Towards Energy Consumption Prediction with Safety Margins for Multicopter Systems

Fast Abstract

Thomas Dietrich
Systems and Software Engineering Group
Technische Universität Ilmenau
Ilmenau, Germany
thomas.dietrich@tu-ilmenau.de

Thomas Hotz
Stochastics Group
Technische Universität Ilmenau
Ilmenau, Germany
thomas.hotz@tu-ilmenau.de

Silvia Krug
Communication Networks Group
Technische Universität Ilmenau
Ilmenau, Germany
silvia.krug@tu-ilmenau.de

Armin Zimmermann
Systems and Software Engineering Group
Technische Universität Ilmenau
Ilmenau, Germany
armin.zimmermann@tu-ilmenau.de

ABSTRACT

Multicopters are robotic systems with a remarkable degree of freedom and applicability. A significant limitation of all mobile robotic vehicles is the restricted on-board energy storage capacity and consequential limited operation time. Uninterrupted mission execution of multicopter swarms thus requires to predict energy depletion and plan maintenance and replacement processes accordingly. This paper presents and discusses challenges of a realistic prediction model for battery energy consumption. To cope with the inherent uncertainty, we are interested not only in the expected values, but also safety margins. The paper discusses common expectations first and presents a solution idea for the underlying key issue.

CCS CONCEPTS

• **Hardware** → *Power estimation and optimization*; • **Mathematics of computing** → *Stochastic processes*;

KEYWORDS

Energy Profiling, Consumption Prediction, System Safety Margins

1 INTRODUCTION AND PROBLEM

Micro-Aerial Vehicles (MAVs), especially multicopter systems, are used in various autonomous mission scenarios and have gained significant interest in science as well as industrial and consumer use. Such missions should be executed without interruptions induced by recharging or battery replacement. This requires a transparent exchange of physical copters acting as logical nodes of a mission task. In order to plan and evaluate such exchange processes, the energy consumption of the system at hand needs to be well understood. In our previous work, we derived an energy consumption

profile based on an empirical study [1]. The profile is used to estimate the average remaining flight time of a multicopter base on the battery charge level, taking into account the different usage levels for certain types of maneuvers. However, with the focus on mission safety and reliability, average estimations are of limited use.

Safety margins need to be included in the execution of replacement processes to ensure probabilities of failure-free mission completion. This is important to evaluate and optimize maintenance processes, while trading off the risks of decisions.

The existing energy consumption profile is able to characterize the energy consumption for certain moments in time, depending on the state and status of the multicopter. However, to predict the overall electric charge consumption Q_p using discrete event simulation to evaluate exchange processes of multicopter systems, several additional questions arise.

The predicted electric charge Q_p is chosen based on the current flow distribution derived from real flight data and based on a quantile value selection (e.g. 95 %) for probabilistic safety assurances. Possible questions that should be addressed in a simulation are:

- "What is the expected mean consumption (in [mA h]) over the course of a 10 min hover flight?"
- "How probable (in [%]) is a predicted consumption of more than 2600 mA h over the course of a 10 min hover flight?"
- "Which quantity of electric charge (in [mA h]) will be consumed over a 10 min hover flight in those 95 % of all cases with the least consumption?"

Such calculations are important for management and maintenance tasks, where probabilistic measures need to be taken into account, to meet safety and availability requirements. This is not possible using simple mean values, which would be taken as input for an otherwise deterministic model.

2 ENERGY CONSUMPTION PREDICTION

Every maneuver can be represented by a parametrized state for which the energy usage is known from the consumption profile.

To calculate the electric charge used over the course of a certain time span (here during one maneuver), the continuous current flow

during that time has to be known:

$$Q = \int_{t1}^{t2} I(t)\, dt \qquad (1)$$

In the context of a sampled measurement environment the above can be discretized, as long as the Nyquist-Shannon sampling theorem is fulfilled. Under the assumption that all T_n are equidistant, the formula can be simplified by one fixed sampling distance T_s:

$$Q_s = I_1 * T_1 + I_2 * T_2 + \ldots + I_n * T_n = \sum_{n=1}^{N} I_n * T_n \qquad (2)$$

$$Q_s = T_s * \sum_{n=1}^{N} I_n \qquad (3)$$

Under the restriction that all samples were taken during one single maneuver, those samples are presumed to be normally distributed around the state specific mean I_m: $I_s \sim \mathcal{N}(I_m, Var(I_s))$:

$$I_s \sim \mathcal{N}(I_m, Var(I_s)) \qquad (4)$$

The mean energy consumed over the course of the whole maneuver is in conclusion defined as

$$Q_p(T) = N * T_s * I = T * I \quad \text{with} \quad I \sim \mathcal{N}(I_m, Var_T(I_m)) \qquad (5)$$

The first of the listed questions can now easily be answered by equation 5 and the known mean current values from the energy profile.

To answer the remaining two questions, the deviation of the distribution of Q_p needs to be known. However, the distribution can not easily be derived from the sampled current flow data. As shown in equation 4 the distribution for one observed maneuver can be derived from the quantity of sampling values. Assuming the generated distribution is a suitable approximation of the real current flow, we should be able to generate an imitating current flow signal. This signal is required to calculate the accumulated consumed energy and a distribution that allows the prediction of safety margins (quantiles).

The signal recreation is, however, not as straight forward. During the sampling process and the reduction to a simple distribution, the time dimension is removed from the sample pool. A short period of sampled measurements shown in figure 1 visualizes the problem: The signal samples are not statistically independent, which would be required for the mentioned recreation.

The deviation of base current measurements results not only from stochastic error and noise but more importantly from external influences like wind. These systematic influences have short-term effects on the measurement series beyond one single sample and need to be considered for a realistic energy consumption prediction.

3 EXPECTATION AND APPROACH

Irrespective of the insights on signal recreation, the overall consumption still has to follow the basic relation defined in equation 5. Therefore, the expectation for the mean consumption calculation is valid. The stochastic uncertainty of the overall consumption should be normally distributed and the standard deviation must be lower than the sample mean deviation. To prove that proposition, mind the following example.
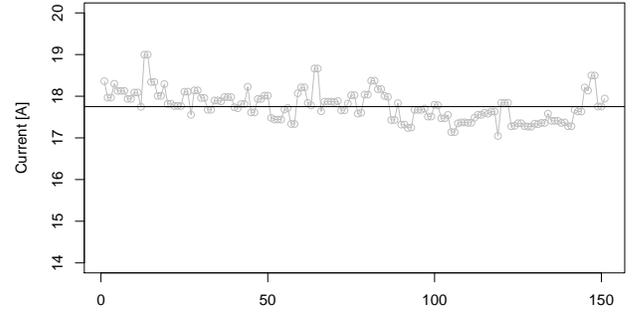

Figure 1: Sample Values over a Short Period of Steady Maneuver Execution (Equidistant Sample Time 100 ms)

Imagine a sampling experiment over a fixed duration. The mean value of the measurement values is calculated for a single experiment trial. Due to the stochastic nature of the base data, subsequent trials will result in slightly different trial means. After the execution of enough trials, the pool of trial means will create a normal distribution by themselves.

Imagine extending the experiment duration from k to $k + 1$ samples. Each draw from the sample duration will, because of the nature of the normal distribution, likely be in close proximity to the mean value. Adding the next sample $k + 1$ to the sample mean will hence reduce the standard deviation of the sample mean distribution.

The described characteristic is known from literature as the "standard deviation of the sampling distribution of the sample mean" [2, p. 185], defined as $\sigma_x = \frac{\sigma}{\sqrt{k}}$.

Due to the discussed effects of higher order influences, a simple relation depending on the sample count is not sufficient. However, the method is able to describe the nature of the expected result and a trend for the standard deviation of the energy consumption.

To take dependence between neighboring samples into account, the auto correlation function for the sample series may be used to generate lag values. Those can then be placed in a covariance calculation of the series with itself, to result in the series variance, applicable for further computations.

4 CONCLUSION AND FUTURE WORK

The problem of a reliable energy consumption prediction method has been discussed in this paper. Estimations based on stochastic safety margins are needed to find a good trade-off between multicopter utilization efficiency and failure probability. We have identified the key issue of the problem and made educated trend assumptions of the solution. In the future, we plan to use an approach based on auto-correlation functions to find accurate consumption distribution characteristics.

REFERENCES

[1] T. Dietrich, S. Krug, and A. Zimmermann. 2017. An Empirical Study on Generic Multicopter Energy Consumption Profiles. In *IEEE Int. Systems Conference (SysCon 2017)*. Montreal, Canada, 1–6. https://doi.org/10.1109/SYSCON.2017.7934762
[2] R. Lyman Ott and Michael Longnecker. 2010. *An Introduction to Statistical Methods and Data Analysis* (6 ed.). Cengage Learning Inc.