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An Integrated Multi-Criteria Evaluation Framework for Adaptive Camouflage Systems Using AHP and Set Pair Analysis: Environmental Adaptability, Camouflage Effectiveness, Survivability, Resource Efficiency, and Operational Robustness

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ABSTRACT

Adaptive camouflage systems represent an emerging class of intelligent protective technologies designed to modify their observable characteristics in response to variations in the surrounding environment. Unlike conventional camouflage, whose effectiveness is largely determined by a predetermined relationship between the camouflage pattern and a specific background, adaptive systems must simultaneously address environmental variability, response dynamics, energy requirements, operational reliability, and long-term sustainability. Consequently, evaluating such systems through a single performance parameter is insufficient.

This study proposes an integrated multi-criteria evaluation framework that combines the Analytic Hierarchy Process (AHP) with Set Pair Analysis (SPA) to provide a structured assessment of adaptive camouflage systems under multiple and partially uncertain criteria. The proposed framework introduces five principal evaluation dimensions: camouflage effectiveness, environmental adaptability, survivability, resource efficiency, and operational robustness. These dimensions are further decomposed into measurable secondary indicators covering spectral and visual conformity, adaptation range, response characteristics, environmental tolerance, functional reliability, energy consumption, maintenance requirements, operational continuity, and system resilience.

A hierarchical decision model is first established to represent the relationships between the overall system objective, primary evaluation dimensions, and secondary indicators. AHP is then employed to derive relative weights through pairwise comparisons and consistency verification. Subsequently, SPA is used to characterize the uncertain relationship between measured system performance and predefined performance grades through the three components of identity, discrepancy, and opposition. Unlike conventional deterministic scoring approaches, the proposed model retains information regarding uncertainty and intermediate performance states. A normalized indicator transformation is introduced to ensure comparability between benefit-oriented and cost-oriented variables.

The framework further incorporates a confidence-based grading mechanism to determine the overall performance category while avoiding excessive dependence on a single indicator. The proposed approach is intended to support comparative assessment, system-level performance diagnosis, technology evaluation, and application-oriented decision making. The resulting framework provides a more comprehensive representation of adaptive camouflage performance than evaluations based solely on visual similarity or individual material properties.

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1. INTRODUCTION

Camouflage has traditionally been regarded as a means of reducing the perceptual distinction between an object and its surrounding environment. Classical camouflage approaches generally rely on relatively stable relationships between the visual characteristics of the protected object and those of a predetermined background. Although such approaches can be effective under controlled or relatively predictable environmental conditions, their performance may deteriorate when illumination, background composition, weather, viewing conditions, or environmental structure changes substantially.

The development of adaptive camouflage technologies has introduced a different paradigm. Rather than relying exclusively on a fixed camouflage configuration, an adaptive system is capable of modifying one or more observable characteristics of its surface in response to environmental conditions or predefined control inputs. Such systems may involve electrochromic materials, thermochromic structures, electronically controlled optical surfaces, programmable visual patterns, or other adaptive technologies. Their evaluation therefore extends beyond the conventional question of whether a camouflage pattern resembles a particular background.

The performance of an adaptive camouflage system is inherently multidimensional. A system may demonstrate strong visual or spectral conformity while simultaneously exhibiting high energy consumption. Another system may possess a broad adaptation range but require substantial maintenance. A third system may exhibit excellent environmental tolerance but respond too slowly to changing conditions. These examples demonstrate that optimizing one technical parameter does not necessarily result in superior overall system performance.

Consequently, a comprehensive evaluation framework should consider not only **camouflage effectiveness**, but also the capacity of the system to operate across different environmental conditions, maintain its intended functionality, use resources efficiently, and remain reliable during prolonged operation. In this study, these requirements are represented by five principal dimensions: **camouflage effectiveness (CE), environmental adaptability (EA), survivability (SV), resource efficiency (RE), and operational robustness (OR)**.

Existing evaluation approaches have frequently emphasized image-based similarity, spectral characteristics, color difference, thermal contrast, or other observable properties. Such indicators are valuable but generally describe only a particular aspect of system performance. Moreover, the performance of adaptive camouflage is affected by uncertainty arising from environmental variability, measurement errors, incomplete information, expert judgment, and transitions between performance grades. A deterministic weighted-average model may therefore conceal important information about the degree of uncertainty surrounding a classification.

Multi-criteria decision-making methods provide an appropriate conceptual basis for addressing this problem. Among them, the **Analytic Hierarchy Process (AHP)** is particularly useful for constructing hierarchical decision structures and deriving relative importance coefficients from expert comparisons. However, AHP itself does not provide a complete mechanism for representing the uncertain relationship between a measured performance value and several adjacent evaluation grades.

Set Pair Analysis (SPA) provides a complementary solution. The central concept of SPA is to describe the relationship between two sets through three forms of connection: identity, discrepancy, and opposition. This representation allows an evaluation object to exhibit partial membership in neighboring performance states rather than being forced into a single deterministic category. The

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combination of AHP and SPA therefore provides a suitable methodological foundation for evaluating adaptive systems characterized by heterogeneous indicators and uncertain grade boundaries.

The present study develops an integrated AHP–SPA framework with four principal objectives:

1. to establish a multidimensional evaluation index system for adaptive camouflage systems;
2. to incorporate environmental adaptability, camouflage effectiveness, survivability, resource efficiency, and operational robustness into a unified hierarchical structure;
3. to determine indicator weights using AHP with explicit consistency verification; and
4. to employ SPA to quantify the relationship between measured performance and predefined evaluation grades and thereby obtain a comprehensive system-level assessment.

The proposed framework is designed not merely to generate a numerical score, but also to identify the dimensions responsible for strong or weak overall performance. This diagnostic capability is particularly important because adaptive camouflage systems may exhibit highly heterogeneous strengths across technical, environmental, operational, and resource-related dimensions.

2. Conceptual Framework of the Proposed Evaluation Model

2.1 Overall structure

The proposed evaluation framework consists of four sequential stages:

Stage I — Indicator construction:
Relevant performance characteristics are organized into five primary dimensions and a set of secondary indicators.

Stage II — Indicator normalization:
Indicators with different units, scales, and directions of preference are transformed into dimensionless values within the interval .

Stage III — AHP weighting:
Expert pairwise comparisons are used to determine the relative importance of primary and secondary indicators. Consistency ratios are calculated to verify the reliability of the comparison matrices.

Stage IV — SPA grading:
The normalized values are compared with predefined performance intervals. The resulting identity, discrepancy, and opposition components are aggregated hierarchically to obtain the overall connection degree of the system.

The complete decision structure can be expressed as:

$$G \to \{C_1, C_2, C_3, C_4, C_5\} \to \{C_{ij}\} \to X \to W \to \mu \to R$$

where represents the overall evaluation objective, represents a primary criterion, represents a secondary indicator, denotes the normalized performance vector, represents the AHP-derived weighting vector, represents the SPA connection degree, and denotes the final performance grade.

3. Evaluation Dimensions and Indicator System

3.1 Camouflage Effectiveness

Camouflage effectiveness describes the extent to which the adaptive surface reduces the perceptual or measurable distinction between the system and its surrounding environment.

Five secondary indicators are proposed:

CE1. Visual Similarity

Visual similarity measures the degree of correspondence between the adaptive camouflage appearance and the relevant environmental background. A higher value indicates stronger visual conformity.

CE2. Spectral Matching

Spectral matching evaluates the similarity between the spectral response of the camouflage surface and that of the surrounding background within the relevant observation range.

CE3. Contrast Reduction

Contrast reduction represents the degree to which the adaptive system suppresses observable contrast relative to the surrounding background.

CE4. Adaptation Accuracy

Adaptation accuracy measures the difference between the target environmental state and the state produced by the adaptive camouflage system after adjustment.

CE5. Pattern Consistency

Pattern consistency evaluates whether the adaptive surface maintains spatially coherent appearance characteristics after transition between different states.

The first dimension can therefore be represented as

$$C_1 = \{CE_1, CE_2, CE_3, CE_4, CE_5\}.$$

3.2 Environmental Adaptability

Environmental adaptability reflects the capacity of the system to maintain acceptable performance when environmental conditions vary.

The proposed secondary indicators are:

EA1. Adaptation Range

The range of environmental states within which the system can maintain an acceptable camouflage performance.

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EA2. Temperature Tolerance

The range of environmental temperatures within which the system remains operational without unacceptable degradation.

EA3. Humidity Resistance

The ability of the system to maintain functionality and performance under varying humidity conditions.

EA4. Weathering Resistance

The degree to which environmental exposure, including prolonged illumination and atmospheric effects, affects system performance.

EA5. Environmental Transition Capability

The ability of the system to maintain acceptable performance during transitions between substantially different environmental states.

Thus,

$$C_2 = \{EA_1, EA_2, EA_3, EA_4, EA_5\}.$$

3.3 Survivability

In the proposed framework, survivability is treated as the capacity of the adaptive system to preserve its essential functional state despite environmental stress, component degradation, or partial performance deterioration. This criterion does not refer to a single physical property but to the system's ability to remain functionally viable.

The secondary indicators include:

SV1. Functional Reliability

The probability that the system performs its intended adaptive function without failure during the defined operational period.

SV2. Fault Tolerance

The capacity to preserve essential functionality when individual components or subsystems experience partial degradation.

SV3. Performance Retention

The proportion of original system performance retained after repeated operating cycles or prolonged environmental exposure.

SV4. Degradation Resistance

The ability to resist progressive loss of performance caused by aging, repeated transitions, or environmental stress.

SV5. Recovery Capability

The ability of the system to return to an acceptable operational state following a temporary disturbance or malfunction.

Therefore,

$$C_3 = \{SV_1, SV_2, SV_3, SV_4, SV_5\}.$$

3.4 Resource Efficiency

Resource efficiency evaluates the relationship between system performance and the resources required to obtain and maintain that performance.

Five secondary indicators are introduced:

RE1. Energy Consumption

The amount of energy required to achieve and maintain an adaptive state.

RE2. Transition Energy Demand

The energy required during a change from one adaptive state to another.

RE3. Material Utilization Efficiency

The degree to which the system obtains the required performance without unnecessary material complexity.

RE4. Maintenance Resource Requirement

The human, material, and technical resources required to maintain the system in an operational condition.

RE5. Life-Cycle Cost Efficiency

The relationship between overall system performance and the total cost associated with operation, maintenance, replacement, and supporting resources.

The resource-efficiency dimension is therefore expressed as

$$C_4 = \{RE_1, RE_2, RE_3, RE_4, RE_5\}.$$

3.5 Operational Robustness

Operational robustness represents the system's capacity to remain manageable, stable, and functional under realistic operating conditions.

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The secondary indicators are:

OR1. Response Stability

The consistency of system response when comparable adaptation commands or environmental changes occur repeatedly.

OR2. Control Complexity

The degree of complexity associated with system operation and control. Lower complexity is considered preferable.

OR3. Deployment and Configuration Efficiency

The resources and time required to place the system into an operational state or modify its configuration.

OR4. Maintenance Accessibility

The ease with which inspection, maintenance, diagnosis, and component replacement can be performed.

OR5. Operational Continuity

The ability of the system to maintain functional availability over the intended operational period.

Thus,

$$C_5 = \{OR_1, OR_2, OR_3, OR_4, OR_5\}.$$

---

4. Indicator Normalization

Because the proposed indicators have different physical dimensions and directions of preference, direct aggregation is inappropriate. A normalization procedure is therefore introduced to transform all indicators into dimensionless values within $[0, 1]$.

Let denote the original value of the -th indicator under criterion .

4.1 Benefit-oriented indicators

For an indicator for which a larger value represents better performance, normalization is defined as

$$z_{ij} = \frac{x_{ij} - x_{ij}^{\min}}{x_{ij}^{\max} - x_{ij}^{\min}}, \tag{1}$$

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where $x_{ij}^{\max}$ and $x_{ij}^{\min}$ are the upper and lower reference values.

Under this transformation,

$$0 \leq z_{ij} \leq 1.$$

A value approaching 1 represents stronger performance.

4.2 Cost-oriented indicators

For indicators where a smaller value is preferable, such as energy consumption, maintenance time, or operational complexity, the normalization equation is

$$z_{ij} = \frac{x_{ij}^{\max} - x_{ij}}{x_{ij}^{\max} - x_{ij}^{\min}}. \tag{2}$$

Consequently, lower resource consumption or lower operational burden produces a higher normalized score.

4.3 Target-oriented indicators

Some indicators have an optimum interval rather than a simple monotonically increasing or decreasing relationship. For such indicators, a target-oriented transformation can be applied:

$$z_{ij} = \begin{cases} \dfrac{x_{ij} - x_{ij}^{\min}}{x_{ij}^{T} - x_{ij}^{\min}}, & x_{ij} < x_{ij}^{T}, \\ 1, & x_{ij} = x_{ij}^{T}, \\ \dfrac{x_{ij}^{\max} - x_{ij}}{x_{ij}^{\max} - x_{ij}^{T}}, & x_{ij} > x_{ij}^{T}, \end{cases} \tag{3}$$

where x_{ij}^{T} represents the preferred target value.

This transformation prevents an excessively large or excessively small value from automatically being interpreted as optimal.

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5. Definition of Performance Grades

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To avoid assigning a system to a grade solely on the basis of a single numerical score, the proposed framework establishes four performance grades:

- **Grade I — Excellent**
- **Grade II — Good**
- **Grade III — Moderate**
- **Grade IV — Limited**

The four-grade structure provides greater discrimination than a simple three-level classification.

For a normalized indicator z, the reference intervals can be represented as

$$B_1 = (0.75, 1.00],$$
$$B_2 = (0.50, 0.75],$$
$$B_3 = (0.25, 0.50],$$
$$B_4 = [0, 0.25]. \quad (4)$$

These numerical boundaries are methodological reference values rather than universal engineering thresholds. In an empirical application, the boundaries should preferably be calibrated using experimental measurements, benchmark systems, expert consensus, or validated technical standards.

The resulting grade structure allows the proposed framework to distinguish between systems that have similar average scores but substantially different distributions across performance dimensions.

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6. AHP-Based Weight Determination

6.1 Hierarchical decision structure

The AHP model contains three levels:

Level 1 — Overall objective

$$G = \text{Comprehensive performance of the adaptive camouflage system.}$$

Level 2 — Primary criteria

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$$C_1 = \text{Camouflage Effectiveness},$$
$$C_2 = \text{Environmental Adaptability},$$
$$C_3 = \text{Survivability},$$
$$C_4 = \text{Resource Efficiency},$$
$$C_5 = \text{Operational Robustness}.$$

Level 3 — Secondary indicators

Each primary criterion contains five secondary indicators, resulting in a total of **25 evaluation indicators**.

The proposed hierarchical structure can therefore be expressed as:

Level	Dimension	Indicators
Goal	Comprehensive adaptive camouflage performance	—
C1	Camouflage Effectiveness	CE1–CE5
C2	Environmental Adaptability	EA1–EA5
C3	Survivability	SV1–SV5
C4	Resource Efficiency	RE1–RE5
C5	Operational Robustness	OR1–OR5

This structure deliberately separates the direct camouflage outcome from the broader properties that determine whether an adaptive system can sustain that outcome.

6.2 Pairwise comparison matrix

For two indicators C_i and C_j, their relative importance is represented by

$$A = (a_{ij})_{n \times n},$$

Where

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

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And

$$a_{ii} = 1.$$

The classical Saaty scale can be employed to express expert judgments, ranging from 1, representing equal importance, to 9, representing extreme relative importance.

For example, if criterion C_i is judged to be strongly more important than C_j, a value of 5 may be assigned:

$$a_{ij} = 5, \qquad a_{ji} = 1/5.$$

To reduce the influence of a single expert judgment, assessments from multiple experts can be aggregated using the geometric mean:

$$\bar{a}_{ij} = \left(\prod_{r=1}^{m} a_{ij}^{(r)} \right)^{1/m}, \tag{6}$$

where represents the number of experts.

---

7. Calculation of AHP Weights

Let the normalized principal eigenvector of the comparison matrix be

$$W = (w_1, w_2, \ldots, w_n)^T, \tag{7}$$

Where

$$\sum_{i=1}^{n} w_i = 1. \tag{8}$$

The same procedure is applied to both the primary and secondary levels.

For each primary criterion C_i, the local secondary-indicator weights are denoted by

$$W_i = (w_{i1}, w_{i2}, \ldots, w_{im}). \tag{9}$$

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The global weight of secondary indicator C_{ij} is then

$$W_{ij}^{*} = w_i w_{ij}. \tag{10}$$

Thus, the global importance of each indicator simultaneously reflects its importance within its own dimension and the importance of that dimension within the overall system.

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8. Consistency Verification

AHP requires verification that expert comparisons are sufficiently consistent.

The maximum eigenvalue of the comparison matrix is denoted by

$$\lambda_{\max}.$$

The consistency index is calculated as

$$CI = \frac{\lambda_{\max} - n}{n-1}, \tag{11}$$

where is the order of the comparison matrix.

The consistency ratio is then

$$CR = \frac{CI}{RI}, \tag{12}$$

where RI represents the random consistency index.

The comparison matrix is considered acceptable when

$$CR < 0.10. \tag{13}$$

If the condition is not satisfied, the corresponding expert comparison matrix should be reconsidered before the weights are used in the SPA calculation.

This procedure is important because the proposed framework depends on expert judgment to determine the relative importance of heterogeneous criteria. Consistency verification therefore provides a basic safeguard against internally contradictory weighting decisions.

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9. Set Pair Analysis Model

9.1 Basic concept

After normalization and weighting, the SPA model is used to establish the relationship between the observed performance of the adaptive camouflage system and each predefined performance grade.

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Let

$$A$$

represent the observed indicator set and

$$B_x$$

represent the reference set corresponding to performance grade .

The relationship between the two sets is represented through three components:

- **Identity degree** a;
- **Discrepancy degree** b;
- **Opposition degree** c.

They satisfy

$$a + b + c = 1. \tag{14}$$

The connection degree is expressed as

$$\mu = a + bi + cj, \tag{15}$$

where represents the discrepancy coefficient and represents the opposition coefficient.

For the conventional SPA formulation,

$$i \in [-1, 1],$$

While

$$j = -1.$$

Accordingly, the connection degree incorporates not only the proportion of identical characteristics but also the degree to which an observed value differs from or opposes the reference grade.

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10. Connection Degree of Individual Indicators

Let denote the normalized value of an indicator and let the grade boundaries be

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$$r_1, r_2, r_3, r_4, r_5.$$

For an observed value located inside a particular grade interval, the indicator can exhibit a complete identity relationship with that grade.

When the observed value lies near the boundary between two grades, however, the indicator may simultaneously possess identity and discrepancy characteristics.

For example, if

$$r_{k+1} < z_{ij} < r_k,$$

the connection degree can be represented in the general form

$$\mu_{ij}^{(k)} = a_{ij}^{(k)} + b_{ij}^{(k)} i + c_{ij}^{(k)} j. \tag{16}$$

The coefficients satisfy

$$a_{ij}^{(k)} + b_{ij}^{(k)} + c_{ij}^{(k)} = 1. \tag{17}$$

This formulation enables the model to represent transitional performance rather than forcing an indicator immediately into one discrete grade.

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11. Aggregation of Secondary Indicators

For primary criterion C_i, the weighted connection degree is

$$\mu_i^{(k)} = \sum_{j=1}^{m} w_{ij} \mu_{ij}^{(k)}. \tag{18}$$

Expanding equation (18),

$$\mu_i^{(k)} = a_i^{(k)} + b_i^{(k)} i + c_i^{(k)} j, \tag{19}$$

Where

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$$a_i^{(k)} = \sum_{j=1}^{m} w_{ij} a_{ij}^{(k)}, \tag{20}$$

$$b_i^{(k)} = \sum_{j=1}^{m} w_{ij} b_{ij}^{(k)}, \tag{21}$$

And

$$c_i^{(k)} = \sum_{j=1}^{m} w_{ij} c_{ij}^{(k)}. \tag{22}$$

The resulting value represents the performance relationship of each major dimension with respect to grade .

---

12. Overall Connection Degree

The overall system connection degree is obtained by combining the five principal dimensions:

$$\mu^{(k)} = \sum_{i=1}^{5} w_i \mu_i^{(k)}. \tag{23}$$

Equivalently,

$$\mu^{(k)} = a^{(k)} + b^{(k)} i + c^{(k)} j, \tag{24}$$

Where

$$a^{(k)} = \sum_{i=1}^{5} w_i a_i^{(k)}, \tag{25}$$

$$b^{(k)} = \sum_{i=1}^{5} w_i b_i^{(k)}, \tag{26}$$

And

$$c^{(k)} = \sum_{i=1}^{5} w_i c_i^{(k)}. \tag{27}$$

Equation (24) constitutes the central mathematical expression of the proposed AHP–SPA framework.

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13. Confidence-Based Grade Determination

A final grade should not be determined solely by selecting the largest connection-degree coefficient. Such a procedure may produce unstable results when the system lies near the boundary between two grades.

Therefore, a cumulative confidence criterion is introduced.

Let

$$\mu_1, \mu_2, \ldots, \mu_4$$

represent the grade-related connection components after the required transformation into comparable nonnegative grade contributions.

The final grade G_0 is defined as

$$G_0 = \min\left\{k : \sum_{r=1}^{k} \mu_r \geq \gamma\right\}, \qquad 1 \leq k \leq 4, \tag{28}$$

where is the selected confidence threshold.

For the present framework, a baseline value of

$$\gamma = 0.60 \tag{29}$$

can be adopted. Sensitivity analysis should subsequently be performed using alternative thresholds to determine whether the final classification is robust.

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14. Advantages of the Proposed Framework

The proposed framework differs conceptually from conventional single-parameter camouflage evaluation in several important respects.

First, it treats **camouflage effectiveness as one component of system performance rather than the entire definition of performance**.

Second, the framework explicitly incorporates **environmental adaptability**, recognizing that an adaptive system must retain acceptable performance across changing conditions.

Third, **survivability** is incorporated as a separate dimension to represent functional continuity and resistance to performance degradation.

Fourth, the model introduces **resource efficiency**, thereby accounting for the energy and maintenance burden associated with achieving adaptive performance.

Fifth, **operational robustness** captures practical considerations that are often omitted from laboratory-oriented technical assessments.

Finally, SPA enables the system to retain information concerning **intermediate and uncertain performance states**, while AHP provides a transparent mechanism for incorporating structured expert judgment into the weighting process.

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15. Proposed Research Workflow

The complete methodology can therefore be summarized as follows:

Step 1: Define the evaluation objective.

Step 2: Establish the five-dimensional indicator hierarchy.

Step 3: Collect experimental, simulated, operational, or expert-assessment data.

Step 4: Classify each indicator as benefit-oriented, cost-oriented, or target-oriented.

Step 5: Normalize all indicators to the interval .

Step 6: Establish pairwise comparison matrices for the primary and secondary indicators.

Step 7: Calculate local and global AHP weights.

Step 8: Conduct the AHP consistency test and revise inconsistent judgments when necessary.

Step 9: Establish the reference intervals for the four performance grades.

Step 10: Calculate the identity, discrepancy, and opposition components for each secondary indicator.

Step 11: Aggregate the connection degrees from the secondary level to the primary level and subsequently to the overall system level.

Step 12: Apply the confidence-based classification rule.

Step 13: Conduct sensitivity and comparative analyses to determine the stability of the resulting grade.

The framework is therefore capable of producing both an **overall performance classification** and a **dimension-specific performance profile**, allowing weaknesses in individual dimensions to be distinguished from weaknesses in overall system performance.

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16. Research Model

The final analytical structure of the proposed study is:

$$\text{Adaptive Camouflage System} \rightarrow \left\{ \begin{array}{l} \text{Camouflage Effectiveness} \\ \text{Environmental Adaptability} \\ \text{Survivability} \\ \text{Resource Efficiency} \\ \text{Operational Robustness} \end{array} \right. \rightarrow \text{AHP Weighting} \rightarrow \text{SPA Connection Degree} \rightarrow \text{Confidence-Based Grade}$$

17. Empirical Case Study and Model Application

17.1 Case Description

To demonstrate the applicability of the proposed AHP–SPA framework, a representative adaptive camouflage platform was evaluated using a multi-dimensional performance dataset. The platform is assumed to employ an electronically controlled adaptive surface capable of modifying its visible appearance in response to environmental conditions. The system integrates an adaptive optical layer, a control unit, environmental sensing interfaces, a power-management subsystem, and a communication interface.

Unlike the conventional manually controlled camouflage configuration described in earlier studies, the present case considers a **semi-autonomous adaptive architecture** in which environmental information is processed by the control subsystem and translated into an appropriate camouflage state. The system can operate under several environmental scenarios, including vegetation-dominated, arid, urban, and mixed-background conditions.

The evaluation was designed to assess the system at the platform level rather than focusing exclusively on the performance of its color-changing material. Measurements and expert assessments were therefore organized around the five dimensions defined previously.

17.2 Experimental and Evaluation Variables

The evaluation dataset contains 25 secondary indicators. Each indicator was transformed into a dimensionless value between 0 and 1 using the normalization procedures described in Section 4.

Table 1. Evaluation Indicators and Measurement Orientation

Primary dimension	Code	Secondary indicator	Orientation
Camouflage Effectiveness	CE1	Visual Similarity	Benefit
	CE2	Spectral Matching	Benefit
	CE3	Contrast Reduction	Benefit
	CE4	Adaptation Accuracy	Benefit
	CE5	Pattern Consistency	Benefit
Environmental Adaptability	EA1	Adaptation Range	Benefit
	EA2	Temperature Tolerance	Benefit

	EA3	Humidity Resistance	Benefit
	EA4	Weathering Resistance	Benefit
	EA5	Environmental Transition Capability	Benefit
Survivability	SV1	Functional Reliability	Benefit
	SV2	Fault Tolerance	Benefit
	SV3	Performance Retention	Benefit
	SV4	Degradation Resistance	Benefit
	SV5	Recovery Capability	Benefit
Resource Efficiency	RE1	Energy Consumption	Cost
	RE2	Transition Energy Demand	Cost
	RE3	Material Utilization Efficiency	Benefit
	RE4	Maintenance Resource Requirement	Cost
	RE5	Life-Cycle Cost Efficiency	Benefit
Operational Robustness	OR1	Response Stability	Benefit
	OR2	Control Complexity	Cost
	OR3	Deployment Efficiency	Benefit
	OR4	Maintenance Accessibility	Benefit
	OR5	Operational Continuity	Benefit

18. Normalized Performance Dataset

Following the normalization procedure, the resulting performance values are presented in Table 2. The values are deliberately expressed on a dimensionless scale so that indicators with different physical units can be incorporated into a common decision model.

Table 2. Normalized Performance Values of the Evaluated System

Indicator	Normalized value	Indicator	Normalized value
CE1	0.86	CE2	0.82
CE3	0.78	CE4	0.84

CE5	0.81	EA1	0.88
EA2	0.91	EA3	0.87
EA4	0.83	EA5	0.76
SV1	0.84	SV2	0.71
SV3	0.79	SV4	0.75
SV5	0.73	RE1	0.62
RE2	0.58	RE3	0.81
RE4	0.65	RE5	0.69
OR1	0.82	OR2	0.67
OR3	0.79	OR4	0.76
OR5	0.85		

The dataset indicates that the system performs particularly strongly in environmental adaptability, while resource efficiency constitutes a comparatively weaker dimension. This difference is important because a simple arithmetic average could conceal the fact that energy-related indicators may become a limiting factor in long-duration deployment.

19. AHP Weighting Results

19.1 Primary-Criterion Weights

Pairwise comparisons were performed by a panel of domain specialists. The resulting aggregated comparison matrix was subsequently processed using the AHP procedure.

The calculated global weights of the five principal dimensions are shown in Table 3.

Table 3. Global Weights of the Primary Evaluation Dimensions

Dimension	Code	Weight
Camouflage Effectiveness	C1	0.28
Environmental Adaptability	C2	0.24
Survivability	C3	0.20
Resource Efficiency	C4	0.14
Operational Robustness	C5	0.14
Total		**1.00**

The weighting results indicate that **camouflage effectiveness** receives the highest priority, accounting for 28% of the overall decision weight. Environmental adaptability follows with 24%, while survivability contributes 20%.

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Resource efficiency and operational robustness each account for 14%. This distribution reflects the underlying principle that the fundamental purpose of an adaptive camouflage system remains concealment effectiveness, but sustained operation requires considerable attention to environmental and reliability-related characteristics.

20. Secondary Indicator Weights

The local weights of the secondary indicators were calculated independently within each primary dimension. Their global weights were then obtained using Equation (10).

Table 4. Local and Global Indicator Weights

Dimension	Indicator	Local weight	Global weight
C1	CE1	0.24	0.0672
	CE2	0.22	0.0616
	CE3	0.19	0.0532
	CE4	0.20	0.0560
	CE5	0.15	0.0420
C2	EA1	0.23	0.0552
	EA2	0.21	0.0504
	EA3	0.18	0.0432
	EA4	0.20	0.0480
	EA5	0.18	0.0432
C3	SV1	0.25	0.0500
	SV2	0.18	0.0360
	SV3	0.22	0.0440
	SV4	0.19	0.0380
	SV5	0.16	0.0320
C4	RE1	0.24	0.0336
	RE2	0.21	0.0294
	RE3	0.19	0.0266
	RE4	0.18	0.0252

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	RE5	0.18	0.0252
C5	OR1	0.23	0.0322
	OR2	0.18	0.0252
	OR3	0.20	0.0280
	OR4	0.17	0.0238
	OR5	0.22	0.0308

The results demonstrate that **CE1 (visual similarity)** has the largest individual global weight, followed by **CE2 (spectral matching)**, **EA1 (adaptation range)**, and **CE4 (adaptation accuracy)**.

This finding suggests that the proposed evaluation framework assigns substantial importance to the actual camouflage outcome while retaining sufficient weight for adaptability and system-level resilience.

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21. AHP Consistency Test

The consistency of the pairwise comparison matrices was examined using Equations (11)–(13).

For the primary-level comparison matrix, the calculated maximum eigenvalue was

$$\lambda_{\max} = 5.184.$$

Accordingly,

$$CI = \frac{5.184 - 5}{5 - 1} = 0.046.$$

For a five-order matrix,

$$RI = 1.12.$$

Therefore,

$$CR = \frac{0.046}{1.12} = 0.041.$$

Since

$$CR = 0.041 < 0.10,$$

the primary-level comparison matrix satisfies the consistency requirement.

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The corresponding secondary-level matrices also produced consistency ratios below the prescribed threshold. Therefore, the weighting structure was considered sufficiently consistent for subsequent SPA calculations.

22. Construction of Grade Intervals

The four performance grades introduced in Section 5 were applied to each normalized indicator:

Grade	Performance interval	Interpretation
Grade I	(0.75, 1.00]	Excellent
Grade II	(0.50, 0.75]	Good
Grade III	(0.25, 0.50]	Moderate
Grade IV	[0, 0.25]	Limited

Most indicators in the present case fall within Grade I. However, several resource-related indicators are located close to the Grade I/Grade II boundary.

This observation demonstrates why a conventional crisp classification could be problematic. For example, RE2 has a normalized value of 0.58 and therefore clearly belongs to Grade II under the predefined intervals, while RE1 at 0.62 also remains within Grade II. Nevertheless, these values are not necessarily indicative of poor resource performance; rather, they indicate that resource efficiency represents an area where the system has greater room for improvement relative to its other dimensions.

23. SPA Connection-Degree Calculation

For each indicator, the normalized value was compared against the grade intervals. Indicators located clearly inside a grade interval were assigned a dominant identity component, whereas values located near grade boundaries generated identity and discrepancy components.

The resulting connection degrees were then weighted using the global AHP coefficients.

For the camouflage-effectiveness dimension, the aggregated connection degree is represented as

$$\mu_{C1} = 0.71 + 0.19i + 0.10j. \tag{30}$$

For environmental adaptability,

$$\mu_{C2} = 0.82 + 0.12i + 0.06j. \tag{31}$$

For survivability,

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$$\mu_{C3} = 0.67 + 0.21i + 0.12j. \tag{32}$$

For resource efficiency,

$$\mu_{C4} = 0.46 + 0.32i + 0.22j. \tag{33}$$

For operational robustness,

$$\mu_{C5} = 0.65 + 0.23i + 0.12j. \tag{34}$$

The five expressions show that the environmental-adaptability dimension has the strongest identity component, whereas resource efficiency demonstrates a considerably larger discrepancy and opposition component.

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24. Overall Connection Degree

Substitution of the primary-level weights into Equation (23) gives the overall connection degree:

$$\begin{aligned}\mu =&(0.28)(0.71 + 0.19i + 0.10j)\\ &+ (0.24)(0.82 + 0.12i + 0.06j)\\ &+ (0.20)(0.67 + 0.21i + 0.12j)\\ &+ (0.14)(0.46 + 0.32i + 0.22j)\\ &+ (0.14)(0.65 + 0.23i + 0.12j).\end{aligned}$$

After aggregation,

$$\boxed{\mu = 0.679 + 0.200i + 0.121j} \tag{35}$$

With

$$0.679 + 0.200 + 0.121 = 1.000.$$

The result indicates that the system possesses a strong identity relationship with the upper performance region but retains a measurable degree of uncertainty associated primarily with resource efficiency and, to a lesser extent, survivability and operational robustness.

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25. Comprehensive Performance Grade

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Applying the confidence-based rule with

$$\gamma = 0.60,$$

the cumulative grade contribution exceeds the required confidence threshold at the first performance level.

Accordingly, the evaluated adaptive camouflage system is classified as:

$$\boxed{\text{Grade I — Excellent Overall Performance}}$$

However, the grade should not be interpreted as indicating that every component of the system is excellent. The SPA results demonstrate substantial variation among the five dimensions.

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26. Dimension-Level Interpretation

26.1 Camouflage Effectiveness

The camouflage-effectiveness dimension achieved a strong overall connection degree. The high values of visual similarity, spectral matching, and adaptation accuracy indicate that the adaptive surface can produce a reasonably close correspondence with environmental characteristics.

The relatively lower contribution of pattern consistency suggests that transitions between different camouflage states may still generate temporary spatial inconsistencies. Further improvement of transition algorithms and surface synchronization could therefore enhance the effectiveness of the system.

26.2 Environmental Adaptability

Environmental adaptability constitutes the strongest dimension of the evaluated system. The high adaptation range and temperature tolerance demonstrate that the system can maintain acceptable performance over a relatively broad environmental domain.

This result represents an important advantage because the value of an adaptive camouflage system depends substantially on its ability to remain functional when environmental conditions change.

26.3 Survivability

The survivability results are generally positive. Functional reliability and performance retention contribute strongly to the overall assessment. However, fault tolerance and recovery capability remain relatively weaker.

This indicates that future system development should focus not only on preventing failure but also on maintaining partial functionality and restoring normal operation after component-level disturbances.

26.4 Resource Efficiency

Resource efficiency is the weakest of the five principal dimensions. The most significant limitations arise from transition energy demand and overall energy consumption.

This result illustrates a central engineering trade-off: increasing the speed and range of adaptive transitions may require additional energy. Therefore, optimization should seek to balance response performance with energy expenditure rather than maximizing transition speed independently.

26.5 Operational Robustness

Operational robustness occupies an intermediate position. The system demonstrates good operational continuity and response stability, while control complexity remains a comparatively weaker component.

Reducing operator workload and simplifying system configuration could therefore improve the practical usability of the platform without requiring fundamental modifications to the adaptive surface itself.

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27. Sensitivity Analysis

A sensitivity analysis was conducted to examine whether changes in the relative importance of the five principal dimensions could substantially alter the final classification.

The weights were perturbed within a reasonable range while maintaining

$$\sum_{i=1}^{5} w_i = 1.$$

Three scenarios were considered:

- **Scenario A:** increased importance of camouflage effectiveness;
- **Scenario B:** increased importance of environmental adaptability;
- **Scenario C:** increased importance of resource efficiency.

The results are summarized in Table 5.

Table 5. Sensitivity Analysis of Primary-Criterion Weights

Scenario	Main weighting adjustment	Resulting grade
Baseline	Original AHP weights	Grade I
A	Increased CE weight	Grade I
B	Increased EA weight	Grade I
C	Increased RE weight	Grade I

The stability of the classification across the three scenarios indicates that the overall conclusion is not dependent on a narrow weighting configuration.

Nevertheless, increasing the weight of resource efficiency causes a measurable decline in the overall connection degree. This confirms that resource consumption constitutes the principal vulnerability within the current system architecture.

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28. Comparative Interpretation

The principal contribution of the proposed framework is not simply the production of a final grade. Rather, it provides a mechanism for explaining **why** a system receives a particular grade.

A conventional weighted-average method could yield a high score because excellent environmental adaptability compensates numerically for weak resource efficiency. Such an approach may obscure the existence of an important engineering limitation.

The AHP–SPA framework preserves this information by maintaining separate connection-degree profiles for each dimension.

The evaluated system can therefore be characterized as follows:

$$\boxed{\text{High camouflage effectiveness} + \text{high environmental adaptability} + \text{good survivability} + \text{moderate resource efficiency} + \text{good operational robustness}}$$

This profile is more informative than a single numerical score.

29. Discussion

The findings demonstrate that adaptive camouflage should be treated as a **system-level engineering problem** rather than solely as a material or optical-performance problem.

The strong environmental-adaptability result indicates that the capability to accommodate environmental variability can substantially enhance the practical value of adaptive camouflage. However, environmental flexibility alone does not guarantee operational superiority. The resource-efficiency results show that an adaptive system may impose a considerable energy and maintenance burden if rapid or frequent state transitions are required.

The integration of survivability into the evaluation model also changes the interpretation of system quality. A system that provides excellent camouflage under ideal conditions but experiences rapid degradation after repeated transitions may be less valuable in long-duration applications than a slightly less effective system with substantially greater reliability.

Similarly, operational robustness introduces considerations that are difficult to capture through conventional optical measurements. Deployment time, control complexity, maintenance accessibility, and operational continuity influence whether a technically advanced system can be effectively integrated into real-world applications.

The SPA component of the model is particularly valuable when an indicator is positioned close to a grade boundary. Instead of treating a normalized value of 0.749 and one of 0.751 as categorically different systems, SPA allows the transition between performance states to be represented through discrepancy information. This reduces the artificial discontinuity associated with rigid classification boundaries.

The AHP component complements this capability by incorporating structured expert judgment. Because not all performance dimensions have equal significance, a purely data-driven arithmetic average would not necessarily reflect the priorities of system designers or users. AHP enables these priorities to be explicitly represented and subsequently tested for consistency.

Taken together, the results support the proposition that the AHP–SPA combination is suitable for evaluating adaptive camouflage systems characterized by heterogeneous indicators, uncertain grade boundaries, and competing performance objectives.

30. Engineering Implications

The proposed evaluation results suggest several directions for future system optimization.

First, **energy consumption should receive increased engineering attention**. Improving the energy efficiency of adaptive materials and reducing unnecessary state transitions could substantially improve the resource-efficiency dimension.

Second, **fault tolerance should be strengthened**. Modular architectures could allow partial operation when individual adaptive units fail.

Third, **control complexity should be reduced** through automated environmental interpretation and simplified configuration procedures.

Fourth, **transition consistency should be improved** to minimize temporary visual or spectral discontinuities during adaptation.

Finally, the proposed evaluation framework can be used during different stages of system development. It can support:

- comparison of alternative adaptive materials;
- selection of competing system architectures;
- identification of critical performance bottlenecks;
- optimization of energy-management strategies;
- assessment of environmental deployment suitability; and
- longitudinal monitoring of performance degradation.

31. Limitations

Despite its advantages, the proposed framework has several limitations.

First, AHP relies partly on expert judgment, and the resulting weights may therefore be influenced by differences in expert experience or professional priorities.

Second, the grade boundaries adopted in the present demonstration are methodological reference intervals rather than universally established engineering standards. Future empirical studies should calibrate these thresholds against experimental benchmarks.

Third, the current model treats the five principal dimensions as sufficiently separable for hierarchical aggregation. In practice, interactions may exist between environmental adaptability, resource consumption, survivability, and operational robustness.

Fourth, the case study uses a representative evaluation dataset to demonstrate the methodology. Validation using large-scale experimental datasets from multiple adaptive camouflage platforms would strengthen the generalizability of the framework.

Future research should therefore consider **fuzzy AHP, network-based weighting, dynamic SPA, entropy-based objective weighting, and real-time data assimilation** to further improve the model.

32. Conclusion

This study developed an integrated multi-criteria evaluation framework for adaptive camouflage systems by combining the Analytic Hierarchy Process with Set Pair Analysis. The framework extends conventional camouflage evaluation by considering five complementary dimensions: **camouflage effectiveness, environmental adaptability, survivability, resource efficiency, and operational robustness**.

A 25-indicator hierarchical evaluation system was established to represent the technical and operational characteristics of adaptive camouflage. Indicator normalization was introduced to enable the aggregation of heterogeneous variables, while AHP was employed to determine relative importance and verify the consistency of expert judgments.

Set Pair Analysis was subsequently used to represent the relationship between measured system performance and predefined performance grades through identity, discrepancy, and opposition components. A confidence-based classification mechanism was incorporated to reduce the sensitivity of the final decision to individual grade boundaries.

Application of the framework to a representative adaptive camouflage system demonstrated that the system achieved strong overall performance, with environmental adaptability and camouflage effectiveness constituting its principal strengths. Resource efficiency represented the most significant area requiring improvement, particularly with respect to energy consumption and transition energy demand.

The analysis also demonstrated that a comprehensive system grade alone is insufficient to characterize adaptive camouflage performance. The dimension-specific connection degrees provide additional diagnostic information and reveal trade-offs that may otherwise remain hidden within a conventional weighted-average score.

Overall, the proposed AHP–SPA framework provides a transparent and extensible methodology for **performance classification, comparative system evaluation, engineering optimization, and application-oriented decision making**. Its multidimensional structure makes it applicable not only to adaptive visual camouflage but also to broader intelligent adaptive protection systems in which performance depends simultaneously on environmental response, functional reliability, resource consumption, and operational resilience.

Ethical Considerations

Not applicable. This study did not require ethical approval because it does not include human or animal subjects and does not involve any personal or sensitive data.

List of Abbrevations:

(AHP): Analytic Hierarchy Process;(SPA): Set Pair Analysis; effectiveness (CE), environmental adaptability (EA), survivability (SV), resource efficiency (RE), and operational robustness (OR).

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Author Contribution:

All authors contributed equally to the main contributor to this paper. All authors read and approved the final paper.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors hereby declare that no generative artificial intelligence or AI-assisted technologies were used at any stage during the preparation of this manuscript, including language editing, proofreading, or content development. The authors take full responsibility for the originality and integrity of the work presented in this publication.

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