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COMPARISON OF EQUIVALENT CIRCUIT AND MACHINE LEARNING METHODS FOR CUBESAT BATTERY DISCHARGE MODELING

The subject of the article is the study and comparison of two approaches to modelling the battery discharge of a CubeSat satellite: analytical using equivalent circuit and machine learning. The article aims to make a reasoned choice of the approach to modelling the battery discharge of a CubeSat satellite. Modelling the battery discharge of a satellite will enable the prediction of the consequences of disconnecting the autonomous power system and ensure the fault tolerance of equipment in orbit. Therefore, the selected study is relevant and promising. This study focuses on the analysis of CubeSat satellite data, based explicitly on orbital data samples of the power system, which include data available at the time of the article's publication. The dataset contains data on the voltage (mV), current (mA), and temperature (Celsius) of the battery and solar panels attached to the five sides of the satellite. In this context, two approaches are considered: analytical modelling based on physical laws and machine learning, which uses empirical data to create a predictive model. Results: A comparative analysis of the modeling results reveals that the equivalent circuit approach has the advantage of transparency, as it identifies possible parameters that facilitate understanding of the relationships. However, the model is less flexible to environmental changes or non-standard satellite behavior. The machine learning model demonstrated more accurate results, as it can account for complex dependencies and adapt to actual conditions, even when they deviate from theoretical assumptions. However, the model requires prior training on a large amount of data and is less well understood in terms of physical laws. General conclusions. The equivalent circuit approach provides high accuracy and reliability under known conditions, but it is limited when external parameters change. The machine learning approach demonstrates better overall accuracy and stability, especially under variable or unpredictable conditions, but requires a large amount of high-quality data and more complex interpretation. Thus, the most effective approach may be a hybrid one, where the analytical model serves as the basis and machine learning is used as a tool for refining or compensating for inaccuracies.

Keywords: *CubeSat; EPS; machine learning; modelling; small satellite.*

1. Introduction

Due to its attractive cost, the availability of commercially ready-made solutions, and a relatively short implementation time, CubeSat has gained popularity among space researchers. It is currently used to solve a wide range of tasks. The general overview for the current state-of-the-art SmallSat technologies [1] states the growing popularity of small satellites in general and CubeSats in particular, and shows that since 2013, the flight heritage for small spacecraft has dramatically increased and has become the main primary source of access to space for commercial, government, private, and academic.

The CubeSat project was initiated in 1999 by scientists from California Polytechnic State University and Stanford University's Space Systems Development Laboratory. Specification [2] defines a 1U (U stands for 'Unit') CubeSat as a small satellite of standard size and shape, which is a 10 cm cube with a mass of up to 2 kg. A CubeSat can consist of several units. The current version of the specification describes the design of CubeSats up to 12U.

1.1. Motivation

According to various estimates, the global CubeSat market will show a GAGR over 15% in the coming years (according to CubeSat Market Research Report https://straitsresearch.com/report/cubesat-market Straits research expects it to reach USD 1,305.56 million by 2032, with GAGR of 15.1% during the forecast period (2024-2032) with base year 2023 while by IMARC Group in its report "CubeSat Market Size, Share, Trends and Forecast by Size, Application, End User, Subsystem, and Region, 2025-2033" expects the market to reach USD 1,608.98 Million by 2033, exhibiting a CAGR of 16.3% during 2025-2033 with base year 2024).

In accordance with [5], the most significant number of CubeSat missions were with a mass of 3U (~45.5% of the total and 53.3% of the successfully launched). CubeSats are being assigned more and more complex tasks, which increases the requirements for their capabilities. Fig. 1 shows the dynamics of the deployment of missions based on CubeSat over the last 20 years. In the previous ten years, missions based on 12U (53 missions, first in 2016), 16U (26 missions, first

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in 2019), and the first 20U mission in 2023 (China, Tianzhi-2D) have been successfully launched. Although the development of CubeSat projects is fast and accessible to a wide range of researchers, providing opportunities for implementing both commercial and educational projects [3], the failure rate of such projects is relatively high [4]. Fig. 2 shows the success (i.e., how successful it was, not the current state) of such satellites for educational and scientific missions from 2003 to 2025 (May). To construct the visual image, data from the nanosatellite and CubeSat database [5] were utilized; the database's last significant update was on April 30, 2025. The paper presents a comparative analysis of analytical and machine learning-based approaches to modeling CubeSat storage battery discharge.

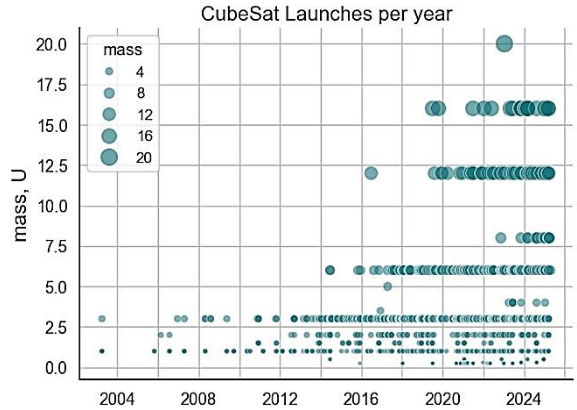

Fig. 1. Dynamics of the launches based on CubeSat missions for the period from 2003 to 2025

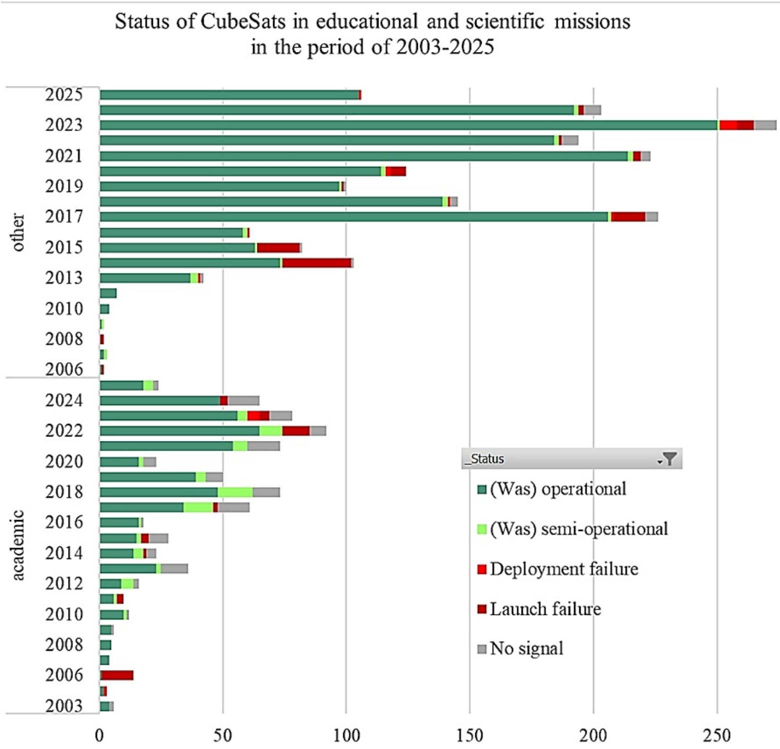

Fig. 2. Status of CubeSats in educational and scientific missions in the period of 2003 to 2025 (May)

1.2. State of the art

According to UNOOSA (United Nations Office for Outer Space Affairs) records, 13,469 satellites are orbiting the Earth as of April 2025, of which only 12,205 satellites are active (as of late April 2025), as shown by the satellite tracking website "Orbiting Now", that maintains the records of the satellites in various Earth orbits.

The report [6] analyzed the reasons for the partial and complete failure of missions with small satellites. According to the report, between 2000 and 2016, 41.3% of mission launches with small satellites failed partially or entirely. Of these, 24.2% of missions suffered complete failure, 11% failed partially, and launch vehicle failures accounted for another 6.1%. In work [7], based on the analysis of failure reports from 2000 to 2012, among the most frequent causes of mission failures are configuration or interface issues between communication hardware (27%), the Electrical Power System (EPS, 14%), and the flight processor (6%). Therefore, it is crucial to predict satellite failures through modelling.

Several papers have investigated ways to improve energy harvesting using solar panels and techniques such as maximum power point tracking (MPPT), with a particular focus on the benefits of implementing machine learning techniques to enhance the performance of EPS. Thus, in paper [8], a deep learning-based MPPT approach is proposed to improve CubeSat power generation; the authors used annual data obtained from simulations of a 3U CubeSat to train the model. The authors of the study [9] provide an overview of various types of MPPT methods, including classical, intelligent, optimization-based, and hybrid methods.

The study [10] provides a general overview of approaches for estimating the state of charge and the state of health of lithium-ion batteries, including several machine learning (ML) techniques: neural networks, support vector machines, fuzzy logic, genetic algorithms. The authors of paper [10] conclude that given large data sets, data-driven methods will outperform model-based approaches. The paper [11] describes a mathematical framework for the EPS design that can be useful for evaluating key parts of a CubeSat EPS. The study [12] presents the benefits of Physics-informed machine learning for accurate state of health estimation of lithium-ion batteries, taking into account aging processes. The research [13] describes a transformer structure for estimation of the battery's state of charge and shows its performance for LiNiMnCoO2 and $LiFePO_4$ datasets. The study [14] considers storage batteries discharge modelling in low Earth orbit satellites. However, there is no comparative analysis of analytical and machine learning approaches to modeling that compare results on the same dataset.

The authors of the study [15] investigated the statistical reliability of small satellites using empirical failure data for the period 2010-2020 and showed a general trend that reflects that at the beginning of the mission the probability of failure of each subsystem is high and constantly decreases during the first two years, then the values gradually decrease and fluctuate around the nominal value. In particular, in the work [15] it is stated that the contribution of the failure of the power subsystem to the satellite failure after a certain specific time in orbit is determined as follows: after 30 days – 17.63%, after one year – 11.78%, after two years – 7.42%, after 10 years – 9.97%.

Study [16] (as of October 2024) states that of the 2,714 CubeSats launched, 677 have experienced problems or failures, not all of which could have resulted in mission loss. According to [16], most failures were caused by launch and deployment failures. Among the problems identified, communication failures, power system failures, and high spin rates were noted as the most common.

2. Objectives and approach

In this study, the primary focus is on analyzing the EPS of 1U CubeSat satellites based on on-orbit data samples from the TSURU satellite dataset [17], which includes data from its deployment into orbit to the present time.

This work investigates the possibility of using machine learning to predict the battery discharge of a CubeSat satellite. By the aim of the study, the following tasks must be solved:

1. Analysis of available observational data and handling outliers (section 3).
2. CubeSat storage battery discharge modeling using equivalent circuit techniques. Evaluation of the model accuracy (section 4.1).
3. CubeSat storage battery discharge modeling based on machine learning approach (section 4.2). It contains data preprocessing (described in section 4.2.1) and further machine learning model training (section 4.2.2). Evaluation of the built machine learning model performance (section 4.2.3).
4. Comparative analysis of the obtained results by the two approaches used (section 5).

3. Data analysis

The source data is based on the BIRDS open-source standardized bus [17]. The dataset contains voltage (mV), current (mA), and temperature (in degrees Celsius) data for the storage battery and solar panels attached to the five sides of the satellite. This data is collected by the onboard computer every 90 seconds in normal mode or every 10 seconds in fast sampling mode. The dataset contains data on solar panels and batteries from the time when they were launched into orbit until the end of life of the UGUISU, RAAVANA, and NEPALISAT satellites. The TSURU satellite dataset contains data since its launch into orbit and will continue to be collected throughout its lifetime.

The sampling interval for UGUISU, RAAVANA, and NEPALISAT was 5 seconds, and for TSURU, it was 10 seconds. NEPALISAT, RAAVANA, and UGUISU operated in orbit for more than two years before their re-entry. TSURU was still operating in orbit when the dataset was released.

Thus, if the solar panel generates too much voltage for the battery, it is limited by the DC/DC converter to 4.2V, preventing overcharging. The generated energy is stored in a battery pack consisting of six rechargeable Eneloop Nickel Metal Hydride (NiMH) batteries, each with a minimum capacity of 1900 mAh, arranged in a 3-series and 2-parallel configuration. A thermistor is installed between the batteries to measure the temperature. Since low temperatures negatively affect battery capacity, the battery is wrapped with Kapton tape and a polyimide heater to help maintain thermal balance. The Electrical diagram is shown in Fig. 3. The dataset is

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missing the solar cell current, Isra, and the load current, I_{raw}.

The usual practice of using a storage battery in a satellite is that when there are signs of approaching full discharge of the storage battery (SB), it is necessary to urgently turn off everything superfluous to preserve the viability of the whole satellite. Excess primarily includes the payload; only the life support systems remain switched on. This certainly reduces the beneficial effect of using the satellite if the load limiting mode is turned on early. Still, such a mode should be activated automatically, as waiting for a human operator to make a decision would result in the loss of the entire satellite.

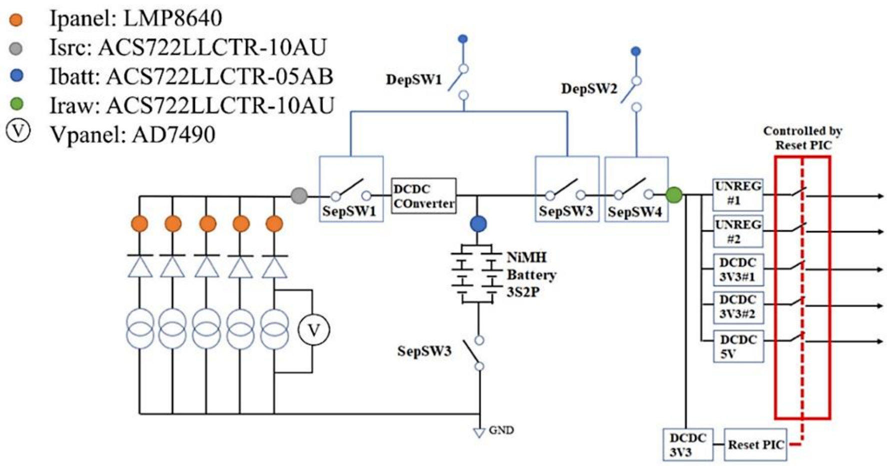


Fig. 3. BIRDS-4 satellite EPS block diagram [17].

Characteristics of the photoconverter are shown in Table 1. The charging and discharge characteristics provided by the manufacturer for each battery are shown in Fig. 4a and Fig. 4b, respectively. A sign of the exhaustion of the battery's capacity is the end of the linear section of the discharge characteristic of the SB. Still, this moment of termination depends significantly not only on the current used to discharge the chemical battery, but also on the history of its operation. It is known that control charge-discharge cycles, which can be carried out in shadowless areas of the orbit, allow not only the estimation of the current capacity of the SB but also the restoration of its characteristics.

Table 1

Dependence of photoconverter characteristics on equivalent radiation dose, source: AZUR SPACE Solar Power GmbH

	BOL	2.5E14	5E14	1E15
Average Open Circuit V_{oc} [mV]	2690	2606	2554	2512
Average Short Circuit I_{sc} [mA]	519.6	517.9	513.4	501.3
Voltage at max. Power V_{mp} [mV]	2409	2343	2288	2244
Current at max. Power I_{mp} [mA]	502.9	501.7	499.1	485.1
Average Efficiency η_{bare} (1367 W/m^2) [%]	29.3	28.4	27.6	26.3
Average Efficiency η_{bare} (1353 W/m^2) [%]	29.6	28.7	27.9	26.6
Standard: CASOLBA 2005 (05-20MV1, etc); Spectrum: AMO WRC = 1367 W/m^2; T = 28 °C				

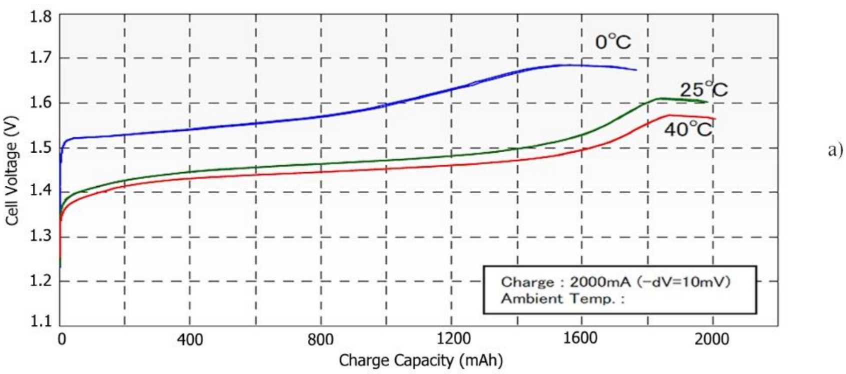
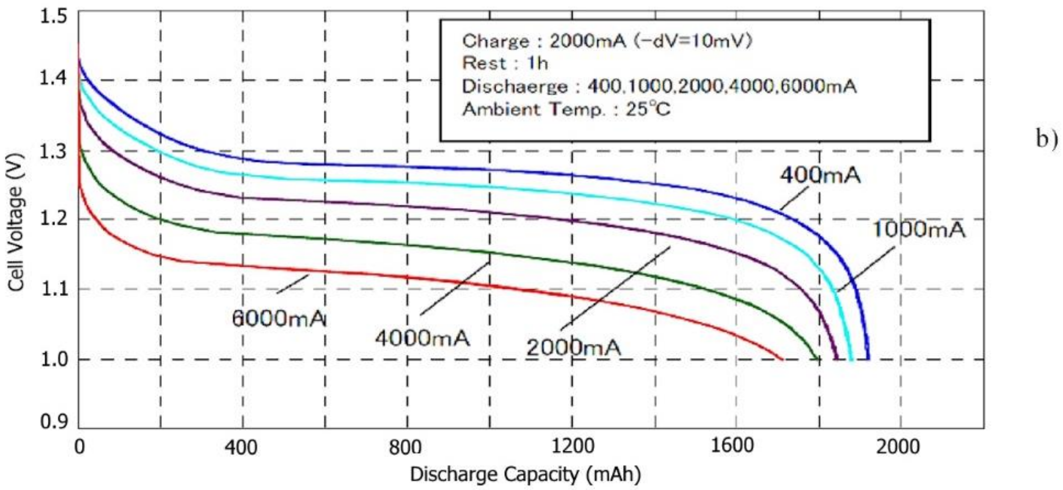


Fig. 4. Charge (a) characteristics of each battery, measured in laboratory conditions, provided by the manufacturer



Continuation of the Fig. 4. Dscharge (b) characteristics of each battery, measured in laboratory conditions, provided by the manufacturer

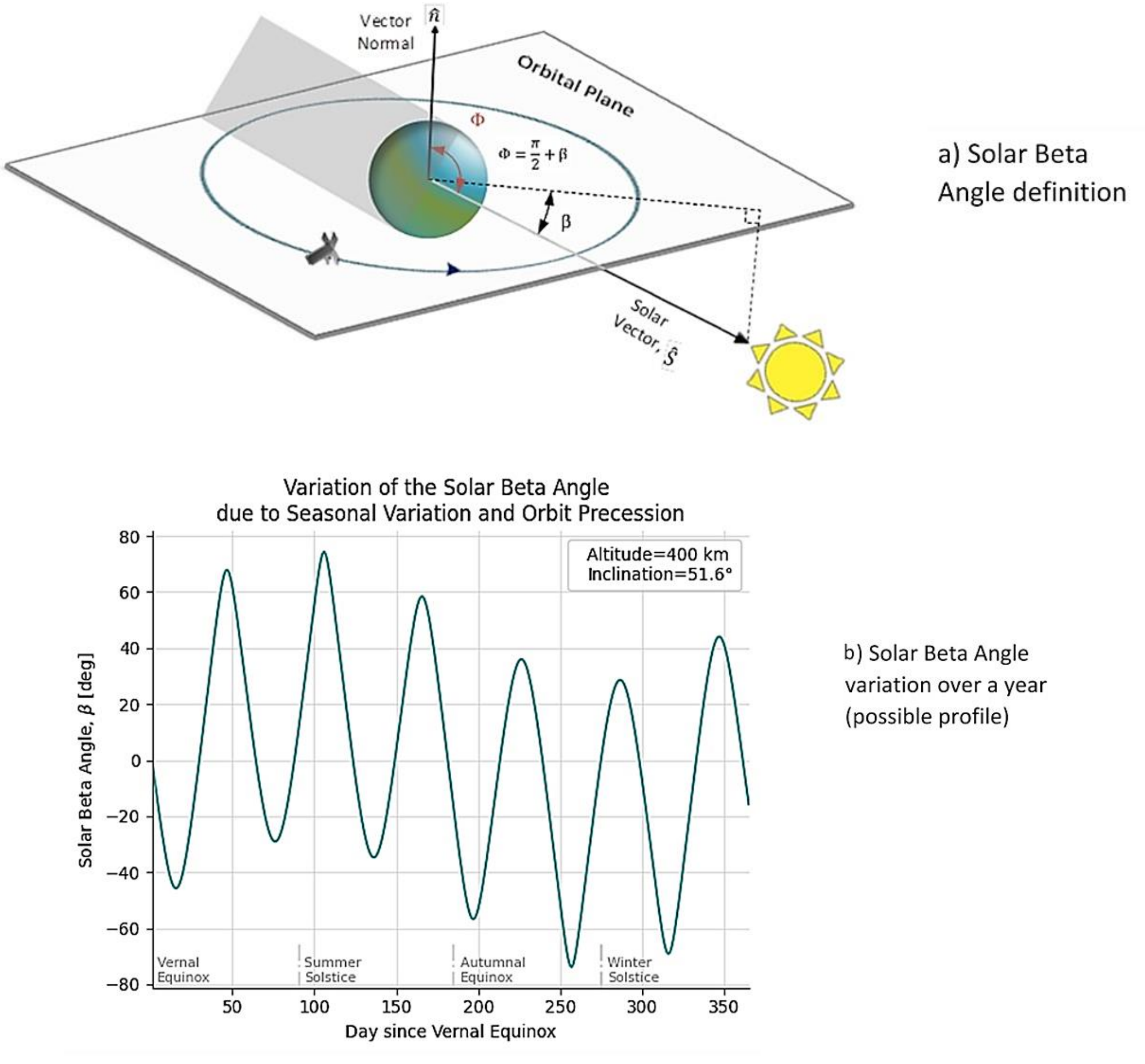


Fig. 5. The periods during which the Satellites are illuminated due to the ISS orbit

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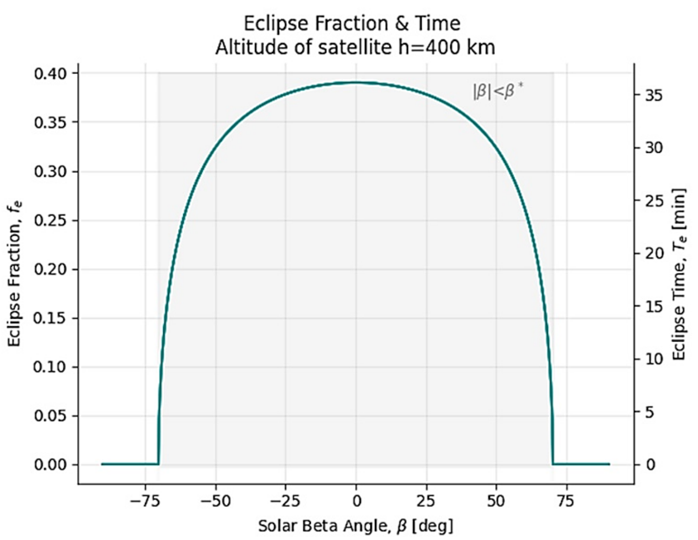
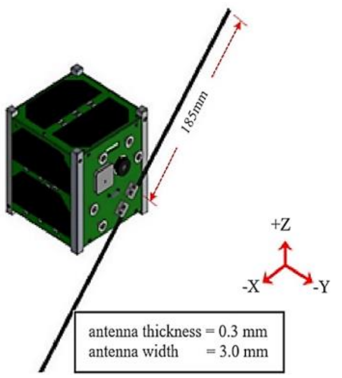


c) Dependency of the Eclipse Fraction and Eclipse Time on the Solar Beta Angle

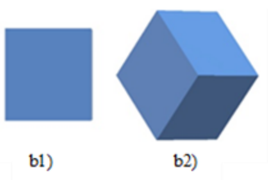
Continuation of the Fig. 5. The periods during which the Satellites are illuminated due to the ISS orbit

When the absolute value of the Solar Beta Angle exceeds 69.9 °, the satellite is in a shadowless orbit (Fig. 5 c) [18]. The satellites of this series have no orientation control, so the satellites rotate freely at a speed of about 3 deg/s on each axis. Five of the six faces of the cubic-shaped satellite provide a power supply.

The orientation and illumination of the solar panels are determined by the satellite's geometry, as shown in Fig. 6a. When the satellite is on the illuminated part of the orbit, the best energy supply will be if it is deployed at 45 ° along two axes. The difference is about 2-2.2 times (Fig. 6b).



a) The geometry of the satellite, source [17]



b) Satellite orientation for the worst (b1) and the best (b2) power harvesting

Fig. 6. Appearance of the satellite

When the device leaves the shadow area, the cooled PB generates maximum energy, which decreases by 50–80% within 5–7 minutes and then changes according to the temperature variation of the photoconverters.

The available data [17] covers the period from March 2021 to January 2022 (namely for dates: March 28, April 20, April 27, May 13, May 21, May 28, June 01, June 25, June 11, June 17, July 05, July 09, August 07, August 22, September 07, September 03, September 11, September 13, September 19, September 25, October 03, October 15, November 02, November 16, November 05, November 22, November 27, December 07, December 20, December 25 and January 24, 2022) for the following characteristics:

– time stamp – the time at which the data sample was measured (sec);

– temperatures of the five surfaces of the photovoltaic cells (°C);

– output voltages of the five photovoltaic cells (mV);

– generated current from the five photovoltaic cells (mA);

– voltage (V), charge-discharge current (mA), and temperature (℃) of the energy storage device.

The dataset is valuable and important because it includes in-orbit data collected by four different CubeSat satellites that share the same bus system structure: the NEPALISAT, RAAVANA, UGUISU, and TSURU satellites. This data can be used to estimate the energy available in orbit for a 1U CubeSat, assessing the feasibility of missions.

In this research for the battery discharge modelling, we analysed available data and extracted the battery discharge periods from this dataset. Data visualization for 20_02_2021 (complete set and selected discharge period) are shown in Fig. 7.

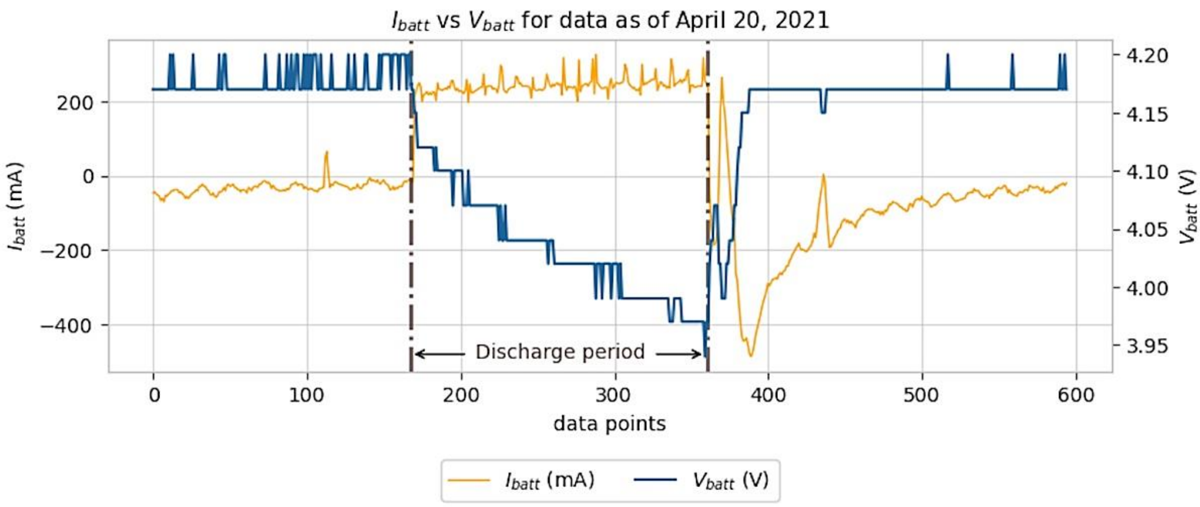


Fig. 7 Data visualization of the whole set and the April 20, 2021, discharge period.

For a better understanding of their composition and range of changes, statistical information was collected, and the DOD was calculated (described in detail in subsection 4.1) and presented in Table 2.

Table 2

Data set features description (5709 measures)

	V_{batt} (V)	I_{batt} (mA)	DOD (mA*hour)	T_{batt} (℃)
mean	4.0298	263.0029	65.9986	6.2552
std	0.0575	76.0496	42.8586	2.7049
min	3.79	5.64	0	1.07
max	4.2	1200.42	225.3272	15.63

During data analysis, a significant deviation in the I_{batt} current values was detected in the data sets for the dates 01/24/2022, 07/05/2021, 07/09/2021, and 05/21/2021, where I_{batt} reached values above 1000 mA (Fig. 8). Also, several data points that represents negative I_{batt} i.e., battery charge instants in the middle of the discharge periods, were found in the discharge data set. Fig. 8 shows the distribution of both typical and untypical (i.e. "too low" – negative I_{batt} values and "too high" – I_{batt} > 500 mA) I_{batt} data.

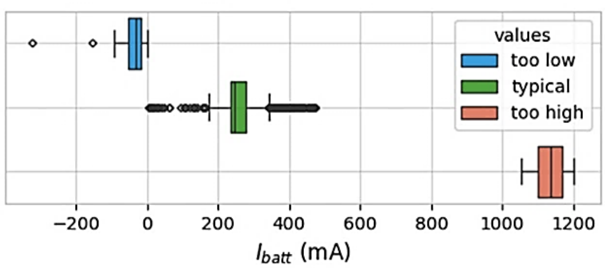


Fig. 8. I_{batt} values distribution visualization for the whole discharge data set.

4. CubeSat storage battery discharge modeling

In this study, CubeSat battery discharge modeling is performed using two approaches: equivalent circuit and machine learning, and the obtained results are analyzed.

4.1. Equivalent circuit based model of the CubeSat storage battery discharge

To build the model, the efficiency of energy transfer from solar batteries to a chemical battery was first determined according to the criterion of the minimum variance of dependency. Based on the block diagram (Fig. 3) and assuming that the losses on the five blocking diodes are the same, we obtain the following formula:

$$N_{Load}(\tau) = N_{SB}(\tau) + \eta \sum_{1}^{5} V_{p_i}(\tau) \cdot I_{p_i}(\tau) \qquad (1)$$

At large intervals of operation time in stationary mode, the energy balance between energy storage and energy consumption must be maintained, this allows applying formula (1) to calculate the efficiency of energy transfer from the photovoltaic battery to the load: η =92.6 %. To confirm the correctness of the calculations, the graph shown in Fig. 9.

The satellite design information has been released as a standardized, open-source BIRDS bus system for the fast and easy development of satellites for educational and research purposes. The data can be used as a standard data set to verify the on-orbit performance of a satellite power system developed using the BIRDS bus.

Typically, the discharge characteristics of the storage battery are of decisive importance when designing a satellite power supply system. The

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manufacturer in its own specifications indicates the dependence of the discharge voltage on the depth of discharge at fixed values of ambient temperature and discharge current. In practice, this is not enough, since the operating parameters are constantly changing. To overcome this problem, approximate solutions are used, the most common of which is the use of an equivalent circuit of the storage battery (Fig.10).

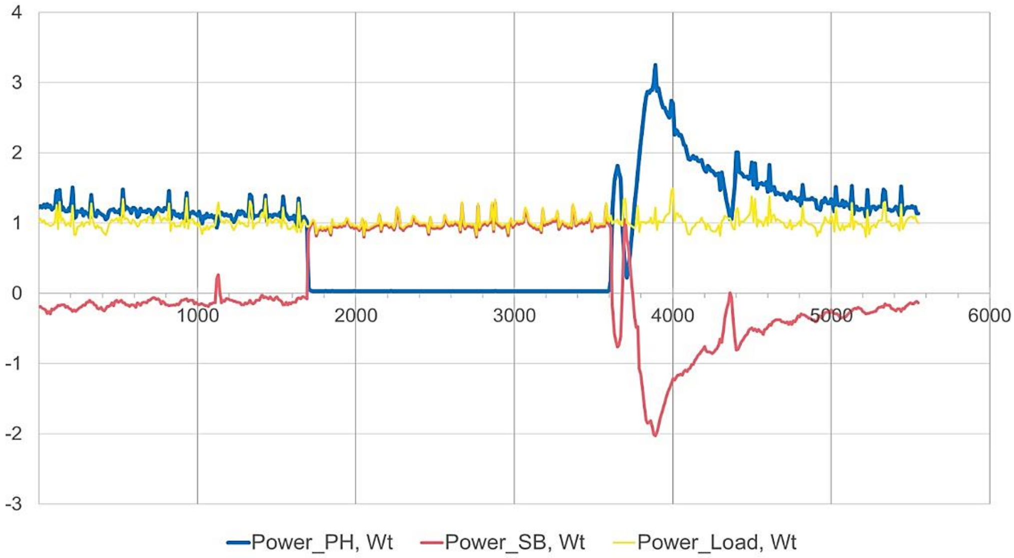

Fig. 9. Confirmation the correctness of the calculations

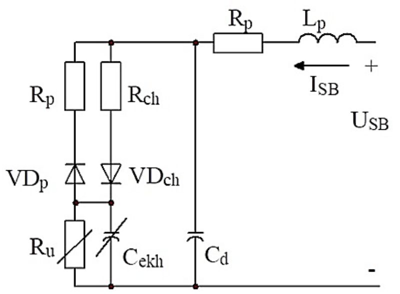

Fig. 10. The equivalent circuit of the storage battery

In Figure 10:

– Rp, Lp – resistance and inductance of external connections, electrodes, and electrolyte;

– Rp, VDp formalize the nonlinear polarization effect as a function of the charge level, discharge current, and battery temperature;

– Rch, VDch are similar to Rp, VDp for the charge mode;

– Cd is the capacitance of the double layer;

– Cekh is the battery capacity as an electrochemical storage; -

– Ru – a non-linear resistor that simulates the processes associated with self-discharge and the occurrence of side chemical reactions.

A simplified mathematical model of discharge characteristics contains the dependence of the depth of discharge as an integral on the discharge current and the battery voltage, which depends on the current, temperature, and depth of discharge:

$$\begin{aligned} & DOD(\tau) = \int_0^{\tau} I_d(t)\,dt, \\ & U(\tau) = U_0 - K_{DOD}(T)\cdot DOD(\tau) - R(T)\cdot I_d(\tau) - \\ & \qquad U_p(T)\cdot \exp\left(-\frac{DOD(\tau)}{DOD_{kp}(T)}\right). \end{aligned} \tag{2}$$

Formula (2) contains 2 equations: the dependence of the depth of discharge on time and discharge current and the approximation of the battery discharge voltage on the depth of discharge.

Identification of the parameters of the discharge characteristic model is the determination of the structure and parameters of the temperature:

$K_{DOD}(T)$ – the angle of inclination of the linear section of the discharge characteristic;

$R(T)$ – internal resistance;

$U_p(T)$ – change in voltage on the initial non-linear section of the discharge characteristic;

$DOD_{kp}(T)$ – the duration of the initial nonlinear section of the discharge characteristic.

To analyze the obtained results, the accuracy of the model was calculated using the complete sets; the results are presented in Fig. 11. Limited and insufficient accuracy of the original data leads to unexpected results: 42% of the model calculations in discrete form coincide with the results of the measurements (what is obtained from the ADC), and the deviation of almost 97 model calculations does not exceed the two least significant bits (LSB) from ADC.

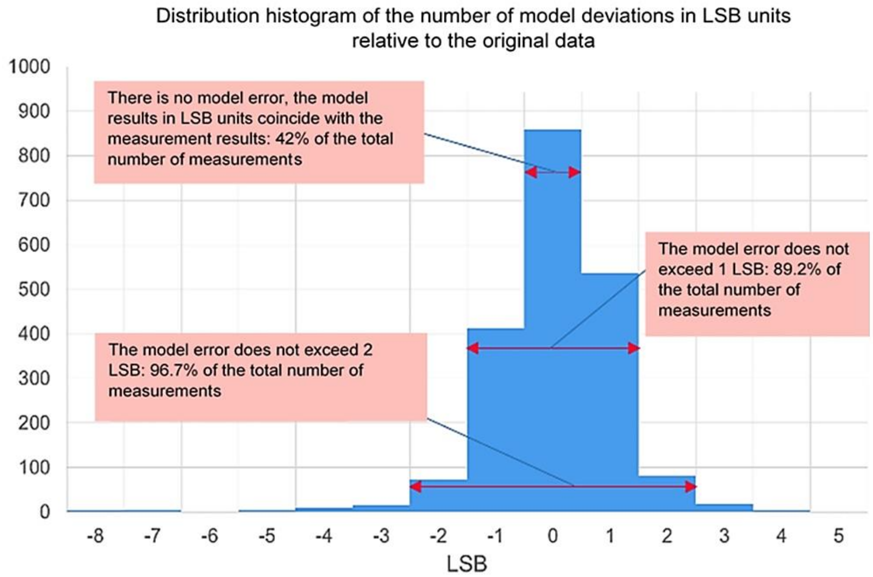

Fig. 11. Accuracy of the model on the complete data set (31-bit characteristics)

4.2. Machine learning based model of the CubeSat storage battery discharge

Based on the results of the data analysis described in Section 3, a dataset was created for further training of the model, containing data corresponding to battery discharge periods. The training data set comprises data on battery discharge periods collected from all available sets (March 2021 to January 2022) for both typical and atypical I_{batt} values. The data set features description for the whole set and for the typical I_{batt} values is represented in Table 2 and Table. 3.

Table 3

Data set features description for the typical I_{batt} values (5024 measures)

	V_{batt} (V)	I_{batt}(mA)	DOD (mA*hour)	T_{batt}(°C)
mean	4.0305	258.6566	64.9712	6.1894
std	0.0547	42.7227	40.8895	2.7484
min	3.87	5.64	0	1.07
max	4.2	474.18	181.4189	15.63

Handling Outliers. Data outliers (data points where a short-term increase of I_{batt} was observed in the middle of the discharge period) were excluded from the set.

Feature Extraction. Taking into account the correlation of the accessible data, the following features were selected: I_{batt} – the current value of the battery in calibrated format (mA), and T_{batt} – the temperature value of the battery in calibrated format (°C), and extracted from the full data set for periods of satellite battery discharge. The data series for all selected features has no missing values.

4.2.1. Feature engineering

Feature Creation. The feature DOD (discharge characteristic, mA*hour) was created using the equation from (2). The selected features correlation study was performed on the whole set for the battery discharge period, the results are shown in Fig. 12.

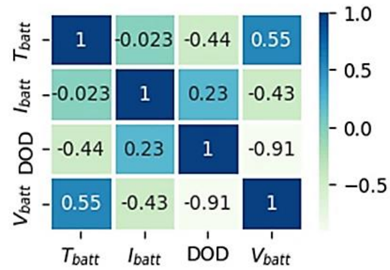

Fig. 12. Visualization of the correlation of dataset features.

As can be seen from the figure, the input characteristics are correlated with the target feature and are not overcorrelated. New feature matrix consisting of all polynomial combinations of the both selected and created features with degree less than or equal to the 8 was generated.

Scaling. Each selected feature was scaled and transformed individually according to the equation (3).

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3}$$

The target feature (label) is V_{batt} – Voltage value of the battery in calibrated format (V).

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4.2.2. Machine learning model creation and training

For CubeSat storage battery discharge prediction, the cross-validated Lasso regressor model (LassoLarsCV), which is based on the least-angle regression (LARS) algorithm [19] and can overcome multicollinearity, was chosen. A cross-validation estimator was selected due to its ability to support warm-starting by reusing precomputed results from previous steps of the cross-validation process, as well as to provide the advantage of the best training/development data set split. The metric used for the model performance evaluation – R2 Score, defined as

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_i - y_i\right)^2}{\sum_{i=1}^{N}\left(y_i - \bar{y}\right)^2}, \quad \bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{4}$$

where: y_i is the predicted value of V_{batt} for the i-th sample and y_i - the corresponding actual value of V_{batt}.

To chain multiple estimators into one, a pipeline (Python, Scikit-learn) was developed. The pipeline consists of the following steps:

1) data normalization using MinMaxScaler with default feature range [0,1];

2) generation a new feature matrix consisting of all polynomial combinations of the features with degree less than or equal to 8-degree using PolynomialFeatures;

3) regressor LassoLarsCV, cv=6.

Before using cross-validation to ensure unbiased model performance estimation, the dataset was split into training and test sets at a ratio of 80:20 %.

A characteristic feature of LARS is its computational efficiency; the algorithm requires the same order of calculations as the ordinary least squares (OLS) method [20]. The LassoLarsCV finds the relevant regularization parameter (alpha) values itself, which can help prevent the model from overfitting. The model's performance (cross-validation R^2 score) on the training set is 0.924, and on the test set, it is also 0.924.

4.2.3. Model results analysis

To analyze the model's performance on the entire dataset, ensuring that the model generalizes appropriately and does not exhibit signs of overfitting, a graph is used. (Fig. 13, 14) of the model's predicted values on the full range of values for I_{batt} at T=5°C and DOD in the range of 0-200 mA*hour with a step of 40 for Fig. 13 and step 20 for Fig. 14 were built.

Shown in the visual, ΔU was calculated according to equation (5):

$$\frac{\Delta U}{\Delta I} = \frac{f\left(I + \Delta I, DOD, T\right) - f\left(I, DOD, T\right)}{\Delta I} \tag{5}$$

U for the visual was calculated using equation (6) for the whole range of values for I_{batt}, i.e., $\left(\overline{0,1200}\right)$ mA:

$$U = f\left(I, DOD, T\right) \tag{6}$$

where the temperature setpoint $T = 5°C$ and DOD varies as $DOD = \left\{\left(\overline{0,200}\right) mA * hour, step = 20\right\}$.

The constant temperature test was chosen to accurately analyze the model's predictions for battery behaviour under different orbital conditions.

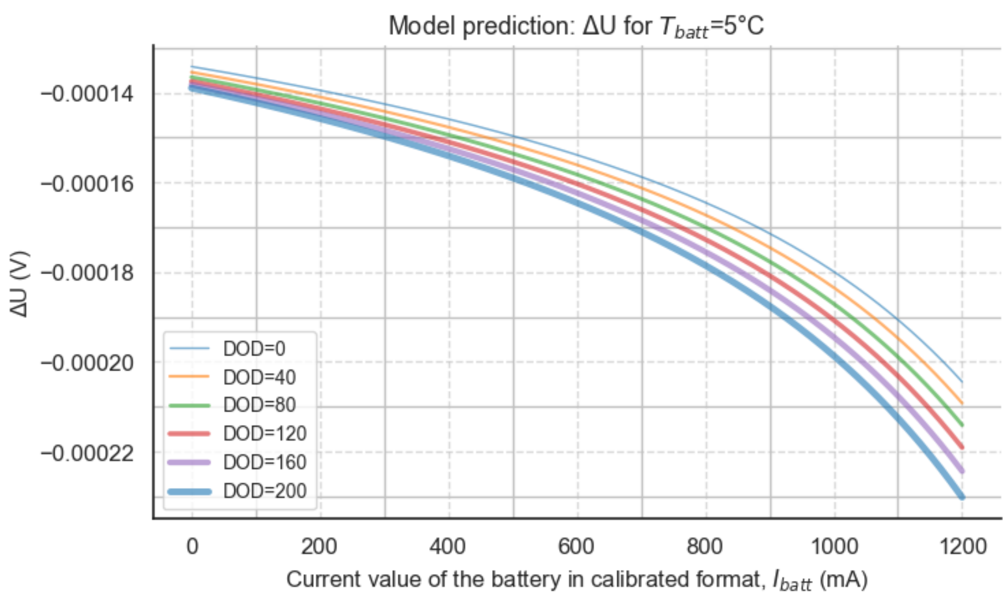

Fig. 13. Dependency graph for $\frac{\Delta U}{\Delta I}$

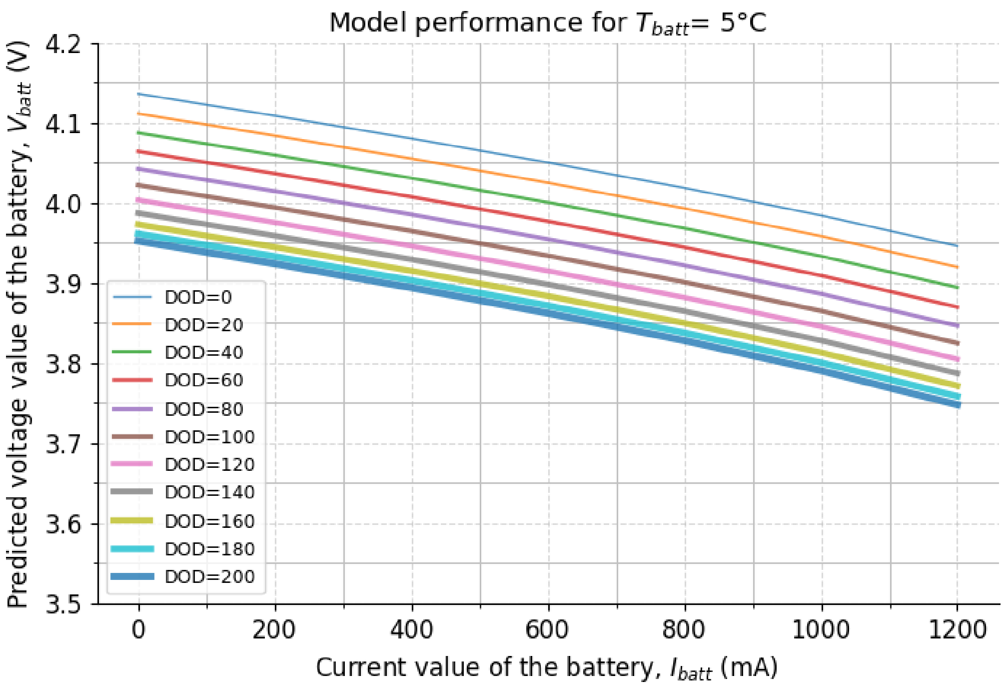

Fig. 14. Dependency graph for V_{batt}

To analyze the model prediction error, a histogram was built as shown in Fig. 15.

The histograms show the error of the model in LSB. The data predicted by the model with an accuracy of the fifth sign were used to construct the histograms.

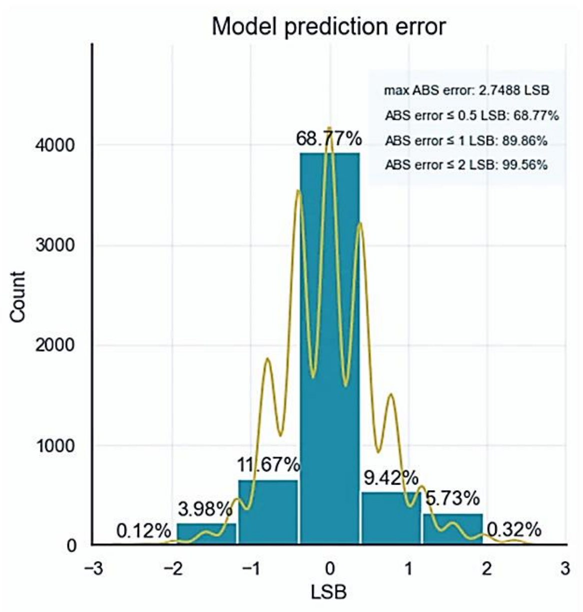

Fig. 15. Model prediction error histogram

The maximum absolute error is 2.7488 LSB. The percentage of the model prediction error above 2 LSB is 0.44%.

5. Comparative analysis of the results of analytical modeling and modeling based on machine learning

The comparative evaluation shows that both models achieve high predictive accuracy, but they differ fundamentally in methodology, interpretability, and adaptability. The analytical model's strength lies in its strict adherence to physical laws, which ensures interpretability and robustness under well-defined conditions. In contrast, the ML model captures nonlinear dependencies in the data, offering superior accuracy in dynamic or atypical operating conditions. Importantly, the ML approach achieves this without requiring explicit knowledge of system physics, instead learning from empirical data.

The error distribution analysis demonstrates that the analytical model already achieves a high degree of precision (96.7% of predictions within 2 LSB), which validates the relevance of equivalent circuit–based approaches in satellite energy system design. However, the ML model surpasses this performance, with 99.56% of predictions within 2 LSB and almost 70% of predictions deviating by less than 0.5 LSB. This suggests that ML models not only match but also refine the predictive capabilities of analytical approaches.

From a systems engineering perspective, the key advantage of the ML approach is its adaptability to real mission data, making it suitable for onboard implementation in future satellites as part of an adaptive energy management system.

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On the other hand, the analytical model remains indispensable for mission design, component specification, and cases where computational simplicity and physical interpretability are required.

Thus, these models are not competitors but complementary tools: the analytical approach provides the theoretical foundation, while ML enhances predictive accuracy under real operating conditions.

6. Discussion

This study highlights several important insights for the design and operation of CubeSat power systems. First, the availability of long-term in-orbit datasets (NEPALISAT, RAAVANA, UGUISU, TSURU) enables systematic evaluation of both physics-based and data-driven models. The demonstrated modeling framework confirms that satellite battery discharge behavior can be predicted with high fidelity using either approach.

The novelty of this work lies in directly comparing analytical and ML models on real CubeSat flight data, quantifying their respective advantages, and showing that ML can achieve higher accuracy while analytical models provide interpretability. Unlike earlier studies that focus solely on one modeling technique, this work establishes a benchmark for combining them.

Practical implications include the potential integration of ML-based predictors into satellite onboard software for real-time state-of-charge estimation and fault detection. Analytical models, meanwhile, remain valuable for mission planning and performance verification. Together, they can form a hybrid predictive framework for next-generation small satellite platforms.

Limitations of this study include the reliance on one satellite bus type (BIRDS series) and the relatively narrow range of mission profiles. Broader validation across different CubeSat platforms and longer operational lifetimes will be necessary to generalize the results. Additionally, the ML model depends heavily on the quality and representativeness of the training dataset, which may not always be available in early mission phases.

7. Conclusions

This work contributes to the field of satellite power system modeling by developing and validating two complementary approaches—an analytical equivalent circuit model and a machine learning–based model—using real in-orbit data from multiple CubeSats. The developed methodology can be used in related areas, if there is a need for automatic determination of the state of a storage battery, and its malfunction leads to the failure of the entire facility.

Main contributions:

– Developed and validated an equivalent circuit model of CubeSat battery discharge, demonstrating that 96.7% of predictions deviate by no more than 2 LSB;

– Developed a machine learning model (LassoLarsCV with polynomial features), achieving 99.56% accuracy within 2 LSB and significantly improving prediction sensitivity (68.77% of results within 0.5 LSB);

– Provided the first direct comparison of analytical and ML approaches using real CubeSat telemetry, highlighting their complementary advantages.

Theoretical significance: The results confirm that battery discharge processes can be effectively modeled both from first principles and from data-driven perspectives, establishing a dual-framework methodology for power system research.

Practical significance: The proposed models can be applied in mission design, onboard energy management, and anomaly detection, increasing reliability of CubeSat operations.

Future research directions:

– Development of hybrid models that combine analytical interpretability with ML adaptability;

– Validation on CubeSats with different bus systems and mission profiles;

– Investigation of onboard implementation of ML predictors for real-time state-of-charge and state-of-health estimation;

– Extension of models to account for aging effects, thermal cycles, and radiation degradation.

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Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship, or otherwise, that could affect the research and its results presented in this paper.

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Data Availability

Data will be made available upon reasonable request.

Use of Artificial Intelligence

The authors used artificial intelligence technologies in their work to ensure the accuracy of translation and proofreading.

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ПОРІВНЯННЯ МЕТОДІВ ЕКВІВАЛЕНТНОЇ СХЕМИ ТА МАШИННОГО НАВЧАННЯ ДЛЯ МОДЕЛЮВАННЯ РОЗРЯДУ АКУМУЛЯТОРНОЇ БАТАРЕЇ CUBESAT

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Предметом статті є дослідження та порівняння двох підходів до моделювання розряду акумулятора супутника CubeSat: аналітичного з використанням еквівалентної схеми та машинного навчання. Метою статті є обґрунтований вибір підходу до моделювання розряду акумулятора супутника CubeSat. Моделювання розряду акумулятора супутника дозволить передбачити наслідки відключення автономної енергосистеми та забезпечити відмовостійкість обладнання на орбіті. Тому обране дослідження є актуальним та перспективним. Це дослідження зосереджено на аналізі даних супутника CubeSat, що базується явно на зразках орбітальних даних енергосистеми, які включають дані, доступні на момент публікації статті. Набір даних містить дані про напругу (мВ), струм (мА) та температуру (за Цельсієм) акумулятора та сонячних панелей, прикріплених до п'яти боків супутника. У цьому контексті розглядаються два підходи: аналітичне моделювання на основі фізичних законів та машинне навчання, яке використовує емпіричні дані для створення прогнозної моделі. Результати. Порівняльний аналіз результатів моделювання показує, що аналітичний підхід має перевагу прозорості, оскільки він визначає можливі параметри, що сприяють розумінню взаємозв'язків. Однак модель менш гнучка до змін навколишнього середовища або нестандартної поведінки супутника. Модель машинного навчання продемонструвала точніші результати, оскільки вона може враховувати складні залежності та адаптуватися до фактичних умов, навіть коли вони відхиляються від теоретичних припущень. Однак модель вимагає попереднього навчання на великій кількості даних і менш зрозуміла з точки зору фізичних законів. Загальні висновки. Аналітичний підхід забезпечує високу точність і надійність за відомих умов, але він обмежений при зміні зовнішніх параметрів. Підхід машинного навчання демонструє кращу загальну точність і стабільність, особливо за змінних або непередбачуваних умов, але вимагає великої кількості високоякісних даних та більш складної інтерпретації. Таким чином, найефективнішим підходом може бути гібридний, де аналітична модель служить основою, а машинне навчання використовується як інструмент для уточнення або компенсації неточностей.

Ключові слова: малий супутник; CubeSat; Електроенергетична система; моделювання; машинне навчання.

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