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Evaluating the Autonomy Level of Unmanned Aerial Vehicles: Methodological Aspects and Fuzzy-Possibilistic Modeling

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Purpose and Content of the Report

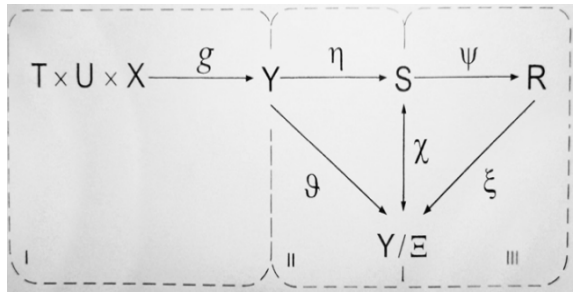
- **The report reviews some comparative characteristics of mathematical methods for evaluating the autonomy level of unmanned aerial vehicles (UAVs).**
- **An original methodological framework is proposed for solving the problem of quantitative autonomy assessment of reconnaissance UAVs using a fuzzy-possibilistic approach (FPA).**
- **The FPA is based on the use of expert knowledge, where the expert themselves function as an "intelligent information-diagnostic system."**
- **The result of applying the FPA is a fuzzy-possibilistic model (FPM) built on a multifactorial set of fuzzy linguistic variables.**
- **The methodological and systematic foundations for the synthesis of the FPM are outlined.**
- **The proposed methodological approach is universal and applicable to solving problems of creating predictive fuzzy-possibilistic models of any complexity in any subject domain.**

Comparative analysis of methods

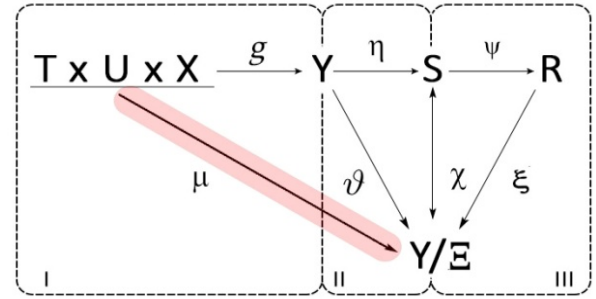
- ***Level-based methods (ACL (Autonomy Control Levels), NASA, SAE (Society of Automotive Engineers)) are simple to apply and provide a clear, visual result; however, they are qualitative in nature and do not allow for fine differentiation between UAVs with a similar level.***
- ***Multidimensional methods (ALFUS, spider model) are more informative but require solving problems related to factor correlation, measurement of values along the axes, and weight distribution.***
- ***Fuzzy methods and methods based on AHP (Analytic Hierarchy Process, T. Saaty) are well-suited for situations where some of the indicators are difficult to quantify and one must rely on expert judgments. Combining AHP with entropy weight allows for a reduction in the subjectivity of expert assessments.***
- ***Metric methods based on OODA (Observe–Orient–Decide–Act decision-making loop) provide the most objective assessment but require detailed knowledge of the internal system architecture and the implementation of all stages of the control cycle.***
- ***The Method for Robust Autonomy Evaluation (MRA) is the only one that accounts for the impact of failures on autonomy, which is critically important for UAV certification.***

The mathematical models or approaches used often require the probability values of the variables involved or their weighting coefficients as subjective expert estimates. Such implicit linearization of the models leads to a significant simplification of the UAV autonomy evaluation problem itself.

Methods for assessing the state of the phenomenon under study

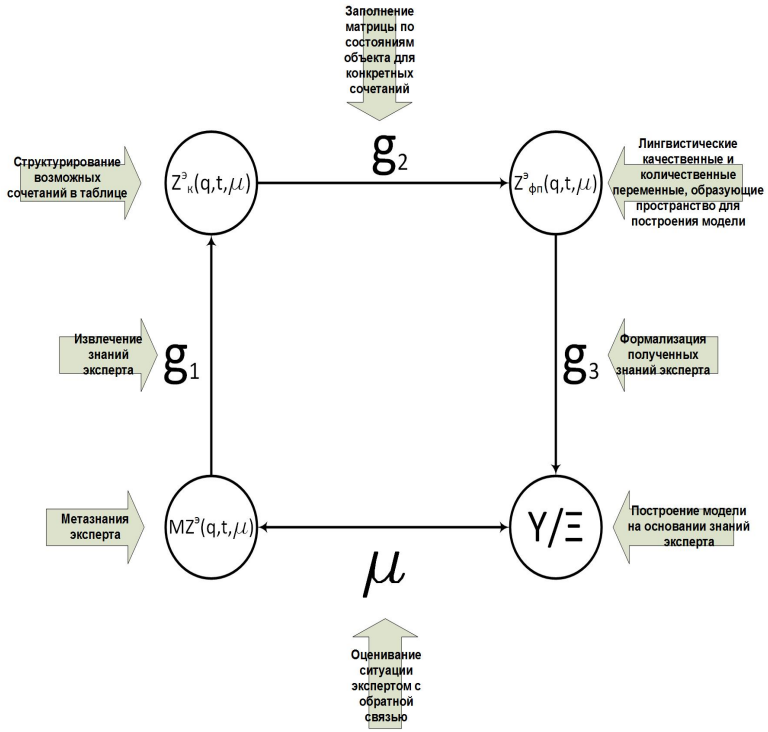


$g \circ \eta \circ \psi \circ \xi: Y \rightarrow Y/\Xi$



$\mu: T \times U \times X \rightarrow Y/\Xi.$

Commutative diagrams of decision-making and generation technologies based on: data - left and expert knowledge - right

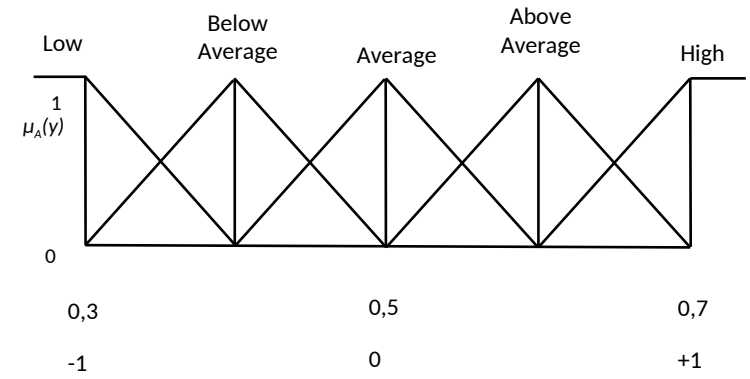


μ – expert situation evaluation operator
g1 – extraction operator
g2 – representation operator
g3 – formalization operator
Y/Ξ – term-set of alternatives to which the result should be classified

$\mu = g_3 \circ g_2 \circ g_1 : T \times U \times X \rightarrow Y/\Xi,$

Algorithm for constructing an FPM to evaluate UAV autonomy status based on explicit and implicit expert knowledge

Step 1. Selection and justification of the factor space (FS) for the purpose of synthesizing a state model of the object, phenomenon, or process under study.
Step 2. Construction of fuzzy linguistic variables—incorporating both verbal and numerical scales—for each factor in the FS, representing expert knowledge.
Step 3. Definition of the objective function Y, aligned with the goals of the research.
Step 4. Development of an expert questionnaire matrix. This matrix is orthogonal; its columns represent the FS variables, while its rows represent the various situations in which the object under study might find itself. Each row embodies expert knowledge in the form of fuzzy production rules, constituting a complete set of scenarios for evaluating the state of the process at the vertices of a hypercube.
Step 5. Expert assessment of all rows in the questionnaire matrix, provided in verbal terms based on the scale defined for the linguistic variable Y.
Step 6. Conversion of the expert's verbal assessments into numerical values to derive a non-linear polynomial expression.
Step 7. Synthesis of a fuzzy-possibilistic model by identifying and retaining the significant coefficients within the polynomial expansion.
Step 8. Validation of the model's accuracy, conducted in two stages: first, verification of the model against the expert's judgment, and second, assessment against the actual (real-world) state of the object..



The linguistic variable model establishes a transition between linguistic and quantitative scales.

The abscissa axis contains three scales: the upper linguistic scale; the natural scale of the attribute at the bottom (e.g., dimensionless) for converting linguistic values of the variable into numerical ones; and a scale in coded values on the interval [–1, +1], which is necessary for implementing the methods of the theory of experimental design. The ordinate axis contains the membership function ∈ [0,1] as a measure of the degree of confidence ("correctness") of the conversion from one scale to another.

Factor space for constructing the FPA Y – UAV autonomy

X1 – Displacement. UAV scanning movements in the target field based on the principle: "minimum scanning path traversal – maximum detection of objects potentially acting as the sought target.“

X2 – Observation. A process measured by the time from the start of scanning movements to the moment of object(s) detection.

X3 – Detection. A short-term process of identifying objects possessing primary features that match the specified image of the target object in the database.

X4 – Recognition (identification). A process developing over time using an analytical onboard computer system, where power consumption occurs in its peak mode. Efficiency is achieved by reaching a high degree of confidence in target object identification.

X5 – Tracking. Tracking implies observing the identified target object to update the database on typical object behavior and monitor its spatial position. From an energetic standpoint, this is expressed by the ratio of onboard power consumption for target monitoring based on its clarity indicator to the tracking duration indicator. Crucially, the lower the clarity of the monitored object, the more energy-consuming the tracking process becomes.

X6 – Goal setting (Targeting). The decision regarding the target status of an object in terms of its significance when ranking among the entire set of detected and identified targets. The factor's efficiency is determined by the differences in energy consumption values for attention and monitoring between individual targets.

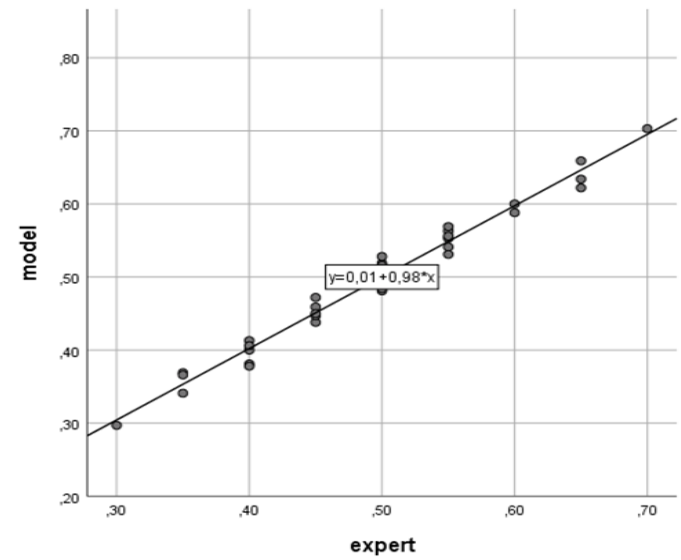
Y – Generalized UAV autonomy indicator (based on battery energy consumption).

Fuzzy-possibilistic model as a reflection of expert knowledge

Fragment of the survey matrix with expert estimates and calculated values

№	x_1	x_2	x_3	x_4	x_5	x_6	YE	YEV	YC
1	-1	-1	-1	-1	-1	-1	B	0,70	0,703
2	1	-1	-1	-1	-1	1	BC-B	0,65	0,634
3	-1	1	-1	-1	-1	1	BC	0,60	0,600
…	…	…	…	…	…	…	…	…	…
32	1	1	1	1	1	1	H	0,30	0,297

Model adequacy evaluation, R=0.98



$$Y=0{,}492-0{,}027\cdot x1-0{,}036\cdot x2-0{,}014\cdot x3-0{,}067\cdot x4-0{,}052\cdot x5-0{,}008\cdot x6+0{,}008\cdot x2\cdot x5,$$

where the expansion terms with only significant coefficients are presented, and all variables are expressed on a standardized scale according to the formulas

$x_i = \frac{X_i - \bar{X}_i}{\Delta X_i}$, $\overline{X}_i = \frac{X_{\max} + X_{min}}{2}$, $\Delta X_i = \frac{X_{\max} - X_{min}}{2}$, i – number of variables.

Model analysis and interpretation of results

The Analysis shows:

- The use of the FPA allows for obtaining quantitative characteristics of both the objective function Y—the generalized UAV autonomy indicator—and the strength of influence of its constituent variables;
- The most significant factors affecting the generalized indicator of energy consumption (and, consequently, inversely proportional to autonomy) are X4 (recognition), X5 (tracking), and X2 (observation);
- The positive coefficient in the interaction X2*X5 indicates the non-linear nature of the studied phenomenon and a weak synergistic effect that increases energy consumption during simultaneous intensive observation and tracking.
- The objective lack of representative baseline data on the energy saturation of individual onboard functions for any specific UAV modification prevented the creation of an FPM for the final quantitative assessment of its degree of autonomy.

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THANK YOU FOR YOUR ATTENTION

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