

DATA-DRIVEN 21700 LITHIUM-ION CELL SORTING AND FAIR COMPARISON OF UAV BATTERY PACK CONFIGURATIONS

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This paper presents a reproducible data-driven framework for selecting 21700-format lithium-ion cells and interpreting UAV battery-pack configurations. The study uses 289,132 sorting-machine measurement records, of which 288,076 OK records were retained after filtering, and six charge-discharge XLSX files with two different voltage windows. The main scientific question is how large-scale internal-resistance and capacity-screening data can be converted into pack-selection criteria without confusing voltage level with total cell count and stored energy. The results show that internal-resistance screening is useful for cell grouping, but the apparent advantage of 8S and 12S configurations must be separated from the effect of additional cells, higher pack energy, and mission-level mass. A simplified pack-level model and stochastic grouping layer are used to compare same-parallel-count and same-total-cell-count cases. The extended 4.50/1.70 V voltage-window tests are treated as boundary or destructive-validation data and not as a recommended reusable UAV operating regime.

Keywords: 12S3P, 21700 cells, 6S3P, 8S3P, battery-pack modelling, cell matching, cell sorting, internal resistance, lithium-ion battery, UAV.

1. INTRODUCTION

In UAV propulsion systems, the battery pack simultaneously acts as an energy source, a load-bearing mass component, a thermal subsystem and a safety-critical element. Modern drones intended for longer endurance and higher payloads increasingly employ higher-voltage configurations because, at a constant mechanical power, a higher system voltage reduces current, thereby decreasing conductor, connector, and MOSFET losses. However, this transition also increases the requirements imposed on battery management systems, insulation, cell balancing, and manufacturing repeatability [1]–[3].

The relevance of this topic is also supported by publicly available market data. The Business Research Company 2026 report states that the drone lithium battery market reached USD 6.44 billion in 2025, is forecast to reach USD 7.44 billion in 2026 and is expected to reach USD 13.28 billion by 2030 [4]. The report links this growth to the expansion of commercial UAV applications, longer flight-time requirements, higher battery energy density, and the use of customised battery packs. These data do not constitute direct evidence of the superiority of any particular cell or configuration; nevertheless, they justify the practical relevance of the study: the UAV battery pack is becoming a technologically significant subsystem whose performance must be evaluated experimentally rather than solely from manufacturer datasheets.

In this context, the transition from 4S/6S packs to 8S and 12S architectures must be evaluated cautiously. A higher voltage reduces the external pack current for a given power level and can reduce losses in cables, connectors, and the electronic speed controller. However, when the number of cells in the pack also changes, the comparison no

longer isolates a voltage-level effect. For this reason, this paper distinguishes between same-parallel-count comparisons, same-total-cell-count comparisons, and mission-level comparisons that include stored energy and mass.

High-power cylindrical cells in the 21700 formats are attractive for UAV applications because they combine relatively high energy density with good pulse-current capability. At the same time, manufacturing tolerances, storage history and differences in internal resistance can cause uneven current distribution in parallel branches. This is particularly important in 3P and 4P groups, where a cell with lower internal resistance may temporarily carry a higher load, heat up more rapidly and age faster [5]–[7].

Chapter 17A of the fifth edition of Linden emphasises that lithium-ion cells operate as an intercalation system: lithium ions cyclically move between the positive and negative electrodes, while practical performance is determined by electrode chemistry, separators, electrolyte, current collectors and cell construction [1]. Consequently, the 21700 cells in this study should not be evaluated only according to nominal capacity; their suitability for UAV pack manufacture must also be related to power capability, internal resistance, thermal behaviour and the requirements of protection electronics.

The practical context of this study is a universal battery-pack technology for UAV platforms developed by SIA DK UNITY and its partners. The project reports analysed 6S3P, 8S3P, 6S4P and 12S3P configurations, but the present paper treats these results as a basis for a reproducible selection workflow rather than as a direct proof that one voltage level is universally superior. The workflow used in this study is shown in Fig. 1.

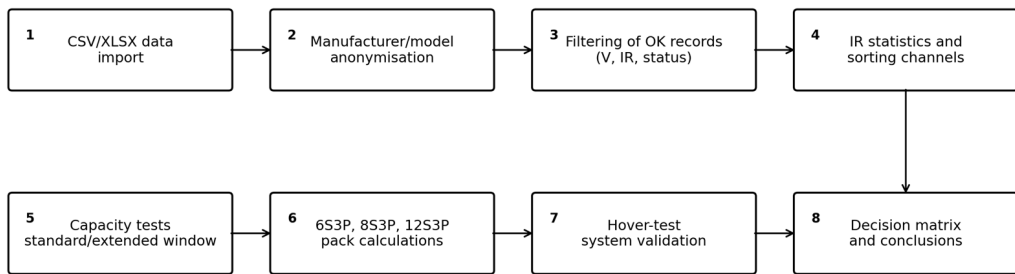


Fig. 1. Research data-processing and validation logic.

2. METHODOLOGY

In the scientific literature on lithium-ion battery systems, three related quality directions are most frequently emphasised: electrodynamic cell modelling, identification of ageing mechanisms and state estimation (SOC/SOH). The works of Plett [2], [3] and equivalent-circuit models [8] show that even a simple R0-RC model becomes useful only when the input data have been obtained under controlled conditions. Therefore, in cell selection, not only the measured value but also the measurement regime, temperature, device and data-quality status must be recorded.

For battery safety and performance testing, comparability with approaches such as IEC 62660-1, IEC 62619 and ISO 12405 is essential [9]–[11]. Although these standards primarily apply to electric-vehicle or industrial batteries, their principles are directly transferable to the development of UAV battery packs: voltage limits, discharge-current profiles, temperature conditions, and test-termination criteria must be defined. In this paper, the standards are used as a methodological framework rather than as a formal certification claim.

Chapter 17A of the handbook complements this standards-based perspective with

a cell-level physical basis. In commercial Li-ion cells, positive electrodes may consist of LCO, NMC/NCA, LMO or LFP materials, while the negative electrode is most commonly graphite or a graphite-silicon composite [1]. These chemistries differ in energy density, power capability, thermal stability and cycle life; therefore, the practical sorting by IR and capacity used in this study should be regarded as a manufacturing-quality filter rather than as a complete electrochemical characterisation of the cell chemistry.

The required integration of the work by Malnaca et al. on the decision-making process for selecting diesel-bus conversion technology [12] is used in this publication as an analogy for structuring technological choice. As in vehicle conversion, selecting a UAV battery pack is not the optimisation of a single property. Energy density, power reserve, safety, cost, manufacturing complexity, serviceability and compatibility with platform aerodynamics must all be compared. Accordingly, the 6S3P, 8S3P, 6S4P and 12S3P configurations in this study are evaluated as multi-criteria alternatives.

The system-reliability perspective is further supported by the work of Zemite

et al. on the use of the A-star algorithm for reliability analysis of power distribution networks [13]. Although that study concerns electrical distribution networks, its methodological relevance to this paper lies in the topological view of an energy-supply system: failure, restoration sequence, alternative supply paths, and user costs must be assessed together with the technical param-

eters of individual elements. In the case of a UAV battery pack, this means that cell internal resistance and capacity are not the only selection criteria; the homogeneity of parallel groups, the topology of busbars and welds, BMS limits, failure consequences and possible safe-mode degradation of the system must also be considered.

3. MATERIALS AND DATA SOURCES

Three groups of sources were used in the analysis. The first group consists of project reports on battery-pack design, manufacture and laboratory validation. These describe welding of 6S3P and 8S3P prototypes, busbar materials, soldering of balancing wires, housing manufacture and platform compatibility. The second group is a cell-sorting CSV file with measurement rows containing timestamp, voltage, internal resistance, channel, and test status. The third group consists of six XLSX files with charge-discharge experiments.

Cell manufacturers and model names are not identified in the publication. The test-group metadata field in the CSV file makes it possible to distinguish four commercial 21700 cell groups, but the available project data do not provide a complete cell-to-pack-to-hover-test traceability chain. Therefore, the unit of analysis is a sorting-machine measurement record, not necessarily a full lifetime record of a unique physi-

cal cell.

An ACEY ACEY-AS11S automatic cell sorting machine was used for preliminary selection and grouping of the 21700 cylindrical cells. The equipment provided initial classification according to measured electrical parameters before deeper capacity testing and pack assembly. The absolute internal-resistance values are therefore interpreted as screening measurements under the sorting-machine procedure rather than as temperature- and frequency-independent electrochemical constants.

The CSV file contained 289,132 measurement records in total, of which 288,076 were classified as OK and 1,056 as NG. During data cleaning, OK records were retained when the voltage was within the 2.5–4.5 V range, and the internal resistance was between 1 and 25 m Ω . Table 1 summarises the basic dataset statistics, while Table 2 clarifies the meaning of the fields used in the analysis.

Table 1. Summary of CSV Cell-Sorting Data Quality and Statistics

Indicator	Value	Interpretation
CSV records	289,132	complete cell-sorting file
Filtered OK records	288,076	dataset used for the analysis
IR mean/median	11.54 / 11.81 m Ω	basic matching indicators
IR 5th-95th percentile interval	10.91-13.03 m Ω	central 90 % measurement band for practical grouping
Mean voltage	3.473 V	storage/state-of-charge indicator

Table 2. Data-Field Interpretation and Limitations of the Sorting-Machine Dataset

Field or item	Meaning in this study	Use and limitation
Record	one sorting-machine measurement entry	used for statistics; not claimed as unique lifetime cell ID
Voltage	measured cell voltage during sorting	used as storage/SOC-related screening indicator
Internal resistance	sorting-machine IR measurement, mΩ	used for relative grouping; method temperature/frequency details not fully documented
Channel/bin	sorting output category or group	used to assess distribution; thresholds are equipment/project specific
Status	OK/NG classification	OK records form the statistical dataset
Traceability	cell-to-pack-to-hover link	not complete; reported as a limitation

The capacity measurements fall into two groups across the six files. The first group uses a maximum voltage of 4.20 V and a minimum voltage of approximately 2.51 V, which is comparable with a typical nominal-capacity test. The second group contains an extended voltage window of approximately 4.50/1.70 V. Therefore, the

absolute Ah values cannot be interpreted as equivalent cell-quality indicators unless the test regime is stated explicitly. This distinction is essential for scientific publication because the extended voltage window can yield approximately 10 % higher measured capacity and energy, but at the cost of increased degradation and safety risk.

4. CALCULATIONS AND FAIR-COMPARISON FRAMEWORK

The methodology combines statistical data cleaning with engineering pack modelling. First, the measurement fields are checked and records with an unsuitable status or unrealistic voltage are removed. Then the IR distribution, percentiles and channel proportions are calculated. In the third step, the capacity-test results are separated according to their voltage window. Finally, the pack configurations are compared using simplified electrical equations. This sequence provides a reproducible link between raw data, cell selection and pack-level interpretation.

A consistent load regime is essential for interpreting capacity and discharge tests. In Linden, C-rate is described as a relative

charge or discharge rate that enables cells of different capacities to be compared, while the discharge regime and voltage limits strongly influence the resulting Ah and Wh values [1]. Therefore, the six capacity files are not treated as a single homogeneous dataset; instead, they are first classified according to the voltage window and only then used for engineering interpretation.

The basic parameters of a battery pack are calculated from the number of cells in series, the number of cells in parallel, the nominal cell voltage and the nominal cell capacity. This simplified approach does not resolve all dynamic effects, but it enables configurations to be compared before a detailed electrical model is developed.

$$V_{pack} = N_s V_{cell}, \quad C_{pack} = N_p C_{cell}, \quad E_{pack} \approx N_s N_p V_{cell} C_{cell}. \quad (1)$$

Equation (1) defines the nominal pack voltage, the usable capacity and the approximate nominal energy. Here, N_s is the number of series stages, N_p is the number of parallel cells in each stage, V_{cell} is the nominal voltage of one cell and Q_{cell} is the nominal

capacity of one cell. The energy calculation is an approximation, because the real cell voltage changes during discharge; nevertheless, it is suitable for comparing configurations.

$$I_{pack} = \frac{P_{load}}{V_{pack}}, \quad I_{cell} = \frac{I_{pack}}{N_p}, \quad \Delta V_{cell} = I_{cell} R_{cell}, \quad P_{loss,pack} = N_s N_p I_{cell}^2 R_{cell}. \quad (2)$$

Equation (2) relates load power to pack current, single-cell current, voltage drop and the calculated internal-resistance losses. Here, R_{cell} is the internal resistance of one cell. This equation shows why a

higher voltage level is important in UAV propulsion: for the same useful power, the pack current is lower and resistive losses decrease.

$$SOC(t) = SOC(0) - \frac{1}{C_n} \int I(t) dt, \quad SOH_Q = \frac{Q_{meas}}{Q_{nom}} \cdot 100\%. \quad (3)$$

Equation (3) describes the charge-balance approach to SOC estimation and a capacity-based SOH indicator. $SOC(t)$ is the state of charge at time t , SOC_0 is the initial state of charge, Q_n is the nominal capacity, $I(t)$ is the discharge or charge current at

time t , Q_{meas} is the measured capacity and Q_{nom} is the nominal capacity. In this paper, this equation is used conceptually to show why the Ah value and the voltage window must be reported together.

$$z_i = \frac{R_i - \mu_R}{\sigma_R}, \quad CV_R = \frac{\sigma_R}{\mu_R} \cdot 100\%. \quad (4)$$

Equation (4) defines two statistical indicators used to evaluate the dispersion of internal resistance within the screened cell dataset. The parameter R_i denotes the internal-resistance screening value of the i -th record, μ_R is the mean value of the filtered dataset and σ_R is the corresponding standard deviation. These indicators are used for relative grouping and mismatch assessment. Because the available project files do not document the full measurement frequency, rest time, temperature and SOC history for

every record, the IR values are not treated as absolute electrochemical constants.

The pack-comparison framework separates two questions that are often mixed in UAV battery discussions. First, increasing the number of series stages at the same number of parallel cells changes both voltage and total cell count. Second, comparing configurations with the same total number of cells tests whether the benefit comes from voltage level or from using more electrochemical material.

5. RESULTS

5.1. Cell Internal Resistance and Sorting Channels

In the filtered dataset, the minimum IR was 3.28 m Ω , the maximum was 16.04 m Ω , and the standard deviation was 1.59 m Ω . The distribution is not perfectly symmetrical because the channels correspond to sorting logic rather than to a random laboratory sample. Nevertheless, the dominant range of 10.9–13.0 m Ω is sufficiently narrow to be used for practical grouping.

The channel distribution shows that most cells fall into channels 4 and 7. This may indicate a relatively homogeneous

production batch, while also showing that the channel thresholds must remain documented. If the thresholds change between test days, the channel number itself loses comparability. Therefore, the main analysis in the publication is based on the continuous IR value, while the channel is used as an operational sorting indicator. Figure 4 shows the distribution of internal resistance for the filtered OK records, while Fig. 5 shows the count structure of the sorting channels.

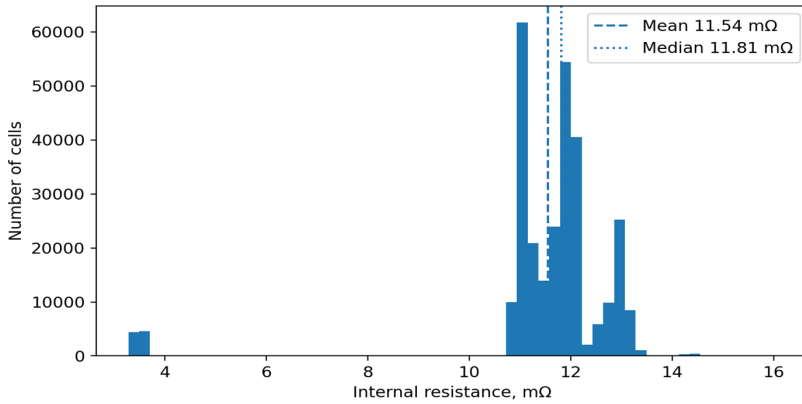


Fig. 2. Distribution of internal resistance for the filtered OK cells.

The voltage and IR dispersion does not show a simple linear relationship that would be sufficient for cell qualification based on voltage alone. This is important because storage voltage is often used as a rapid initial indicator; however, it is insufficient for high-power UAV packs. Cell selection should include at least three parameters: voltage, internal resistance and capacity under a uniform test regime. This relationship is visualised in Fig. 6, where voltage is compared with internal resistance in a

sample of records.

This observation is consistent with Linden’s explanation that cell impedance is not a single invariant constant. It changes with discharge or charge duration, current, SOC, temperature and measurement frequency or method [1]. Consequently, the IR value used in this paper is a practical sorting and pack-assembly parameter, but it is not sufficient on its own to predict the complete dynamic voltage drop under a real flight-load profile.

The boxplot analysis by channel shows that some channels have very narrow IR dispersion, whereas channel 2 shows greater dispersion. Such differences should be used in practice as a signal for additional inspection. If a channel contains a small number of cells or a large dispersion, it

should not be mechanically mixed with the dominant groups during pack assembly. In Fig. 3, this dispersion is shown for the main sorting channels; it should be interpreted as channel-level quality control rather than as a manufacturer comparison.

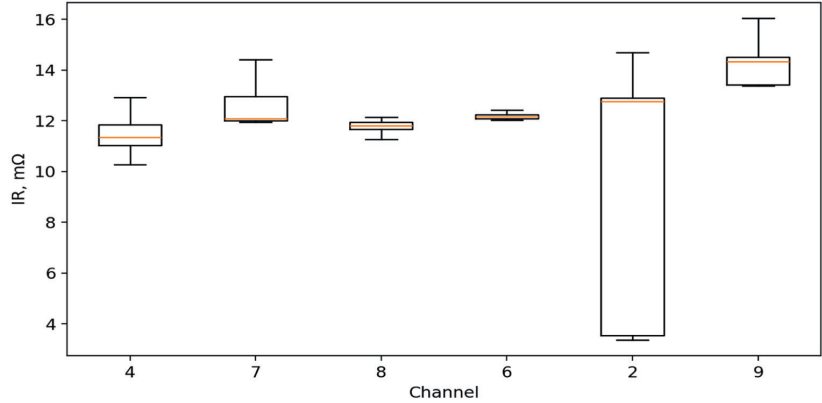


Fig. 3. IR dispersion in the main sorting channels.

5.2. Comparison of Capacity Tests

The most important observation in the capacity tests is the effect of two voltage windows. The first three files, with an upper limit of approximately 4.20 V and a lower limit of approximately 2.51 V, represent a standard operating window. The last three files, with an upper limit of approximately 4.50 V and a lower limit of approximately 1.70 V, represent an extended-window boundary or destructive-validation regime. This regime is useful for understanding the additional energy that may be released

under mission-specific conditions, but it is not proposed as a reusable UAV operating mode.

From a publication perspective, this is an important methodological point. Different voltage windows, currents, C-rates and temperatures must not be mixed as directly comparable capacity results. In this paper, the extended-window data are used only to indicate boundary energy potential, while the standard-window results remain the basis for reusable-pack interpretation.

Table 3. Summary of the Six Capacity Tests and Interpretation of the Voltage Window

File	Discharge Ah	Min. V	Max. V	Regime
Data84239.xlsx	5.0044	2.5095	4.2005	standard 4.2/2.5 V window
Data84406.xlsx	5.0271	2.5095	4.2005	standard 4.2/2.5 V window
Data84507.xlsx	5.0032	2.5094	4.2007	standard 4.2/2.5 V window
Data84539.xlsx	5.5026	1.6980	4.5004	extended window
Data84557.xlsx	5.5003	1.6982	4.5003	extended window
Data84616.xlsx	5.5188	1.6977	4.5003	extended window

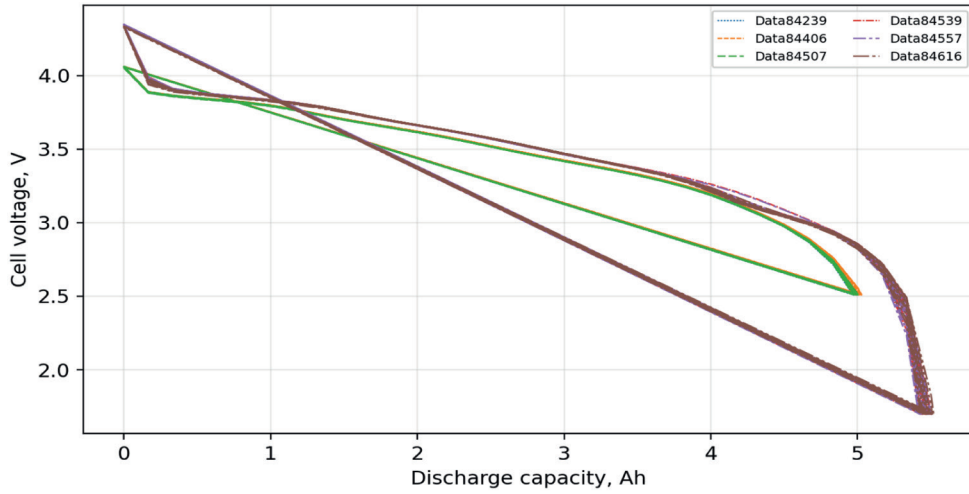


Fig. 4. Comparison of discharge curves from capacity tests using different line styles.

5.3. Fair Interpretation of Pack Configurations

When selecting a configuration for a UAV platform, pack voltage affects the external current and therefore the losses in wiring, connectors, protection devices and ESC input stages. However, the cell-inter-

nal loss comparison must also consider total cell count. Table 4 separates same-parallel-count comparisons from same-total-cell-count checks.

Table 4. Fair Configuration Comparison at a 1.2 kW Load and Mean Cell IR

Basis	Config.	Cells	Vnom, V	Estd, Wh	11.2kW, A	PIR, W
same N _p =3	6S3P	18	21.6	324.7	55.6	71.3
same N _p =3	8S3P	24	28.8	433.0	41.7	53.4
same N _p =3	12S3P	36	43.2	649.5	27.8	35.6
same cell count	6S4P	24	21.6	433.0	55.6	53.4
same cell count	6S6P	36	21.6	649.5	55.6	35.6

The 6S3P, 8S3P and 12S3P comparison shows what happens when N_s increases while N_p remains equal to three; in that case the total number of cells and stored energy also increase. The 6S4P versus 8S3P and 6S6P versus 12S3P checks show that, for identical cells and the same total cell count, the calculated cell-internal I²R loss is not automatically reduced by voltage level alone.

The practical advantage of a higher-

voltage pack is therefore mainly system-level: lower external current, lower cable and connector stress, and better compatibility with higher-power ESC and propulsion systems. The trade-off is increased series-cell monitoring, BMS complexity, insulation requirements and stricter safety procedures. The fully charged voltage of a 12S lithium-ion pack reaches 50.4 V, which also affects ESC component selection and protection strategy.

The battery-pack design chapter particularly emphasises that the safety of series/parallel packs is determined not only by cell type, but also by connections, enclosure, cooling, protection electronics and cell balancing [1]. Temperature gradients can promote cell imbalance, while balancing in

series packs increases usable capacity and extends cycle life. Therefore, the selection of a 12S3P configuration must be related to BMS measurement accuracy, voltage monitoring of each series group and a thermal-validation protocol.

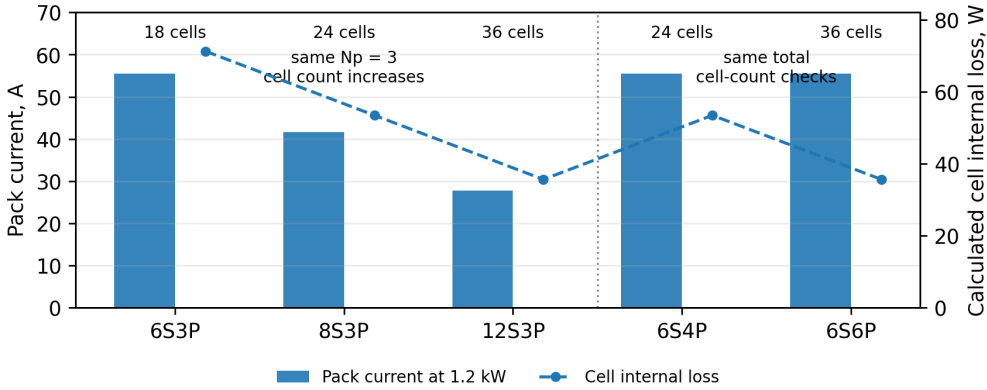


Fig. 5. Current and cell internal losses under same-parallel-count and same-total-cell-count assumptions.

The fair-comparison result follows directly from the pack equations. If all cells are assumed identical, the pack resistance is $R_{\text{pack}} = N_s R_{\text{cell}} / N_p$ and the pack current is $I_{\text{pack}} = P_{\text{load}} / (N_s V_{\text{cell}})$. Because the total number of cells is $N_{\text{tot}} = N_s N_p$, the calculated cell-internal loss becomes proportional to $P_{\text{load}}^2 R_{\text{cell}} / (N_{\text{tot}} V_{\text{cell}}^2)$. Under these assumptions it is independent of the chosen series count when the total number of cells is fixed. This identity explains why the 6S4P and 8S3P cases have the same calculated cell-internal loss, and why 6S6P gives the same cell-internal loss as 12S3P in Table 4.

This does not mean that voltage level

is irrelevant. It means that the benefit of a higher-voltage architecture must be assigned to the correct part of the system. Higher voltage lowers the external DC-bus current and can reduce losses in harnesses, connectors, fuses, switches and ESC input stages. It can also improve compatibility with high-power propulsion electronics. Conversely, higher series counts increase the number of monitored cell groups, balancing channels, insulation requirements and fault-propagation paths. Therefore, the proposed selection workflow treats voltage level, total cell count and mission energy as separate decision variables rather than combining them into a single ranking.

5.4. Data-Driven Pack-Level Computational Model

The battery-pack assessment was implemented as a simplified data-driven engineering model. The deterministic layer

calculates pack voltage, current, resistance and cell-internal losses, while the stochastic layer evaluates how random or matched

IR grouping can influence current sharing inside parallel groups. This change is important because the main practical value of a large sorting dataset is not only to estimate average pack resistance, but also to avoid unfavourable cell mismatch inside 3P groups.

The model does not aim to reproduce electrochemical ageing, thermal gradients,

welding resistance, busbar losses, BMS cut-off behaviour or complete UAV aerodynamics. Instead, it converts the measured screening parameters into pack-level indicators relevant for engineering selection: current, calculated I²R loss, idealised electrical-energy-based hover time and mismatch sensitivity. Its structure is shown in Fig. 7.

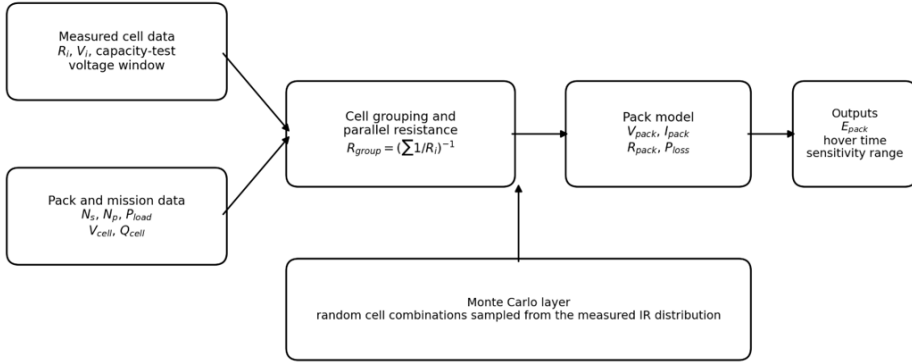


Fig. 7. Structure of the simplified data-driven pack-level computational model used to convert cell-level measurements into pack-level performance indicators.

The calculation logic of the implemented model is summarised in Table 6. The model first calculates the equivalent resistance of each parallel group, then sums

the series groups into pack resistance and calculates losses. The Monte Carlo layer compares random grouping with an idealised IR-matched grouping assumption.

Table 6. Calculation Logic of the Simplified Data-Driven Pack-Level Computational Model

Model step	Calculation or operation	Output used in the article
Cell input	R _i , V _i , capacity-test regime and voltage window.	cleaned dataset
3P group	R _{group} =(Σ1/R _i) ⁻¹ ; current sharing between cells.	group resistance; worst-cell current
Pack model	V _{pack} =N _s V _{cell} ; I=P _{load} /V _{pack} ; R _{pack} =ΣR _{group} .	pack voltage, current and resistance
Loss/energy	P _{loss} =I ² R _{pack} ; usable energy from selected voltage window.	losses and idealised hover-time estimate
Monte Carlo	random versus IR-matched 3P grouping from measured IR distribution.	mismatch sensitivity and current imbalance

In the example implementation, V_{cell} = 3.6 V, Q_{cell} = 5.0 Ah, P_{load} = 1.2 kW and the measured internal-resistance statistics were μ_R = 11.54 mΩ and σ_R = 1.59 mΩ. Monte Carlo sampling was used as a

sensitivity tool. It does not claim to predict complete flight time, because capacity spread, pack mass, propeller efficiency, ESC efficiency, cell temperature, welding resistance and ageing were not included.

Table 7. Monte Carlo Grouping Sensitivity and Idealised Energy-Based Model Output

Metric	Result	Interpretation
Random 3P grouping from IR distribution	maximum cell-current deviation: mean $\approx 12\%$, P95 $\approx 27\%$; max/min current ratio: mean ≈ 1.28 , P95 ≈ 1.60	random grouping can overload the lowest-IR cell and increase worst-cell heating
Idealised IR-matched grouping	cell-current deviation $\approx 0\%$ and max/min ratio ≈ 1.00 in the ideal sorted case	illustrates the value of matched grouping when traceability is available
Hover-time output	reported only as an idealised electrical-energy estimate	not a complete flight prediction; mass, efficiency, temperature and cut-off must be validated experimentally

The model output should therefore be interpreted as an electrical screening result. The same-total-cell-count cases show that the calculated cell-internal loss can be similar even when pack voltage differs. The strongest benefit of higher voltage is expected in the external power path, while the strongest benefit of sorting is reduced parallel-group

mismatch and lower worst-cell stress.

The same framework can evaluate extended-window energy by replacing the standard-window energy with experimentally measured boundary-test energy. Such calculations should be labelled as idealised electrical-energy-based estimates and not as reusable UAV operating recommendations.

6. DISCUSSION AND LIMITATIONS

In addition to laboratory discharge and capacity measurements, the project reports contain UAV hover-test data. These data are applicable in the publication as system-level validation rather than as a primary electrochemical comparison of cells, because flight results are influenced by propeller efficiency,

air turbulence, control algorithms, ESC thermal behaviour and mass distribution. Nevertheless, the 10-inch UAV tests with a 3 kg payload show well that the laboratory profile and a real hover regime produce comparable operating times. Table 5 summarises the applicability of these data to the publication argumentation.

Table 5. Applicability of UAV Hover-Test Data to Battery-Pack Validation

Test	Theoretical time	Laboratory profile	Hover test	Interpretation in the publication
10 in UAV, 3 kg, 6S3P	15 min 30 s	15 min 30 s	14 min 22 s	Real time 7.3 % lower; after flight $T \approx 93^\circ\text{C}$, compared to 110°C under laboratory load.
10 in UAV, 3 kg, 8S3P	21 min 00 s	20 min 38 s	18 min 18 s	Real time 11 % lower; approximately +28 % hover time relative to 6S3P at lower current.
10 in UAV, 12S3P with 12S ESC	not directly compared	not directly compared	21 min 45 s	Indicative system-level result; suitable as justification of the potential of the 12S architecture, not as a direct cell comparison.

The practical context of the hover-mode validation experiments is illustrated in Fig. 6, which shows the UAV platform with the tested battery pack. This platform was used for system-level comparison between dif-

ferent pack configurations and served as additional experimental evidence for the practical significance of the laboratory conclusions.



Fig. 6. UAV platform used for hover-mode validation with the tested lithium-ion battery pack.

These hover results are not used to calculate new cell parameters. They support the practical relevance of the pack-selection methodology, but they do not constitute a controlled comparative validation of all pack configurations. The results are affected by UAV mass, propeller and motor selection, ambient conditions, airflow, cut-off threshold and the absence of identical repeated tests for every configuration.

The results confirm that the manufacturing dataset is sufficiently large to identify the structure of the cell distribution and to establish practical sorting criteria. At the same time, the dataset is not complete from the perspective of academic reproducibility because the CSV file does not contain separate fields for measurement temperature and cell cycling history. The test equipment had been purchased new before the study and was supplied with manufacturer certification.

A second limitation is the heterogeneity of the capacity tests. The extended-voltage-window tests deliberately examine operation outside the normal reusable-cell window. They may be relevant for boundary or single-mission assessment, but should not be interpreted as a recommendation for routine UAV pack operation because safety margin, cycle life, gas generation and thermal behaviour may be compromised.

A third limitation is that the thermal behaviour of the packs is evaluated in this paper at the level of calculations and project reports. To fully validate the 8S3P and 12S3P solutions, thermocouple or thermal-camera data for each parallel group, synchronisation of the load profile with ESC telemetry and repeated post-test measurement of cell IR are required. Such an approach would make it possible to separate the effects of welding, cell properties and cooling.

For practical selection, the most robust decision path is to combine three levels of evidence: cell-level IR and voltage sorting, standard-window capacity testing, and system-level UAV validation. A high-voltage

configuration should be selected only when the gain in external-current reduction and mission energy outweighs the additional cell count, pack mass, BMS complexity and safety requirements.

10. CONCLUSIONS

The large filtered dataset of 288,076 OK measurement records supports reproducible cell screening according to internal resistance and voltage. Still, the records should be interpreted as sorting-machine measurements rather than fully traceable lifetime histories of unique cells.

The mean internal-resistance screening value of 11.54 m Ω and the 5th-95th percentile interval of 10.91–13.03 m Ω indicate a practically useful level of batch homogeneity for grouping, while still requiring matching rules to reduce current imbalance inside 3P groups.

The comparison of 6S, 8S and 12S configurations must distinguish between same-parallel-count, same-total-cell-count and mission-level cases. Higher voltage reduces

external pack current, but lower cell-internal loss may also result from using more cells and greater stored energy.

The standard 4.20/2.50 V capacity tests and the extended 4.50/1.70 V boundary tests are not directly interchangeable. The extended window can indicate additional mission-specific energy potential, but it is not recommended here as a reusable UAV operating regime.

The simplified data-driven model is most useful as a selection and mismatch-screening tool. It links sorting data with pack resistance, idealised energy-based hover estimates and parallel-cell current sharing, while leaving thermal, ageing, welding and full UAV aerodynamic validation for a dedicated qualification protocol.

ACKNOWLEDGEMENTS

SIA DK UNITY is participating in research project No. 5.1.1.2.i.0/2/24/A/CFLA/004, entitled “Development of Efficient, Sustainable, and Universal Battery

Packs for Unmanned Aerial Vehicles”, implemented within SIA VMKC’s project “Support Instrument for Research and Internationalization”.

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