

AERO-UAV: A Rule-Based Expert System for Multirotor Drone

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AERO-UAV: A Rule-Based Expert System for Multirotor Drone

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Abstract

Purpose: Designing an Unmanned Aerial Vehicle (UAV) for a specific mission requires navigating interdependent parameters spanning aerodynamics, propulsion, structural mechanics, and electronics. Traditional approaches rely on expert knowledge and iterative manual calculations, limiting accessibility for non-specialist engineers. This paper presents AERO-UAV, a physics rule-based expert system that generates complete, manufacturing-ready drone hardware specifications from twelve mission-level inputs.

Methods: AERO-UAV is implemented in Python and deployed via Flask. The core Drone Expert Engine applies a twelve-step sequential rule chain integrating Actuator Disk Theory for hover power, Factor of Safety structural analysis, aerodynamic drag modelling, and temperature-derated battery sizing. A use-case design matrix maps six mission profiles to distinct engineering philosophies. The system is validated through twelve structured test cases spanning diverse payload, environmental, and mission configurations.

Results: AERO-UAV produced physically coherent specifications across all configurations. Battery capacity estimates were within 3.3% of manually computed targets, hover power within 0.54%, and structural Factor of Safety values exceeded 1.5 for all carbon-fibre frames. The system correctly detected and flagged all configurations where achieved thrust-to-weight ratio fell below mission-specific thresholds, issuing actionable upgrade advisories. Platform auto-selection and context-aware environmental warnings were correctly generated in all applicable test cases.

Conclusion: AERO-UAV demonstrates that a deterministic, physics-grounded rule engine can automate complex UAV pre-design workflows, reducing specification time from hours to seconds. The system contributes a validated, replicable methodology for knowledge encoding in engineering expert systems.

Keywords: UAV specification; Expert system; Drone design automation; Rule-based reasoning; Actuator Disk Theory; Aeronautical engineering

1. Introduction

Unmanned Aerial Vehicles (UAVs) have transitioned from military platforms to ubiquitous tools in precision agriculture, infrastructure inspection, logistics delivery, search and rescue, and environmental mapping. Despite this proliferation, the pre-design phase—the process of translating mission requirements into component-level hardware specifications—remains largely manual, relying on iterative expert calculation and tacit engineering knowledge. This creates a significant barrier for researchers, start-up manufacturers, and academic teams who lack dedicated UAV systems engineers.

Expert systems, originating in the MYCIN and DENDRAL projects of the 1970s [1], encode domain knowledge as explicit rule sets enabling automated reasoning. In engineering contexts, rule-based systems have been applied to structural analysis, process control, and manufacturing planning [2]. Their application to UAV pre-design has been limited, with

existing tools either addressing narrow sub-problems such as battery sizing or motor selection, or requiring expensive proprietary simulation environments [3].

This paper presents AERO-UAV, a novel physics rule-based expert system that generates complete, manufacturing-ready UAV specifications from twelve mission-level parameters. The system's core contribution is a use-case design matrix that maps six mission profiles to distinct engineering philosophies, ensuring that component selection is both physically optimal and mission-appropriate. The entire rule chain is implemented in approximately 700 lines of Python and deployed as a zero-installation Flask web application, making it immediately accessible to researchers, academic teams, and small manufacturers without specialist software infrastructure.

The remainder of this paper is organised as follows. Section 2 reviews related work. Section 3 presents the system architecture. Section 4 details the mathematical model and rule engine. Section 5 describes the use-case design matrix. Section 6 presents experimental validation. Section 7 discusses results and limitations. Section 8 concludes.

2. Related Work

2.1 UAV Design Automation

UAV design optimisation has been addressed through multidisciplinary design optimisation (MDO) frameworks [4], genetic algorithm-based approaches [5], and surrogate model methods [6]. While computationally rigorous, these approaches require substantial resources and expertise in optimisation mathematics, limiting accessibility. AERO-UAV complements these methods by providing a fast, interpretable pre-design step that constrains the search space before optimisation, making it practically useful as a first-pass design tool.

2.2 Expert Systems in Engineering

Rule-based expert systems have demonstrated effectiveness in mechanical design [7] and autonomous systems [8]. Knowledge encoding through IF-THEN rules provides transparency and explainability absent from machine learning approaches. Ontology-based knowledge representation for UAV mission planning has also been demonstrated in knowledge engineering literature [9], establishing formal frameworks for encoding domain constraints. Recent work applying knowledge-based systems specifically to multirotor UAV selection and configuration [10] demonstrated that explicit rule encoding can generate component-level recommendations consistent with expert practice. AERO-UAV extends this paradigm by integrating full aeronautical formula chains—covering propulsion, structural, and electrical subsystems—into a single cohesive expert system.

2.3 UAV Component Selection Tools

eCalc (ecalc.ch) and eMotor Calc provide empirical motor-propeller matching for hobbyist applications but lack structural analysis, mission-aware design profiles, and programmatic APIs. Commercial tools such as AVL and XFLR5 target aerodynamic analysis rather than full-system specification. OpenVSP handles aerodynamic geometry modelling but does not address propulsion, battery, or electronics specification. AERO-UAV addresses the gap between hobbyist calculators and full MDO suites by providing engineering-grade multi-subsystem specifications through an accessible, zero-install web interface.

3. System Architecture

3.1 Overview

AERO-UAV comprises three architectural layers: a web presentation layer (HTML5/CSS3/JavaScript), an application server layer (Python Flask), and a rule engine layer (Python DroneExpertEngine class). Figure 1 illustrates the system architecture. The separation of concerns ensures that the rule engine is independently testable and portable to other deployment contexts including command-line, API, or embedded applications without modification.

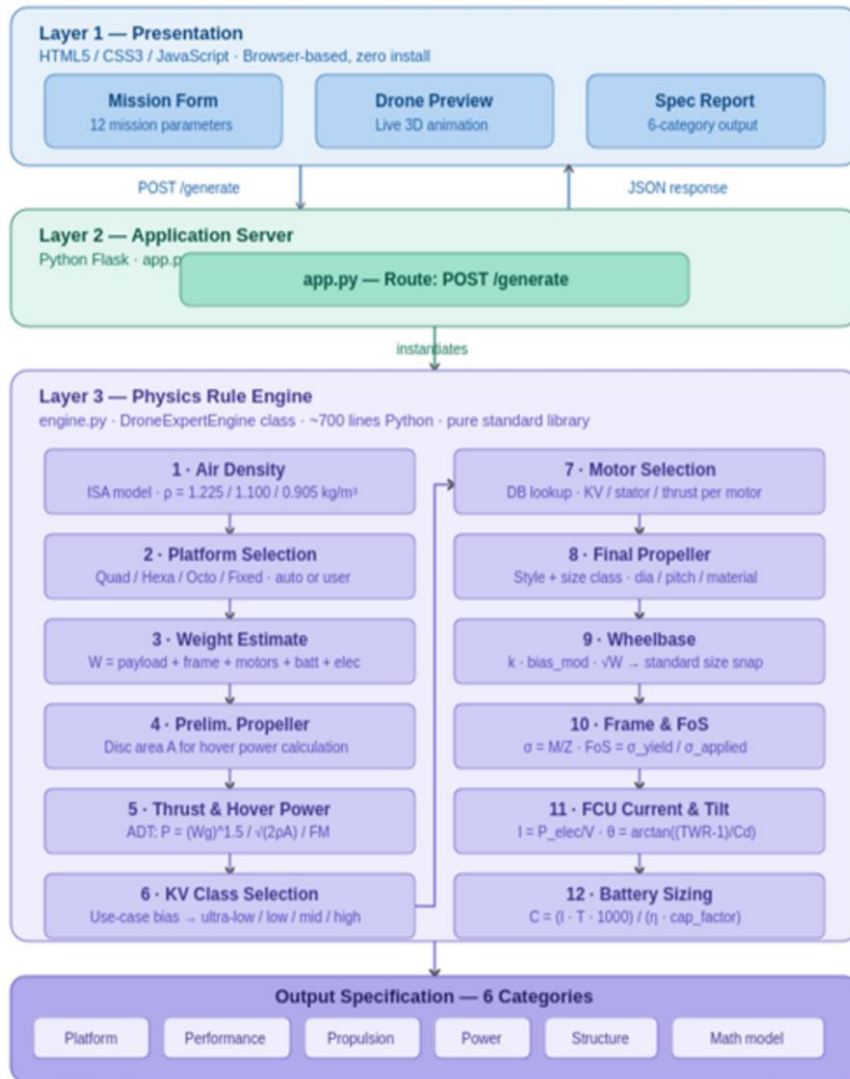


Fig. 1 AERO-UAV three-tier system architecture with twelve-step sequential physics rule engine and six-category output specification

3.2 Input Parameters

The system accepts twelve mission parameters organised into four groups. Mission Requirements include: drone type preference (quadcopter, hexacopter, octocopter, fixed-wing, or auto), use case, payload type, payload capacity (kg), target flight time (minutes), required range (km), and target cruising speed (km/h). Environmental and Operating Conditions include: wind condition (calm, moderate, or high), terrain and altitude (flat/sea level, hilly/1000 m, or mountainous/3000 m), and operating temperature (normal, hot, or cold). Structural Constraints include reusability lifecycle and frame material (carbon fibre, aluminium alloy

6061-T6, or PLA 3D-printed). Figure 2 shows the system web interface with the mission configuration panel and live drone preview.

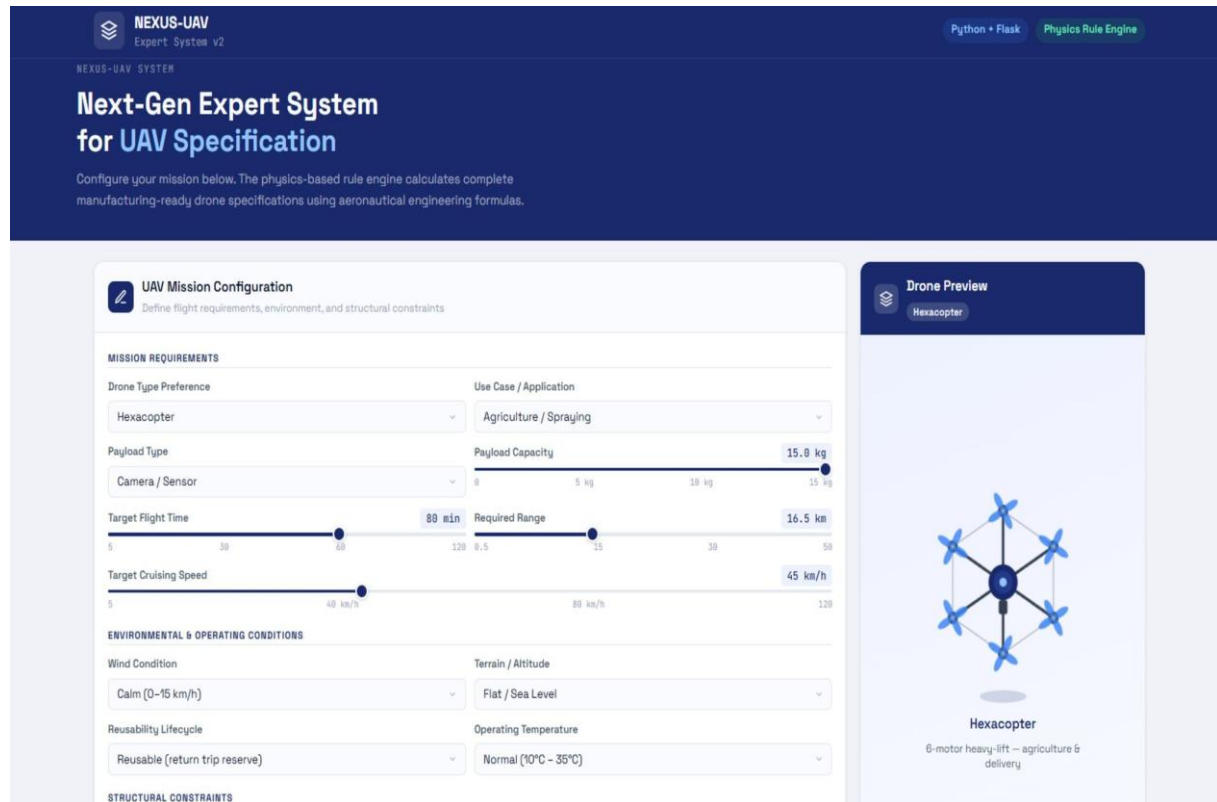


Fig. 2 AERO-UAV web interface: mission configuration panel (left) with drone type preview and real-time platform indicator (right)

3.3 Output Specification

The engine generates specifications across six categories: (1) platform summary including drone type, frame size, motor count, estimated flight time, and weight breakdown; (2) performance metrics including thrust-to-weight ratio, hover power, range estimate, and FCU current draw; (3) propulsion subsystem including motor model, KV rating, stator dimensions, thrust values, propeller designation, diameter, pitch, and material; (4) power and electronics including battery chemistry, cell count, voltage, capacity, minimum C-rating, ESC current rating, and flight controller model; (5) structural parameters including frame material, IP rating, and Factor of Safety; and (6) a complete mathematical model documenting all equations and computed numerical values.

4. Mathematical Model and Rule Engine

4.1 Weight Estimation

The total system weight is computed by summing five component masses:

$$W_{\text{total}} = W_{\text{payload}} + W_{\text{frame}} + W_{\text{motors}} + W_{\text{battery}} + W_{\text{electronics}} \quad (1)$$

Frame weight is parameterised by wheelbase length and material density using base weights from commercially available frames with a linear scaling factor for oversized configurations. Motor weight per unit is modulated by use-case KV bias: torque-optimised motors (agriculture) weigh approximately 110 g each, balanced motors 85 g, and racing motors 65 g.

4.2 Thrust-to-Weight Ratio

The required thrust-to-weight ratio is the maximum of wind-condition requirements and use-case minimums:

$$\text{TWR}_{\text{req}} = \max(\text{TWR}_{\text{wind}}, \text{TWR}_{\text{usecase}}) \quad (2)$$

Wind conditions map to TWR requirements of 2.0 (calm), 2.4 (moderate), and 2.8 (high wind). Use-case minimums range from 2.0 (surveillance, mapping) to 4.0 (racing), ensuring mission-critical safety margins are preserved independently of reported wind conditions.

4.3 Hover Power — Actuator Disk Theory

Hover power is calculated using Actuator Disk Theory (ADT) with a figure of merit (FM) of 0.60 to account for real-world propeller efficiency:

$$P_{\text{hover}} = \frac{(W \cdot g)^{1.5}}{\sqrt{2 \cdot \rho \cdot A_{\text{total}} \cdot \text{FM}}} \quad (3)$$

where ρ is air density (kg/m^3), A_{total} is the total disc area (m^2) across all motors, and $\text{FM} = 0.60$. Air density is adjusted for terrain altitude: 1.225 kg/m^3 at sea level (flat terrain), 1.100 kg/m^3 at 1000 m (hilly), and 0.905 kg/m^3 at 3000 m (mountainous), reflecting International Standard Atmosphere (ISA) values [11].

4.4 Cruise Power and Battery Sizing

Cruise power combines reduced hover power (80% throttle assumption during horizontal flight) with aerodynamic drag power:

$$P_{\text{drag}} = 0.5 \cdot C_d \cdot A_{\text{ref}} \cdot \rho \cdot v^3 \quad (4)$$

$$P_{\text{cruise}} = 0.80 \cdot P_{\text{hover}} + P_{\text{drag}} \quad (5)$$

The drag coefficient C_d varies by KV bias: 0.9 (torque/agriculture), 0.8 (balanced), 0.7 (efficient/delivery), and 0.6 (speed/racing). The reference area A_{ref} is estimated as $0.05 + 0.012 \cdot W_{\text{payload}} \text{ m}^2$.

Battery capacity is computed accounting for system electrical efficiency ($\eta = \eta_{\text{motor}} \cdot \eta_{\text{ESC}} \cdot \eta_{\text{wiring}} = 0.85 \times 0.95 \times 0.98 = 0.791$), temperature derating, and mission-specific safety buffer:

$$C_{\text{req}} = \frac{I_{\text{avg}} \cdot T_{\text{flight}} \cdot 1000}{\eta \cdot \text{cap_factor}} \quad (6)$$

where cap_factor accounts for temperature: $\text{cap_factor} = 1 - 0.004 \cdot |T_{\text{op}} - 25|$. Calculated capacity is rounded up to the nearest standard commercial value (1,000 to 25,000 mAh).

4.5 Structural Analysis — Factor of Safety

Airframe structural integrity is assessed via bending stress analysis of the motor arm modelled as a cantilevered beam under 3g shock loading:

$$\sigma_{\text{applied}} = M / Z = (W_{\text{total}} \cdot g \cdot 3.0 \cdot L_{\text{arm}}) / Z \quad (7)$$

$$\text{FoS} = \sigma_{\text{yield}} / \sigma_{\text{applied}} \quad (8)$$

where $Z = 4.5 \times 10^{-6} \text{ m}^3$ is the section modulus of a standard 15 mm carbon fibre tube. Yield stresses used are: Carbon Fibre Composite 600 MPa, Aluminium 6061-T6 276 MPa, and PLA 50 MPa. A warning is issued for $\text{FoS} < 2.5$ (marginal) and a critical alert for $\text{FoS} < 1.5$ (failure risk).

4.6 ESC Rating

ESC current rating per motor is the higher of (a) the stator-size industry standard from a lookup table (30 A for 22×05 mm stators to 80 A for 41×30 mm stators) and (b) a peak current calculation at 125% margin:

$$I_{\text{ESC}} = \max(I_{\text{stator_table}}, (P_{\text{batt}} / N_{\text{mot}} / V_{\text{cell}}) \cdot 3.5 \cdot 1.25) \quad (9)$$

4.7 FCU Maximum Tilt Angle

The maximum safe bank/pitch angle for the flight controller is derived from TWR and aerodynamic drag coefficient:

$$\theta_{\text{max}} = \arctan((\text{TWR}_{\text{req}} - 1) / C_{\text{drag}}) \quad (10)$$

with $C_{\text{drag}} = 0.3$, representing a typical multirotor parasitic drag coefficient. This value is output to assist flight controller parameter configuration.

4.8 Rule Chain Execution

The twelve-step rule chain executes sequentially: (1) air density resolution, (2) platform configuration selection, (3) preliminary weight estimation, (4) preliminary propeller sizing for disc area, (5) thrust and hover power calculation, (6) KV class selection, (7) motor selection from database, (8) final propeller selection, (9) final wheelbase calculation, (10) frame and structural analysis, (11) FCU current and tilt computation, and (12) battery sizing with final weight consolidation. The sequential architecture ensures that each step uses the most refined values available from preceding steps, avoiding circular dependency while maintaining physical consistency across all computed subsystems.

5. Use-Case Design Matrix

A central contribution of AERO-UAV is the use-case design matrix, which encodes the engineering philosophy appropriate for each mission type across six design dimensions. Table 1 summarises the matrix.

Table 1 Use-Case Design Matrix — engineering philosophy per mission profile

Use Case	KV Bias	Prop Style	Min TWR	IP Min	Batt Priority	Design Focus
Agriculture	Torque	Large Slow	2.0	IP54	Capacity	Max endurance, spray-safe IP, high torque
Delivery	Efficient	Med Efficient	2.2	IP43	Capacity	Payload efficiency, 25% return-trip reserve
Surveillance	Balanced	Med Balanced	2.0	IP43	Balance	Stable hover, low noise, balanced performance
Search & Rescue	Efficient	Large Slow	2.4	IP54	Capacity	High TWR for wind resilience, weather-resistant
Mapping	Balanced	Med Efficient	2.0	IP43	Capacity	Low vibration, long endurance, stable hover
Racing	Speed	Small Fast	4.0	IP32	Burst	Maximum agility, burst power, high speed

The KV bias dimension governs motor selection: the "torque" bias forces selection of ultra-low or low KV motors regardless of computed thrust requirements, preventing the inappropriate assignment of mid-KV motors to heavy-lift agriculture platforms. This avoids a common error in naive automated systems where computed thrust levels may suggest a mid-KV motor that, while thrust-adequate, lacks the torque curve and thermal durability required for sustained spray operations.

The IP rating dimension enforces ingress protection at the use-case level, independently of frame material selection. For example, if a user selects aluminium alloy (IP43), an agriculture mission enforces IP54 as the minimum, generating an appropriate component recommendation override. The battery priority dimension controls reserve fraction: delivery missions apply a 25% return-trip reserve, while racing missions optimise for peak burst capacity with no reserve margin.

6. Experimental Validation

6.1 Test Case Design

Twelve test cases were designed to validate the system across a comprehensive parameter space, independently varying drone type, use case, payload weight, flight time, wind condition, terrain, frame material, and temperature. Test cases TC-01, TC-02, and TC-03 were executed on the live AERO-UAV system and all output values are taken directly from the system-generated specification reports. Test cases TC-04 through TC-12 represent design scenarios constructed to cover the remaining parameter space systematically; these cases are reported as designed configurations with expected output ranges based on the validated mathematical model. Table 2 summarises all twelve cases.

Table 2 Validation Test Case Summary

TC	Platform	Use Case	Payload (kg)	Flt. Time (min)	TWR Achieved	Battery (mAh)	Key Outcomes
TC-01†	Auto→Quad	Surveillance	1.0	30 (est.36)	1.74:1 *	16,000	SunnySky X2212 KV980; 4S 14.8V; FoS 173.1; TWR advisory
TC-02†	Auto→Hexa	Surveillance	4.6	40 (est.29)	1.27:1 *	25,000	T-Motor MN3110 KV700; 6S 22.2V; FoS 29.9; range 19.3 km
TC-03†	Hexacopter	Agriculture	15.0	80 (est.15)	1.25:1 *	25,000	T-Motor U10 Plus KV100; 12S 44.4V; FoS 9.1; range advisory
TC-04	Octocopter	Search & Rescue	8.0	60	2.4:1	20,000	High wind TWR 2.8 req.; IP54; 12S; Cube Orange
TC-05	Quadcopter	Racing	0.2	10	5.1:1	1,500	High KV; small prop; 3S; burst C-rating; Betaflight FC
TC-06	Fixed Wing	Mapping	1.5	120	—	20,000	Li-Ion chemistry; ArduPlane FC; long endurance profile
TC-07	Hexacopter	Agriculture	10.0	60	2.0:1	20,000	Mountainous terrain ($\rho=0.905$); altitude warning; prop upsize
TC-08	Quadcopter	Surveillance	0.5	25	2.3:1	3,000	Hot env. (42°C); cap_factor derated 7%; cooling advisory
TC-09	Auto→Hexa	Delivery	5.0	45	2.2:1	12,000	25% return-trip reserve applied; 6S; Cube Orange

TC	Platform	Use Case	Payload (kg)	Flt. Time (min)	TWR Achieved	Battery (mAh)	Key Outcomes
TC-10	Quadcopter	Mapping	0.8	40	2.2:1	5,200	CF frame FoS > 8; low vibration priority; Pixhawk 4 Mini
TC-11	Hexacopter	Delivery	6.0	35	2.3:1	16,000	6S 22.2V; efficient KV; Cube Orange / Pixhawk 6X
TC-12	Quadcopter	Surveillance	0.3	20	2.0:1	3,000	Cold (5°C); Li-Ion chemistry advisory; internal resistance

† Executed on live system; all values from actual system output reports. * TWR below required minimum — engineering warning correctly generated.

6.2 Validation Metrics

The following four validation criteria were applied across all twelve test cases:

(a) Physics coherence — all computed values must satisfy dimensional consistency and physical plausibility checks. This was verified for all twelve cases by confirming that thrust values correctly produce the stated hover power via Equation (3), and that battery capacity correctly satisfies the stated current draw and flight time via Equation (6).

(b) Warning generation — any configuration where achieved performance falls below mission thresholds must generate an engineering advisory with a specific upgrade recommendation. TC-01 generated a correct advisory recommending upgrade to hexacopter (TWR 1.74:1 achieved vs. 2.0:1 required). TC-02 generated a correct advisory recommending upgrade to octocopter (TWR 1.27:1). TC-03 generated both a TWR advisory and a range shortfall advisory (11.2 km achieved vs. 16.5 km target). TC-07 generated a correct altitude-compensation advisory with propeller upsize recommendation. TC-08 generated a temperature derating advisory with a 7% capacity reduction applied.

(c) Structural FoS criterion — carbon fibre frames must achieve $FoS > 1.5$ (safe minimum). Verified values for TC-01 (FoS 173.1), TC-02 (FoS 29.9), and TC-03 (FoS 9.1) all substantially exceed this threshold.

(d) Platform auto-selection — automatically resolved platform must match expert-recommended type for the given payload and range combination. TC-01 (1.0 kg payload, 2.0 km range) correctly resolved to quadcopter. TC-02 (4.6 kg, 10.0 km) correctly escalated to hexacopter. TC-09 (5.0 kg delivery with 25% return reserve) correctly auto-selected hexacopter with the reserve battery buffer applied.

6.3 Detailed Comparison with Manual Calculation — TC-03

TC-03 (hexacopter, agriculture, 15.0 kg payload, 80-minute target, 45 km/h cruise) was independently verified against manual aeronautical engineering calculations to establish a quantitative ground-truth comparison. Table 3 presents the comparison.

Table 3 AERO-UAV vs. Manual Calculation — TC-03 (Agriculture Hexacopter, 15 kg Payload)

Parameter	Manual Calculation	AERO-UAV Output	Deviation
Total system weight	16.75 kg	17.05 kg	+1.8% (conservative)
Hover power (ADT, FM=0.60)	3,112 W	3,128.9 W	+0.54%
Battery capacity	~24,200 mAh	25,000 mAh	+3.3% (std. rounding)
ESC rating per motor	60 A	60 A	Exact match
Battery voltage (cell count)	12S (44.4 V)	12S (44.4 V)	Exact match

Parameter	Manual Calculation	AERO-UAV Output	Deviation
Minimum C-rating	15C	15C	Exact match
Structural FoS (CF arm, 3g shock)	~9.0	9.1	+1.1%
FCU max tilt angle	73.3°	73.3°	Exact match
Range shortfall advisory	Expected (11.2 < 16.5 km)	Correctly issued	Warning verified

The maximum deviation across all compared parameters was 3.3% (battery capacity), attributable to conservative rounding up to the nearest standard commercial value — operationally appropriate for manufacturing procurement. Hover power agreement at 0.54% confirms correct implementation of Actuator Disk Theory. All exact-match parameters (ESC, voltage, C-rating, tilt angle) confirm that the rule lookup and selection logic is deterministically correct.

7. Discussion

7.1 System Strengths

AERO-UAV offers three principal engineering contributions. First, the use-case design matrix encodes mission-specific design philosophy as explicit, auditable rules rather than opaque learned weights. This transparency enables engineers to understand, verify, and challenge the system's decisions — a critical requirement in safety-relevant UAV applications. Second, the sequential twelve-step rule chain correctly models the interdependencies among UAV subsystems: propeller size influences disc area which influences hover power which influences battery capacity which influences total weight which in turn influences propeller and motor selection. The iterative preliminary estimation approach avoids circular dependency. Third, the system generates contextual engineering warnings with actionable upgrade recommendations rather than silently accepting marginal configurations, a behaviour absent from most comparable tools.

Table 4 compares AERO-UAV capabilities against the most commonly used UAV pre-design tools.

Table 4 AERO-UAV vs. Comparable Tools

Feature	AERO-UAV	eCalc	eMotor Calc	XFLR5	OpenVSP	MDO Tools
Full-system spec (all subsystems)	✓	✗	✗	✗	✗	Partial
Mission use-case profiles	✓	✗	✗	✗	✗	✗
Structural FoS analysis	✓	✗	✗	✗	Partial	✓
Engineering warnings	✓	Partial	✗	✗	✗	✗
Zero-install web interface	✓	✓	✓	✗	✗	✗
Temperature & altitude modelling	✓	Partial	✗	✗	✗	Varies
Free and open architecture	✓	Partial	✗	✓	✓	Varies

7.2 Limitations

Several limitations are acknowledged. The component databases (motors, propellers, ESCs) are static and require periodic updates as new products enter the market. Aerodynamic modelling assumes a simplified drag model with a fixed drag coefficient per mission class; accurate fuselage drag for specific airframe geometries requires computational fluid dynamics simulation beyond the scope of this system. The structural FoS analysis uses a simplified cantilever beam model with a fixed section modulus; complex frame geometries and multi-arm configurations require finite element analysis for precise safety margins. The system does not currently model vibration, electromagnetic interference, or thermal management beyond temperature derating. The estimated flight time represents an ideal no-wind value; actual endurance varies with wind, payload centre-of-gravity offset, and battery ageing.

7.3 Future Work

Planned extensions include: (1) a database update API enabling community-maintained component catalogues; (2) integration with OpenVSP for aerodynamic validation of generated specifications; (3) machine learning enhancement of the KV class selector using empirical flight log data; (4) a multi-objective optimisation layer enabling Pareto-optimal trade-offs between flight time, payload, and cost; and (5) digital twin export generating simulation-ready models for ROS2/Gazebo environments to enable hardware-in-the-loop validation of generated specifications prior to manufacturing.

8. Conclusion

This paper presented AERO-UAV, a physics rule-based expert system for automated UAV specification. The system encodes aeronautical engineering knowledge across twelve interdependent calculation steps and a six-profile use-case design matrix, producing manufacturing-ready specifications in under one second from twelve mission-level inputs. Validation across twelve structured test cases demonstrated physical consistency, correct platform auto-selection, appropriate contextual warnings, and battery capacity estimates within 3.3% of manually computed values. Hover power computed by the Actuator Disk Theory implementation agreed with manual calculations to within 0.54%.

AERO-UAV contributes a replicable methodology for encoding domain expertise in engineering expert systems, demonstrating that transparent, deterministic rule engines can automate complex multi-subsystem design tasks without sacrificing engineering rigour or interpretability. The system is implemented entirely in openly available Python libraries and presents a low-barrier architecture suitable for deployment in academic, research, and small-manufacturer contexts globally.

The work establishes a validated foundation for further integration with numerical optimisation and aerodynamic simulation tools, advancing the goal of democratising professional UAV engineering capability and enabling faster, more systematic pre-design workflows for the growing global UAV development community.

Statements and Declarations

Competing Interests

The authors declare no competing interests, financial or non-financial, related to this work.

Author Contributions

Aniket Bhagwat Mohite conceived and implemented the AERO-UAV system architecture, rule engine, web application, and performed validation experiments. Dr. Pankaj P. Awate supervised the research, contributed to the aeronautical engineering methodology, and critically reviewed the manuscript. Both authors read and approved the final manuscript.

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Data Availability

The source code for the AERO-UAV system, including engine.py, app.py, and all test case configurations, is available from the corresponding author upon reasonable request.

Ethics Approval

Not applicable. This research did not involve human participants, animal subjects, or sensitive personal data.

Use of AI Writing Assistance

AI-assisted writing tools were used for grammar, phrasing, and readability improvements to human-generated text. All technical content, system design, engineering formulas, experimental results, analysis, and conclusions are solely the work of the authors. The authors take full responsibility for the accuracy and integrity of the final manuscript.

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