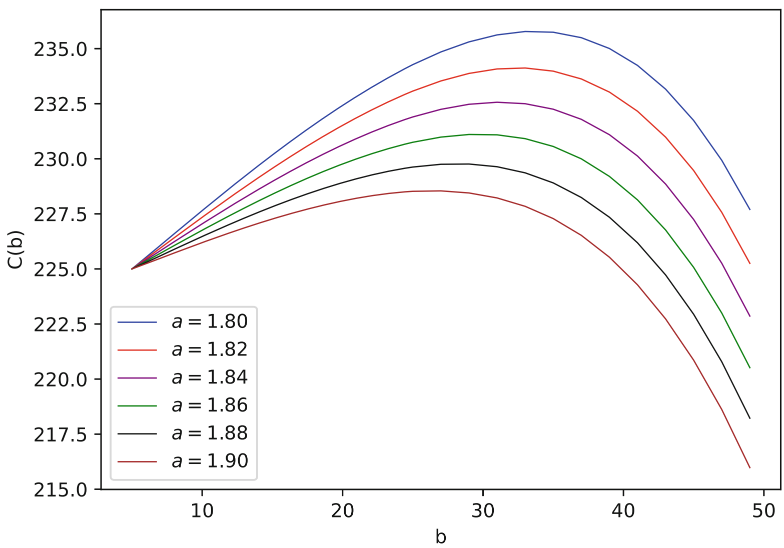

Fig. 3. The reward function $C(b)$ defined by Eq. (9) and to be maximized; b is the energy level switching the performance of UAV from normal mode to energy saving mode, for exponential function Θ defining the decrease with time of the value of previously gathered data, see Eq. (10), with parameters $\mu_2 = 0.1$, $a \in [1.8, 1.9]$

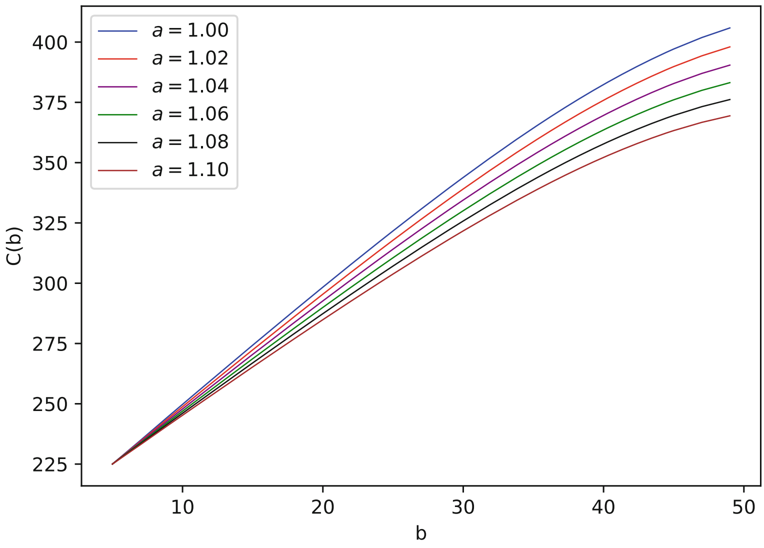

Fig. 4. The reward function $C(b)$ defined by Eq. (9) and to be maximized; b is the energy level switching the performance of UAV from normal mode to energy saving mode, for exponential function Θ defining the decrease with time of the value of previously gathered data, see Eq. (10), with parameters $\mu_2 = 0.1$, $a \in [1.0, 1.1]$

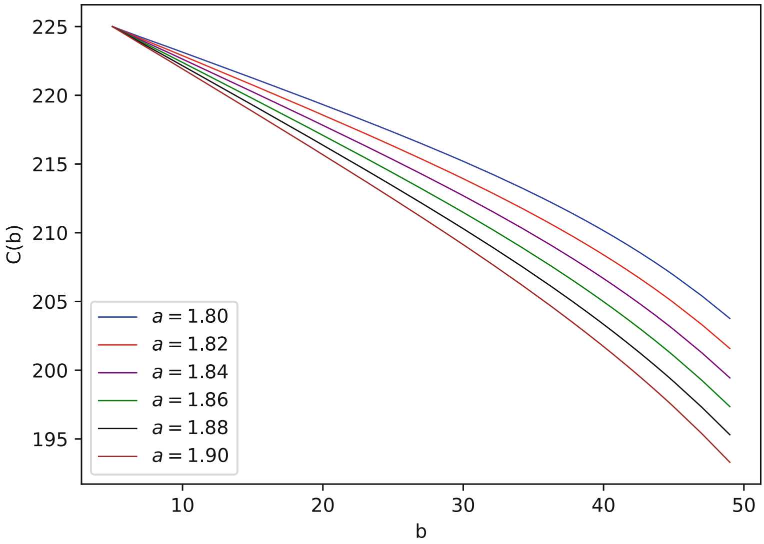

Fig. 5. The reward function $C(b)$ defined by Eq. (9) and to be maximized; b is the energy level switching the performance of UAV from normal mode to energy saving mode, for exponential function Θ defining the decrease with time of the value of previously gathered data, see Eq. (10), with parameters $\mu_2 = 0.12$, $a \in [1.8, 1.9]$

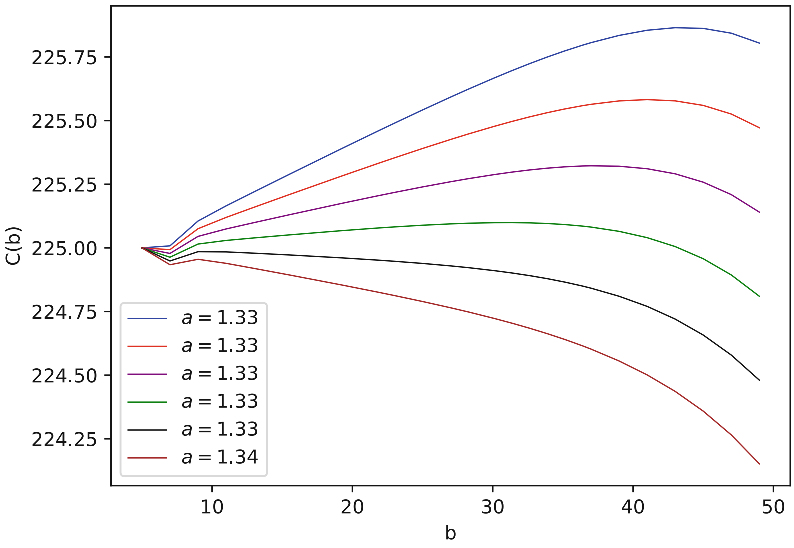

Fig. 6. The reward function $C(b)$ defined by Eq. (9) and to be maximized; b is the energy level switching the performance of UAV from normal mode to energy saving mode, for exponential function Θ defining the decrease with time of the value of previously gathered data, see Eq. (10), with parameters $\mu_2 = 0.15$, $a \in [1.326, 1.336]$

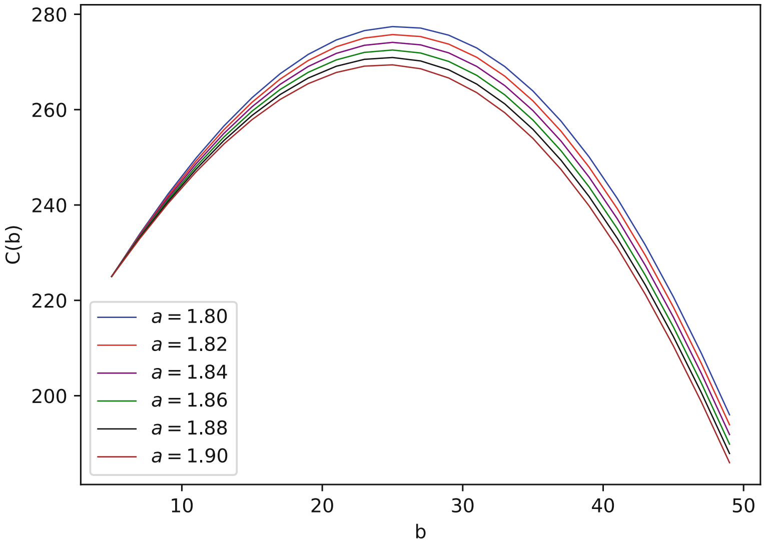

Fig. 7. The reward function $C(b)$ defined by Eq. (9) and to be maximized; b is the energy level switching the performance of UAV from normal mode to energy saving mode, for exponential function Θ defining the decrease with time of the value of previously gathered data, see Eq. (10), with parameters $\mu_2 = 0.05$, $a \in [1.8, 1.9]$

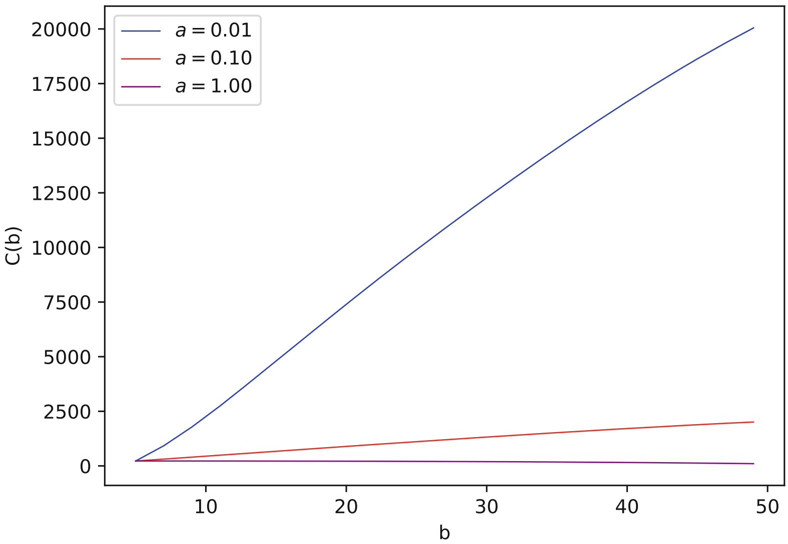

Fig. 8. The reward function $C(b)$ defined by Eq. (9) and to be maximized; b is the energy level switching the performance of UAV from normal mode to energy saving mode, for linear function Θ defining the decrease with time of the value of previously gathered data, see Eq. (11), with parameters $\mu_2 = 0.10$, $a = 0.01, 0.1, 1000$

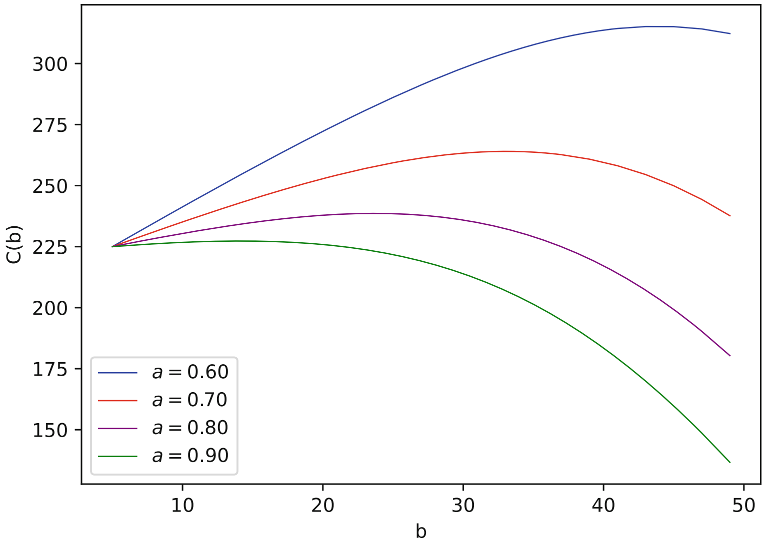

Fig. 9. The reward function $C(b)$ defined by Eq. (9) and to be maximized; b is the energy level switching the performance of UAV from normal mode to energy saving mode, for linear function Θ defining the decrease with time of the value of previously gathered data, see Eq. (11), with parameters $\mu_2 = 0.10$, $a \in [0.6, 0.9]$.

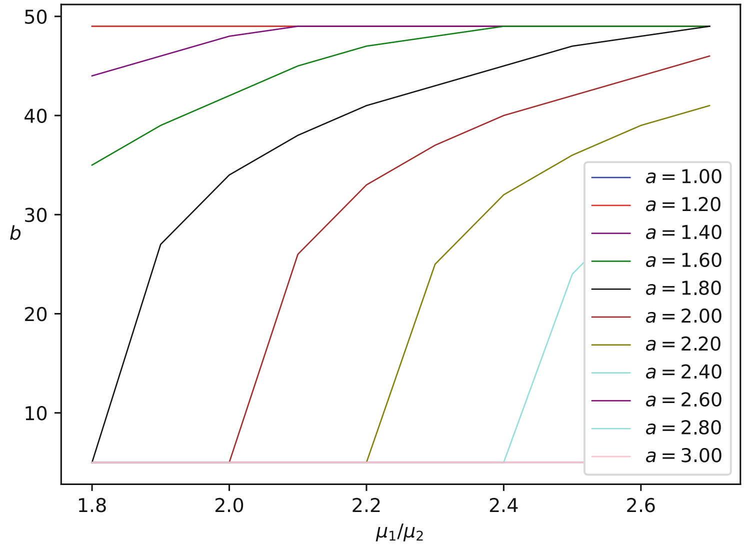

Fig. 10. The value of b, i.e. the energy level switching the performance of UAV from normal mode to energy saving mode, maximizing the reward function $C(b)$ defined by Eq. (9) plotted as a function of μ_1/μ_2, where μ_1 is the speed of energy consumption in normal mode and μ_2 is the speed of energy consumption in energy saving mode, for fixed $\mu_1 = 0.2$.

delayed results. We see it in a more general way in Fig. 10 where the values of b giving the maximum of C are plotted as the function of μ_1/μ_2 ($\mu_1 = 0.2$).

5 Conclusions

The duration of a done's mission depends on the amount of energy required to perform some manoeuvering actions (takeoff, level flight, hovering, and landing) [3] and the energy required to power the ICT modules in the drone. The energy required to drive the drone depends on the manoeuvering action taken, the drone's speed, payload, and the wind. Although the amount of energy required to drive the drone is often far greater than the energy required to power the ICT modules, the influence of ICT energy consumption on the duration of the drone's mission could become significant (especially for drones that draw small amount of energy for flight but perform complex ICT functionalities). Also, cyber security attacks designed to increase the amount of transmission or computations executed by the drone and deplete its battery faster could rapidly deplete the energy stored in the battery.

Since for some set of parameters, the reward function $c(b)$ has a maximum for $b \in [0, B-S]$, the by devising strategies to reduce the energy consumption, when the energy in the battery reaches a define threshold level b, increases the chances that it will complete its mission and land safely. Therefore, the decision point to transition from the normal phase to the energy saving phase to be chosen in such as way as to minimise the energy consumption and maximise the battery lifetime.

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