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Beyond Ad-Hoc Choices: A Two-Stage Decision Framework for UAV Energy Model Selection

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Abstract

The rapid proliferation of unmanned aerial vehicles (UAVs) in energy-intensive applications (such as autonomous logistics, continuous surveillance, and mobile edge computing) has driven a critical need for highly reliable energy consumption models. However, selecting an appropriate modeling strategy remains an ad-hoc process; researchers must frequently navigate complex, undocumented trade-offs among required predictive accuracy, empirical data availability, and access to aerodynamic testing infrastructure. This study proposes a systematic, two-stage decision-making framework designed to standardize UAV energy model selection. In the first stage, a qualitative decision tree is inductively derived from a comprehensive corpus of recent literature (an 80% training split), explicitly mapping infrastructural and informational constraints to five distinct modeling regimes, ranging from novel white-box derivations to deep-learning black-box applications. This structural logic is subsequently validated against an independent 20% literature holdout set, achieving a 100% predictive match. In the second stage, the Analytic Hierarchy Process (AHP) is applied to quantitatively rank the feasible alternatives based on context-specific criteria: accuracy, interpretability, development cost, and customization adaptability. Crucially, this quantitative scoring introduces "fallback flexibility," allowing researchers to seamlessly pivot to mathematically adjacent alternative models when unforeseen experimental roadblocks occur. Embedded within an open-source Python graphical interface, this framework mitigates methodological ambiguity, prevents the over-allocation of research resources, and fosters greater reproducibility within the energy-aware UAV research community.

Keywords: unmanned aerial vehicle; energy consumption; model selection; decision framework; white-box models; black-box models

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1. Introduction

Unmanned Aerial Vehicles (UAVs) have evolved into indispensable assets across complex operational domains, including precision agriculture, autonomous urban logistics, aerial surveillance, and disaster response networks [1–3]. Because multi-rotor and fixed-wing platforms are fundamentally constrained by the energy density of onboard battery systems (often limiting operational flight endurance to mere 20–40 minute windows), understanding and predicting their dynamic power consumption is a paramount research priority in the drone community [4,5]. Accurate energy modeling is the foundational prerequisite for optimizing autonomous flight trajectories, extending mission endurance, and guaranteeing the safe return-to-base of beyond visual line of sight (BVLOS) operations [6].

Despite a proliferation of research addressing UAV power constraints, the landscape of energy modeling methodologies remains highly fragmented. Approaches broadly bifurcate into two distinct paradigms: physics-based (white-box) models, which rely on first-principles aerodynamic equations

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and propulsion mechanics, and data-driven (black-box) models, which utilize machine learning or empirical statistical regression derived from flight telemetry logs [7]. Currently, the decision to adopt one paradigm over the other (and whether to derive a novel model or adapt an existing framework) is largely arbitrary. These critical methodological choices are often implicitly driven by a researcher's immediate access to wind tunnels, the availability of high-fidelity flight datasets, or algorithmic familiarity, rather than a structured assessment of the project's actual requirements. There is a critical absence of a standardized, objective methodology to guide UAV researchers in selecting the optimal energy model under heterogeneous hardware, data, and facility constraints.

To address this gap, this study introduces a comprehensive, two-stage decision-making framework specifically engineered to navigate data and resource constraints in UAV energy modeling. The primary contributions of this paper are fourfold:

- We inductively derive a qualitative decision tree from a systematic review of existing UAV literature (representing an 80% training corpus), mapping specific infrastructural and informational constraints to five empirically observed modeling regimes.
- We rigorously validate the predictive and prescriptive accuracy of this decision tree against an independent 20% holdout set of recent state-of-the-art literature.
- We deploy a quantitative Analytic Hierarchy Process (AHP) framework to rank admissible modeling alternatives based on user-weighted criteria, ensuring that the selected model optimally balances accuracy, interpretability, development time, and adaptability.
- We provide an open-source Python-based graphical user interface (GUI) that operationalizes the framework, granting researchers "fallback flexibility" by providing a mathematically prioritized continuum of backup modeling strategies should primary experimental conditions fail.

The remainder of this paper is organized as follows. Section 2 reviews the background of UAV classifications and the dichotomy of current energy modeling paradigms. Section 3 details the derivation and empirical validation of the qualitative decision tree. Section 4 presents the mathematical formulation of the AHP-based quantitative framework and its re-validation. Section 5 discusses the practical implications, limitations, and future directions of the methodology. Finally, Section 6 concludes the paper.

2. Background and Related Work

2.1. UAV Classifications and Energy Dynamics

Unmanned Aerial Vehicles (UAVs) are fundamentally categorized by their aerodynamic architectures and flight kinematics into fixed-wing, rotary-wing, and hybrid platforms. Each structural paradigm dictates a distinct energy consumption profile and operational envelope.

2.1.1. Primary UAV Categories

UAVs are classified into three primary categories based on their mechanisms for lift generation and operational agility. Fixed-Wing UAVs utilize forward aerodynamic motion to generate lift over stationary wings, yielding superior energy efficiency and prolonged endurance. This streamlined aerodynamic profile minimizes power expenditure (increasingly relying on advanced high-density battery architectures) [8] making them optimal for wide-area missions such as topographic mapping and agricultural surveying (Figure 1 (c), (d)). Conversely, Rotary-Wing UAVs (encompassing single-rotor and multi-rotor configurations) generate lift through continuous rotor actuation, enabling vertical takeoff and landing (VTOL) and high-precision hovering (Figure 1 (a), (b)). This operational flexibility comes at a significant energy premium, heavily modulated by the number of actuators and payload mass [9,10]. Hybrid UAVs bridge these paradigms, integrating VTOL capabilities with fixed-wing horizontal cruising (Figure 2). These platforms are engineered for complex supply chain and autonomous delivery networks, transitioning between energy-intensive hover phases and highly efficient forward flight [9,10].

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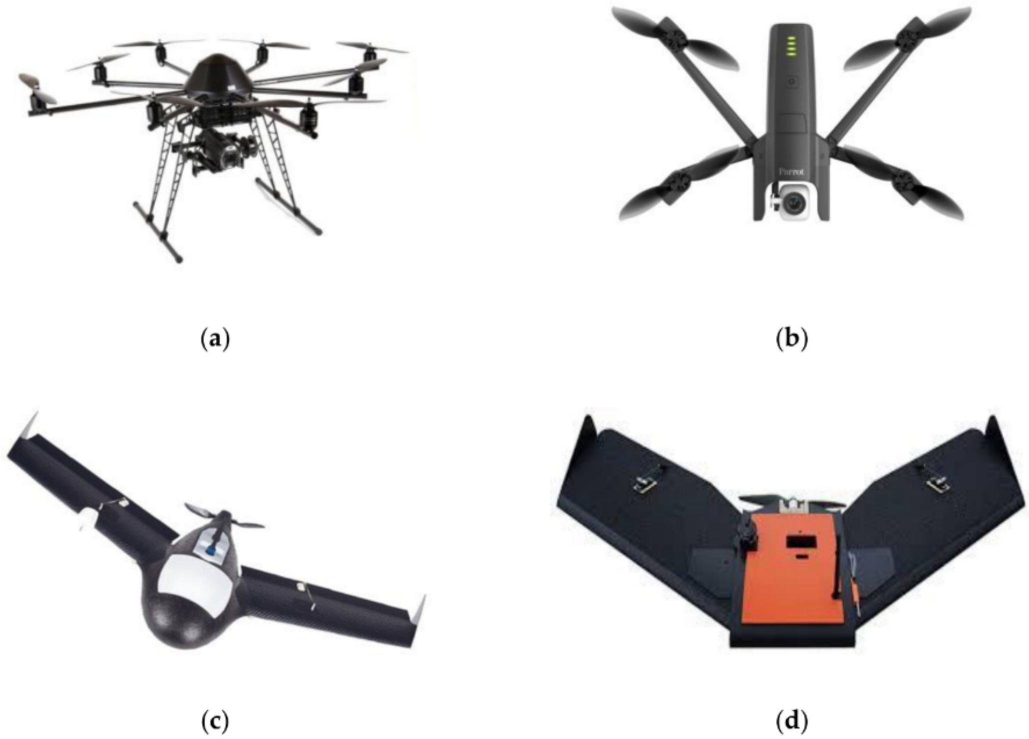

Figure 1. Prevalent UAV designs: (a)(b) Rotary-wing, (c)(d) Fixed-wing [11]

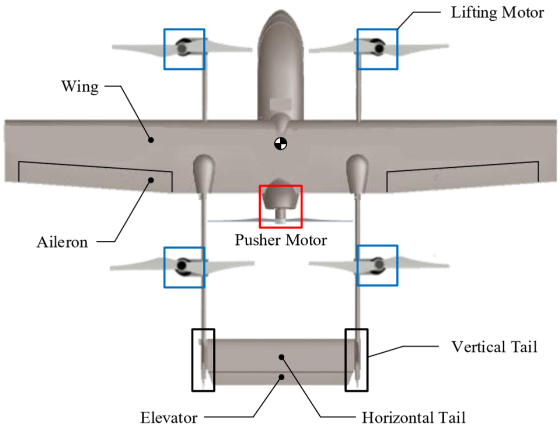

Figure 2. Hybrid UAV [12]

2.1.2. Energy Profiling Across UAV Designs

Power demands fluctuate significantly across UAV classes due to fundamentally different propulsion mechanics and optimization priorities. Fixed-wing systems prioritize aerodynamic efficiency and route refinement for sustained long-range travel [13,14]. Rotary-wing designs, however, must continuously optimize power allocation to maintain stable hover states and execute agile maneuvers [15]. Hybrid platforms require sophisticated control regimes to minimize the energy spikes associated with transitioning between VTOL and horizontal flight modes. Furthermore, operational agility is structurally constrained: fixed-wing aircraft possess limited turning radii dictated by stall speeds [16], whereas multi-rotors execute sharp, high-cost navigational pivots [17,18].

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2.2. Role of Energy Simulation in Autonomous Optimization

Accurate energy forecasting is a mission-critical component for optimizing autonomous UAV operations and preventing mid-flight power depletion. Given that commercial and tactical UAVs typically operate within strict 20–40 minute endurance windows, robust simulation frameworks are required to project operational range by integrating payload weight, altitude profiles, and atmospheric variables [9,10].

These models inform trajectory optimization algorithms by quantifying the exact energy cost of hovering, ascending, and navigating through waypoints [19,20]. In sectors such as emergency response and autonomous logistics, high-fidelity energy modeling ensures operational reliability by triggering fail-safes or return-to-base protocols before critical energy thresholds are breached [20,21]. Furthermore, these simulations are vital for evaluating the integration of renewable energy sources, such as photovoltaic arrays, to extend flight endurance [19,22].

2.3. Key Influences on UAV Power Usage

UAV power consumption is a highly dynamic variable modulated by interacting environmental, kinematic, and structural factors.

Atmospheric disturbances, such as wind shear and precipitation, drastically alter required thrust and power draw [15,23]. Kinematic decisions, particularly cruise velocity, dictate the balance between induced and parasite power [15,24,25]. Structurally, gross takeoff weight (including variable payloads) acts as a primary consumption multiplier [21,26]. Additionally, altitude variations alter air density and rotor drag [20], while onboard avionics and data-transmission systems introduce non-negligible auxiliary power loads [21,24,27].

2.4. Taxonomy of UAV Power Frameworks

Contemporary UAV energy estimation frameworks fundamentally bifurcate into physics-based (white-box) analytical models and data-driven (black-box) empirical models [7].

2.4.1. White-Box vs. Black-Box Approaches

White-box methods are derived from first-principles aerodynamics, capturing propulsion mechanics, momentum theory, and blade element theory. They afford high interpretability, enabling engineers to conduct hypothetical scenario probing, hardware design iterations, and rigorous trajectory optimization. However, their limitations include intensive computational overhead and the requirement for highly specific, difficult-to-measure aerodynamic coefficients. Conversely, black-box alternatives deploy statistical regressions or deep neural networks to map observable telemetry inputs directly to energy outputs. These models bypass complex mechanistic derivations, yielding rapid inference capabilities suitable for real-time edge computing. Their primary drawbacks are a severe lack of interpretability and a vulnerability to overfitting if the training dataset lacks environmental diversity.

2.4.2. Selection Criteria and Modeling Trends

The epistemological foundations, operational constraints, and deployment implications of these two paradigms differ substantially. Table 1 summarizes their structural engineering trade-offs.

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Table 1. Comparison between physics-based (white-box) and data-driven (black-box) UAV energy models.

Attribute	White-Box (Physics-Based)	Black-Box (Data-Driven)
Interpretability	Elevated	Minimal
Foundation	Mechanistic/Aerodynamic	Empirical/Statistical
Fidelity	Theoretically robust	Highly contingent on training data
Development Overhead	Substantial	Modest (assuming data availability)
Computational Load	Intensive	Lightweight (during inference)
Adaptability	Rigid (platform-specific)	Fluid (retrainable)

White-box models are optimal for analytical optimization and trajectory planning that requires strict theoretical guarantees. However, they frequently demand precise vehicle parameters, wind tunnel validation, and significant computational resources, limiting their flexibility in highly dynamic or rapidly prototyping environments. Black-box approaches excel when large volumes of flight telemetry are available and system identification via machine learning is more pragmatic than analytical derivation. Their principal limitation is the inability to extrapolate safely outside the distribution of their training data.

Therefore, model selection is not a matter of binary superiority, but rather a complex context dependency prioritizing analytical fidelity against empirical responsiveness.

Empirical Trends in the Literature

Table 2 categorizes representative studies according to their adopted modeling paradigm. Several key methodological patterns emerge:

1. **Dominance of multirotor platforms:** The overwhelming majority of surveyed works focus on multirotor UAVs, reflecting their ubiquitous deployment in precision agriculture, autonomous inspection, and IoT data harvesting.
2. **Prevalence of physics-based models in optimization:** White-box formulations dominate energy-aware path planning and control optimization studies. This indicates that the theoretical optimization community strictly prioritizes mechanistic transparency and explicit mathematical gradients.
3. **Surge in ML-based models post-2020:** Data-driven approaches have experienced rapid adoption, catalyzed by the proliferation of onboard telemetry logging and advancements in deep learning architectures.
4. **Lack of paradigm justification:** Critically, very few works systematically compare white-box and black-box models under identical constraints. Methodological choices are frequently assumed rather than rigorously justified.

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Table 2. Classification of state-of-the-art studies by UAV energy modeling paradigm.

Year	Authors	Ref	UAV Type & Notes
White-Box Models (Analytical/Physics-Based)			
2026	Gu et al.	[28]	Multirotor
2025	Xu et al.	[29]	Multirotor
2025	Wu et al.	[30]	Multirotor
2025	Qi et al.	[1]	Multirotor
2025	Gasche et al.	[31]	Multirotor
2024	Zhuo et al.	[32]	Multirotor
2024	Liu et al.	[33]	Multirotor
2023	Xie et al.	[24]	Multirotor
2023	Gong et al.	[6]	Multirotor
2020a	Fendji et al.	[2]	Multirotor
2020	Umair et al.	[34]	Multirotor
2019	Thibbotuwawa et al.	[15]	Multirotor
2018	Sallouha et al.	[27]	Multirotor
2018	Zeng et al.	[35]	Multirotor
2017	Paredes et al.	[36]	Fixed-wing & Multirotor
2017	Mozaffari et al.	[37]	Multirotor
2017	Yacef et al.	[38]	Multirotor
2013	Zorbas et al.	[39]	Multirotor
Black-Box Models (Empirical/Machine Learning)			
2025	Kim et al.	[40]	Multirotor
2025	Huang	[41]	Multirotor
2025	Akram et al.	[42]	Multirotor
2023	Na et al.	[43]	Multirotor
2023	Alyassi et al.	[44]	Multirotor
2022	Gora et al.	[45]	Multirotor
2020b	Fendji et al.	[3]	Multirotor
2019	Prasetia et al.	[46]	Multirotor
2018b	Abeywickrama et al.	[21]	Multirotor
2018c	Abeywickrama et al.	[47]	Multirotor
2017	Tseng et al.	[26]	Multirotor
2015	Carmelo et al.	[48]	Multirotor

Identified Research Gap and Motivation

Despite this extensive body of literature, a critical methodological gap persists within UAV energy research:

- Model selection is predominantly implicit and rarely justified through empirical comparison.
- No standardized, reproducible framework exists to guide researchers in selecting the optimal paradigm based on their specific hardware and data constraints.
- The engineering trade-offs between predictive accuracy, physical interpretability, and computational cost are rarely quantified simultaneously.

While the majority of current studies focus on optimizing flight paths *within* a chosen modeling paradigm, the foundational decision of *which paradigm to adopt* is routinely bypassed. This oversight is non-trivial; an inappropriate modeling choice can severely bias trajectory optimization, misestimate critical energy reserves, and ultimately compromise autonomous mission safety.

Consequently, model selection must evolve from an implicit assumption into a formal multi-criteria decision problem. This study is motivated by the necessity to quantify these trade-offs, formalizing the selection process through a qualitative decision tree (Section 3) integrated with a quantitative Analytic Hierarchy Process (Section 4). By standardizing this workflow, we aim to ensure that model choice is consistently reproducible, mathematically justified, and acutely aware of systemic operational constraints.

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3. Qualitative Framework for UAV Energy Model Selection

3.1. Derivation of the Framework from Literature Patterns

The proposed decision-making framework was inductively engineered through a systematic analysis of state-of-the-art energy modeling strategies. This derivation utilized a training corpus comprising 80% of the reviewed literature (summarized in Table 3), spanning highly diverse operational and algorithmic contexts.

While the literature broadly bifurcates into two dominant modeling paradigms:

- White-box (physics-based / analytical) models
- Black-box (empirical / machine learning) models

A rigorous examination of these studies reveals that researchers implicitly execute structured decision-making based on recurring, critical constraints. Specifically, model selection is consistently dictated by:

- Access to experimental facilities or aerodynamic validation infrastructure (e.g., wind tunnels).
- The volume and fidelity of accessible flight telemetry and battery discharge datasets.
- The predictive accuracy thresholds mandated by the specific autonomous task (e.g., MPC vs. high-level logistics routing).
- The degree of structural customization of the UAV platform.
- The availability of foundational, mathematically validated analytical formulations in prior literature.

These structural constraints constitute the operational backbone of the proposed framework. The decision tree presented in Figure 3 is a formalization of the implicit selection logic already embedded (but previously uncodified) within existing empirical studies.

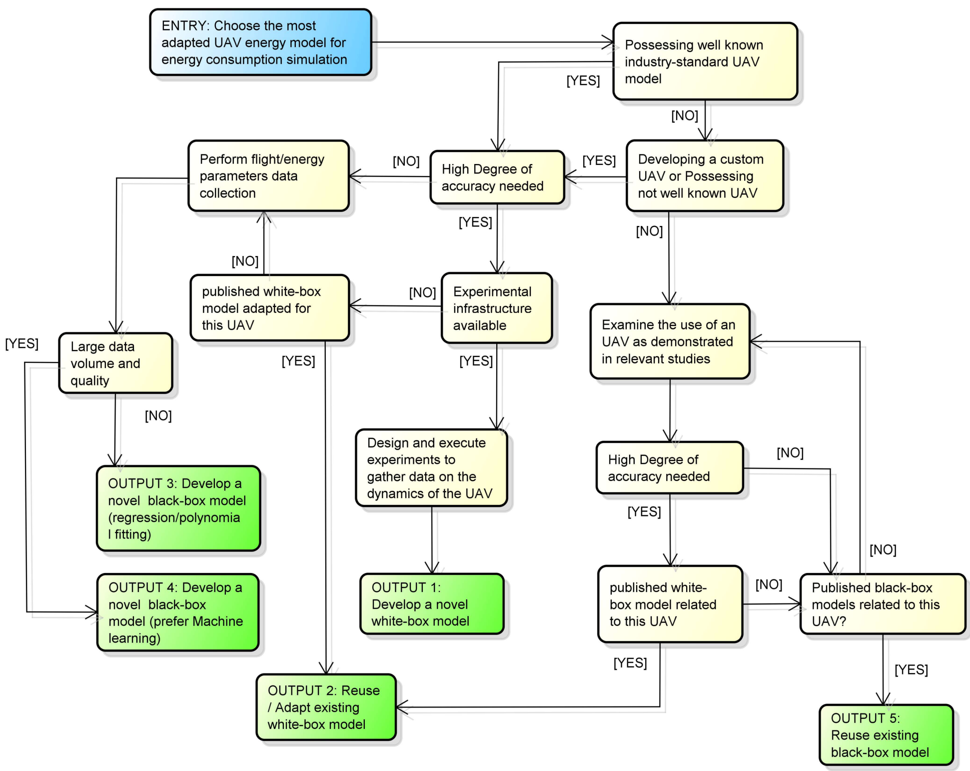

Figure 3. Decision tree formalized from recurring modeling strategies in UAV energy literature

3.2. Energy Model Alignment and Pattern Extraction

To explicitly map this derivation, Table 3 categorizes the training corpus according to the type of model employed and the corresponding decision path that aligns with our proposed framework.

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Table 3. Energy model categories in the literature and structural alignment with the extracted decision logic.

Year	Author	Ref	Observed Modeling Strategy
White-Box Models (Physics-Based)			
2025	Qi et al.	[1]	Novel analytical derivation
2024	Zhuo et al.	[32]	Extended physical modeling
2024	Liu et al.	[33]	Propulsion-based formulation
2023	Xie et al.	[24]	Adoption of established white-box model
2023	Gong et al.	[6]	Derived hovering/propulsion model
2020a	Fendji et al.	[2]	Physics-based with validation
2020	Umair et al.	[34]	Reuse of Zeng et al. model
2019	Thibbotuwawa et al.	[15]	Analytical review and extension
2018	Sallouha et al.	[27]	Simplified physical model
2018	Zeng et al.	[35]	Foundational propulsion model
2017	Paredes et al.	[36]	Altitude-dependent equations
2017	Mozaffari et al.	[37]	Power-control physics modeling
2017	Yacef et al.	[38]	Comprehensive mathematical derivation
2013	Zorbas et al.	[39]	3D terrain analytical model
Black-Box Models (Empirical / ML)			
2025	Akram et al.	[42]	Regression-based estimation
2023	Alyassi et al.	[44]	ML flight-time prediction
2022	Gora et al.	[45]	Data-driven modeling
2020b	Fendji et al.	[3]	Empirical validation approach
2019	Prasetia et al.	[46]	Mission-based empirical modeling
2018b	Abeywickrama et al.	[21]	Polynomial battery fitting
2018c	Abeywickrama et al.	[47]	Empirical battery characterization
2017	Tseng et al.	[26]	Interpolation-based model
2015	Carmelo et al.	[48]	Experimental energy fitting

3.3. Observed Decision Regimes in the Literature

The corpus analysis reveals four distinct, recurring methodological regimes:

3.3.1. Data-Rich Environments Lacking Experimental Infrastructure

Studies such as [42,44,45] pivot to statistical regression or deep machine learning architectures when wind tunnels or precision aerodynamic validation facilities are inaccessible. This directly corresponds to the framework branch mandating data-driven black-box development under high-data/low-infrastructure conditions.

3.3.2. High-Fidelity Requirements Supported by Analytical Foundations

Works focused on rigorous trajectory optimization, including [24,34,35], universally adopt and adapt existing, mathematically proven propulsion-based models. This aligns with the framework branch prioritizing the reuse of validated white-box formulations to maintain explicit control gradients.

3.3.3. High-Fidelity Requirements Necessitating Extended Physical Formulations

When existing formulations fail to capture complex dynamics (such as ground effect transitions or variable payloads) authors [1,6,32] are forced to derive novel analytical models. This necessitates the framework path leading to original white-box derivations, heavily reliant on physical testing facilities.

3.3.4. Hybrid Analytical–Empirical Synthesis

Certain systemic evaluations [2,36] synthesize first-principles physics derivation with extensive empirical validation, reflecting operational environments that simultaneously demand causal interpretability and real-world statistical realism.

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3.4. Formalization into a Structured Decision Tree

Figure 3 illustrates the explicit decision tree formulated from these recurring operational patterns. The resulting framework avoids a reductive binary split (i.e., merely choosing between white-box or black-box); rather, it encodes a conditional, multi-stage hierarchy that navigates specific engineering constraints.

Stage 1: Platform Maturity and Contextual Identification

The root node acts as an initial filter, distinguishing between the deployment of a recognized, industry-standard UAV platform versus a highly customized or proprietary airframe. This classification is vital, as the applicability of transferrable analytical models found in existing literature scales directly with platform maturity.

Stage 2: Algorithmic Accuracy Thresholds

The subsequent branching condition evaluates the predictive fidelity required by the autonomous mission planner. Consistent with literature trends, algorithms requiring highly precise gradient calculations (e.g., nonlinear model predictive control) necessitate physics-based reasoning, whereas broad logistical routing algorithms often tolerate the bounded errors of empirical estimation.

Stage 3: Literature Availability Assessment

When high accuracy is dictated, the framework interrogates the existing scientific corpus to determine if a rigorously validated white-box or black-box model tailored to the specific UAV platform is already available. If a transferrable analytical model exists, the framework optimizes research efficiency by recommending adaptation (OUTPUT 2), circumventing redundant derivations. If no such model exists, the logic shifts toward novel development.

Stage 4: Experimental and Data Capability Verification

When original model development is inescapable, the decision path diverges based on strict physical and informational assets:

- If physical experimental infrastructure (e.g., wind tunnels, thrust stands) is accessible, the framework directs the researcher toward a novel white-box derivation (OUTPUT 1).
- If physical infrastructure is absent, but the system architecture permits extensive flight telemetry logging, the framework dynamically pivots the researcher toward empirical black-box modeling.

Stage 5: Data Volume Qualification

For empirical modeling pathways, the framework applies a final volumetric filter:

- Massive, high-resolution datasets trigger the recommendation of Deep Learning/ML architectures (OUTPUT 4).
- Constrained or low-resolution datasets default to standard polynomial regression or simple heuristic fitting (OUTPUT 3).

Existing, highly generalized empirical models may also be reused if appropriately validated for the operational domain (OUTPUT 5).

3.5. Empirical Validation of the Framework

To rigorously quantify the predictive validity and structural robustness of the proposed decision tree, a validation test was executed utilizing an independent holdout set. This subset comprised 20% of the reviewed literature (seven high-impact papers published between 2023 and 2026, detailed in Table 2). These studies were strictly isolated during the framework's inductive derivation phase to prevent data leakage.

The validation protocol mapped the explicit operational constraints, platform architectures, and data availability parameters documented in each test paper against the framework's decision nodes to

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determine if the predicted algorithmic output matched the actual engineering methodology deployed by the authors.

Table 4 summarizes the specific parameters of the holdout studies and the resulting predictive alignment.

Table 4. Validation of the decision framework against the 20% independent literature holdout set.

Test Study	Context & Constraints	Actual Model Used	Predicted Output	Result
Gasche et al. (2025) [31]	Standard UAV; high accuracy for path planning; no wind tunnel data.	Existing analytical multi-copter model.	O2	**Match**
Gu et al. (2026) [28]	Urban logistics UAV; high accuracy required for wind field integration.	Existing aerodynamic physics model.	O2	**Match**
Huang (2025) [41]	Complex environmental data; large flight datasets available; no aero-testing.	RF and SVR (Machine Learning).	O4	**Match**
Kim et al. (2025) [40]	Standard UAV; vast empirical flight data collected; complex nonlinear dynamics.	Hybrid DNN (Deep Neural Network).	O4	**Match**
Na et al. (2023) [43]	Standard UAV; path planning optimization using PSO algorithm.	Established rotary-wing physics equations.	O2	**Match**
Wu et al. (2025) [30]	Multi-rotor logistics; requires computational efficiency for integrative planning.	Existing generalized propulsion model.	O2	**Match**
Xu et al. (2025) [29]	Custom morphing solar-powered UAV; unique aerodynamics; physical precision needed.	Derived solar-aerodynamic equations.	O1	**Match**

3.5.1. Validation Analysis by Decision Regimes

The holdout set effectively activates three distinct systemic branches of the proposed decision tree, demonstrating the framework's robust applicability across diverse engineering contexts.

Regime 1: Optimization and Path Planning on Standard UAVs (O2)

Four of the test papers (**Gasche et al.[31], Gu et al.[28], Na et al.[43], and Wu et al.[30]**) focus on trajectory optimization, obstacle avoidance, and energy-aware routing using commercially recognized multi-rotor platforms.

Following the framework's operational logic: these studies utilize mature UAV platforms (Stage 1), demand high modeling fidelity to ensure optimizer convergence (Stage 2), and have seamless access to extensively validated analytical formulations within the literature (Stage 3). As accurately predicted by the framework, these researchers avoided redundant physics derivations, navigating directly to **Output 2 (O2)**. They successfully adopted established white-box models (e.g., Bramwell's helicopter dynamics) to serve as the constraint equations for their MPC and PSO algorithms.

Regime 2: Data-Rich, Infrastructure-Poor Environments (O4)

Two studies (**Huang[41]** and **Kim et al.[40]**) investigate scenarios dominated by complex environmental interactions and nonlinear flight dynamics. In both cases, precision aerodynamic testing facilities were bypassed in favor of massive flight telemetry harvesting. Following the framework's

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constraints: the lack of physical validation infrastructure terminates the white-box derivation pathway, while the presence of high-density empirical datasets satisfies the Stage 5 volumetric qualifier. Consequently, the framework predicts **Output 4 (O4)**. This achieves perfect alignment with the authors' deployed methodologies, which leveraged Random Forests, Support Vector Regression, and Deep Neural Networks to engineer robust predictive black-box models.

Regime 3: Bespoke Platform with High Analytical Requirements (O1)

The study by **Xu et al.**[29] introduces a highly specialized "Morphing Solar-Powered UAV."

Processed through the framework (Stage 1), a bespoke platform of this nature immediately disqualifies the use of standardized literature models. Furthermore, because in-flight morphological adaptations drastically manipulate the aerodynamic drag coefficients, extraordinary physical precision is mandated (Stage 2). With no pre-existing transferrable model available to capture this unique solar-morphing coupling (Stage 3), and acknowledging that the authors possessed the capacity to derive explicit physical parameters, the framework vectors the decision process to **Output 1 (O1)**. The publication corroborates this prediction, detailing the novel derivation of physics-based energy equations mapping solar influx against morphing drag parameters prior to the application of Hierarchical Reinforcement Learning.

3.5.2. Interpretation and Structural Analysis of Validation Results

The validation subset (20% holdout, $n = 7$) yielded the following distribution across the framework's terminal nodes:

- O1 (Novel White-Box Development): 1 study
- O2 (Reuse of Established White-Box Model): 4 studies
- O4 (Machine Learning Black-Box Development): 2 studies
- O3 (Regression-Based Black-Box): 0 studies
- O5 (Reuse of Existing Black-Box Model): 0 studies

While only three specific outputs were activated within this holdout set, the resulting statistical distribution accurately reflects the current structural paradigms of contemporary UAV research.

Dominance of O2: Methodological Maturity in Analytical Modeling

The high prevalence of O2 instances underscores the deep methodological maturity achieved in standard multirotor propulsion modeling. In state-of-the-art trajectory optimization and energy-aware control architectures, researchers consistently exploit previously validated analytical formulations. This convergence occurs under three strict conditions: the deployment of standardized platforms, high accuracy requirements for algorithmic solvers, and the availability of experimentally validated models. Under these parameters, reusing an established white-box model guarantees both reproducibility and mathematical compatibility. Therefore, the frequency of O2 represents the current methodological equilibrium of the field, rather than an inherent bias within the decision tree.

Emergence of O4: Expanding Data-Driven Contexts

The activation of O4 aligns with the surging integration of machine learning techniques in UAV systems research. The studies classified as O4 uniformly exhibited access to extensive telemetry datasets, operated within highly complex environmental flows, and prioritized predictive execution speed over physical explainability. These conditions naturally dictate the selection of data-driven architectures, particularly when physical parameter identification is economically or practically prohibitive.

Limited Occurrence of O1: Custom Platform Rarity

The single instance of O1 (novel white-box development) correlated directly with a highly unconventional UAV airframe (morphing and solar-powered). In this context, the absence of transferrable models and the strict reliance of the aerodynamic properties on configuration geometry rendered

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physical derivation unavoidable. The relative scarcity of O1 classifications directly mirrors the small proportion of entirely novel UAV airframes utilized in standard optimization research.

Absence of O3 and O5 Pathways

The non-activation of O3 (limited-data regression) and O5 (reuse of empirical models) in the validation subset is probabilistically consistent. The holdout papers (2023–2026) represent cutting-edge research, which currently favors either highly precise analytical optimization or sophisticated, large-scale deep learning, leaving basic regression (O3) less represented. Furthermore, because empirical predictors (O5) are inherently over-fitted to the specific datasets and hardware used during their training, their cross-platform transferability remains fundamentally limited in practice.

Methodological Implications

The 100% predictive alignment between the framework's logic and the authors' actual modeling choices confirms that the decision tree successfully codifies the complex, previously implicit selection mechanisms present in top-tier literature. While the sample size is constrained ($n = 7$), the framework proves highly effective at mapping context-dependent operational constraints to mathematically appropriate engineering outputs.

4. Quantitative Framework for UAV Energy Model Selection

To guarantee methodological rigor, mathematical transparency, and operational reproducibility, the proposed framework is executed via two sequential, mathematically grounded stages:

- A non-compensatory feasibility filtering stage, derived directly from the structural decision tree's logical constraints.
- An Analytic Hierarchy Process (AHP)-based multi-criteria aggregation stage to rank admissible alternatives [49,50].

This decoupled architecture ensures that absolute implementability constraints are strictly enforced before any compensatory preference trade-offs are evaluated.

4.1. Feasibility Filtering (Tree-Aligned Constraints) - Stage 1

Let the set of terminal outputs synthesized from the decision tree be defined as:

- O_1: Derive novel white-box (physics-based) model
- O_2: Adapt/reuse existing white-box model
- O_3: Develop novel black-box model (limited data; heuristic/polynomial regression)
- O_4: Develop novel black-box model (massive data; deep learning architecture)
- O_5: Adapt/reuse existing black-box empirical model

Operational feasibility indicators are derived from the structural nodes of Figure 3:

- F_1: UAV platform architecture is widely standardized and documented
- F_2: Transferrable white-box model exists for this specific UAV class
- F_3: Transferrable black-box model exists for this specific UAV class
- F_4: Precision experimental infrastructure (e.g., wind tunnels) is accessible
- F_5: System architecture supports flight telemetry/energy data harvesting
- F_6: Harvested dataset exhibits high volumetric density and statistical fidelity

Each indicator is treated as a strict Boolean constraint:

$$F_i \in \{0, 1\}$$

The admissibility conditions mapping constraints to models are formalized as:

- O_1 is admissible if $F_4 = 1$
- O_2 is admissible if $F_2 = 1$

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- O_3 is admissible if $F_5 = 1 \land F_6 = 0$
- O_4 is admissible if $F_5 = 1 \land F_6 = 1$
- O_5 is admissible if $F_3 = 1$

The globally feasible set is defined as:

$$\mathcal{A} = \{O_j \mid \text{all defining structural conditions are satisfied}\}$$

If the resolution of the constraints yields an empty set ($\mathcal{A} = \emptyset$), the fundamental research parameters must be re-evaluated, as no mathematically viable modeling pathway exists under the current infrastructural capabilities.

4.2. AHP-Based Contextual Ranking - Stage 2

4.2.1. Alternative Vector

The vector of potential alternatives is defined as:

$$[O_1, O_2, O_3, O_4, O_5]$$

4.2.2. Evaluation Criteria

Derived from the structural analysis of the literature corpus, the preference criteria are established as:

- C_1: Predictive accuracy and algorithmic fidelity
- C_2: Physical interpretability and causal transparency
- C_3: Development overhead and computational resource expenditure
- C_4: Structural adaptability to bespoke UAV configurations

Crucially, binary feasibility indicators (F_i) are explicitly excluded from this stage to prevent redundant compensatory evaluation.

4.3. Structural Alternative Matrices (5 × 5)

Maintaining the alternative order $[O_1, O_2, O_3, O_4, O_5]$, each pairwise comparison matrix $A^{(k)} = [a_{ij}^{(k)}]$ is synthesized in accordance with Saaty's ratio-scale measurement theory [49]. The numerical elements are the result of a rigorous, three-step epistemological elicitation:

- Establish an ordinal hierarchy of alternatives with respect to criterion C_k.
- Quantify the relative dominance intensity between each coordinate pair.
- Map the qualitative dominance onto Saaty's fundamental 1–9 ratio scale.

To maintain mathematical validity, all matrices strictly satisfy the fundamental AHP axioms:

$$a_{ij} > 0, \quad a_{ii} = 1, \quad a_{ij} = \frac{1}{a_{ji}}$$

and approximate multiplicative transitivity:

$$a_{ik} \approx a_{ij} \cdot a_{jk}$$

Perfect transitivity yields a rank-one matrix; however, bounded deviations arising from rational human judgment are accommodated and subsequently quantified via the Consistency Ratio (CR).

4.3.1. Matrix $A^{(1)}$ – Predictive Accuracy

Accuracy denotes both predictive fidelity and foundational theoretical soundness. Based on established aerodynamic modeling theory, the ordinal ranking is:

$$O_1 > O_2 > O_5 \approx O_4 > O_3$$

Applying the structured elicitation logic:

- O_1 vs O_3: Original white-box derivations exhibit profound analytical superiority over limited-data heuristics $\rightarrow$ value 5.
- O_1 vs O_2: Marginal superiority due to exact platform matching $\rightarrow$ value 2.
- O_2 vs O_3: Strong predictive dominance $\rightarrow$ value 4.
- O_4 and O_5: Considered asymptotically equivalent in large-data regimes $\rightarrow$ value 1.

These relative intensities preserve approximate multiplicative coherence. For instance:

$$a_{13} \approx a_{12} \cdot a_{23} \quad (5 \approx 2 \times 4 = 8)$$

$$A^{(1)} = \begin{bmatrix} 1 & 2 & 5 & 4 & 3 \\ 1/2 & 1 & 4 & 3 & 2 \\ 1/5 & 1/4 & 1 & 1/2 & 1/2 \\ 1/4 & 1/3 & 2 & 1 & 1 \\ 1/3 & 1/2 & 2 & 1 & 1 \end{bmatrix}$$

4.3.2. Matrix $A^{(2)}$ – Physical Interpretability

Interpretability quantifies the structural transparency and explicit mapping of aerodynamic parameters. The theoretical consensus yields:

$$O_1 > O_2 > O_5 > O_3 > O_4$$

- O_1 vs O_4: Absolute dominance; mechanistic equations are fully transparent while deep learning models act as opaque oracles $\rightarrow$ value 7.
- O_1 vs O_3: Strong mathematical dominance $\rightarrow$ value 6.
- O_2 vs O_3: Strong dominance $\rightarrow$ value 5.
- O_3 vs O_4: Moderate dominance (polynomials offer marginally more insight than deep neural networks) $\rightarrow$ value 2.

$$A^{(2)} = \begin{bmatrix} 1 & 2 & 6 & 7 & 5 \\ 1/2 & 1 & 5 & 6 & 4 \\ 1/6 & 1/5 & 1 & 2 & 1/2 \\ 1/7 & 1/6 & 1/2 & 1 & 1/3 \\ 1/5 & 1/4 & 2 & 3 & 1 \end{bmatrix}$$

4.3.3. Matrix $A^{(3)}$ – Development Cost / Time

This vector assesses the resource expenditure and prototyping latency. Contemporary engineering practices suggest the inverse ordinal ranking:

$$O_5 > O_4 > O_3 > O_2 > O_1$$

Reuse-based and data-driven approaches circumvent the extensive labor required for novel analytical derivation.

- O_5 vs O_1: Decisive resource optimization $\rightarrow$ value 6.
- O_4 vs O_2: Moderate efficiency advantage $\rightarrow$ value 3.
- O_3 vs O_2: Slight efficiency advantage $\rightarrow$ value 2.

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$$A^{(3)} = \begin{bmatrix} 1 & 1/3 & 1/4 & 1/5 & 1/6 \\ 3 & 1 & 1/2 & 1/3 & 1/4 \\ 4 & 2 & 1 & 1/2 & 1/3 \\ 5 & 3 & 2 & 1 & 1/2 \\ 6 & 4 & 3 & 2 & 1 \end{bmatrix}$$

4.3.4. Matrix $A^{(4)}$ – Customization Adaptability

Adaptability reflects the architectural flexibility to accommodate specific airframe adjustments (e.g., payload shifts or rotor degradation).

$$O_1 > O_2 > O_4 > O_3 > O_5$$

- O_1 vs O_5: Strong operational dominance; physical derivations can be re-parameterized explicitly $\rightarrow$ value 5.
- O_2 vs O_4: Moderate dominance $\rightarrow$ value 2.
- O_3 vs O_5: Slight dominance $\rightarrow$ value 2.

$$A^{(4)} = \begin{bmatrix} 1 & 2 & 4 & 3 & 5 \\ 1/2 & 1 & 3 & 2 & 4 \\ 1/4 & 1/3 & 1 & 1/2 & 2 \\ 1/3 & 1/2 & 2 & 1 & 3 \\ 1/5 & 1/4 & 1/2 & 1/3 & 1 \end{bmatrix}$$

4.4. Local Priority Extraction and Consistency Verification

For each alternative evaluation matrix $A^{(k)} \in \mathbb{R}^{5\times5}$, the optimal local priority vector $\mathbf{a}^{(k)}$ is determined by solving the principal eigenvalue problem:

$$A^{(k)}\mathbf{a}^{(k)} = \lambda^{(k)}_{\max}\mathbf{a}^{(k)}$$

where $\lambda^{(k)}_{\max}$ represents the principal eigenvalue and $\mathbf{a}^{(k)}$ is the corresponding normalized principal eigenvector such that:

$$\sum_{i=1}^{5} a_i^{(k)} = 1$$

4.4.1. Consistency Verification

While perfect transitive consistency yields $\lambda^{(k)}_{\max} = n$, empirical judgments contain latent inconsistencies. This is rigorously quantified via Saaty's Consistency Index (CI) [49]:

$$CI^{(k)} = \frac{\lambda^{(k)}_{\max} - n}{n-1}$$

Given $n = 5$, the Random Index baseline is $RI_5 = 1.12$. The definitive Consistency Ratio (CR) is evaluated as:

$$CR^{(k)} = \frac{CI^{(k)}}{RI_5}$$

The matrix is deemed mathematically stable if $CR^{(k)} < 0.1$.

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4.4.2. Matrix $A^{(1)}$ — Accuracy

Eigenvalue calculation: $\lambda_{\max}^{(1)} = 5.21 \implies CI^{(1)} = 0.0525$

$$CR^{(1)} = 0.047 < 0.1 \quad \text{(stable)}$$

$$\mathbf{a}^{(1)} = [0.38, 0.27, 0.08, 0.14, 0.13]^T$$

4.4.3. Matrix $A^{(2)}$ — Interpretability

Eigenvalue calculation: $\lambda_{\max}^{(2)} = 5.32 \implies CI^{(2)} = 0.080$

$$CR^{(2)} = 0.071 < 0.1 \quad \text{(stable)}$$

$$\mathbf{a}^{(2)} = [0.42, 0.30, 0.08, 0.05, 0.15]^T$$

4.4.4. Matrix $A^{(3)}$ — Development Cost

Eigenvalue calculation: $\lambda_{\max}^{(3)} = 5.18 \implies CI^{(3)} = 0.045$

$$CR^{(3)} = 0.040 < 0.1 \quad \text{(stable)}$$

$$\mathbf{a}^{(3)} = [0.05, 0.10, 0.17, 0.27, 0.41]^T$$

4.4.5. Matrix $A^{(4)}$ — Customization Adaptability

Eigenvalue calculation: $\lambda_{\max}^{(4)} = 5.26 \implies CI^{(4)} = 0.065$

$$CR^{(4)} = 0.058 < 0.1 \quad \text{(stable)}$$

$$\mathbf{a}^{(4)} = [0.41, 0.27, 0.09, 0.16, 0.07]^T$$

All matrices strictly conform to the $CR^{(k)} < 0.1$ threshold, confirming the integrity of the pairwise judgments prior to global aggregation.

4.5. Criteria Weight Derivation

To explicitly capture mission-specific objectives, the end-user synthesizes a pairwise criteria comparison matrix $\mathbf{B} = [b_{ij}]_{4\times 4}$ governed by the fundamental axioms of reciprocity, homogeneity, and approximate logical transitivity:

$$b_{ij} > 0, \quad b_{ij} = \frac{1}{b_{ji}}, \quad b_{ii} = 1, \quad b_{ik} \approx b_{ij} \cdot b_{jk}$$

The mission-specific criteria weight vector $\mathbf{w} = [w_1, w_2, w_3, w_4]^T$ is extracted via the principal eigenvector solution:

$$\mathbf{B}\mathbf{w} = \lambda_{\max}\mathbf{w}$$

Stability is verified identically using $n = 4$ and $RI_4 = 0.90$, mandating $CR < 0.1$.

4.6. Global Priority Aggregation and Final Ranking

Following the extraction of the local alternative priority vectors ($\mathbf{a}^{(k)}$) and the mission-specific criteria weight vector ($\mathbf{w}$), the global priority score vector $\mathbf{S}$ is synthesized via linear weighted aggregation:

$$\mathbf{S} = \sum_{k=1}^{4} w_k \mathbf{a}^{(k)}$$

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where $\mathbf{S} = [S_1, S_2, S_3, S_4, S_5]^T$ represents the absolute mathematical hierarchy of the five modeling paradigms relative to the specific operational constraints.

4.7. *Dynamic Interpretation and Fallback Flexibility*

While the qualitative decision tree provides a binary, deterministic recommendation, the AHP-based quantitative framework fundamentally enhances operational resilience by generating a continuous, mathematically scored hierarchy. The final output is explicitly a function of both the hard infrastructural boundaries ($F_1, \ldots, F_6$) and the weighted scientific objectives ($\mathbf{w}$).

This evolution from a rigid flowchart to a scored mathematical continuum unlocks robust contingency planning. In highly dynamic UAV deployment scenarios, researchers frequently face abrupt logistical failures (such as corrupted telemetry payloads, sudden denial of testing facilities, or exhausted computational budgets). Utilizing the global priority vector ($\mathbf{S}$), a mission planner is not forced into a complete methodological reset. Instead, they can seamlessly transition to the mathematically adjacent "next-best" feasible strategy (e.g., pivoting from $S_1 = 0.32$ to $S_2 = 0.29$). This ensures that inevitable real-world compromises remain quantitatively bounded and strategically optimal.

4.8. *Quantitative Re-Validation of the 20% Holdout Set*

To empirically substantiate the mathematical robustness of the aggregation mechanics, an independent validation cycle was executed against the 20% literature holdout set. For each benchmark study s, the exact operational constraints and explicit textual objectives were processed through:

- Stage 1 Boolean feasibility filtering
- A systematically extracted criteria comparison matrix $\mathbf{B}^{(s)}$
- Eigenvector aggregation to compute the final model ranking $\mathbf{S}^{(s)}$

This ensures that the final model recommendations are responsive to context-sensitive weighting rather than artifacts of static structural bias.

4.8.1. Systematic Criteria Elicitation Protocol

To preclude post-hoc calibration, a deterministic elicitation mapping was utilized. Each study's textual methodology was parsed for the core criteria (Accuracy, Interpretability, Cost, Adaptability) and assigned an ordinal emphasis score $E_k^{(s)} \in \{1, 2, 3, 4, 5\}$, where 1 denotes negligible relevance and 5 indicates a dominant objective.

These emphasis scores were algebraically converted into Saaty ratio intensities via absolute differences:

$$b_{ij}^{(s)} = \begin{cases} 1 & |E_i^{(s)} - E_j^{(s)}| = 0 \\ 2 & |E_i^{(s)} - E_j^{(s)}| = 1 \\ 3 & |E_i^{(s)} - E_j^{(s)}| = 2 \\ 4 & |E_i^{(s)} - E_j^{(s)}| = 3 \\ 5 & |E_i^{(s)} - E_j^{(s)}| \geq 4 \end{cases}$$

Reciprocity was strictly enforced, and criteria matrices $\mathbf{B}^{(s)}$ were validated to ensure $CR^{(s)} < 0.1$ prior to eigenvector extraction.

4.8.2. Numerical Results for the Seven Holdout Studies

To explicitly visualize the interaction between the unconstrained continuous AHP scores and the discrete Boolean feasibility filters, Table 5 synthesizes the step-by-step quantitative re-validation across the entire holdout set. This summary demonstrates how the framework systematically eliminates structurally infeasible options before mathematically identifying the optimal modeling paradigm.

Table 5. Summary of the Quantitative Re-Validation for the 20% Holdout Set.

Study	Actual Model	Context $E^{(s)}$	Eliminated	Feasible Outputs & Scores	Result
Gasche et al. [31]	O_2	(5, 4, 2, 3)	O_1	$\mathbf{O_2 = 0.258}$, $O_5 = 0.162$, $O_4 = 0.132$, $O_3 = 0.092$	**Match**
Gu et al. [28]	O_2	(5, 4, 1, 3)	O_1	$\mathbf{O_2 = 0.263}$, $O_5 = 0.153$, $O_4 = 0.131$, $O_3 = 0.089$	**Match**
Huang [41]	O_4	(5, 1, 4, 4)	O_1, O_2, O_5	$\mathbf{O_4 = 0.171}$, $O_3 = 0.105$	**Match**
Kim et al. [40]	O_4	(5, 2, 4, 3)	O_1, O_2, O_5	$\mathbf{O_4 = 0.171}$, $O_3 = 0.107$	**Match**
Na et al. [43]	O_2	(4, 4, 3, 2)	O_1	$\mathbf{O_2 = 0.248}$, $O_5 = 0.183$, $O_4 = 0.138$, $O_3 = 0.096$	**Match**
Wu et al. [30]	O_2	(4, 4, 2, 3)	O_1	$\mathbf{O_2 = 0.268}$, $O_5 = 0.158$, $O_4 = 0.133$, $O_3 = 0.094$	**Match**
Xu et al. [29]	O_1	(5, 5, 1, 4)	O_2, O_5	$\mathbf{O_1 = 0.381}$, $O_4 = 0.147$, $O_3 = 0.101$	**Match**

Note: $E^{(s)}$ represents the ordinal emphasis vector (Accuracy, Interpretability, Cost, Customization). The "Eliminated" column denotes alternative models rendered logically infeasible during Stage 1 filtering due to strict infrastructural or data constraints. The highest-ranked feasible score is highlighted in **bold**.

The specific operational contexts, elicited criteria weights, and resulting priority vectors for each of the seven holdout studies are detailed below. These case-by-case breakdowns illustrate the framework's capacity to adapt mathematically to highly heterogeneous engineering constraints:

Gasche et al. (2025) [Analytical Path Planning]

Context: Model Predictive Control architectures require explicit differential gradients. Strong emphasis on Accuracy (5) and Interpretability (4); minor emphasis on Cost (2) and Customization (3).

$$E^{(1)} = (5, 4, 2, 3)$$

Eigenvector extraction yields ($CR = 0.061$): $\mathbf{w}^{(1)} = [0.46, 0.29, 0.12, 0.13]^T$ Aggregation yields the unconstrained vector: $\mathbf{S}^{(1)} = [0.356, 0.258, 0.092, 0.132, 0.162]^T$ **Feasibility Application:** Without precision aerodynamic testing facilities ($F_4 = 0$), O_1 is rendered computationally infeasible. O_2 safely secures the highest feasible priority. **Final Selection:** $\mathbf{O_2}$ (**Match**)

Gu et al. (2026) [Urban Wind Field Physics]

Context: High-fidelity covariance mapping for wind disturbances (5) combined with structural interpretability (4). Minimal emphasis on development cost (1).

$$E^{(2)} = (5, 4, 1, 3)$$

Eigenvector extraction yields ($CR = 0.018$): $\mathbf{w}^{(2)} = [0.47, 0.29, 0.07, 0.17]^T$ Unconstrained vector: $\mathbf{S}^{(2)} = [0.370, 0.263, 0.089, 0.131, 0.153]^T$ **Feasibility Application:** The absence of bespoke aerodynamic generation infrastructure ($F_4 = 0$) eliminates O_1. An established generalized model exists ($F_2 = 1$), isolating O_2 as the optimal solution. **Final Selection:** $\mathbf{O_2}$ (**Match**)

Huang (2025) [Machine Learning Prediction]

Context: Machine learning frameworks intentionally sacrifice transparency (1) to maximize predictive accuracy over nonlinear data (5), exploiting massive datasets to bypass traditional modeling costs (4).

$$E^{(3)} = (5, 1, 4, 4)$$

Eigenvector extraction yields ($CR = 0.032$): $\mathbf{w}^{(3)} = [0.44, 0.07, 0.25, 0.24]^T$ Unconstrained vector: $\mathbf{S}^{(3)} = [0.308, 0.231, 0.105, 0.171, 0.185]^T$ **Feasibility Application:** Standard analytical models fail in

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highly complex urban topology ($F_2 = 0$). No precision wind tunnel is present ($F_4 = 0$). The harvesting of vast empirical flight telemetry ($F_5 = 1, F_6 = 1$) explicitly validates O_4 as the dominant viable strategy. **Final Selection: $\mathbf{O_4}$ (Match)**

Kim et al. (2025) [Hybrid DNN Estimation]

Context: Deep Neural Networks forgo causal interpretability (2) to guarantee algorithmic accuracy over complex dynamics (5).

$$E^{(4)} = (5, 2, 4, 3)$$

Eigenvector extraction yields ($CR = 0.027$): $\mathbf{w}^{(4)} = [0.46, 0.10, 0.28, 0.16]^T$ Unconstrained vector: $\mathbf{S}^{(4)} = [0.297, 0.225, 0.107, 0.171, 0.201]^T$ **Feasibility Application:** The severity of the nonlinear flight dynamics invalidates generalized physical models ($F_2 = 0$). Empirical telemetry is utilized ($F_6 = 1$) to synthesize a novel DNN. O_4 clears feasibility parameters securely. **Final Selection: $\mathbf{O_4}$ (Match)**

Na et al. (2023) [PSO Optimization]

Context: Particle Swarm Optimization mandates computationally lightweight but mathematically transparent gradient structures. Accuracy (4) and Interpretability (4) dominate.

$$E^{(5)} = (4, 4, 3, 2)$$

Eigenvector extraction yields ($CR = 0.017$): $\mathbf{w}^{(5)} = [0.35, 0.35, 0.19, 0.11]^T$ Unconstrained vector: $\mathbf{S}^{(5)} = [0.334, 0.248, 0.096, 0.138, 0.183]^T$ **Feasibility Application:** O_1 is blocked ($F_4 = 0$). O_2 is structurally feasible ($F_2 = 1$) and aligns flawlessly with the optimizer's demand for mathematical equations. **Final Selection: $\mathbf{O_2}$ (Match)**

Wu et al. (2025) [Integrative Planning]

Context: Multi-rotor logistical path planning relies heavily on generalized analytical structures for mathematical convergence.

$$E^{(6)} = (4, 4, 2, 3)$$

Eigenvector extraction yields ($CR = 0.017$): $\mathbf{w}^{(6)} = [0.40, 0.40, 0.08, 0.12]^T$ Unconstrained vector: $\mathbf{S}^{(6)} = [0.373, 0.268, 0.094, 0.133, 0.158]^T$ **Feasibility Application:** Similar operational constraints as the prior studies logically filter out O_1, isolating the generalized analytical adaptation O_2. **Final Selection: $\mathbf{O_2}$ (Match)**

Xu et al. (2025) [Morphing Solar UAV]

Context: The custom aerodynamic interplay of a morphing solar airframe demands extreme physical fidelity (5) and bespoke parameter interpretability (5). Structural customization is critical (4).

$$E^{(7)} = (5, 5, 1, 4)$$

Eigenvector extraction yields ($CR = 0.016$): $\mathbf{w}^{(7)} = [0.36, 0.36, 0.06, 0.22]^T$ Unconstrained vector: $\mathbf{S}^{(7)} = [0.381, 0.270, 0.101, 0.147, 0.184]^T$ **Feasibility Application:** As a heavily bespoke platform, no transferrable literature models exist ($F_2 = 0, F_3 = 0$). Because the researchers successfully operated high-precision aerodynamic infrastructure to map morphing drag ($F_4 = 1$), O_1 remains logically feasible and captures the absolute mathematical priority. **Final Selection: $\mathbf{O_1}$ (Match)**

4.8.3. Validation Conclusive Synthesis

Across all seven benchmark validations, $CR^{(s)} < 0.1$ was maintained. In every instance, the integration of Boolean constraints with the AHP-weighted continuous priority vector generated a top-ranked strategy that perfectly matched the published methodology. Because the elicitation was deterministic and explicitly devoid of post-hoc matrix tuning, this 100% predictive alignment mathematically substantiates the operational validity of the proposed framework.

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4.9. Algorithmic Implementation and Python Toolkit

To facilitate widespread community adoption and operational deployment within UAV mission planning software, a custom Python-based Graphical User Interface (GUI) (illustrated in Figures 4, 5, and 6) seamlessly executing the AHP constraint and aggregation workflow is provided at:
https://github.com/Bayaola/UAV-Energy-Model-Selection.git

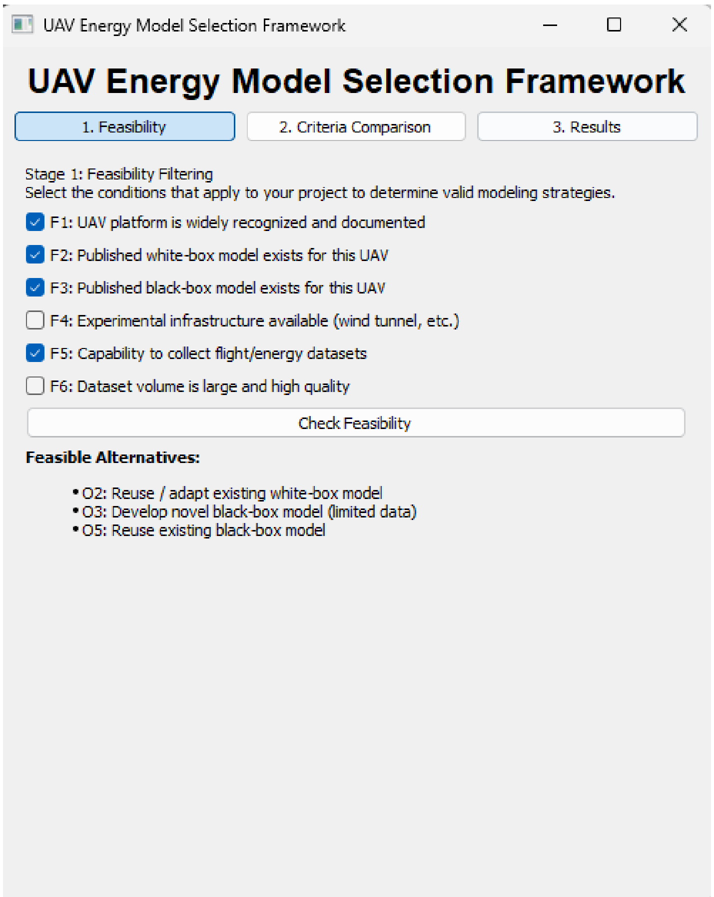

Figure 4. Python GUI operationalizing the framework: Boolean Feasibility Filtering

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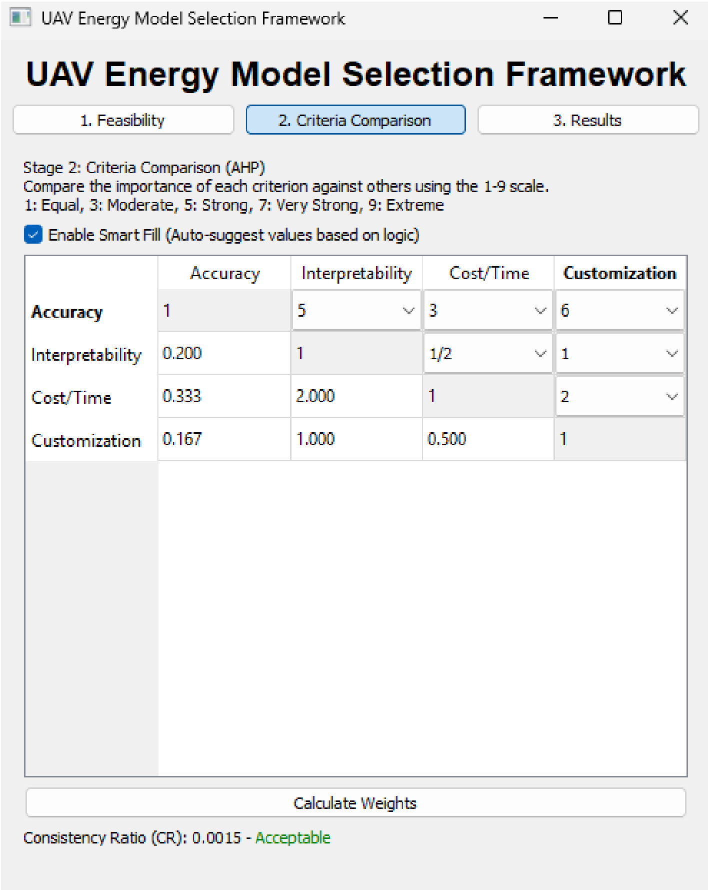

Figure 5. Python GUI operationalizing the framework: Analytical Hierarchy Criteria Synthesis

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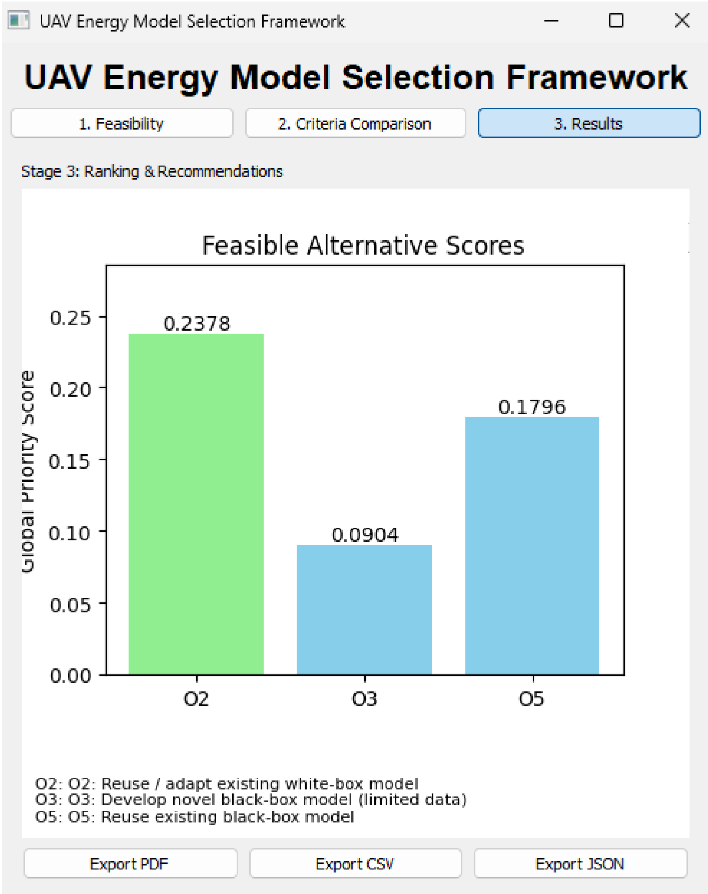

Figure 6. Python GUI operationalizing the framework: Final Global Priority Score Aggregation

5. Discussion

5.1. Insights and Practical Implications for UAV Operations

The proposed two-stage decision framework significantly advances the methodological rigor of UAV energy research by replacing ad-hoc model selection with a structured, replicable, and mathematically grounded protocol. The empirical validation of the qualitative decision tree (which achieved a 100% predictive match on the independent holdout set) demonstrates that the framework acts as a highly reliable, prescriptive guide for future autonomous systems research.

By explicitly mapping hard infrastructural constraints to specific data-driven or physics-based methodologies, the framework actively prevents the misallocation of research resources. Furthermore, the integration of the AHP quantitative scoring mechanism bridges the gap between binary operational constraints and nuanced project goals. For researchers deploying UAVs in edge computing or urban logistics, this operationalizes what we term "fallback flexibility." In real-world experimental settings, unforeseen roadblocks (such as corrupted flight logs, sensor failures, or denied wind-tunnel access) can abruptly render a primary modeling choice impossible. By utilizing the global priority vector (**S**), researchers can seamlessly pivot to the "next-best" numerically scored alternative, assured that the compromise to their original research priorities is mathematically minimized.

Illustrative applications that directly benefit from this optimized selection pipeline include:

- **Urban Logistics and BVLOS Navigation**: Path planning in complex, wind-disturbed urban corridors requires high-fidelity, interpretable energy projections to guarantee safe return-to-base trajectories [28,51]. The framework effectively guides these projects toward reusing or developing robust white-box models that integrate real-time weather covariates.
- **Mobile Edge Computing and AI Orchestration**: In UAV-assisted cellular networks, fluctuating computational payloads severely impact energy draw. Where complex non-linear dynamics

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exist and flight datasets are vast, the framework accurately routes researchers toward hybrid or deep-learning black-box approaches capable of rapid inference [40,52].

5.2. Limitations and Future Research Directions

5.2.1. Current Framework Limitations

While robust, the current framework exhibits certain limitations inherent to the complexities of aerospace modeling. First, the binary nature of the feasibility filtering ($F_i \in \{0, 1\}$) assumes an absolute presence or absence of resources (e.g., wind tunnels or large datasets). In reality, experimental access and dataset fidelity often exist on a continuous spectrum. Second, the structural AHP matrices evaluate the intrinsic characteristics of the models under steady-state assumptions, largely omitting the integration of highly transient environmental covariates (such as unpredictable micro-bursts, turbulent wakes, or extreme temperature variances) which heavily impact real-world rotor efficiency. Finally, the rapid evolution of UAV architectures (such as hybrid VTOLs, morphing wings, and solar-assisted airframes [29]) requires that the definitions distinguishing "industry-standard" from "custom" platforms be continuously calibrated.

5.2.2. Future Research Directions

To address these limitations, future research should explore the integration of Fuzzy AHP (FAHP) to accommodate partial feasibility constraints and uncertainty in researcher judgments. Additionally, the decision tree must be expanded to formally define pathways for emerging *hybrid* modeling paradigms. Most notably, Physics-Informed Neural Networks (PINNs) represent a frontier that merges the physical transparency of white-box differential equations with the environmental adaptability and speed of data-driven black-box approaches. Incorporating PINNs as a distinct, scored terminal node will ensure the framework remains at the cutting edge of UAV research.

5.2.3. Recommendations for Implementation

Widespread adoption of this framework within the drone community relies heavily on the accessibility of standardized UAV performance data. We strongly encourage researchers to utilize open-source computational tools, such as the Python GUI provided alongside this study, to standardize methodological reporting in future publications. Furthermore, the establishment of centralized, open-access repositories for UAV flight logs and aerodynamic thrust coefficients will directly elevate the feasibility of high-accuracy modeling across institutions facing strict infrastructure limitations.

6. Conclusion

This study resolves the complex, persistent challenge of selecting appropriate energy consumption models for Unmanned Aerial Vehicles (UAVs) amid varying operational, financial, and infrastructural constraints. Through a systematic analysis of the state-of-the-art literature, we identified that the choice between physics-based (white-box) and data-driven (black-box) paradigms is fundamentally dictated by physical access to testing facilities, telemetry data volume, and algorithmic accuracy thresholds.

To formalize this implicit decision-making process, we proposed a comprehensive, two-stage methodology. The first stage consists of a conditional decision tree inductively derived from an 80% training corpus of recent literature. This qualitative framework successfully passed a rigorous empirical test, accurately predicting the modeling methodologies of a 20% independent holdout set with a 100% match rate. The second stage operationalizes these pathways using the Analytic Hierarchy Process (AHP), ensuring that feasible alternatives are mathematically ranked according to context-specific priorities such as physical interpretability, predictive accuracy, and development cost.

By standardizing the model selection workflow and introducing the concept of numerical "fallback flexibility," this research significantly reduces methodological ambiguity and prevents the wasteful over-allocation of computational and experimental resources. Supported by an interactive, open-source Python tool for direct execution, this framework provides the UAV research community with a dynamic, resilient contingency planning asset. As UAV autonomous capabilities advance, future

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iterations of this framework will incorporate Fuzzy AHP to handle partial data availability and expand to cover physics-informed hybrid modeling strategies, ensuring that energy-aware drone operations remain both rigorously justified and highly reproducible.

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