Machine Learning-Based Power Consumption Prediction for Unmanned Aerial Vehicles in Dynamic Environments

Julian Gatscher
University of Bayreuth
julian.gatscher@uni-bayreuth.de

Johannes Breitenbach
University of Bayreuth
johannes.breitenbach@uni-bayreuth.de

Ricardo Buettner
University of Bayreuth
Fraunhofer FIT
ricardo.buettner@uni-bayreuth.de

Abstract

Unmanned aerial vehicles are becoming integrated into a wide range of modern IoT and CPS environments for various industrial, military, and entertainment applications. With growing estimations for this market in the future, the problem of energy consumption and its prediction is becoming increasingly important for optimal battery-saving, as well as the safety of the application and thus protection of surrounding persons near the drone flight. This paper presents a machine learning-based approach for the prediction of the power consumption of unmanned aerial vehicles at certain times of the flight. Instead of predicting the power consumption in prescribed environments with complex, time-consuming measurement techniques, our approach is fast, easy to implement, and predicts real-world power consumption in five classes, with a balanced accuracy of 66.7 percent.

Keywords: UAV, drones, power consumption, machine learning, dynamic environments

1. Introduction

The exceptional growth of the unmanned aerial vehicle (UAV) sales is expected to continue with shipments of over 90 million consumer UAVs to be recorded in 2025 alone (Yuan et al., 2018). UAVs are nowadays used for various applications, like mailing, delivery of products, inspection of hard-to-reach areas like pipelines and bridges, military usage, and other industrial applications (Hassanalian & Abdelkefi, 2017; Lee & Choi, 2016). The benefit of using UAVs for companies is having lower cost, increased speed, and reduced greenhouse gas emissions (Zhang et al., 2021). Additionally, for consumers, the usage of drones for entertainment becomes more and more popular (Quiroz & Kim, 2017).

With the increasing use of drones and the population density rising, a new problem, besides surveillance fear of inhabitants, arose. Namely, the fear of falling drones causing physical injuries to people (Dalamagkidis et al., 2008; Schenkelberg, 2016). Not only does the weight significantly impact the potential damage caused by falling drones, but also the propeller blades can harm persons.

There were over 4,250 registered drone injuries between 2015 and 2020 (Gorucu & Ampatzidis, 2021). With over 70 percent, most injury diagnoses were lacerations, followed by contusion or abrasion with about ten persons, and strain and internal injuries each with 5 percent. The most injured body parts are the fingers and the head of victims. The impacts on the body can therefore be drastic (Dalamagkidis et al., 2008; Duma et al., 2021; Gorucu & Ampatzidis, 2021), which leads to the first researchers assessing the risk of drone flights (Dalamagkidis et al., 2008).

With growing estimations for the UAV market, this number of accidents is also expected to grow in the future (Clothier et al., 2015; Giones & Brem, 2017). One major issue causing this is the fact that most regulations are still superficial (Dalamagkidis et al., 2008). This is why damage prevention by falling drones is important (Schenkelberg, 2016) and should be implemented by developers. As stated previously, the technology of drones is developing rapidly, but safety regulations do not (Dalamagkidis et al., 2008; Zhang et al., 2021).

Limited battery life and its estimation are one of the biggest challenges in drone development (Abeywickrama et al., 2018; Mansouri et al., 2017). This fact also significantly influences the emergency

URI: https://hdl.handle.net/10125/103473
978-0-9981331-6-4

rate and success rate of drone applications (Prasetia et al., 2019). It is essential to know the future power consumption to forecast how many flights can be made and thus improve security and the service quality of companies (Baek et al., 2018). Therefore, developing reliable energy consumption models that can accurately predict the energy use and End of Discharge (EoD) is essential for improving safety, and efficiency (Abeywickrama et al., 2018; Dalamagkidis et al., 2008; Liu et al., 2017; Mansouri et al., 2017; Zhang et al., 2021).

In general, energy models are clustered into black-box models and white-box models. White box modeling approaches use statistical and mathematical, mostly linear models, but also specific machine learning models, like decision trees, to estimate energy consumption (Prasetia et al., 2019). White box models are explainable for humans but usually less accurate (Loyola-Gonzalez, 2019). In contrast, black-box methods do not require any physical or theoretical models and parameters. This approaches primarily uses machine learning methods, like support vector machines, gradient boosted trees (Loyola-Gonzalez, 2019; Prasetia et al., 2019), or convolutional networks, which also showed good performance when using image data (e.g., quality control of electrical components (Breitenbach, Gross, Baumgartl, et al., 2022) or medical products (Breitenbach, Gross, Buettner, et al., 2022)). These models are more accurate but hard to explain (Loyola-Gonzalez, 2019).

White box models are often time-consuming and complex to implement. Additionally, those approaches are difficult to apply to different scenarios and types of drones. Most studies only observed individual parameters but did not represent a holistic picture of energy models (Abdilla et al., 2015; Bezzo et al., 2016; Figliozzi, 2017; Liu et al., 2017; Schacht-Rodrıguez et al., 2018; Shan et al., 2020). Studies done in the field of black-box modeling have grown in the past years. Several machine learning approaches, like Non-recursive Least Squares, Kalman Filters, ELM neural networks, Long-Short Term Memory, linear sparse models, support vector regressions, multilayer perceptrons, and advanced tree-based algorithms have been used for different cases, and measurements (Abeywickrama et al., 2018; Costa et al., 2019; Mansouri et al., 2017; Prasetia et al., 2019; Saha et al., 2012). The effects of different parameters were identified, and the first holistic approaches for energy models were described and evaluated (Abeywickrama et al., 2018; Ahmed et al., 2016; Choudhry et al., 2021; Mansouri et al., 2017; Prasetia et al., 2019).

Although many studies in the field of energy consumption models of UAVs have been conducted, there is still a lack of realistic energy models for drones that can be used for different cases (Si et al., 2011; Trihinas et al., 2021). Most models in the field of energy consumption for UAVs are still not accurate enough (Mansouri et al., 2017), and therefore reliable results cannot be guaranteed with most of the models currently available (Prasetia et al., 2019). One major problem causing this is that current techniques are insufficient to manage when having different loads in dynamic environments (Saha, Koshimoto, et al., 2011; Saha, Quach, & Goebel, 2011). There are only a few holistic models (Abeywickrama et al., 2018) that include payload, wind speed, speed, different maneuvers, and communication. Most studies only included certain parameters in their experiments (Ahmed et al., 2016; Alyassi et al., 2022; Liu et al., 2017; Valenti et al., 2007). This is also one of the reasons why there is no "consensus on standards for drone energy consumption, nor on how to model drone energy consumption" (Zhang et al., 2021). To sum up, "various drone energy models can produce widely divergent results in terms of the energy consumed for essentially the same drone delivery operation" (Zhang et al., 2021) since most studies only conducted a few flights and therefore collected few data. Thus, the energy consumption rate varies by a factor of 3 to 5 across the models (Rodrigues et al., 2021).

Accurate energy prediction requires a reliable and realistic energy consumption model (Abeywickrama et al., 2018). Mathematical models are usually very complex and, in numerous instances, not transferable to other scenarios. The work usually only relates to individual scenarios, and truly overarching models cannot be mapped. There are too many parameters and environmental influences on drone flights, which mathematical functions cannot depict. Therefore, these proposed energy consumption models vary strongly (Rodrigues et al., 2021). To build an accurate, fully comprehensive energy prediction model that is considering all relevant parameters influencing a drone flight, a machine learning approach is necessary. Such an approach ensures higher accuracies, more efficient, less time-consuming algorithms, and the use of large amounts of data, which allows consistent and comprehensive research results.

For improving security, improving public perception, and thus increasing the market size, it is highly relevant for companies to use drones containing accurate power consumption predictions since high reliability is one of the primary goals when using drones (Schenkelberg, 2016). Therefore, we will look at the topic of drone power consumption prediction from an economic and financial point of view with a focus on security. We will specifically focus on the security aspect regarding power consumption. Security aspects like hacking, sensor malfunction, or external influences, like humidity or fog mentioned in (Schenkelberg, 2016) will not be considered.

The most important contributions of this paper are:

- We develop a random forest classifier with five power consumption classes of each 200W that achieves a balanced accuracy of 66.7 percent.
- We contribute to research in the field of power consumption prediction for UAVs.
- We underpin the impact of payload and wind speed on the power consumption of UAVs.

The paper is organized accordingly: First, we present an overview of the research background on the power consumption of drones, prediction of energy consumption using different models, and machine learning approaches in the field of drones. After that, we describe the used methodology, including the machine learning model and the dataset. Afterward, we show the results of the machine learning approach and discuss the results. Finally, we outline the limitations and questions for future research.

2. Research Background

2.1. Drone Power Consumption

There has been much research on how different factors affect the power consumption of drones. The study of Zhang et al. (2021) identifies four key aspects influencing drone power consumption. First, drone design has a significant impact on power consumption. These include, for example, the weight and size of the drone, the number of rotors, the weight of the battery, the maximum speed and much more. But also, the number and type of sensors can consume lots of energy (Schenkelberg, 2016). Second, environmental factors like weather, temperature, and wind speed influence power consumption. Third and fourth, dynamics like altitude, speed, acceleration as well as weight, and size of payload have an impact on the battery consumption. This means that different maneuvers affect energy consumption in different ways (Prasetia et al., 2019). A straight flight consumes less energy than a flight at different heights, or directions (Shan et al., 2020).

If all these factors are combined, the total energy consumption can be mapped using different mathematical or data-driven models (Abeywickrama et al., 2018; Zhang et al., 2021). The same works for estimating the future energy consumption, where research proposed several models, which will be discussed in the next two chapters. In order to make a basic prediction, the State of Charge (SoC) is usually used in the literature. This shows what percentage of the battery is still available for use, for example, three percent. However, the SoC is practically less relevant than the metric of Remaining Useful Life (RUL), which describes how long it takes for the battery to run out of charge (Mansouri et al., 2017). The RUL is commonly used in current research.

2.2. Common Mathematical and Statistical Approaches for Predicting Power Consumption

Several mathematical and statistical studies to model energy consumption using linear, statistical, and mathematical methods have been conducted. In general, these methods can be classified as white-box modeling approaches (Prasetia et al., 2019). Such methods usually require different physical parameters and use theoretical models (Abdilla et al., 2015; Bezzo et al., 2016; Figliozzi, 2017; Liu et al., 2017; Schacht-Rodrıguez et al., 2018; Shan et al., 2020). Thus, the application is rather time-consuming and complex. For non-physics, it is therefore hard to understand and build such models.

Figliozzi (2017) focussed on lifecycle modelling and co2 emissions. To estimate emissions, they had to estimate power consumption first. Therefore, they analyzed deliveries that went directly to the delivery destination and back, as well as multiple deliveries at the same time before heading back to the station. For those scenarios, they used different analytical frameworks. They found that payload can heavily impact the efficiency of drone battery and deliveries, which makes drone delivery of heavy packages less CO_2-efficient than a typical US Van. Abdilla et al. (2015) used a battery model and rotorcraft power model to estimate the endurance. The authors validated the results experimentally through flight tests. This model and experimentation reached solid results but is quite time-consuming to implement and hard to adapt to other flight scenarios.

Bezzo et al. (2016) tried to plan a policy for minimum energy path planning of UAVs, with the goal of improving the operation of drones. The experiment was conducted in the real world, also including environmental disturbances. They used a non-linear model and could, as stated by themselves, improve existing models. Still, they could not prove with numbers an exact improvement in the accuracy of their model.

Schacht-Rodrıguez et al. (2018) also used a mathematical model to predict flight endurance and remaining mission time. The authors used a so-called Extended Kalman filter to estimate the State of Charge. In the next step, they used a polynomial function to predict the SoC and, therefore, the End of Discharge during the flight mission. The authors conclude that it is possible to predict flight endurance using this approach. Still, their approach is quite time-consuming and not accurate enough (Prasetia et al., 2019).

The study by Liu et al. (2017) focused mainly on long drone flights and was one of the first approaches that used helicopter theory. The authors used an analytical model including six non-dimensional parameters, which is few. Important factors like wind speed and payload are not considered. This also makes their energy model incomplete.

Shan et al. (2020) focussed on speed as a metric. To do so, they disclose a speed-related flight energy consumption model. Instead of flight time or distance, they observed the effect of the speed for the respective time and distance. A looking before the crossing algorithm was used to map a consumption model accurately. This speed-related energy model is especially useful for wireless communication (Shan et al., 2020).

To sum up, all studies conducted added significant value and insights into energy models. Still, most approaches are time-consuming and very complex and, therefore, also hard to adapt to different scenarios. For mathematical approaches, there is no complete energy model that includes all relevant parameters influencing drone flights.

2.3. White and Black Box Machine Learning Approaches for Predicting Power Consumption

Several studies used data-driven methods for estimating drone energy consumption. Especially in the past years, the popularity of such Machine Learning approaches grew strongly. In the literature, these methods are described as black-box modeling (Prasetia et al., 2019). It is believed that Machine Learning is the easiest method for implementing energy consumption models (Prasetia et al., 2019). This is mostly since it is less time-consuming and less complex. In this chapter, an insight into state-of-the-art literature in the field of ML approaches for predicting power consumption for UAVs will be given.

Chen and Pecht (2012) combined Machine Learning approaches with model-based approaches from the previous chapters to estimate RUL accurately. Research results show that for the used example of the authors, the RUL can be predicted precisely. Unfortunately, the same model cannot be applied for different circumstances and battery ages.

Mansouri et al. (2017) implemented a relatively extensive approach, using four machine learning techniques. These are a sparse linear model, a support vector regression, a multilayer perceptron, and an advanced tree-based algorithm, namely a gradient boosted tree. They concluded that non-linear methods usually outperform linear ones, which also shows that mathematical models have certain limitations (Prasetia et al., 2019). Furthermore, they found out that the gradient boosted tree performed best and suggested using a dataset with more parameters in the future (Mansouri et al., 2017).

Saha et al. (2012), Trihinas et al. (2021), and Costa et al. (2019) also used different, but rather superficial ML approaches. However, Trihinas et al. (2021) are still lacking accuracy and scope of energy profiles. Costa et al. (2019) used a Non-recursive Least Squares, a Kalman Filter, and an ELM neural network in their study. The used algorithms are not robust enough, and results still have to be evaluated with different models. Saha et al. (2012) did not validate and test the results. Furthermore, they only analyzed SoC, but not RUL, just like Charkhgard and Farrokhi (2010). Saha, Koshimoto, et al. (2011) also primarily focused on SoC but then used a particle filter to forecast RUL to improve system safety.

Ahmed et al. (2016) focused on black model approaches, too. They only analyzed a few basic maneuvers, like hovering, flying 180 degrees upwards and downwards. Ahmed et al. (2016) expanded these metrics by also taking into consideration the impact of payload and wind on the power consumption of drones. Factors like communication, take-off and speed were not observed in these studies of Ahmed et al. (2016). This is the same for Choudhry et al. (2021), who used a deep learning model, which works highly accurate but unfortunately only includes data from standard maneuvers of drones.

Abeywickrama et al. (2018) were the first to provide a comprehensive and entirely energy model. Their model has an error rate of only 4.3 percent and can be used for mission planning. They analyzed the power consumption on the ground, impact of communication via Wi-Fi, taking off, and different vertical and horizontal movements. Furthermore, the effect of payload, wind, and speed was observed and included in the energy model. However, the amount of data used and conducted flights is relatively small and, therefore, hard to use for other types of drones.

Wei et al. (2019) used a dataset from NASA, which is not available anymore to the public domain. The support vector machine model achieved an accuracy of 98.42 percent. It is especially accurate during discharging processes of batteries.

Prasetia et al. (2019) made a big advance, proposing their energy prediction model with an accuracy of 98.773 percent. In the preprocessing, they separated the different movements, accelerations, and decelerations from one another. The regression was done using Elastic Net Regression from Sklearn. The authors suggest that the accuracy can be improved even more and suggest using different ML approaches like Long-Short Term Memory to predict the energy consumption of UAVs. Furthermore, the data used is relatively small, conducting only a few flights, and therefore does not include all relevant parameters influencing drone flights.

Concluding, the different machine learning algorithms used in the above-mentioned studies already delivered accurate and valuable results. Over the past years, all relevant metrics like payload, speed, payload wind have been taken under consideration. The approaches made with ML are already accurate, but often miss the use of sufficient data points (Prasetia et al., 2019). Also, the "energy consumption rate (J/m) varies by a factor of 3 to 5 across the models" (Rodrigues et al., 2021). To build an accurate, fully comprehensive energy prediction model that is considering all relevant parameters influencing a drone flight, a Machine Learning approach is necessary. Mathematical and statistical models have limitations in complex scenarios, including multiple parameters. A Machine Learning approach ensures higher accuracies, more efficient, less time-consuming algorithms and use of big amount of data, which allows consistent and comprehensive research results. A big dataset as the one used within this study helps to achieve this goal.

3. Method

The methodological approach can be clustered in three steps. The first step was data preprocessing to prepare the data for training the models. Thereby, we eliminated excessive data points and reduced the amount of data for processing in the different classification models. Afterwards, the models were trained using a test-train split of 70-30. Finally, the classification models were divided into different classes of 5,10 and 20. The evaluation is based on the balanced accuracy, precision-score, recall-score and f1-score. In addition, the kappa score was also used.

Table 1. ML Approaches for Modelling Energy Consumption of UAVs

Reference	Methods	Dataset	Investigation
(Mansouri et al., 2017)	LASSO, Support Vector Machine, Multilayer Perceptron, Gradient Boosted Tree	Different maneuvers excluding payload and current	RUL prediction
(Wei et al., 2019)	Support Vector Machine	NASA dataset (Saha & Goebel, 2007)	SOC prediction
(Costa et al., 2019)	Kalman Filter, ELM Neural Network, Non-Recursive Least Squares	NASA dataset (Saha & Goebel, 2007)	SOC prediction
(Choudhry et al., 2021)	Temporal Convolutional Networks	Dataset by Rodrigues et al. (2021)	Conditional Value at Risk
(Charkhgard & Farrokhi, 2010)	Neural networks and Kalman Filter	Self-recorded dataset of different maneuvers	SOC prediction
(Prasetia et al., 2019)	Elastic Net Regression	Self-recorded dataset of different maneuvers	Prediction of energy consumption of mission

3.1. Date Preprocessing and Machine Learning Model

After the dataset was read in, it was reviewed. Thereby, it was relevant to see how many flights were performed with different speed, payload and on different altitudes. Additionally, different speed variables like accelerations and velocities were checked with correlations matrixes and if necessary eliminated.

In order to see the power consumption for the respective times of the flights, it was necessary to calculate it from the two values ”battery current” and ”battery voltage”. Then the distribution of power consumption was considered and a normal distribution was detected. Only around the value ”0” is a large outbreak. This is due to the fact that for the individual flights, the data collection already started before and after the flight. For this reason, all rows with a power consumption of less than 10 were eliminated. In the dataset from Rodrigues et al. (2021), it is described that the payloads are present with data sets of 0, 250 and 500. However, it was found that there is also a flight with 750. For this reason, this flight was eliminated. Since most of the columns in the data set contain many decimal places, these values were rounded to five decimal places to reduce the complexity of the data.

A decision tree and a random forest algorithm were then trained with this processed data. As a target variable, we used the parameter power consumption. Both models were assigned with different categories, which were 5 classes (classes of 200 Watt each), 10 classes (97 Watt), 20 classes (48 Watt) and 60 classes (16 Watt).

In order to achieve the best possible results and to optimally configure and train the models, individual parameters were changed. For example, the maximum depth of the tree was influenced and changed. For performance reasons, the random forest was left to determine the best maximum depth. It was also necessary to adjust imbalances in the distribution. In the variant of the random forest that was used, not all features were used because the amount of data in the data set was too large to achieve accurate results. For example, only $\sqrt{n}$ features were used here so that the model can be trained more quickly and fewer data points are included.

3.2. Evaluation method

For evaluation, we used a hold-out k-fold cross-validation. This method splits the dataset into subsets for training and testing. For our work, 10 random splits into 70 percent training data and 20 percent unseen testing data, along with 10 folds for each split, were performed. Only the testing data is used for evaluation. Before evaluation, this data is not shown to the model (Yadav & Shukla, 2016).

3.3. Dataset

The used dataset for this Machine Learning Approach consists out of 209 flights using a small quadcopter of the type DJI Matrice 100 (M100) (Rodrigues et al., 2021). The drone is fully programmable and customizable, which made it especially suitable for this experiment. The DJI Matrice 100 was equipped with the DJI 3510 motors (350 Kv), DJI E SERIES 620D ESCs, and the DJI 1345s for the rotor blades. Its standard battery has a capacity of 4500 mAh and the weight of this UAV totaled 3680g, without payload.

Rodrigues et al. (2021) varied different parameters such as speed, payload and speed of UAV as well as for example the altitude to have a broad spectrum of data. The drone flew autonomously making different maneuvers like take off, different flight patterns, and landing. For recording the flights, they used different onboard sensors, such as a GPS, IMU, voltage and current sensors, and an ultrasonic anemometer, to do so. Furthermore, the power consumption and battery voltage has been tracked constantly.

The flight time totals to 10 hours and 45 minutes and covers a distance of approximately 65 kilometers. Data was collected from April to October 2019. The quadcopter flew the same route with varying altitude (25 m, 50 m, 75 m and 100 m), speed (4 m/s, 6 m/s, 8 m/s, 10 m/s and 12 m/s) and payload mass (no payload, 250 g and 500 g). Each combination of settings was repeated at least three times, totaling 195 flights. To get further insights, 14 recordings were performed with the drone in hover and idle modes, which leads to the total number of 209 flights.

Since UAV field test have strict requirements and take significant effort, there are only few datasets in this field published. The dataset from Rodrigues et al. (2021) was used because it contains a large our knowledge, there are no other equally extensive data sets available at the time of this research. In addition, the collection of the data set, and its methodology is transparently described, which is often not the case with other data sets.

4. Results

By analyzing the correlation and line plots between the individual parameters and power consumption, a big impact of payload and wind speed was identified. However, speed and altitude as an example had no visible impact on the overall power consumption. The mean power consumption for the different flights started at 470W with 0g payload and increased to 515W with 250g payload and 565W with 500g payload. In contrast, for different speeds and altitudes, the power consumption only varied around 10 to 20 Watt.

The decision tree was trained without maximal depth and the random forest was trained at 200 trees. Both models performed differently when using a different number of classes. In general, the random forest performed better than the decision tree. For five classes, the random forest achieved and balanced accuracy of 66.7 percent, for ten classes, 50.8, for twenty classes, 32.7 and for sixty classes of 14.7 percent (see Table 2).

Table 2. Performance of Both Models Over 10 Train-Test Splits

Number of Classes	Balanced Accuracy of Decision Tree Classifier	Balanced Accuracy of Random Forest Classifier
5	63.8%	66.7%
10	46.6%	50.8%
20	28.3%	32.7%
60	11.8%	14.7%

5. Discussion

The results of our research show that the accuracy of the random forest decreases as the number of classes increases. However, it is not possible to make a general statement that the model with higher balanced accuracy also performs better in practice. The hit rate is higher, but in the case of a wrong hit, the consequence is also very high because in extreme cases, the energy consumption is extremely wrongly estimated by up to 200 watts. This can, of course, have a great influence on the safety of the flight and the prediction of the battery's duration (Baek et al., 2018; Zhang et al., 2021).

So, might a lower balanced accuracy be more sensible and even better? With 60 classes, for example, the confusion matrix has shown that the estimates are usually only off by a maximum of two to three classes. This would then be only 45 watts, which were predicted too much or too little.

This remaining inaccuracy of the estimation naturally also has an influence on the safety of the flight. With the data available so far, it is not yet possible to guarantee sufficient flight safety. This also raises the question of when a flight is ultimately safe? How high must the accuracy be for it to be reliable? How accurate does the forecast have to be (Schenkelberg, 2016)?

However, it is clear that the Random Forest is currently the best used model, with about three to six percent better performance in comparison to a decision tree. Unfortunately, the used regression model had significantly weaker performance values. Furthermore, it was confirmed that payload and wind speed have a high influence on power consumption (Abeywickrama et al., 2018; Figliozzi, 2017).

6. Conclusion

We used a new Machine Learning approach in this field of research to predict power consumption based on different parameters at a given time. The results are novel due to the comprehensive data set and the methodological approach. With the use of a random forest, a balanced accuracy of 66.7 percent was achieved. The results of this work confirm findings from other models. Payload and wind speed are very influential on power consumption (Abeywickrama et al., 2018; Prasetia et al., 2019). The inclination and flight altitude of the drone have hardly been researched so far. It has been shown that these have no discernible influence on consumption. In contrast to the study of Mansouri et al. (2017), the Gradient Boosted Tree performed less accurate in our research. Also, most Machine Learning approaches like the one in the study of (Mansouri et al., 2017) did not include payload. Therefore, the proposed model also extends the field of research for this parameter. Practically, the model cannot be used yet, as it should only be used for the drone mentioned and therefore not be transferred to other drone models (Rodrigues et al., 2021). This is similar to other research in this area (Abeywickrama et al., 2018). A similar measurement procedure would therefore have to be carried out for other drones with their measured values to see how the same values change the power consumption of another drone. Accordingly, the significance of our current research is still limited, as the model still has to be applied to entire flight sequences and achieve increasing accuracy. As soon as entire flights can be covered, such an algorithm can also find practical application.

6.1. Limitations

The main limitation of this research is the data set. Rodrigues et al. (2021) conducted the flights autonomously. If the drone is controlled by a person, for example for entertainment or military use, the changes in direction are likely to be more abrupt. Of course, this could then also influence the final energy model. Since the measurements were carried out accurately, the measurement errors and deviations are also minimal, as described by the authors. This limitation therefore has only very little influence on the research results. In addition, for the research, mostly short flights with a duration of less than 3 minutes were carried out. Longer flights would have been interesting here, for example, to see how the energy behaves in the long term. Furthermore, the survey of the flights was mostly conducted in triangles. The flights were carried out using five fixed routes. This means that really complex maneuvers are not covered and thus do not affect the energy model. Finally, the measurements were carried out at irregular intervals. The sampling does not take place regularly, for example of one second, but varies. If this were the case, even better and, above all, more realistic energy models could probably be implemented here.

6.2. Future Work

In the future, a more comprehensive data set with longer flights and different maneuvers could be used. Here, it would be useful to use another drone to see how much the energy model proposed here changes with the use of another drone (Abeywickrama et al., 2018). The expansion of the parameters would also be important to explore. How does the drone behave with extremely high payloads or also with strong external influences such as strong wind, high humidity or other climatic extremes (Prasetia et al., 2019).

In addition, since in this research the prediction was made for individual flights and for specific times of the flight, it would also be interesting to see how the RUL changes during the entire flight (Chen & Pecht, 2012). In this way, a practice-relevant and operational algorithm can be designed. Finally, it would also be interesting to use or even combine other machine learning models with the existing data set. This includes the use of regression models or a combination of the Support Vector Machine and a Gradient Boosted Tree (Mansouri et al., 2017).

References

Abdilla, A., Richards, A., & Burrow, S. (2015). Power and Endurance Modelling of Battery-Powered Rotorcraft. *Proceedings of the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 675–680.

Abeywickrama, H. V., Jayawickrama, B. A., He, Y., & Dutkiewicz, E. (2018). Comprehensive Energy Consumption Model for Unmanned Aerial Vehicles, Based on Empirical Studies of Battery Performance. *IEEE Access*, *6*, 58383–58394.

Ahmed, S., Mohamed, A., Harras, K., Kholief, M., & Mesbah, S. (2016). Energy Efficient Path Planning Techniques for UAV-based Systems with Space Discretization. *Proceedings of the 2016 IEEE Wireless Communications and Networking Conference*, 1–6.

Alyassi, R., Khonji, M., Karapetyan, A., Chau, S. C.-K., Elbassioni, K., & Tseng, C.-M. (2022). Autonomous Recharging and Flight Mission Planning for Battery-Operated Autonomous Drones. *IEEE Transactions on Automation Science and Engineering*, 1–13.

Baek, D., Chen, Y., Bocca, A., Macii, A., Macii, E., & Poncino, M. (2018). Battery-Aware Energy Model of Drone Delivery Tasks. *Proceedings of the International Symposium on Low Power Electronics and Design*, 1–6.

Bezzo, N., Mohta, K., Nowzari, C., Lee, I., Kumar, V., & Pappas, G. (2016). Online Planning for Energy-efficient and Disturbance-aware UAV Operations. *Proceedings of the 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 5027–5033.

Breitenbach, J., Gross, J., Baumgartl, H., Ulrich, P. S., & Buettner, R. (2022). Artificial Intelligence for Industry 4.0: Automated In-Line Quality Control of Electrical Cable Ends Based on Convolutional Neural Networks. *Proceedings of the 2022 Pacific Asia Conference on Information Systems (PACIS)*, Paper No. 1840.

Breitenbach, J., Gross, J., Buettner, R., Baumgartl, H., Bayerlein, S., Flathau, D., & Sauter, D. (2022). A Deep Learning-Based Cyber-Physical System for the Detection of Defective Capsules Using a Transfer Learning Strategy. *Proceedings of the 2022 Pacific Asia Conference on Information Systems (PACIS)*, Paper No. 1847.

Charkhgard, M., & Farrokhi, M. (2010). State-of-Charge Estimation for Lithium-Ion Batteries Using Neural Networks and EKF. *IEEE Transactions on Industrial Eelectronics*, *57*(12), 4178–4187.

Chen, C., & Pecht, M. (2012). Prognostics of Lithium-Ion Batteries Using Model Based and Data-Driven Methods. *Proceedings of the IEEE 2012 Prognostics and System Health Management Conference (PHM-2012 Beijing)*, 1–6.

Choudhry, A., Moon, B., Patrikar, J., Samaras, C., & Scherer, S. (2021). CVaR-based Flight Energy Risk Assessment for Multirotor UAVs using a Deep Energy Model. *Proceedings of the 2021 IEEE International Conference on Robotics and Automation (ICRA)*, 262–268.

Clothier, R. A., Greer, D. A., Greer, D. G., & Mehta, A. M. (2015). Risk Perception and the Public Acceptance of Drones. *Risk Analysis*, *35*(6), 1167–1183.

Costa, E. F., Souza, D. A., Pinto, V. P., Araújo, M. S., Peixoto, A. M., & da Costa, E. P.

(2019). Prediction of Lithium-Ion Battery Capacity in UAVs. *Proceedings of the 6th International Conference on Control, Decision and Information Technologies (CoDIT)*, 1865–1869.

Dalamagkidis, K., Valavanis, K. P., & Piegl, L. A. (2008). Evaluating the Risk of Unmanned Aircraft Ground Impacts. *Proceedings of the 16th Mediterranean Conference on Control and Automation*, 709–716.

Duma, L. A., Begonia, M. T., Miller, B., & Duma, S. M. (2021). Proposed injury threshold for drone blade lacerations. *Annals of Biomedical Engineering*, *49*(4), 1125–1127.

Figliozzi, M. A. (2017). Lifecycle modeling and assessment of unmanned aerial vehicles (Drones) CO2e emissions. *Transportation Research Part D: Transport and Environment*, *57*, 251–261.

Giones, F., & Brem, A. (2017). From toys to tools: The co-evolution of technological and entrepreneurial developments in the drone industry. *Business Horizons*, *60*(6), 875–884.

Gorucu, S., & Ampatzidis, Y. (2021). Drone Injuries and Safety Recommendations: AE560/AE560, 06/2021. *EDIS*, *2021*(3).

Hassanalian, M., & Abdelkefi, A. (2017). Classifications, applications, and design challenges of drones: A review. *Progress in Aerospace Sciences*, *91*, 99–131.

Lee, S., & Choi, Y. (2016). Reviews of unmanned aerial vehicle (drone) technology trends and its applications in the mining industry. *Geosystem Engineering*, *19*(4), 197–204.

Liu, Z., Sengupta, R., & Kurzhanskiy, A. (2017). A power consumption model for multi-rotor small unmanned aircraft systems. *Proceedings of the 2017 International Conference on Unmanned Aircraft Systems (ICUAS)*, 310–315.

Loyola-Gonzalez, O. (2019). Black-box vs. white-box: Understanding their advantages and weaknesses from a practical point of view. *IEEE Access*, *7*, 154096–154113.

Mansouri, S. S., Karvelis, P., Georgoulas, G., & Nikolakopoulos, G. (2017). Remaining useful battery life prediction for UAVs based on machine learning. *IFAC-PapersOnLine*, *50*(1), 4727–4732.

Prasetia, A. S., Wai, R.-J., Wen, Y.-L., & Wang, Y.-K. (2019). Mission-based energy consumption prediction of multirotor uav. *IEEE Access*, *7*, 33055–33063.

Quiroz, G., & Kim, S. (2017). A Confetti Drone: Exploring Drone Entertainment. *Proceedings of the 2017 IEEE International Conference on Consumer Electronics (ICCE)*, 378–381.

Rodrigues, T. A., Patrikar, J., Choudhry, A., Feldgoise, J., Arcot, V., Gahlaut, A., Lau, S., Moon, B., Wagner, B., Matthews, H. S., et al. (2021). In-flight positional and energy use data set of a DJI Matrice 100 quadcopter for small package delivery. *Scientific Data*, *8*(1), 1–8.

Saha, B., & Goebel, K. (2007). NASA Ames prognostics data repository. *NASA Ames, Moffett Field, CA, USA*.

Saha, B., Koshimoto, E., Koshimoto, E., Quach, C., Quach, C., Vazquez, S., Hogge, E., Hogge, E., Strom, T., et al. (2011). Predicting battery life for electric uavs. *Proceedings of the Infotech@ Aerospace 2011 Conference*, 1517–1525.

Saha, B., Quach, C. C., & Goebel, K. (2012). Optimizing battery life for electric UAVs using a Bayesian framework. *Proceedings of the 2012 IEEE Aerospace Conference*, 1–7.

Saha, B., Quach, C. C., & Goebel, K. F. (2011). Exploring the model design space for battery health management. *Proceedings of the Conference of the Prognostics and Health Management*, (ARC-E-DAA-TN4023).

Schacht-Rodrıguez, R., Ponsart, J.-C., Garcia-Beltran, C. D., & Astorga-Zaragoza, C. M. (2018). Prognosis and Health Management for the prediction of uav flight endurance. *IFAC-PapersOnLine*, *51*(24), 983–990.

Schenkelberg, F. (2016). How Reliable Does a Delivery Drone Have to Be? *Proceedings of the 2016 Annual Reliability and Maintainability Symposium (RAMS)*, 1–5.

Shan, F., Luo, J., Xiong, R., Wu, W., & Li, J. (2020). Looking before crossing: An optimal algorithm to minimize uav energy by speed scheduling with a practical flight energy model. *Proceedings of the IEEE Conference on Computer Communications (INFOCOM)*, 1758–1767.

Si, X.-S., Wang, W., Hu, C.-H., & Zhou, D.-H. (2011). Remaining useful life estimation–A review on the statistical data driven approaches. *European Journal of Operational Research*, *213*(1), 1–14.

Trihinas, D., Agathocleous, M., & Avogian, K. (2021). Composable energy modeling for ml-driven drone applications. *Proceedings of the 2021*

IEEE International Conference on Cloud Engineering (IC2E), 231–237.

Valenti, M., Bethke, B., How, J. P., De Farias, D. P., & Vian, J. (2007). Embedding health management into mission tasking for UAV teams. *Proceedings of the 2007 American Control Conference*, 5777–5783.

Wei, K., Wu, J., Ma, W., & Li, H. (2019). State of charge prediction for UAVs based on support vector machine. *The Journal of Engineering*, *2019*(23), 9133–9136.

Yadav, S., & Shukla, S. (2016). Analysis of k-Fold Cross-Validation over Hold-Out Validation on Colossal Datasets for Quality Classification. *Proceedings of the 6th IEEE International Conference on Advanced Computing (IACC)*, 78–83.

Yuan, Z., Jin, J., Sun, L., Chin, K.-W., & Muntean, G.-M. (2018). Ultra-Reliable IoT Communications with UAVs: A Swarm Use Case. *IEEE Communications Magazine*, *56*(12), 90–96.

Zhang, J., Campbell, J. F., Sweeney, D. C., & Hupman, A. C. (2021). Energy consumption models for delivery drones: A comparison and assessment. *Transportation Research Part D: Transport and Environment*, *90*, Article 102668.