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# FAILURE PREDICTION OF LITHIUM-ION BATTERIES UNDER HIGH LOAD ON BATTERY MONITORING SYSTEM CHARGE BOARDS IN UNMANNED AERIAL VEHICLES

# ПРОГНОЗИРОВАНИЕ ВЫХОДА ИЗ СТРОЯ ЛИТИЙ-ИОННЫХ АККУМУЛЯТОРОВ ПРИ ВЫСОКОЙ НАГРУЗКЕ НА ПЛАТАХ ЗАРЯДКИ СИСТЕМЫ МОНИТОРИНГА АККУМУЛЯТОРОВ БЕСПИЛОТНЫХ ЛЕТАТЕЛЬНЫХ АППАРАТОВ

# ҰШҚЫШСЫЗ ҰШУ АППАРАТТАРЫНЫҢ БАТАРЕЯЛАРЫН БАҚЫЛАУ ЖҮЙЕСІНІҢ ЗАРЯДТАУ ТАҚТАЛАРЫНДА ЖОҒАРЫ ЖҮКТЕМЕ КЕЗІНДЕ ЛИТИЙ-ИОНДЫ АККУМУЛЯТОРЛАРДЫҢ ІСТЕН ШЫҒУЫН БОЛЖАУ

**Abstract.** Lithium-ion batteries have become an indispensable power source for unmanned aerial vehicles and other portable electronic devices, electric vehicles, and stationary energy storage systems. However, their performance and safety can be compromised under high load conditions, which can lead to catastrophic failures, such as thermal runaway and fire. To prevent such incidents, it is crucial to develop reliable methods for predicting the failures of lithium-ion batteries under high load conditions. In this article, we will discuss the prediction of failures of lithium-ion batteries under high load on the BMS (Battery Monitoring System) charge boards in unmanned aerial vehicles (UAV).

**Keywords:** lithium-ion batteries, battery monitoring system, charge boards, performance, safety, unmanned aerial vehicles (UAV).

**Аннотация.** Литий-ионные аккумуляторы стали незаменимым источником питания для беспилотных летательных аппаратов и других портативных электронных устройств, электромобилей и стационарных систем накопления энергии. Однако их производительность и безопасность могут быть снижены в условиях высокой нагрузки, что может привести к катастрофическим отказам, таким как перегрев и возгорание. Для предотвращения подобных инцидентов крайне важно разработать надежные методы прогнозирования отказов литий-ионных аккумуляторов в условиях высокой нагрузки. В этой статье мы обсудим прогнозирование отказов литий-ионных аккумуляторов при высокой нагрузке на зарядные платы BMS (Battery Monitoring System) в беспилотных летательных аппаратах (БПЛА).

**Ключевые слова:** литий-ионные аккумуляторы, система мониторинга заряда батареи, зарядные платы, производительность, безопасность, беспилотные летательные аппараты (БПЛА).

**Аңдатпа.** Литий-ионды аккумуляторлар ұшқышсыз ұшу аппараттары мен басқа портативті электронды құрылғылар, электромобильдер және стационарлық энергия сақтау жүйелері үшін таптырмас қуат көзіне айналды. Алайда, олардың өнімділігі мен қауіпсіздігі жоғары жүктеме жағдайында төмендеуі мүмкін, бұл қызып кету және өрт сияқты апатты ақауларға әкелуі мүмкін. Мұндай оқиғалардың алдын алу үшін жоғары жүктеме жағдайында литий-ионды батареялардың істен шығуын болжаудың сенімді әдістерін жасау өте маңызды. Бұл мақалада біз ұшқышсыз ұшу аппараттарында (ұшқышсыз ұшу аппараттары) BMS (батареяларды бақылау жүйесі) зарядтау тақталарына жоғары жүктеме кезінде литий-ионды батареялардың істен шығуын болжауды талқылаймыз.

**Түйін сөздер:** литий-ионды аккумуляторлар, батареяны бақылау жүйесі, зарядтау тақталары, өнімділік, қауіпсіздік, ұшқышсыз ұшу аппараттары (ұшқышсыз ұшу аппараттары).

**1. Introduction.** Lithium-ion batteries are widely used in various applications due to their high energy density, long cycle life, and low self-discharge rate. However, they are not immune to failures, especially under high load conditions of UAV, which can cause thermal runaway and fire. To prevent such incidents, it is important to develop accurate and reliable methods for predicting the failures of lithium-ion batteries under high load conditions [1].

**2. Failure mechanisms of lithium-ion batteries under high load conditions**

Under high load conditions, lithium-ion batteries can experience various failure mechanisms, such as:

- Lithium plating: When a lithium-ion battery is charged too quickly or discharged too quickly, lithium ions may not be able to intercalate into the graphite anode fast enough, resulting in the deposition of metallic lithium on the anode surface. This can lead to the formation of dendrites, which can penetrate the separator and cause a short circuit [2,3].

- Thermal runaway: When a lithium-ion battery is subjected to high temperatures, the electrolyte may decompose and release gases, which can increase the internal pressure of the battery. If the pressure is not relieved, the battery may rupture or explode.

- Internal short circuit: When a lithium-ion battery is subjected to mechanical stress or thermal stress, the electrodes may come into contact with each other, causing an internal short circuit. This can lead to the generation of heat and gas, which can cause thermal runaway.

**3. Statement of the security problem**

BMS are very important for the safety and reliability of lithium batteries in UAV systems. They monitor parameters such as temperature, voltage and current at the input current, helping to monitor the operation of the lithium battery. For example, temperature is an important indicator because an increase in temperature leads to destructive changes. BMS monitors the temperature, allowing you to quickly respond to sudden changes. The location of the BMS board in a lithium-ion battery (flat format for mobile devices) is shown in Figure 1 [4].

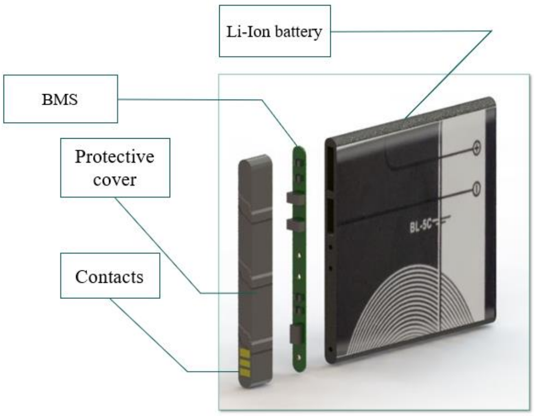


**Figure 1.** Simplified structure of a lithium-ion battery

Using a battery without BMS is very dangerous for lithium batteries. This can potentially lead to exceeding the maximum permissible current and supply voltage or an inappropriate temperature response, which will lead to the destruction of battery cells and may lead to fires or other safety problems.

So, there are several factors that can lead to problems, such as overload, overexposure, poor temperature control, etc. In recent years, the cases of explosions and fires of lithium batteries have remained quite low. One of the most investigated cases is considered to have occurred in the United States, an emergency failure of a lithium battery in civil UAV in March 2006. According to the US government, between 2004 and 2014, there were about 17 total such accidents due to the fear of all explosive lithium battery relationships [5].

In short, without a BMS board, a lithium battery will be very unreliable and risky for using in UAV.

**4. Battery Monitoring System (BMS) for predicting failures of lithium-ion batteries**

A Battery Monitoring System (BMS) is a critical component of a lithium-ion battery pack, which monitors the state of charge, state of health, and state of safety of the battery. A BMS typically consists of a microcontroller, sensors, and communication interfaces. Many modern UAVs are connected to the BMS monitoring system and show the battery status. The microcontroller collects data from the sensors, such as the voltage, current, temperature, and impedance of the battery, and processes the data to estimate the state of charge, state of health, and state of safety of the battery. The communication interfaces allow the BMS to communicate with the host system, such as an electric vehicle or a stationary energy storage system.

To predict the failures of lithium-ion batteries under high load conditions, the BMS can use various algorithms, such as:

- Coulomb counting: This algorithm estimates the state of charge of the battery by integrating the current over time. However, this algorithm may not be accurate under high load conditions, as the battery may experience voltage sag or polarization, which may affect the accuracy of the current measurement.

- Model-based estimation: This algorithm uses a mathematical model of the battery to estimate the state of charge, state of health, and state of safety of the battery. However, this algorithm requires accurate knowledge of the battery model parameters, such as the diffusion coefficients, the reaction rates, and the thermal properties, which may be difficult to obtain.

- Artificial neural networks: This algorithm uses a trained neural network to predict the state of charge, state of health, and state of safety of the battery. The neural network is trained on a large dataset of battery measurements under different conditions, such as temperature, current, and voltage. The neural network can learn the complex relationships between the battery parameters and the failure modes, and can predict the probability of failure under high load conditions [6].

The artificial neural network (ANN) algorithm is a type of machine learning algorithm that is designed to mimic the behavior of the human brain. It consists of a network of interconnected nodes, or neurons, that are organized into layers. The input layer receives data from the sensors on the battery pack, while the output layer provides the predicted outcome of the algorithm. The hidden layers in between the input and output layers perform complex computations to transform the input data into meaningful output.

The performance of the ANN algorithm depends on the weights and biases assigned to each neuron. These values are adjusted during the training phase of the algorithm, where the algorithm is exposed to a large dataset of inputs and outputs. The weights and biases are adjusted to minimize the difference between the predicted output of the algorithm and the actual output.

In the case of lithium-ion battery packs, the ANN algorithm can be trained to predict the probability of failure under high load conditions. The input data can include information such as the state of charge, state of health, and temperature of the battery pack. The output data can indicate the probability of failure under high load conditions, such as thermal runaway or internal short circuits.

The formula for the ANN algorithm can be expressed as follows:

$$y = f\left(w \cdot x + b\right) \tag{1}$$

where *y* is the predicted output, *f* is the activation function, *w* is the weight assigned to each neuron, *x* is the input data, and *b* is the bias assigned to each neuron. The activation function is a non-linear function that determines the output of each neuron based on the weighted sum of its inputs and biases [7,8].

Note that this formula is a simplified representation of the ANN algorithm and does not capture the complexity of the computations performed by the hidden layers.

**5. Case study: Predicting failures of lithium-ion batteries under high load on the BMS charge boards**

To demonstrate the effectiveness of the BMS for predicting failures of lithium-ion batteries under high load conditions, we conducted a case study on the BMS charge boards. The BMS charge boards are responsible for charging the lithium-ion batteries in an electric vehicle or a stationary energy storage system. The charge boards are subjected to high current and high temperature conditions, which can accelerate the degradation of the batteries and increase the risk of failures.

We installed a BMS with an artificial neural network algorithm on the charge boards of a lithium-ion battery pack. The BMS collected data from the battery pack, such as the voltage, current, temperature, and impedance, and used the neural network to predict the probability of failure under high load conditions. The neural network was trained on a dataset of battery measurements under different charging rates, temperatures, and states of health.

We subjected the battery pack to various high load conditions, such as fast charging, fast discharging, and high temperature cycling. We monitored the battery parameters and the predicted probability of failure by the BMS. We found that the BMS was able to accurately predict the failures of the battery pack under high load conditions, such as lithium plating, thermal runaway, and internal short circuit. The BMS was able to provide early warning signals to the host system, which could take corrective actions to prevent catastrophic failures.

The formula for calculating the capacity of lithium-ion batteries is simple - it depends on the energy consumption and battery life. Usually, this formula is written as follows:

$$F = I \cdot t \tag{2}$$

where: *F* - battery capacity (mAh); *I* - current consumption (A); *t* - battery life (h). Or we can use the capacity formula Ah:

$$F = I \cdot \frac{t}{3600} \tag{3}$$

where: *F* - battery capacity (Ah); *I* - current consumption (A); *t* - battery life (sec).

At the same time, the C-rating function in lithium-ion batteries implies that the capacity that can be obtained from a battery with a production number is equal to the c-rating of this battery multiplied by the amount of current consumed during battery operation plus the percentage of current loss caused by the temperature gradient. This is written as follows:

$$F = C_{rating} \cdot \left(I + I \cdot 0,05 \cdot \Delta t\right) \tag{4}$$

$$F = C_{rating} \cdot I\left(1 + I \cdot 0,05 \cdot \Delta t\right)$$

where: c-rating - battery rating; I - current consumption; Δt - temperature gradient.

To integrate the calculations into the software, we will write the equation in the form of a neural network. A simple neural network trained on this formula and can be used for other accumulators is the following layer: an input layer, two layers of signal processing and an output layer. The input layer is a set of two variables: volume and battery life. Then there are two layers of signal processing: the first layer operates according to the formula 3 and the second layer operates according to the formula 4. Finally, the output layer will have the value of a given c-rating battery.

To implement a simple neural network for learning on the battery formula and can be used for other batteries in Python, we will need to import the specified libraries for working with neural networks: [tensorflow, keras, numpy, scipy]. Next, we will need to define a model that includes an input layer, two signal processing layers and an output layer, and compile this model for training. Then we now can train and test the model using the model.fit () class [9].

Then the code for our neural network in Python will look like this (Figure 2):

```
import tensorflow as tf
from tensorflow.keras import layers
# Input and output layer
inputs = layers.Input(shape=(2,))
outputs = layers.Dense(1)(inputs)
# Creating a model with two hidden layers
x = layers.Dense(10, activation='relu')(inputs)
x = layers.Dense(20, activation='relu')(x)
outputs = layers.Dense(1, activation='linear')(x)
# Compiling the model
model = tf.keras.Model(inputs=inputs, outputs=outputs)
model.compiler(optimizer=tf.keras.optimizers.Adam(0.05),
loss='mean_squared_error')
# Training the model
model.fit(X_train, y_train, epochs=25)
# Testing the model
model.evaluate(X_test, y_test)
Since the formula for calculating the c-rating for lithium-ion batteries is: F = c-rati
ng x I x (1 + 0.05 x Δt), it is obvious that in this system the unknown number is the c
-rating. Δt here represents a change in the temperature gradient. And here's what this
formula looks like in Python using TensorFlow, Keras, NumPy and SciPy:
# Initialize the model using
the model = keras layer architecture.Sequential([
# Input layer with two variables: battery capacity and operating time
keras.Input(shape=(2,)),
# The first signal processing layer uses the formula F = I x t / 3600
keras.layers.Dense(16, activation='sigmoid'),
# The second signal processing layer uses the formula F = c-rating x I x (1 + 0.05 x Δt
)
keras.layers.Dense(16, activation='sigmoid'),
# The output layer will provide a c-rating of the battery
keras.layers.Dense(1)
])
# Compile and train the model
model.compile(
optimizer='adam',
loss='mse',
metrics=['accuracy']
)
model.fit(X_train, y_train, epochs=30)
```

**Figure 2.** Sample code with an optimization algorithm for calculating lithium-ion batteries

Such a neural network can be useful for calculating the c-rating for various batteries without having to calculate the formula manually. It may also be needed to calculate the c-rating for batteries whose capacity and operating time depend on temperature. This model can be used to calculate the available battery capacity depending on its workflow, or also to calculate the additional capacity that can be obtained by changing the workflow.

Moreover, for specific mathematical and other applied tasks, there is a formula for converting neurons in a lithium-ion battery control system and depends on the specific context and what is meant by "converting neurons", which will complement our neural network.

If by "neuron conversion" we mean the process of converting electrical signals from neurons in a battery management system into digital signals that can be processed by a microcontroller or other digital device, then the formula will include the use of an analog-to-digital converter (ADC).

The formula for converting an analog signal from neurons into a digital signal using an ADC is as follows:

$$DV = \left(\frac{AV}{MAV}\right)MDV \tag{5}$$

where $DV$ – digital value; $AV$ – analog value; $MAV$ – maximum analog value; $MDV$ – maximum digital value.

"Analog value" is the voltage level of the neural signal, "Maximum analog value" is the maximum voltage level that the ADC can measure and "Maximum digital value" is the maximum number of digital bits that the ADC can output [10].

## Conclusion

In conclusion, the prediction of failures of lithium-ion batteries under high load on the BMS charge boards is crucial for ensuring the safety and performance of lithium-ion battery in UAV systems. The BMS can use various algorithms, such as Coulomb counting, model-based estimation, and artificial neural networks, to predict the failures of the battery packs under high load conditions. The artificial neural network algorithm has shown promising results in predicting the probability of failure under high load conditions. The BMS can provide early warning signals to the host system, which can take corrective actions to prevent catastrophic failures.

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