UAV BATTERY LIFE-CYCLE MANAGEMENT WITH EDGE-CLOUD BASED SERVICE

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Lappeenranta–Lahti University of Technology LUT

Degree Program in Electrical Engineering, Bachelor’s thesis

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Abstract

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In this thesis different methods for evaluating lithium-ion batteries (LIBs) state of health (SOH) in unmanned aerial vehicles (UAVs) are explored. Additionally an EDGE-cloud based solution for storing and processing data measured from battery packs is presented as a solution for tracking LIB SOH. This thesis is based on books and articles and is conducted as a literature review.

As utilization of UAVs in fields such as public-safety, industry and private use have expanded rapidly, the need for managing UAV's battery packs have become relevant as current battery technologies such as lithium-polymer do not last as long as the UAV itself. Battery pack management and tracking is vital in UAV applications as highest reliability is required to ensure safe operation (Goebel & Saha, 2015).

Determining LIBs SOH is challenging because several variables need to be measured from a battery pack to model its state. Battery pack measurements should be done on every cycle to ensure the most accurate modelling for each battery pack as changes happen in the battery pack cells during every cycle (Goebel & Saha, 2015). The modelling can be done with a mathematical model or data-driven model such as machine learning (ML) model. Aforementioned need for constant data collection requires good connectivity and data storage. This is why EDGE-cloud based system is investigated as a solution to track battery health over its life-cycle. This is why a EDGE-cloud based service is presented as a good solution for tracking LIB SOC in UAVs.

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Miehittämättömien ilma-alusten akkupakettien elinkaaren hallinta EDGE-pilvipalvelun avulla

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Tässä opinnäytetyössä tutkitaan eri menetelmiä litiumioniakkujen (LIB) kunnon (SOH) arvioimiseksi miehittämättömissä ilma-aluksissa (UAV). Lisäksi esitetään EDGE-pilvipohjainen ratkaisu akkupakettien mittausdatan tallentamiseen ja käsittelyyn ratkaisuna LIB:n SOH:n seurantaan. Tämä opinnäytetyö perustuu kirjoihin ja artikkeleihin ja se on toteutettu kirjallisuuskatsauksena. Kun UAVien käyttö esimerkiksi julkisen turvallisuuden, teollisuuden ja yksityisen käytön aloilla on laajentunut nopeasti, UAVien akkupakettien hallinnan tarve on muodostunut ajankohtaiseksi, sillä nykyiset akkuteknologiat, kuten litium-polymeeri, eivät kestä yhtä kauan kuin itse UAV. Akkupakettien hallinta ja seuranta on elintärkeää UAV-sovelluksissa, koska korkea luotettavuus on tarpeen turvallisen toiminnan varmistamiseksi.

LIBien SOH:n määrittäminen on haastavaa, koska akkupaketista on mitattava useita muuttujia mallintaakseen sen tilaa. Akkupakettien mittaukset tulisi tehdä jokaisessa syklissä varmistaakseen tarkimman mallinnuksen jokaiselle akkupaketille, koska muutoksia tapahtuu akkupaketin kennoissa jokaisen syklin aikana. Mallinnus voidaan tehdä matemaattisella mallilla tai datapohjaisella mallilla, kuten koneoppimismallilla.Edellä mainittu jatkuva tiedonkeruun tarve edellyttää hyvää yhteyttä ja datan tallennusta. Tämän vuoksi EDGE-pilvipohjaista järjestelmää tutkitaan ratkaisuna akun terveyden seurantaan sen elinkaaren aikana. Tämän vuoksi EDGE-pilvipohjainen palvelu esitetään hyvänä ratkaisuna LIB:n SoH:n seurantaan UAVeissa.

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Symbols and abbreviations

Abbreviations

AI	Artificial intelligence
API	Application programming interface
BMS	Battery Management System
DNN	Deep neural network
EoL	End of life
FNN	Feed-forward neural network
LIB	Lithium-ion battery
ML	Machine learning
NN	Neural network
RUL	Remaining useful life
SoH	State of Health
UAV	Unmanned aerial vehicle

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1 Introduction

Unmanned Aerial Vehicle (UAV) is a craft which can be described as a flying robot under autonomous or remote control (Boukoberine, Zhou & Benbouzid, 2019). Examples of UAVs include fixed-wing planes, multi copter drones and other vehicles alike. UAVs are usually small and compact which makes them uniquely useful in certain applications (Al-Turjman, 2020). Adoption and interest in UAVs has been increasing during the past years, because UAVs can perform difficult and dangerous tasks with high mobility and low cost. As an example there is a UAV solution on market from Nokia that is utilized in public safety supporting emergency services from the air (Nokia, 2024). They are utilized in applications such as aerial surveillance, asset inspection and Light Detection And Ranging (LIDAR)-mapping (Al-Turjman, 2020). Currently UAV, computing and Artificial Intelligence (AI) technologies have evolved to the point that so called smart UAVs, vehicles with a high level of automation are possible. This has lead to wider adoption of UAVs enabling previously impossible applications (Boukoberine, Zhou & Benbouzid, 2019).

A key term when defining state of the battery in terms of its life-cycle is State of Health (SoH). Constant cycling of lithium batteries causes electrochemical processes inside the battery to cause irreversible performance degradation. SoH describes the health of a battery or a cell has left as a percentage. Simplified this term generally can be defined as:

$$SoH = C_{cycle}/C_N \tag{1}$$

, where C_{cycle} is discharge capacity measured from one cycle and C_N is the discharge capacity when the battery was new. (Khumprom & Yodo, 2019) In other words battery SoH can be evaluated by comparing current battery capacity to when it was new. This type of SoH definition is called a capacity defined SoH, which usually ranges from 100% to $70 - 80\%$, when the battery is considered as End of Life (EoL) (Che et al., 2022). This is the simplest method that can be used, but it does not give a full picture as battery wear includes other factors that limit its usable life. For example cell internal resistance can also be used as an health indicator, but again considering only one parameter does not give accurate results as some processes cause the battery to be unusable before other limiting factors. This is why a better methods are researched in this thesis which take environmental parameters and internal processes in to account using methods that require measurements that can be done outside of the battery cells.

When tracking a battery's life-cycle data collection is required. This is why a EDGE-cloud based system is proposed in the thesis. EDGE-cloud is a term that means processing and storage resources provided by peer devices and servers located near the client or user location instead of using traditional highly centralized data-centers further away. In other words EDGE-cloud can be thought as cloud computing at the EDGE of the wireless network. (Senjyu et al., 2022) This approach improves latency of the system and provides more possibilities to run real-time systems in the EDGE-cloud (Tu et al., 2023).

Aim of this thesis is to determine the most practical way to evaluate and track UAVs lithium-ion battery (LIB) packs State of Health. In previous studies it has been proven that there is no one standardised way to evaluate SoH accurately (Goebel & Saha, 2015). Different methods of determining SoH are analyzed in terms of complexity and accuracy to find a practical solution. In this thesis a system is presented, in which LIB parameters such as SoH are constantly processed and stored in EDGE-cloud to track a LIB through its life-cycle. As UAVs are increasingly utilized in new applications, the need for proper management of LIBs SoH is needed to ensure safe operation and good user experience (Goebel & Saha, 2015).

Most common battery chemistry type used in UAVs is Lithium-ion. More specifically, Lithium-ion polymer cells are the most common, as they offer good volumetric and gravimetric energy capacity and high discharge rates (Boukoberine, Zhou & Benbouzid, 2019). These properties are important in UAVs as they make up the flight time and maximum thrust. Other advantages of Li-poly cells are high specific power, high efficiency during charging/discharging and low self discharge rate (Boukoberine, Zhou & Benbouzid, 2019). The limiting disadvantage of Li-poly cells is the limited cycle-life of the cells, which usually is around few hundred cycles (Korthauer, 2017). This means that in use-cases where UAV is operated frequently, battery packs need to be replaced after certain period. In this process it is clear that determining that life left in the batteries is important information especially for 24/7 stand up deployments. Insight into battery health enables better operations and maintenance planing, higher reliability and safety, as well better prediction of the maintenance costs.(Goebel & Saha, 2015).

In determining the battery state of health (SoH) the accurate models require many measurements to be made periodically to form a digital model of the state of the battery (Tu et al., 2023). This means that sufficient data transfer speeds and storage capacities are needed in the system. Because of this a EDGE-cloud based solution is presented to form efficient data storage and computation system (Senjyu et al., 2022) to track battery SoH in this thesis.

This thesis is structured by and aims to answer the following questions:
1) What variables need to be measured in order to model a lithium battery?
2) In which ways can a LIB state of health can be modelled?
3) How measured data can be utilized in EDGE-cloud based service to ensure safe operations with UAVs?

2 Methods

In this thesis life cycle management of lithium-ion batteries in UAV applications is researched to find a feasible system for integration. For this it is important to know what UAVs are and what special requirements they have. This is why ion batteries are presented with their properties and requirements to compare them with UAV spesific requirements. Also special requirements and challenges with modelling lithium-ion battery packs in UAV applications are investigated. After which the focus moves to lithium-ion battery degradation analysis as it is one main phenomena affecting a lithium-ion battery's life cycle in the scope of the thesis. All of this information is researched from peer reviewed papers to present the reader with perquisite knowledge to grasp the system to be researched.

After the problem has been presented with sufficient background, the focus changes to the SoH modelling techniques. First requirements of modelling SoH are presented in general terms. After that every relevant modelling technique is explained. The section ends in a comparison of most feasible models for implementation. In the evaluation of different models a common metric root mean square error was selected to be show on the summary table, as it provides an indication of model performance. More performance parameters were not shown in the table as model parameters, input values, test data and model types make the comparison of number values challenging.

The chosen modelling technique is presented with a system level solution. First the basics of the EDGE-cloud system structure and relevant terms are explained after which the solution to calculate the model and store data inside the EDGE-cloud solution is presented. Lastly a high level system diagram is shown to summarize the solution for managing lithium-ion battery's life cycle.

Researching the sub components separately is possible as components and model discussed do already exists separately, so they can be presented and researched individually. After researching the components they are brought together as a complete system to present a solution to the research questions.

3 UAV battery packs

In this section information on design requirements and properties of battery packs in UAV applications is presented. First LIB properties, degradation processes and features are discussed. After which special use-case specific aspects of LIB packs in UAV applications are presented. Lastly what properties need to be measured to assess a battery packs state are discussed.

3.1 Lithium-ion battery packs

Battery packs in general are comprised of cells which can be arranged in different configurations (Che et al., 2022). When two cells are put in series the output voltage is the sum of the cell voltages, while the capacity stays the same, this can be noted as “2s”. If cells are wired in parallel maximum output current is increased and capacities are summed. For example two cells in series and parallel is noted with “2s2p” - in total 4 cells. Usually in battery packs the configuration is a combination of these two methods, to increase voltage to required level while providing good current output capability and capacity(Korthauer, 2017). This is because lithium battery packs maximum output current is limited by its internal resistance. Maximum output current rating is commonly noted as a C rating which describes the output current as a multiple of rated capacity of the battery. For example $2Ah$ cell with $0.5C$ rating would have maximum rated output current of $1A$.

Generally optimum configuration of cells is the one that gives the maximum voltage that the consumer accepts and required current, as this results in lower losses in the system. Because of efficiency “6s” is a common configuration to use in larger drones, as otherwise the losses and heating would be unpractical. As UAV technology has developed ever higher system voltages have been used. With lower series configurations system voltage would be lower and require more current to achieve same energy transfer amount. This increased current causes resistance losses in the conductors between the battery and UAV motors. This loss is defined with Ohms law as 2.

$$P_{loss} = I^2 * R \tag{2}$$

Lithium batteries have many advantages, but if properties like cell voltage and temperature is not managed and tracked properly catastrophic failures can occur. This is why it is vital to combine these lithium-ion battery packs with a Battery Management System (BMS), which ensures the battery does not operate outside of its operating conditions. State of the art battery management systems can also run models to evaluate SOH, SOC and other states. This architecture is efficient as data is gathered and processed in the battery module.

A lithium cell is a complex and sensitive electrochemical system. This is why variance of cell characteristics caused by manufacturing tolerances is unavoidable. This variance can cause voltage imbalances in battery packs when the cells are cycled, as cell efficiencies differ. Also external factors such as temperature, humidity, storage temperature and mechanical stress affect the performance of a cell. In addition to all of these effects, calendar aging, storage charge level, chemistry type and charging parameters add to degradation and cell imbalance in a battery pack. All of the degradation processes are illustrated in figure 1. This is why it is almost mandatory to have a BMS to track the health and operation of a lithium-ion battery pack. At minimum the BMS should prevent catastrophic failure of the battery pack and ensure safe operation, but it would be preferable that prognostics would be calculated to aid in the battery pack's life cycle planning.

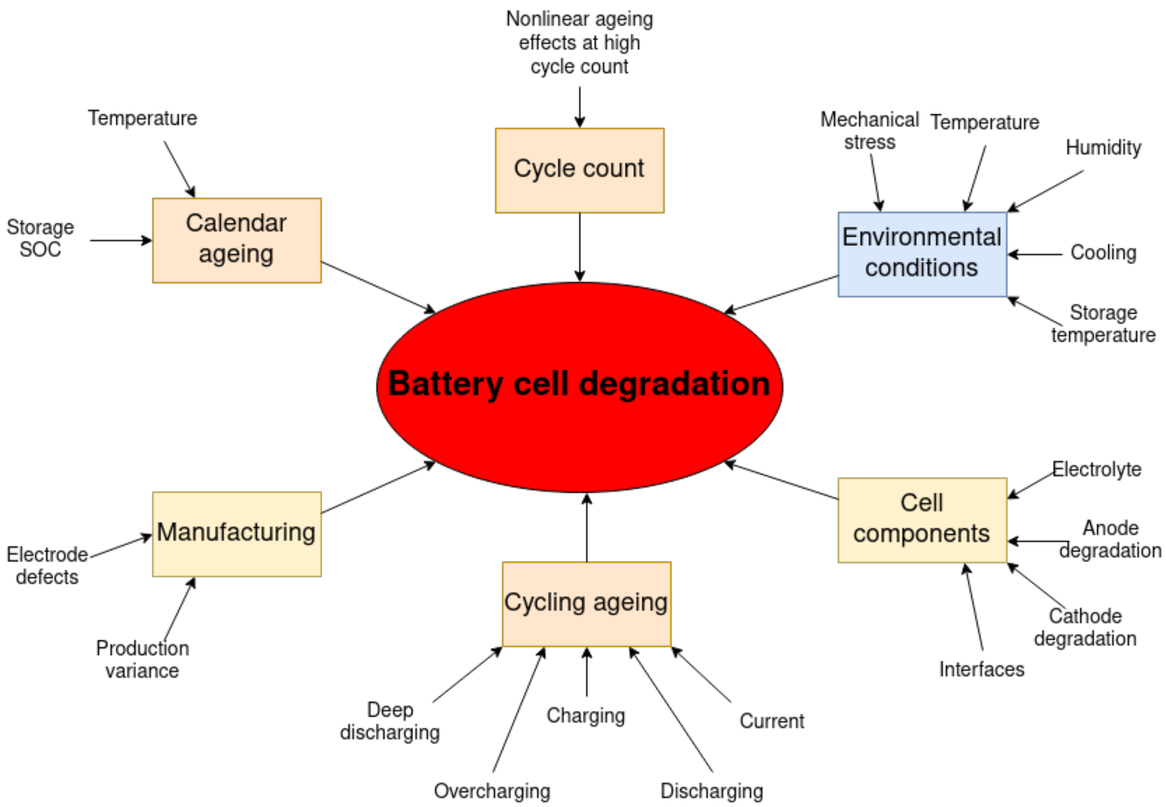

Figure 1: Factors impacting lithium-ion battery cell degradation paraphrasing(Rauf, Khalid & Arshad, 2022)

As the battery cell operation and degradation is affected by so many measured parameters it is logical to state that processing should be done as close as possible to the battery pack it self to refine the data and transfer only desired parameters to a higher level in the system. In other words it would be most efficient to have a BMS system on the battery pack assembly, which could constantly measure the battery - even when not in use. This topology present problems as it is not very modular and is hardware dependent. For easier integration EDGE-cloud data processing solution is presented in chapter 4. This is a good compromise as data transfer speeds have constantly increased as a results of for example 5G networks. Also software updates and remote support can be done swiftly in the cloud domain.

3.2 Requirements of lithium-ion battery packs in UAV applications

In UAV applications high gravimetric and volumetric density is required to maximise flight time. This limits the selection of usable battery technologies in this use case. Lead-acid, nickel cadmium and nickel-metal hydride chemistry's have too high gravimetric and volumetric density and they do not provide as good cycle life and peak discharge rate as lithium-based batteries as can be seen from figure 2. This is why lithium based batteries are used in battery operated UAVs.

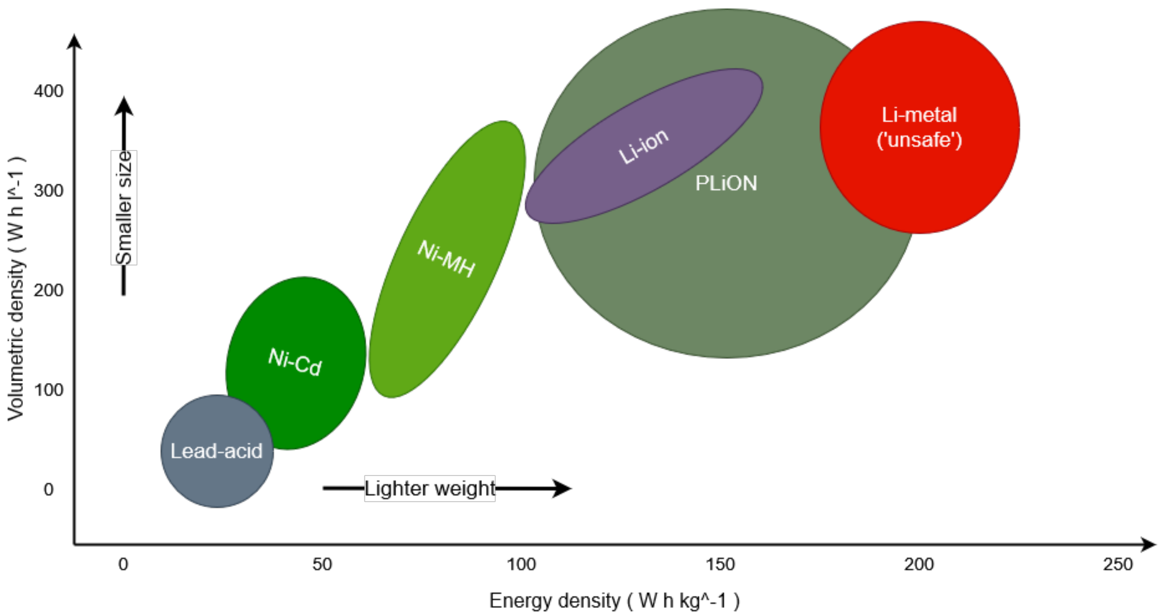

Figure 2: Battery technologies by their energy capacity paraphrasing (Claude, Becherif & Ramadan, 2017)

3.3 Lithium-ion battery cell degradation

Lithium-ion batteries have strict temperature requirements for optimum operating conditions. Common operating range is defined between 20-40°C for charging and discharging (Korthauer, 2017). If battery is operated at a high temperature its degradation is considerably accelerated causing capacity fade, decreased charge/discharge current and increased battery heating(Leng, Tan & Pecht, 2015). Figure 3 illustrates this temperature dependency with experimental data. With low temperatures discharging causes less damage than charging, but also maximum output current is greatly decreased. All these temperature effects 4 have to be considered in evaluating battery SoH. This is why constant temperature measurement is required for tracking LIBs life cycle.

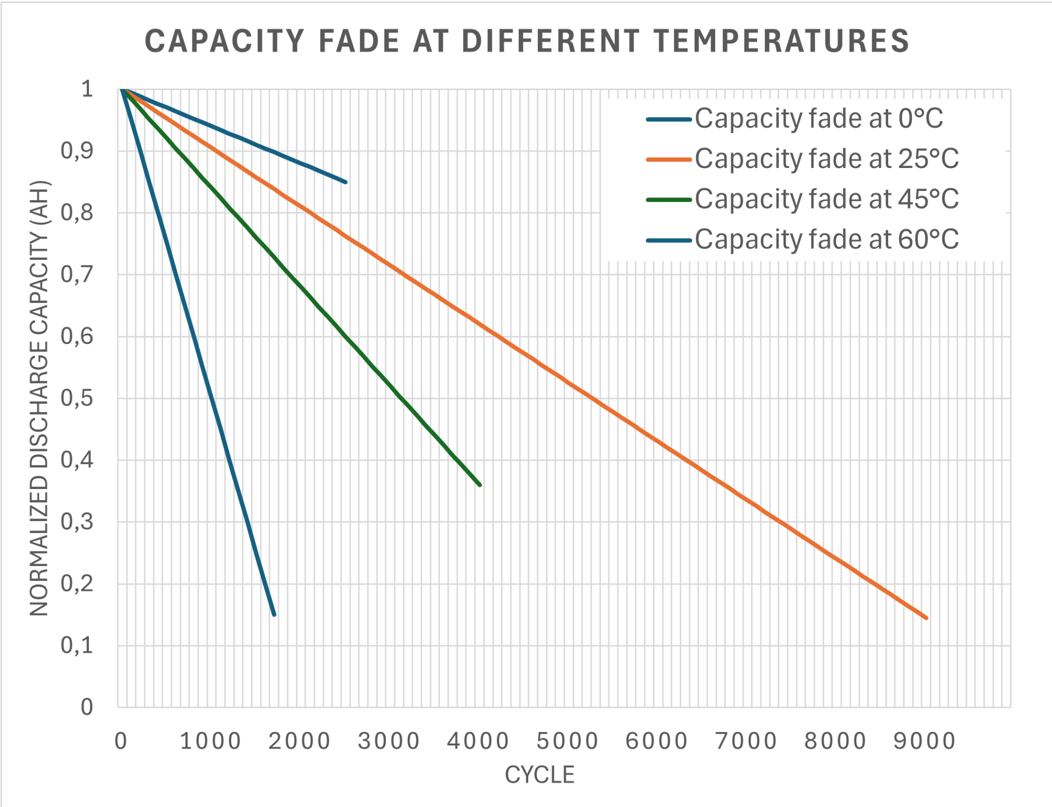

Figure 3: Discharge at different temperatures affecting capacity fade paraphrasing (D. Wang et al., 2020)

Operating temperature	-20°C	0°C	20°C	60°C
Max power & availability	< 70 %, Very high internal resistance	90%, High internal resistance	100%	100% > 0% Throttling
Service life	Cell aging during charging	Slow aging	Optimum temperature	Cell aging / Thermal runaway
Needed thermal management	Heating	Heating	None	Cooling

Figure 4: Temperature affecting LIB degradation speed paraphrasing (Korthauer, 2017)

In addition temperature affecting aging of a LIB, discharge rate has a great impact on aging speed as illustrated by figure 5. If UAV charging profile does not change between cycles, the process can be defined as a constant. Then mostly discharge properties would affect the degradation speed. This would make SoH modelling easier, because we do not need to track charging parameters. For a perfect model all parameters would be tracked, but this aforementioned simplification would improve feasibility of implementation.

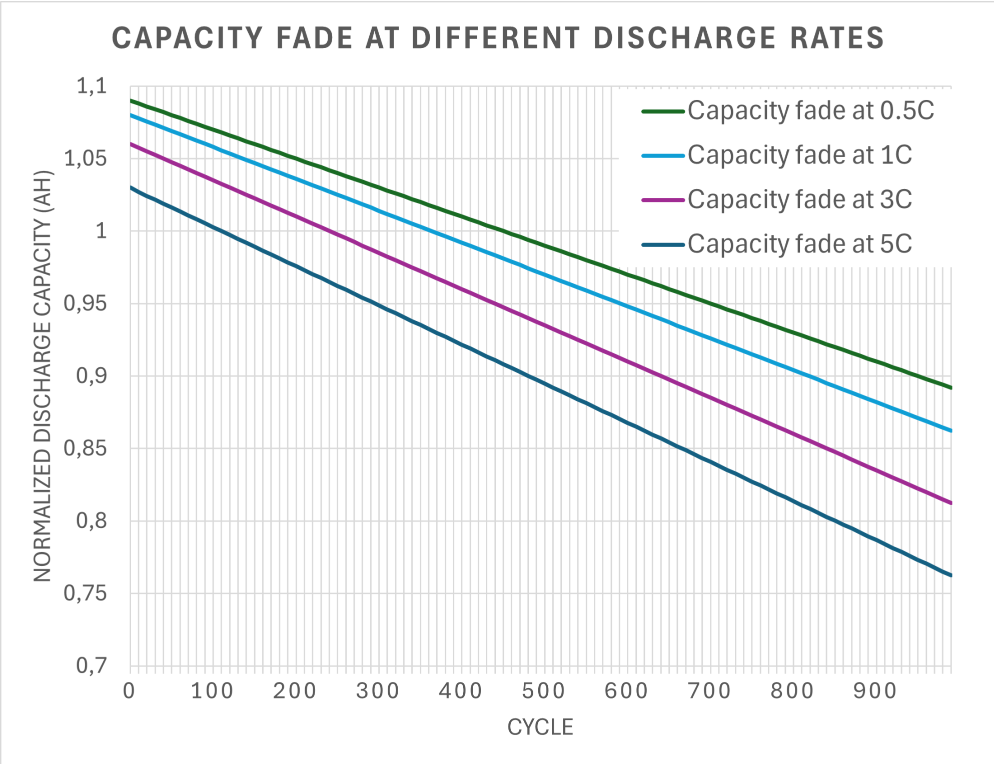

Figure 5: Discharge rate of a LIB affecting capacity fade paraphrasing (D. Wang et al., 2020)

4 Lithium battery pack SoH modelling

Modelling SoH in lithium battery packs is challenging as a lithium-ion cell is a complex system with many interdependent variables. Multiple variables with nonlinear dependencies makes the modelling complex. Also battery pack SoH modelling is even more complicated as the pack consists of multiple cells that have individual characteristics, which means that the cells could fail at different ages - if one cell fails the whole pack cannot be used. Although usually the cells are from the same manufacturing batch and have similar characteristics, which results minimal degradation variance. This is why multiple battery pack modelling methods have been proposed with different complexity and accuracy. There are three categories that the models are based on: physics models, data driven models and hybrid models which combine the first two techniques (Che et al., 2022). These models have different complexity, limitations and computational requirements that are discussed and compared in this section.

4.1 Lithium-ion battery pack state of health modelling requirements

To model lithium-ion batteries measurements can be done to derive the desired values and states, in this paper primarily state of health (SoH) calculation is discussed for tracking and managing the battery's life-cycle. Lithium-ion battery's SoH can also be measured directly, but that requires additional hardware to be fitted to the UAV system, which requires significant integration efforts. This is why it is only introduced in this section, but not considered as a feasible option.

Different models are compared to each other in terms of accuracy and complexity. In this section accuracy is evaluated using root mean square error (RMSE) which can be calculated with equation 3.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[x_i - \bar{x}_i]^2} \tag{3}$$

, where n is the number of datasets, x_i real measured values and $\bar{x}_i$ is the calculated prediction. (Khumprom & Yodo, 2019) RMSE comparison is only an indicator of model performance, since different datasets are used to test the models in different papers, which makes direct comparison impossible.

Differing computational requirements is one main property when evaluating which model is best for modelling a lithium-ion battery in a UAV applications. In UAVs computational power is limited and might not accommodate the most complicated models. This why a balance between computational complexity and accuracy has to be determined. As can be seen from figure 6 machine learning presents new possibilities as it can be very efficient way to model very complex dynamic systems.

Pack total voltage is one main indicator of state of charge and it is the most basic way to determine battery packs state of charge (Korthauer, 2017). Voltage based SoC estimation is commonly used in lead-acid batteries as they have a strong dependency between voltage and SoC (Korthauer, 2017). In lithium batteries this relationship is not as distinct and linear, which creates the requirement to also measure the current of the battery to determine its state precisely (Korthauer, 2017). SoC is required either directly as an input to an SoH model or the model determines it from other parameters. It is required as Lithium-ion batteries suffer from calendar aging, which means degradation that happens as time passes. This degradation is faster if SoC is very low or full, thus it is one variable in a battery degradation model.(Korthauer, 2017)

Lithium battery's SoH is affected by temperature. For example aging reactions are accelerated at higher temperatures, which makes temperature measurement important in determining LIB SoH (Korthauer, 2017). Also charge/charge current and cell voltage difference in lithium battery packs affects its SoH development(Claude, Becherif & Ramadan, 2017). The problem with determining the state of a time-varying nonlinear electrochemical battery system is inaccuracies in determining accurate mathematical descriptions of the reactions in the battery(Huang et al., 2023). For example determining SoC from battery pack voltage is problematic as when discharging with high current (C-rate) and different environmental conditions the voltage value changes as compared to unloaded and ideal condition voltage values. Continuing with battery pack voltage measurement as an example, differing voltage measured during high discharge currents of the battery pack is caused by its crystalline structure changing during charging and discharging, but is has also been suggested to be caused by caused by different chemical reaction pathways for charging and discharging(Calpa et al., 2023). This works as an great example, how physical models will be lacking as the reactions in the battery are not fully understood. Here a data driven model is more feasible, as it learns and adapts from what it perceives - it learns all the important relations by it self. The drawback with this method is that the model is essentially a black box, which also makes developing it quite challenging.

4.2 Parameters for SoH estimation

Lithium-ion batteries SoH is dependant on the chemical processes that are happening during normal cycling. These processes affect variables that can be measured from outside of the battery, for example electrical measurements. One measurement that has been proven to strongly correlate with SoH is internal resistance measurement of a battery. This parameter changes as chemical reactions happen at the electrodes. One common internal resistance

Table 1: Battery SoH estimation method types paraphrasing (Rauf, Khalid & Arshad, 2022)

Methods	Benefits	Drawbacks
Mathematical models	Precise, simple, dynamic	High computation load, difficult modelling, complex model parameters
Physics based models	Simple, fast, easy to implement	Affected by conditions, low robustness, physical model not fully established
Data driven methods	Accurate, robust, relatively simple	Sensitive to data quality, over-fitting and under-fitting problems, heavy computation needs
Hybrid models	Better accuracy and performance, complex	Requires multiple models, high computational needs

based SoH calculation method is impedance spectroscopy.
Clear sign of SoH degradation is capacity fade which is a process where battery's capacity slowly degrades over time. This lost capacity affects usable capacity which can be defined as the practical capacity which can be used from the battery accounting losses and degradation of the battery. This is why SoH can be evaluated by how the usable capacity in the battery changes during cycles. Battery capacity measurement is a simple way to estimate battery SoH, but it does not account environmental parameters as they do affect present capacity of the battery pack.

4.3 Lithium-ion battery aging modelling

Lithium-ion battery's aging or degradation can be modelled with many techniques, in the following chapters physics based, data-driven and hybrid models are discussed. These are listed with most relevant differences in table 1, to give a initial sense of relevant options for degradation modelling. (Korthauer, 2017)

4.4 Physics based methods in modelling SoH of a lithium-ion battery pack

In physics based modelling approaches degradation modelling by describing the behavior of the damage occurring inside the battery. Because of this they have an advantage of predicting long-term damage behavior, but on the other hand these models should always be validated and tuned by testing as most models make assumptions and approximations. (An, Kim & Choi, 2015)

To utilize these physics based models, model parameters must be determined from measurement data. As many unknown parameters exist in these models, a estimation algorithm is required to derive model parameters from measured parameters. For this most common algorithms are Kalman Filter, extended Kalman filter and particle filter. From these three options usually particle filters are used most as they are well applicable to non-linear systems with non-Gaussian noise. (An, Kim & Choi, 2015)

The problem of using this method to track UAV battery life-cycle is that this model does not adapt well to conditions and reactions it does not take in to account. For example if cell type is changed in a product full characterization of the new cell and its parameters must be done to tune the physics model for that particular cell type. If careful design and characterization is not done for the physical model and model parameter algorithms accuracy will be poor. As suppose to data-driven models which take all apparent patterns in to account, provided that it is trained with data from various operation conditions.

4.5 Direct measurement of lithium-ion battery SoH

Direct measurement of SoH is also possible, but it has many challenges associated with it. Methods like electrochemical impedance spectroscopy require additional hardware to generate the measurement conditions, which is not desirable as it increases implementation costs and complexity. In the following chapters most common direct measurement methods are shortly introduced.

Coulomb counting methods requires accurate current measurement of the battery terminal to determine the transferred charge, from this SoC can be derived, which in turn can be used to calculate SoH.(Dai et al., 2019) This requires accurate sensing and does not take external factors such as temperature in to account. This increases the SoH evaluation error as conditions differ.

Open circuit voltage measurement method uses the same logic as coulomb counting method. From the measured open circuit voltage SoC can be derived which can be used to evaluate SoH.(Dai et al., 2019) This method requires the battery to be completely unloaded and in resting state, which means that SoC and SoH cannot be evaluated during operation. Also same drawbacks apply with this method as with coulomb counting method - external factors are not taken in to account.

Internal resistance based estimation relies on the change of battery internal resistance when degradation of the battery progresses.(Dai et al., 2019) This is a proven method to evaluate SoH and it is widely used, but again this requires controlled conditions as external factors affect the result. For example when temperature drops LIBs internal resistance gets higher which does not mean that degradation happens.

Because of all mentioned reasons direct measurement methods are not considered for application in UAV life cycle management, as the system is very dynamic and conditions change.

4.6 Data driven methods to estimating SoH of a lithium-ion battery pack

Models based on measured data fitting are data driven models which are based on specific aging conditions present at the measurement time. They often model the most distinct degradation modes in the measurement data, which makes them vulnerable to differing conditions if sufficient data sets are not used in the making of the model. Many different indicators and variables are used in these models, such as depth of discharge, discharge/charge rate, voltage and temperature (El Mejdoubi et al., 2019). Other data driven models and filters are used in battery modelling like extended Kalman filters and particle filters which are mathematical algorithms expressing the nonlinear phenomena in the battery based on data used in creating them.(Zhang et al., 2018). Additionally the model may include equivalent circuit models to further specify different aging mechanisms using physics equations with parameters derived from battery pack circuit models (Che et al., 2022). This type of modelling is very accurate if conditions do not change, which is rarely the case in UAV operations. Purely physics based models often are not very suitable for UAV battery SoH evaluation as these models are very tailored to specific conditions.

Data driven methods refer to mathematical models created using gathered measurement data from the system itself. This process of teaching a model its properties is referred to as training. A drawback in data driven methods is that data needs to be gathered from this system before a model can be created. This is the downside to data driven methods, as they require more resources for data gathering. There are ways to mitigate this downside, like transfer learning which uses prior models to teach the created model the system properties, but challenges still remain as training process is sensitive which makes all of it challenging.

After the widespread adoption of machine learning modelling in a number of applications, battery state modelling is increasingly implemented with these data driven methods, because battery packs are very complex systems requiring advanced models. Data driven models are well suited for complex systems analysis with a lot of unknown variables. Solutions available on the market usually refer to this technology as Artificial Intelligence (AI), Artificial Neural Networks (ANNs), Deep Neural Networks (DNNs) or Neural Networks (NNs).

Deep Learning was introduced by Geoffrey Hinton in 2006 and it has since become widely adopted method in industry and academia. If compared to traditional neural networks, deep learning adds more neuron layers to the network, which causes more subtle and detailed patterns to be learned from the data. In many cases very complex patterns can be taught to a DNN. But there is also the risk of so called hallucinations, which refer to false positives generated by the complex DNN. Since a trained model acts as a black box, diagnosing issues can be challenging due to its opaque nature. Additionally as DNN are very large neural networks their training requires considerable amount of computational resources and consideration of training process parameters.

Data driven methods can be used to evaluate battery packs SoH very accurately. These data driven methods are based on data on which a model is formed by a computer program learning the properties and patterns of the input data. These models can be very accurate and relatively easy to implement comparing to physical models as the model learns all apparent patterns from the data and it can adapt tyo varying conditions. This makes them also more efficient, if proper size neural network is used as can bee seen from figure 6. The problem with these methods is that for a machine learning model to be accurate it needs to be trained with a large amount of data. In other words the system needs to run without the model for many times to gather the data to teach the model what the systems properties are. Additionally ML based systems can suffer from problems such as over fitting and false predictions if the model is not trained with careful consideration of system dynamics and data properties.

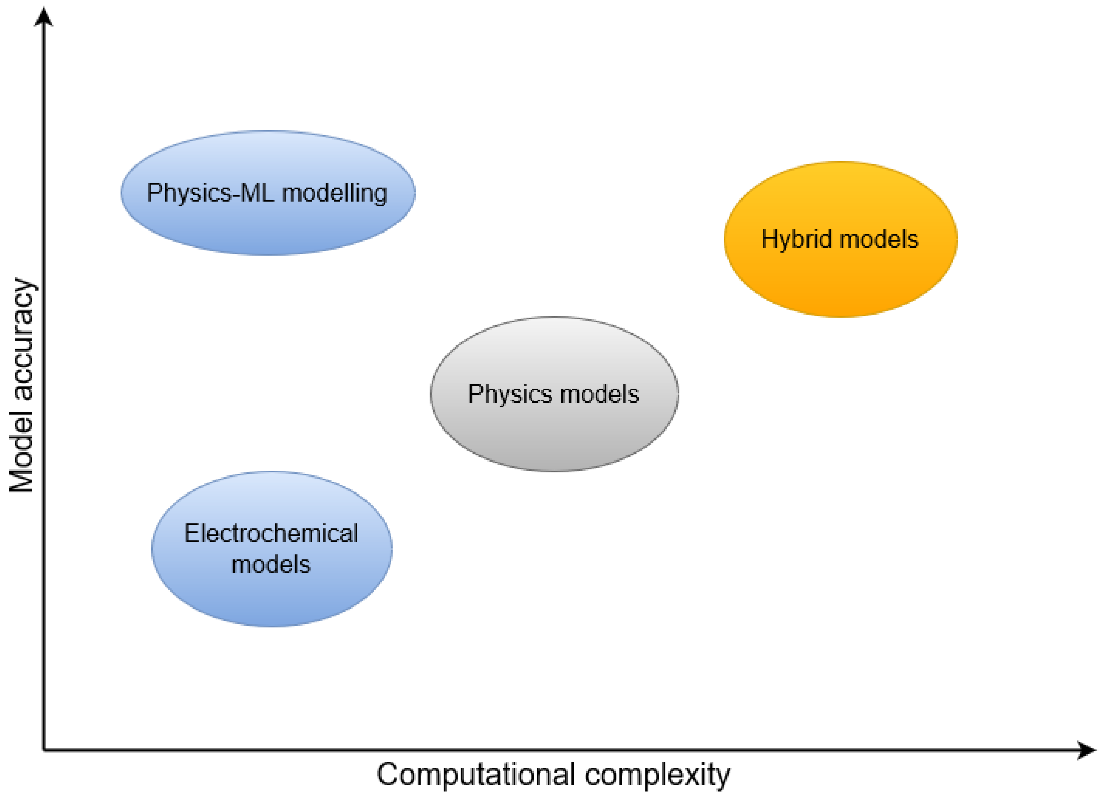

Figure 6: Computational requirements versus accuracy of battery pack modelling paraphrasing (Tu et al., 2023)

Most modern machine learning models will do initial parameter identification, which makes the model less dependent on other batteries training data as the data does not need to be so called label data. Labeled data has features and parameters marked for the neural network to model. This is why if the model is trained with initial parameter identification, implementation of the model would be fast and the model would be accurate as larger data sets can be used with ease. This is assuming that the parameter identification is performed with accuracy. (Senjyu et al., 2022) In all data driven modelling techniques this method of creating the model is the most attractive and promising for an engineering implementation to a product. The risks are that some rare condition would cause this model to give false values, but i think the risk is lower than with a physics model with more deficiencies.

Support Vector Machine (SVM) is a machine learning (ML) algorithm which is commonly used in linear, non-linear and regression, which makes it also suitable for LIB battery modelling. It has a good balance of modelling a complex system like a LIB and requires relatively little computing as compared to DNN. It has been successfully used in LIB SoH modelling before and it has become quite popular in this application. This is why it is the most feasible to fit a UAV LIB SoH modelling application. (Khumprom & Yodo, 2019) (Senjyu et al., 2022)

4.7 Hybrid modelling in estimating SoH of a lithium-ion battery pack

There are also so called hybrid models which combine one or more neural nets with physics based models. This approach constrains the complete hybrid model to have correct characteristics, which usually creates a more accurate model. Hybrid models are relatively new field of research in terms of battery SoH evaluation. The drawback with this modelling technique is the complexity of merging many smaller models to a large system. Especially when troubleshooting and developing such a system, the system behavior can be challenging to manage as the combination of several systems may cause unseen instability or inaccuracy.

4.8 Comparison of most feasible solutions

Modern data driven techniques have been developing very quickly in the past decade as their good accuracy and relatively easy implementation to complex systems. These data driven techniques main drawback is their data requirement, but as connectivity and data storage technologies have developed data collection is not a problem in the modern day. This is why the conclusion of the thesis model research is that deep learning models in general do fit the application as abundant computing resources are available in the cloud. Also good accuracy is warranted by the safety critical application in UAVs. Deep learning models possesses good resistance to disturbances in the system, which fits the highly dynamic environments of aerospace applications.

For easy comparison most relevant models are listed in table 2. Every models type and

RMSE have been compiled to justify conclusions of deep learning being the most suitable model for a cloud computing based solution.

Table 2: Most relevant modelling techniques compared in accuracy

Model	Model type	RMSE
Deep learning (Khumprom & Yodo, 2019)	Deep neural network	3.247
Support vector machine (Khumprom & Yodo, 2019)	Machine learning algorithm	3.247
Long short-term memory (Aliberti et al., 2022)	Neural network	0.064
1 Dimension convolutional neural network (Aliberti et al., 2022)	Neural network	0.035
Convolutional neural network and long short-term memory hybrid model (Aliberti et al., 2022)	Neural network	0.04
Gaussian process + particle filter (Li & Xu, 2015)	Hybrid	<0.0102
Neural network (Q.-K. Wang et al., 2017)	Artificial neural network	<0.012

5 Lithium-ion battery life-cycle management using EDGE-cloud based solution

In the proposed system architecture, battery parameter measurement data is transferred to servers in EDGE-cloud. This design has the benefit of extensive data analysis and storage capabilities that can be run in the cloud as resources are abundant. Before the data can be stored and processed in the EDGE it has to be transfered from the UAV with a wireless link, for example over a 5G cellular network. Because of such modern wireless data transfer technologies it is possible to transfer these measurements at high data rates and low latency, which makes the modelling more accurate and real-time.

With the data in the cloud it could function as a part of digital twin concept. The digital twin concept refers to a replica of real world formed into the digital domain. This digital twin world is a dynamic representation of the real world usually formed by input from different sensors in the real world. These digital models can be used to simulate conditions and interactions in the real world to improve decision making and awareness of systems operating in the physical world. Digital twin consists of three components: measured physical entity, digital representation of the physical entity and data that connects the two. High level system diagram 7 explains the digital twin system proposed in this section. In these systems the digital twin is updated constantly to keep the digital twin up to date and relevant for analysis and monitoring. Digital twins are used in a wide ranges of applications such as: manufacturing, smart cities and aerospace. These systems are used as they increase operational efficiency, improved design in products and predictive maintenance, which is the main point discussed in this thesis.

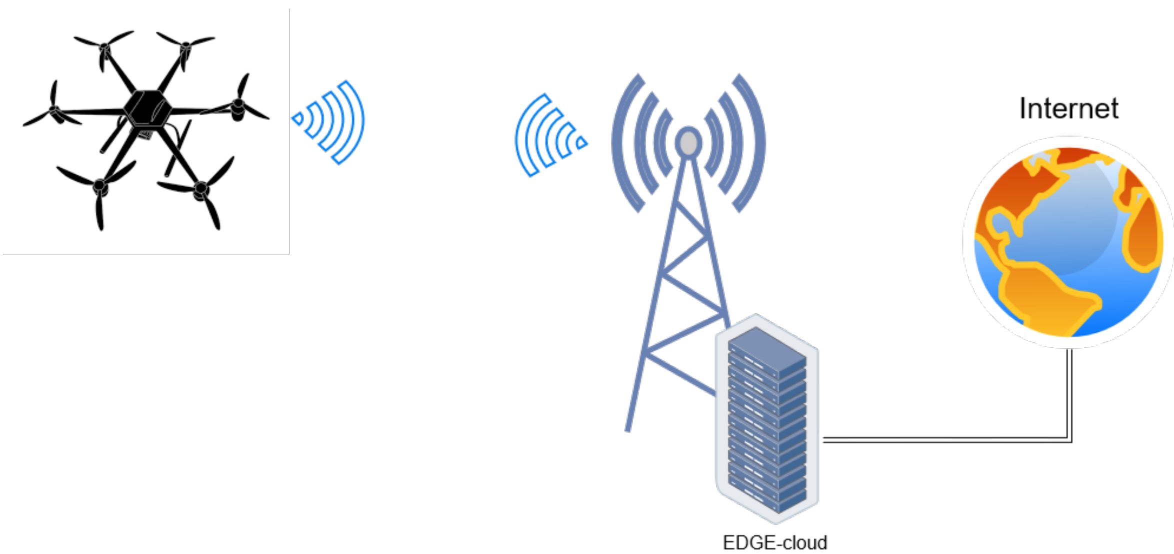

Figure 7: System diagram of a EDGE-cloud based battery life-cycle management of an UAV

5.1 Benefits of EDGE-cloud based battery management

In section 4 different models for SoH modelling were discussed. One of the mentioned drawbacks on some models, were high computation requirements. If the data is processed in the EDGE-cloud, computational resource requirements have less weight as high power processors can be utilized there. This open many possibilities to run prognostics on the gathered data.

The cloud based digital twin solution enables automated functionality to make UAV flight operations more traceable and safe. For example if the battery has reached the end of its life the system would prevent take-off with that battery. The drone operator also could have an estimate of when the battery reaches the end of its life to plan replacement procurement. If the manufacturer would have access to this data they could make an sales offer prior to battery end of life, to enable the operator to continue operations without interruptions. When the data is readily available for system functions in the cloud it also could be used to evaluate and judge warranty cases. In other words the benefit is that the data can be viewed and analyzed at anytime with minimal latency.

5.2 Challenges with EDGE-cloud based battery management system

To form a complete model for a lithium battery, its parameters should ideally be measured at all times. This means also when the battery is in storage. This would result in a very accurate and reliable model as there is no gaps in the data. In the EDGE-cloud UAV combination case it is not feasible to send data constantly, for example when the equipment is in storage. This poses a challenge for the model used, as it has to be able to adapt to the current battery state, even if the battery parameters have changed considerable since the last use.

5.3 Suggested system structure for battery pack life-cycle tracking

The suggested structure 8 proposes a software service running on the UAV, which tracks the required parameters and communicates them through an Application Programming Interface (API). The API is basically an common structuring format between the UAV and the server. All other systems of the UAV that operate in the cloud form a digital twin system that increases operational efficiency and safety.

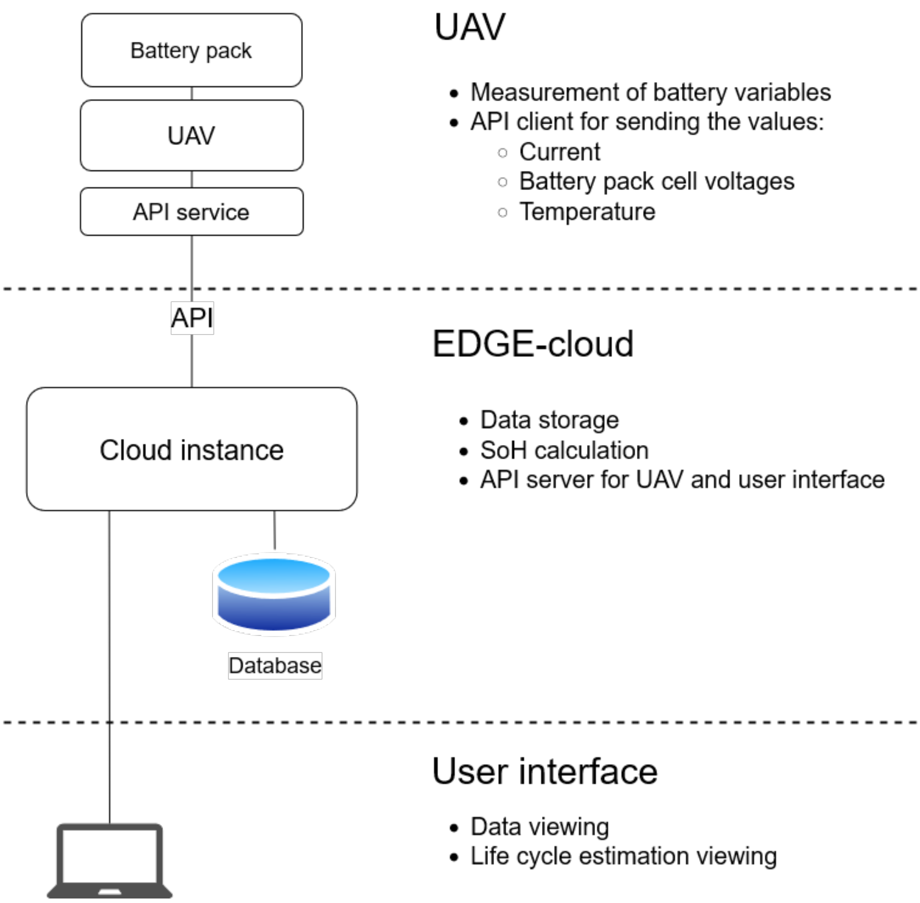

Figure 8: Software architecture

6 Discussion

Undoubtedly there are concrete benefits in managing a UAVs life cycle with a EDGE-cloud and machine learning model combination. Generally control over the UAV system performance can be tracked and evaluated more flexibly with history logs for incident analysis and design improvement. This is why it is probable that a similar solution will be widely used in the future as UAVs are used in even more tasks. As the presented system scales well it can be used in large deployments helping fast adoption of UAV technology. But there are limitations and challenges that must be considered to decide the value of such a system. These considerations are discussed in this section.

6.1 Complexity and feasibility consideration of battery life-cycle management system architecture

As mentioned before the most efficient solution to evaluate battery's values would be a service on the UAV it self which would run diagnostics and management of the battery. This service could report the values to a cloud instance for easy and fast data utilization purposes. As this need additional hardware it can be viewed as the ideal solution if costs of such implementation are not considered. Usually cost is a limiting factor, which makes a cloud run solution more attractive as cloud development is standardized and the cloud computing platforms are well established, which makes development of such battery management service faster and cheaper in the cloud. Of course battery measurement values will have to be transmitted from the drone to the cloud, which will need a small software layer on the drone. Bandwidth of the wireless link to the cloud could be a limiting factor, but with modern wireless technologies and the small size of battery measurement numbers it is very feasible to stream all the values to the cloud for processing. All of these considerations makes the cloud processing platform the most simple and fast to deploy solution and the recommended system architecture of this thesis.

6.2 Issues in UAV battery life cycle management systems

As the processing and storage of data is done in the cloud computing platform, the system requires wireless connectivity to compute and communicate the state of UAVs LIB. The wireless network is a dependency that adds to possible unavailability of this proposed service. Modern data centers and EDGE-cloud computing platforms with wireless technologies such 5G-networks have very good reliability which partly mitigates this issue. Additionally the system needs the EDGE-cloud connection to function, so it cannot be operated as a stand-alone system for example in remote areas. Also the constant streaming of measured battery parameters use wireless network bandwidth which could be a problem in highly congested networks, this is also can be mitigated with proper network planning with modern technologies such 5G-networks.

6.3 Thoughts on EDGE-cloud possibilities

An EDGE-cloud based LIB management system creates many possibilities in UAV operation. For example pre-flight checks could be implemented to include the health status stored on the servers, which could prevent takeoff if the components are not going to be performing at the required level. Also estimations of performance development could be used during every flight, to prevent crashes caused by for example sudden environmental changes affecting the battery performance. Also estimations could be made, when this end of life state is reached which could be used for maintenance planning. When all the data is available, the complete history of an battery pack could be used to derive whether a fault is covered by the battery pack manufacturers warranty, or has the battery been used in conditions that are not allowed in the product specification. As all the data is store in a database in EDGE-cloud, it could be utilized in creating better battery packs by analyzing the performance of the measured battery pack.

The benefit doing SoH evaluation in the EDGE-cloud instead of processing the data locally presents possibilities in large scale deployments where there are multiple UAVs operated by one entity. This fleet wide management creates safety and savings to a large fleet operator. General consumer electronics such as laptops or mobile phones do not need this type of fleet wide management as the processing power, storage and accessibility requirements are not the same as only one device is concerned. Although the modelling techniques discussed in the thesis can be applied in various applications such as electric vehicles and phones if customised accordingly.

6.4 Further research

Different modelling techniques have been researched widely, but evaluation of system level functionality and requirements could be further researched. This paper is aiming to present such a solution, but there are other ways of achieving UAVs battery's life cycle management. For example smart BMS solutions integrated to the pack it self could always keep track of the battery's state, this could be compared to cloud based solutions. Additionally real world test data and evaluation would be beneficial further research.

7 Conclusions

As unmanned aerial vehicles are increasingly used in safety critical applications such as search and rescue or supporting emergency services it has become imperative to create a system to track and manage UAVs component wear and degradation. In this thesis UAVs lithium-ion batteries state of health modelling was researched to find a proper solution for integration in to a UAV system. Different modelling techniques and their dependencies were evaluated to find ideal methods to determine the health of an lithium-ion battery. During the research it was found out that constant measurement of battery parameters would be needed to form the best possible degradation model needing a BMS in the battery pack. As no additional hardware type system were preferred, the investigation to focused on machine learning based methods as they can adapt to situations where there are gaps in data caused by measurements being done only during operation. These gaps exists when for example the batteries are in storage, but are still in fact degrading. Combined best found modelling technique support vector machine / deep learning with a cloud based solution running in EDGE-cloud, many additional benefits were presented, to manage a large fleet of batteries in flight operations. When the battery data is stored and analyzed in the cloud, it can be accessed quickly and can be used in for example preventive maintenance, engineering analysis or crash investigations.

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