

Entropy Approach to Detection of Anomalies in UAV Trajectories

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ABSTRACT The paper presents a comprehensive entropy-based approach for anomaly detection in the trajectories of agents within a multi-component dynamic system of unmanned aerial vehicles (UAVs). The proposed mathematical model represents the movement of agents using a directed graph that takes into account kinematic parameters (spatial coordinates, velocity, and acceleration), stochastic factors, and topology of interactions. Potential anomalies are detected using combined entropy statistics that integrate local and structural entropy estimated via the Kozachenko–Leonenko method. Model hyperparameters are then optimized by stratified cross-validation using modern machine learning algorithms. Experimental evaluation on the SynDrone-Swarm dataset shows that ML-based calibration substantially improves detection quality, increasing ROC-AUC from 0.748 to 0.915 and PR-AUC from 0.768 to 0.924, while reducing false positives and improving temporal and spatial localization of anomalous events. The practical significance of this work lies in improving the efficiency of monitoring and managing UAV groups by enabling real-time detection of complex and latent anomalies.

KEYWORDS dynamic network topology; UAV trajectory analysis; data-driven modelling; anomaly detection; Kozachenko–Leonenko entropy (KLE); combined entropy statistic; trajectory hyperparameter optimization.

I. INTRODUCTION

Increasing the efficiency of monitoring and control systems for complex fleets of unmanned aerial vehicles (UAVs) is an important scientific and applied task that is directly related to maintaining a high level of safety and efficiency of logistics processes in the Supply Chain sector [1]. In conditions of complex and dynamically changing environments, the need for prompt and reliable detection of anomalous deviations in UAV flight paths is becoming more urgent. Such deviations can be caused by both external factors (for example, intentional GPS jamming, natural obstacles, extreme weather conditions) and internal factors, including equipment failures, sensor noise, and control errors [2]. Modern regional situation centers (RSCs) are widely used to ensure centralized control, coordination, and operational planning of UAV flights [3]. These centers enable rapid response to deviations in the behavior of individual

agents, adjust routes, minimize potential risks, and increase the overall efficiency of logistics tasks. However, traditional monitoring approaches based on heuristic or statistical criteria demonstrate low efficiency in detecting complex anomalies that manifest themselves at the level of collective behavior of agents or as subtle structural changes in their interaction networks.

Known classical methods of trajectory monitoring are characterized by limited sensitivity to complex, nonlinear, or latent deviations in the behavior of agents, especially in the case of multicomponent dynamic systems with a high level of interaction between agents. In this context, a promising approach is the use of information theoretic indicators, in particular entropy, which allows the quantitative assessment of the uncertainty and information complexity of the system's behavior, providing a universal and objective criterion for

identifying potential anomalies regardless of their specific nature.

In this research, a comprehensive entropy approach to anomaly detection in multifactorial trajectories of UAV fleet movement is developed, based on the analysis of local kinematic changes and structural rearrangements of interactions between agents. A directed dynamic graph is used to model interactions, where vertices correspond to individual UAVs and edges represent physical or informational connections between them. The proposed mathematical model takes into account the kinematic parameters of each agent (spatial coordinates, speed, acceleration), stochastic environmental factors, as well as errors in sensor measurements. Optimization of the anomaly detector parameters was carried out using modern machine learning methods, in particular stratified cross-validation, which ensures statistical stability, adaptability, and high sensitivity of the model to various fleet behavior scenarios.

The scientific novelty of the work lies in the synergistic combination of information entropy analysis methods with machine learning tools for automated and effective identification of potential anomalies. This allows for a significant increase in monitoring effectiveness and ensures a timely response to deviations of agent behavior from normal operating modes.

II. REVIEW OF EXISTING APPROACHES

Monitoring and detecting anomalies in the trajectories of dynamic systems, particularly unmanned aerial vehicles (UAVs), is a key focus of modern research in automated control and transport safety [4–6]. The main existing approaches can be conditionally classified into statistical, information theoretic, clustering, machine learning methods, and deep neural models.

Statistical approaches to trajectory analysis are based on classical probabilistic characteristics and metrics, including central moments of distributions, covariance structures, and various distance measures. The main advantages of these approaches are simplicity of implementation, high speed of calculations, and transparency of result interpretation. At the same time, statistical methods have significant limitations in detecting complex, nonlinear, and multidimensional anomalies that often arise in multicomponent dynamic systems [7].

Information theoretic approaches, particularly those based on entropy, mutual information, and system complexity, enable the assessment of uncertainty in system behavior and the detection of latent structural shifts. Recently, special attention has been paid to methods of local entropy estimation. These methods can capture even short-term and insignificant changes in the trajectory dynamics, which is important in the conditions of highly dynamic and stochastic environment [8]. However, classical applications of such methods are mainly focused on global analysis and may not effectively take into account the spatiotemporal structure of trajectories.

Clustering methods (e.g., k-means, DBSCAN, spectral clustering) are used to group similar trajectories and identify such anomalies as deviations from the main clusters. Their advantage is the ability to detect isolated patterns in the data. Despite this, these methods are too sensitive to the choice of metrics and clustering parameters and have low effectiveness in analyzing sequences with high temporal variability [9-10].

Machine learning supervised methods, such as ensemble classifiers (random forest, gradient boosting), allow more

efficient detection of complex patterns in trajectory data by using labeled or partially labeled samples. However, the performance of these algorithms is significantly dependent on the amount and quality of training data, which may limit their practical applicability in conditions of uncertainty and a small number of examples of anomalies. Deep learning and recurrent networks (LSTM, GRU, attention-based models, variational autoencoders, graph neural networks) represent the most advanced and effective solutions for detecting complex anomalies [11-12]. They are able to capture long-term and hidden dependencies in trajectories, demonstrating high quality results on large datasets. At the same time, these approaches have significant computational requirements, complex interpretability, and a potential tendency to overfitting.

In the context of multi-component dynamic systems, such as a fleet of UAVs, the task of localizing potential anomalies in spatiotemporal sequences is particularly relevant. Beyond statistical deviations, structural and informational shifts that indicate potential risks are critical. Therefore, the presented study justifies the use of local entropy analysis combined with machine learning methods [13-14]. Such a combined approach provides a balance between high sensitivity to complex, latent changes, transparency of result interpretation, and adaptability to various operational scenarios. The introduction of automated optimization of entropy model parameters using modern ML algorithms further increases the efficiency and speed of real-time response.

Thus, the proposed local entropy approach combined with machine learning has significant advantages for anomaly detection in the trajectories of multi-component dynamic UAV systems, meeting modern requirements for reliability, interpretability, and monitoring efficiency.

III. PROBLEM STATEMENT

In the context of the monitoring task, each UAV is treated as a separate dynamic agent with its own set of motion parameters that change over time and space, forming a complex network of interactions. Therefore, developing an approach that ensures prompt detection and localization of potential anomalies in the time series of agent parameters is both scientifically and practically important. Such an approach should be based on formalized information criteria that are adaptive to changes in group behavior dynamics and are capable of detecting even minor local shifts in the distributions of kinematic characteristics.

An important challenge is the integration of information-theoretic indicators (in particular, local entropy measures) with modern machine learning algorithms for automated data analysis. Such integration enhances the situational awareness of operators at regional situation centers (RSCs), increases the speed and accuracy of decision-making, and significantly reduces the likelihood of risky situations during system operation.

Thus, the main goal of the research is to develop, formalize, and practically test an entropy approach with parameter optimization based on machine learning, which will ensure effective and timely detection of complex anomalies in UAV trajectories in multidimensional spatiotemporal systems.

IV. MATHEMATICAL MODEL OF THE MOTION AND STRUCTURE OF AGENT INTERACTIONS

Let $V = \{v_i | i, \dots, N\}$ denote the set of agent identifiers observed by regional situation centers (RSCs), and $\mathcal{X}(t) =$

$\{\mathbf{x}_i(t)|i, \dots, N\}$ denote the set of their corresponding state vectors describing the system dynamics at time t .

The interaction between agents is modeled by a directed graph $G(t) = (V, E(t))$, where $E(t)$ is the set of ordered pairs of agents (i, j) , each of which represents the existence of a directed influence or interaction from agent i to agent j at time t . The composition and directions of connections can change depending on the spatial location, information state, or network dynamics. For each agent v_i , the state vector $\mathbf{x}_i(t) = [\mathbf{r}_i(t), \mathbf{v}_i(t), \mathbf{a}_i(t)]^T \in \mathbb{R}^9$, $t \in T$, is determined at discrete points in time $t = k\Delta t$ based on sensor data containing additive noise $\eta_i(k) \sim \mathcal{N}(0, \Sigma_\eta)$. Accordingly, the agent's state is described by the vector:

$$\mathbf{x}_i(t) = [\mathbf{r}_i(t), \mathbf{v}_i(t), \mathbf{a}_i(t)]^T + \eta_i(k),$$

where $\mathbf{r}_i(t) = (x_i, y_i, z_i)$ are the spatial coordinates of the agent; $\mathbf{v}_i(t)$ is the speed of the agent; $\mathbf{a}_i(t)$ is the acceleration of the agent's speed; $\eta_i(t)$ is the additive noise that models random errors and fluctuations in sensor data and is assumed to follow a normal distribution with zero mathematical expectation and a covariance matrix Σ_η . These variables characterize the individual features of each agent's measurements and do not directly affect the topology of the inter-agent connection graph. However, they can be adjusted during estimation and updating of $E(t)$ to increase the reliability of the model.

The dynamics of each agent's movement in the system are modeled by a system of second-order differential equations:

$$\begin{cases} \mathbf{r}_i(t) = (x_i, y_i, z_i) \\ \mathbf{v}_i(t) = \frac{d}{dt} \mathbf{r}_i(t) \\ \mathbf{a}_i(t) = \frac{d}{dt} \mathbf{v}_i(t) = f_i \end{cases}, \quad (1)$$

where the acceleration f_i is defined as follows:

$$f_i = \frac{1}{m_i} (\mathbf{F}_i^{\text{ctrl}}(t) + \mathbf{F}_i^{\text{env}}(t) + \sum_{j:(i,j) \in E(t)} w_{ij}(t) \mathbf{F}_{ij}^{\text{int}}(t)) + \sigma_i \xi_i(t),$$

where m_i is the mass of the agent; $\mathbf{F}_i^{\text{ctrl}}(t)$ is the control force; $\mathbf{F}_i^{\text{env}}(t)$ is the environmental influence (wind, gravity, obstacles); $W(t) = [w_{ij}]$ is the weight matrix (connection intensity) in the interaction graph, which characterizes the presence and strength of information or structural connections between agent i and agent j at time t ; $\mathbf{F}_{ij}^{\text{int}}(t)$ is the strength of interaction between agents; σ_i is the intensity of stochastic disturbance (noise) in the dynamics of the i -th agent; $\xi_i(t)$ is a Wiener vector (white noise), which models the stochasticity of the dynamics.

In practical terms, the weight w_{ij} can be defined as a function of the distance between agents (for example, $w_{ij}(t) = \phi(\|\mathbf{r}_i(t) - \mathbf{r}_j(t)\|)$, where smaller distances correspond to greater influence), the interaction zone can be reflected as ($w_{ij}(t) = 0$ at $\|\mathbf{r}_i(t) - \mathbf{r}_j(t)\| > R$, where R is the interaction radius), and topological aspects such as leadership, communication channels or visibility zones are taken into account.

Within the framework of this study, the influence between

agents can be both physical and informational. Physical interactions include collision avoidance through repulsive forces, maintenance of group cohesion, and coordination of movement direction with neighboring agents. Such rules are commonly implemented in Boids models or based on potential fields. Informational interactions include the exchange of coordinates or velocities for synchronization, as well as the transmission of signals about anomalies or route changes. Thus, the weight coefficients w_{ij} reflect how strongly a change in the trajectory or state of one agent can affect others, both through physical interactions and information exchange in the model.

The set of edges $E(t)$ of the graph $G(t)$ is determined by weight coefficients w_{ij} , which depend on the current state of the agents $\mathbf{x}_i(t)$ (for example, distance, direction of movement, signal strength, or other informational features): an edge (i, j) is considered to exist in the graph $G(t)$, if $w_{ij} > 0$. Weights w_{ij} directly affect the dynamics through the forces $\mathbf{F}_{ij}^{\text{int}}(t)$ in the equations of motion (1).

The introduced definitions form a unified mathematical basis that connects the kinematics of individual agents with the network of their interactions and allow for the correct accounting of noise effects and missing data during subsequent entropy analysis.

V. DETECTION OF ANOMALIES

Within the entropy approach, anomalies are understood as local deviations from nominal motion modes that manifest themselves as sharp kinematic perturbations or structural changes in the statistical characteristics of trajectories. For example, abrupt changes in speed or acceleration that significantly exceed permissible maneuvering limits lead to a local increase in entropy within the observation window. Similarly, instantaneous 180° turns or "jumps" in coordinates that are not typical for regular routes indicate a violation of the expected dynamics and are also recorded as anomalies [15]. A separate category consists of deviations from group behavior, such as when one of the UAVs moves away from the cluster or the topology of the interaction graph changes. In such cases, local entropy adapts to the new configuration of the environment, enabling the detection of isolation or emergence of "leaders" in the fleet. Structural shifts in the distribution of motion parameters due to sensor noise or data loss are also detected through anomalous weight matrices or increased divergence between distributions in successive windows. In addition, the system's response to external influences, such as sudden obstacles, GPS jamming, or intentional control interference, is accompanied by atypical motion patterns and unstable entropy measures. Intentionally created "dropout" segments or changes in noise characteristics are used to test the robustness of the algorithm and simulate real-world operating conditions.

From a safety perspective, timely detection of these anomalies enables operators to respond promptly to potential deviations and prevent dangerous situations.

A. DETECTION OF POTENTIAL ANOMALIES IN MOTION TRAJECTORIES

For anomaly detection, two information measures are considered:

1. Local entropy of the trajectory of an individual agent, estimated on a sliding window $S_i(k, l) = \{\mathbf{x}_i(k - l +$

$1), \dots, \mathbf{x}_i(k)\}$ of discrete time k [16]. Let $\hat{H}_{KL}(S_i(k, l))$ be the unbiased estimate of the local differential entropy of Kozachenko–Leonenko [17]:

$$\hat{H}_{KL}(S_i(k, l)) = \psi(l) - \psi(k_{NN}) + \log c_d + \frac{d}{l} \sum_{m=1}^l \log \varepsilon_m, \quad (2)$$

where $\psi(\cdot)$ is the digamma function; c_d is the volume of a unit sphere $\mathbb{R}^d$, $\left(c_d = \frac{\pi^{\frac{d}{2}}}{\Gamma(1+\frac{d}{2})}\right)$; ε_m is the distance from point $\mathbf{x}_m(k)$ to its k_{NN} -th nearest neighbor in the sample (system); l is the number of points in the sliding window; k_{NN} is the number of neighbors used in the estimation.

Accordingly,

$$H_i^{\text{loc}}(k, l) = \hat{H}_{KL}(S_i(k, l)). \quad (3)$$

Jump-like changes in velocity, acceleration, or coordinates lead to a sharp increase in this quantity, since the local density of the sample is spread out in the phase space.

2. Structural entropy of the graph topology $G(t)$ at time k . Let $\mathbf{w}(k)$ be formed by successively expanding the matrix of weight coefficients $W(t) = [w_{ij}]$, where each element reflects the presence and strength of the connection between agents in the interaction graph at time k . Let $\hat{H}_{KL}(S_i(k, l))$ be the unbiased estimate of the Kozachenko–Leonenko topological entropy:

$$\hat{H}_{KL}(S_i(k, \delta)) = \psi(\delta) - \psi(k_{NN}) + \log c_d + \frac{d}{\delta} \sum_{m=1}^d \log \varepsilon_m, \quad (4)$$

where d is the dimension of the vector $\mathbf{w}(k)$ (the number of nonzero edges in the graph at k moment); ε_m is the distance from the m -th point to its k_{NN} -th neighbor in $S_i(k, \delta)$; δ is the length of the sliding window for the structural entropy of the graph, i.e., the number of consecutive discrete time steps (indices k), over which the sample is accumulated for estimating the topological entropy.

Accordingly, the entropy of the graph topology $G(t)$ is defined as:

$$H_i^{\text{topol}}(k, \delta) = \hat{H}_{KL}(S_i(k, \delta)). \quad (5)$$

The average local entropy of the graph topology $G(t)$ is defined as follows:

$$H_{\text{mean}}^{\text{topol}}(k, \delta) = \frac{1}{N} \sum_{i=1}^N H_i^{\text{topol}}(k, \delta). \quad (6)$$

Reconfiguration of edges, isolation of an agent or the appearance of a “leader” change the empirical distribution of weights and increase $H_{\text{mean}}^{\text{topol}}(k, \delta)$.

For integrated estimation, combined entropy statistics are introduced [18-20]:

$$Q_i(k) = \alpha \frac{H_i^{\text{loc}}(k, l) - \mu_i^{\text{loc}}}{\sigma_i^{\text{loc}}} +$$

$$+ (1 - \alpha) \frac{H_i^{\text{topol}}(k, \delta) - \mu_i^{\text{topol}}}{\sigma_i^{\text{topol}}}, \quad (7)$$

$$0 \leq \alpha \leq 1,$$

where $\mu_i^{\text{loc}}, \sigma_i^{\text{loc}}, \mu_i^{\text{topol}}, \sigma_i^{\text{topol}}$ are the parameters of the nominal regime estimated on the validation sample.

The first term is sensitive to kinematic perturbations of an individual agent (UAV), while the second is sensitive to collective or topological deviations; the choice of the coefficient regulates the balance between these sources of information.

The hypothesis of the anomaly presence is formulated as:

$$\begin{cases} H_0: Q_i(k) \in [\tau^-, \tau^+] \Rightarrow \text{normal} \\ H_1: Q_i(k) \notin [\tau^-, \tau^+] \Rightarrow \text{anomaly} \end{cases} \quad (8)$$

where τ is the threshold value of the combined entropy statistic. The exceeding or falling below τ is interpreted as an indication of a possible anomaly in the motion trajectory.

B. THRESHOLD STRATEGIES AND RSC RESPONSE PROTOCOL

Threshold values for the combined statistics (7) are determined in two steps. In the first stage, based on the training sample formed from nominal (safe) flights, the probability density $f_Q(\cdot | H_0)$ for the statistics $Q_i(k)$ is estimated under the null hypothesis, i.e., in the normal mode of operation of the system without anomalies. In the second stage, the distribution of the standardized statistics $Q_i(k)$ (obtained according to (7)) is analyzed, where each of the entropy components is previously transformed into standardized form based on the nominal statistical parameters. The empirical distribution of $Q_i(k)$ usually approaches the standard normal distribution $\mathcal{N}(0,1)$; the assumption of normality is checked, for example, using the Shapiro–Wilk test. In case of deviation from normality, a non-parametric (for example, kernel) probability density $f_Q(\cdot | H_0)$ estimate is used to further determine the threshold values.

Once the distribution of the statistics $Q_i(k)$ in the normal mode has been determined, the threshold value τ is set accordingly. To generate an anomaly message, this value is chosen to ensure a given level of acceptable false alarm probability β :

$$P(Q_i(k) > \tau | H_0) = \beta. \quad (9)$$

Condition (9) guarantees that the false alarm probability does not exceed the specified level β in the nominal mode of operation of the system.

If the statistic $Q_i(k)$ has a standard normal distribution $\mathcal{N}(0,1)$, the threshold value can be determined analytically as:

$$\tau = \Phi^{-1}(1 - \beta), \quad (10)$$

where $\Phi^{-1}(\cdot)$ is the inverse cumulative distribution function of the standard normal distribution.

If the distribution of $Q_i(k)$ differs significantly from normal one, the threshold value τ is chosen as the $(1 - \beta)$ -th quantile of the empirical density $f_Q(\cdot | H_0)$.

To ensure an urgent response protocol for regional RSCs, an additional, critical threshold is introduced $\tau_c > \tau$. It is

chosen as a solution to the problem of minimizing the risk function:

$$J(\tau_c) = \alpha_{FN} P(Q_i(k) \leq \tau_c | H_1) + (1 - \alpha_{FN}) P(Q_i(k) > \tau_c | H_0), \quad (11)$$

where $\alpha_{FN} \in [0,1]$ is the weight coefficient reflecting the relative importance of the risk of missed anomaly.

To reduce the number of false positives due to sporadic noise, an alarm signal is generated only when the condition $Q_i(k) > \tau$ is met for at least m consecutive steps; experimental practice shows that the value $m \in \{2,3,4\}$ is sufficient for $\Delta t < 1s$. For the “critical” threshold τ_c , no delay is allowed: $Q_i(k) > \tau_c$ immediately triggers the RSC urgent intervention protocol.

In collective scenarios, to assess the situation at the level of the entire fleet, the aggregated statistics are additionally considered:

$$Q^{\text{fleet}}(k) = \max_{i \in V} \{Q_i(k)\}, \quad (12)$$

and the weighted sum

$$Q^w(k) = \sum_i c_i Q_i(k), \quad (13)$$

where c_i are the weight coefficients proportional to the centrality of the node in the graph $G(t)$.

The corresponding thresholds τ^{fleet} and τ_c^w are set using the same method, taking into account the aggregated distribution of statistics in the fleet. This approach allows the detection of situations when anomalous values are concentrated in topologically important agents or cover a significant part of the group. The threshold hierarchy $\tau_c > \tau$ provides multi-level control over both the amplitude and stability of the deviation from the norm, which enables the achievement of a balance between the sensitivity of the monitoring system and the timeliness of the RSC response.

C. OPTIMAL SLIDING WINDOW SIZE AND PARAMETERS

Choosing the optimal sliding window size and parameters is crucial to ensure a balance between sensitivity, statistical reliability, and response speed of the anomaly detector in multi-agent systems. An excessively short window makes entropy analysis sensitive to noise, while a long one reduces the ability to detect short-term disturbances and increases the response delay.

The initial bounds for l (local entropy) and δ (topological entropy) are determined analytically, taking into account the dimensionality of the feature and the minimum statistical stability. The lower bounds are set by the signal-to-noise ratio and the sample size:

$$l_{\min} = \max\{d + k_{NN}, \lceil c_{\text{var}} / \sigma_\eta^2 \rceil\}, \quad (14)$$

$$\delta_{\min} = \max\{|E|_{\min} + k_{NN}, k_{NN}\}, \quad (15)$$

where d is the dimensionality of the state vector; k_{NN} is the minimum number of points required for a stable k -NN entropy estimate; c_{var} is an empirical coefficient, which determines the minimum permissible ratio of signal variance to noise variance to ensure statistical stability of the entropy estimate (so that the

sample contains enough information to separate significant changes from random noise fluctuations), $c_{\text{var}} \in [3,5]$; σ_η^2 is the sensor noise variance; $|E|_{\min}$ is the minimum value of the number of existing connections (edges) in the topology of the network between agents (UAA) for the graph $G(t)$ at a certain time t .

The upper limit depends on the maximum permissible reaction time: $l_{\max} \lceil \frac{\tau_{\text{anom}}}{\Delta t} \rceil$, $\delta_{\max} \lceil \frac{\tau_{\text{topol}}}{\Delta t} \rceil$, where Δt is the sampling step.

On the training sample with marked anomalies, the optimal l^* and δ^* are determined by minimizing the loss function:

$$J(l, \delta) = \alpha_{FN} \lambda_1(l, \delta) + \alpha_{FP} \lambda_2(l, \delta) + \alpha_{\text{lat}} \mathbb{E}[t_{\text{delay}}(l, \delta)], \quad (16)$$

$$(l^*, \delta^*) = \arg \min_{l \in [l_{\min}, l_{\max}], \delta \in [\delta_{\min}, \delta_{\max}]} J(l, \delta), \quad (17)$$

where λ_1 is the frequency of missed anomalies; λ_2 is the false positive rate; t_{delay} is the average delay of anomaly detection; α_{FN} , α_{FP} , α_{lat} are weighting factors.

In practical problems, the weight coefficients α_{FN} , α_{FP} , α_{lat} are set to quantitatively reflect the system priorities: minimizing the number of missed anomalies (associated with a security risk) is considered to be significantly more important than minimizing the frequency of false alarms or response delay, which are of lower priority in UAV monitoring scenarios. For example, $\alpha_{FN} : \alpha_{FP} : \alpha_{\text{lat}} = 100 : 10 : 1$.

In the absence of reference anomalies, the optimum is sought based on the informativeness of the entropy gain:

$$\text{SNR}_{\text{loc}}(l) = \frac{\mathbb{E}[(H_i^{\text{loc}}(k, l) - \mathbb{E}[H_i^{\text{loc}}(k, l)])^2]}{\mathbb{E}[(\hat{\eta}_i(k) - \mathbb{E}[\hat{\eta}_i(k)])^2]}, \quad (18)$$

$$\text{SNR}_{\text{topol}}(\delta) = \frac{\mathbb{E}[(H_i^{\text{topol}}(k, \delta) - \mathbb{E}[H_i^{\text{topol}}(k, \delta)])^2]}{\mathbb{E}[(\hat{\eta}_w(k) - \mathbb{E}[\hat{\eta}_w(k)])^2]}, \quad (19)$$

where $\hat{\eta}_i$ is the noise estimate in the local entropy of the agent's trajectory; $\hat{\eta}_w$ is the noise estimate in the structural entropy of the graph topology.

In real conditions, drift in the statistical characteristics of entropy features is possible. At a certain frequency (for example, every 2 minutes), the noise variance in the local entropy of trajectories (σ_i^{loc}) and in the structural entropy of the graph topology (σ_i^{topol}), as well as the corresponding mathematical expectations (μ_i^{loc} , μ_i^{topol}) are updated based on the latest values of the entropy characteristics calculated in sliding windows of length l and δ , respectively. If the noise variance of the corresponding entropy statistics increases by more than 30%, the parameters of the sliding window l and δ are increased by one step to increase the stability of the estimate; if the variance decreases, these parameters are correspondingly reduced to decrease the response delay.

VI. ML-PROCEDURE FOR OPTIMIZATION OF HYPERPARAMETERS IN THE PROBLEM OF ANOMALIES DETECTION

Automated selection of the parameter vector $\theta = (l, \delta, \alpha, k_{NN}, \tau)$ is carried out using modern methods of

hyperparameter optimization, such as grid search, random search, Bayesian optimization or specialized AutoML frameworks (for example, Optuna, Hyperopt, AutoGluon). These tools systematically iterate over hyperparameter configurations in the admissible space $D = \{\theta | l \in [l_{min}, l_{max}], \delta \in [\delta_{min}, \delta_{max}], \alpha \in [0, 1], k_{NN} \in \mathbb{N}, \tau \in [\tau_{min}, \tau_{max}]\}$, run a full processing cycle on the training or validation sample for each configuration, and evaluate the detector's performance by the objective function.

As the objective function for optimization, a generalized loss function $J^{(m)}(\theta)$ is used, defined as the value of the generalized loss function (16), calculated on the m -th block of the cross-validation sample for a given set of hyperparameters θ . To prevent overfitting, the optimization of each configuration θ is performed using a cross-validation scheme (e.g., stratified K-fold), and the selected value of the objective function is averaged over all blocks:

$$J^*(\theta) = \frac{1}{K} \sum_{m=1}^K J^{(m)}(\theta). \quad (20)$$

Alternatively, a weighted logistic (cross-entropy) function is used:

$$\mathcal{L}^*(\theta) = \frac{1}{K} \sum_{m=1}^K \mathcal{L}^{(m)}(\theta), \quad (21)$$

where $\mathcal{L}^{(m)}(\theta)$ is the value of the weighted logistic (cross-entropy) loss function calculated on the m -th cross-validation block for the current set of parameters θ . The weighted logistic (cross-entropy) function is defined as:

$$\mathcal{L}^{(m)}(\theta) = -\sum_{(i,k) \in B_m} [\lambda_1 y_{ik} \log \hat{p}_{ik}(\theta) + \lambda_2 (1 - y_{ik}) \log(1 - \hat{p}_{ik}(\theta))], \quad (22)$$

where y_{ik} is the binary anomaly label for agent i at time k ; $\hat{p}_{ik}(\theta)$ is the predicted probabilistic output of the detector (for example, the estimated probability that $Q_i(k)$ exceeds the threshold τ for the current set of hyperparameters θ); B_m is the index pairs (i, k) belonging to the m -th validation partition block.

To enhance reproducibility, computational efficiency, and practical applicability of the optimization procedure, the model class for approximating anomaly probabilities is specified. A Histogram-Based Gradient Boosting (HGB) [21-23] algorithm is employed as the core supervised component. For each pair i, k , a feature vector:

$$\mathbf{z}_{ik} = (H_i^{loc}(k, l), H_i^{topol}(k, \delta), Q_i(k), \Delta H_i(k), \dots), \quad (23)$$

is constructed, including derivatives of entropy-based measures and aggregated topological indicators.

The predictive model is defined as

$$\hat{p}_{ik}(\theta) = \mathbb{P}(y_{ik} = 1 | \mathbf{z}_{ik}; \theta), \quad (24)$$

where $\hat{p}_{ik}(\theta)$ denotes the estimated probability of an anomalous state.

Histogram binning reduces the computational cost of tree construction and improves estimation stability on large-scale datasets. The HGB parameters (number of trees, maximum depth, learning rate, and number of bins) are incorporated into

the extended hyperparameter vector $\theta = (l, \delta, \alpha, k_{NN}, \tau, \theta_{HGB})$ and optimized within the cross-validation framework. This formulation captures nonlinear dependencies between entropy-derived features and anomalous behavior while maintaining a balance between interpretability, robustness to noise, and predictive performance.

As a result, the optimal configuration of parameters θ^* is defined as the one that minimizes the corresponding objective function, providing a balanced compromise between sensitivity, specificity and response speed of the entropy anomaly detector:

$$\theta^* = \arg \min_{\theta \in D} (J^*(\theta)), \quad (25)$$

or

$$\theta^* = \arg \min_{\theta \in D} (\mathcal{L}^*(\theta)). \quad (26)$$

To ensure stable operation of the detector in variable real-world operating conditions, the calibrated parameters are regularly checked and updated. When noise characteristics, graph structure or anomalous scenarios change, the optimization procedure is repeated automatically using the accumulated flight data and the warm start strategy. This allows the detector to flexibly adapt to new operating modes without operator intervention, minimizing the risk of missing anomalies or generating unnecessary false alarms.

The computational complexity of the proposed optimization pipeline is determined by three main components: local entropy estimation, topological feature extraction, and HGB calibration. For each agent, KLE is computed in a sliding window of length l ; with efficient k -nearest-neighbor search, one update requires $O(l \log l)$, so over N agents and T time steps the corresponding complexity is $O(NT \log l)$. The extraction of topology-dependent features is governed by the current interaction graph $G(t)$ and, for sparse connectivity, scales as $O(\sum_{t=1}^T |E(t)|)$, where $|E(t)|$ is the number of active edges at time t . The subsequent HGB calibration operates on a feature matrix of size $M \times d$, where $M \approx NT$ and d is the number of entropy-derived and kinematic-topological descriptors; under fixed tree depth and binning resolution, training is approximately linear in M , while inference is $O(M)$. Therefore, for fixed l, δ , and bounded graph density, the overall computational complexity is near-linear in the number of agent-time observations, which makes the proposed detector compatible with large-scale UAV trajectory monitoring.

To ensure high statistical stability of the optimization and compliance with modern machine learning standards, it is advisable to implement an explicit mechanism for stratified k-fold cross-validation in the algorithm when determining the optimal vector of hyperparameters θ . Thus, the ML-calibration process is reduced to the automatic search for optimal parameters $(l, \delta, \alpha, k_{NN}, \tau)$ of the integral entropy statistics (7) for a given quality function based on labeled or unlabeled data. This ensures high efficiency and adaptability of the detector in various operating scenarios of the multi-agent UAV system.

An important aspect of modern detection systems is their ability to adapt to changes in data distribution through regular re-optimization of parameters. For this purpose, it is proposed to periodically perform parameter re-estimation of θ using warm-start strategies, AutoML tools, or other re-optimization mechanism after the accumulation of new observations. In

addition, when using automated selection procedures (Grid Search, Bayesian optimization, etc.), it is important to ensure the possibility of varying the loss function: optimization can be performed using either the F1-score or a latency-penalized loss, which is especially important for real-time observation tasks time [24-25].

The proposed machine learning approaches enable a significant increase in the versatility, reliability and adaptability of entropy models in anomaly detection tasks in multi-component dynamic systems.

VII. MODEL TESTING

In this section, the effectiveness of the entropy-based approach for detecting local kinematic and structural anomalies in UAV swarm dynamics is evaluated, together with the impact of ML-based calibration on detection performance. The considered setting corresponds to task-oriented operational monitoring of coordinated multi-agent swarm behavior, where timely detection of local deviations is essential for maintaining collective stability and consistency of the system dynamics.

Experimental validation is performed on the SynDrone-Swarm dataset [26], organized into two domains (*A* and *B*) and four scenarios of increasing inter-agent interaction complexity: *BAS*, *MED1*, *MED2*, and *DEN*. For each agent, on the discrete time grid $t_k = k\Delta t$ with $\Delta t = 0.1$ s, the state vector $\mathbf{x}_i(t_k) = [\mathbf{r}_i(t_k), \mathbf{v}_i(t_k), \mathbf{a}_i(t_k)]^T$ is reconstructed, where acceleration is obtained by numerical differentiation of velocity.

In the detection phase, local and topological entropies are estimated using the KLE method (2)–(6) over sliding windows, followed by computation of the combined statistic $Q_i(k)$ for each agent according to (7). To improve detector selectivity, an ML-based calibration stage based on the HGB algorithm is employed to approximate the probability of an anomalous state from the feature vector $\mathbf{z}_{ik}(23)$.

As the SynDrone-Swarm dataset [26] does not provide a priori anomaly labels, reference labels are generated via controlled injection of scenario-specific perturbations into telemetry sequences. These labels are used exclusively for validation, whereas anomaly detection follows the procedure described in Sections IV–VI.

The quantitative structure of the dataset is defined at the levels of scenarios, agents, and time steps. For each scenario, a dedicated UAV telemetry file is provided, containing approximately 3×10^4 – 8×10^4 records. Formally, the sample size is given by $N = N_{\text{agents}} \times N_{\text{frames}}$, where each record corresponds to a single agent at a specific time instant. Across all scenarios, the total volume reaches 10^5 – 10^6 observations, ensuring statistically stable estimation of system dynamics while maintaining computational tractability.

The number of agents per scenario is $N_{\text{agents}} \approx 8$ – 20 , corresponding to small- and medium-scale swarm configurations. Temporal resolution is defined by the time variable with a step $\Delta t \approx 0.1$ – 0.3 s, yielding a sampling frequency of approximately 3–10 Hz. Under these conditions, the number of frames per scenario reaches $N_{\text{frames}} \sim 10^3$ – 10^4 , with a total duration of $T \sim 10^2$ – 10^3 s.

These data volumes support efficient execution of the proposed detection pipeline. In the experimental setup (Google Colab Pro environment with A100/L4 GPUs and high-memory configuration), full processing of a single scenario (which includes entropy estimation, topological feature extraction, and HGB-based calibration) requires from seconds to tens of

seconds, depending on scenario complexity. Inference latency remains sub-second per trajectory, enabling near real-time monitoring. This scaling indicates that the method is suitable for task-oriented monitoring of coordinated swarm behavior without requiring specialized distributed infrastructure.

Within the experimental framework, four types of anomalies are analyzed: *velocity spike*, *yaw jump*, *angular burst*, and *position jump*. The first three correspond to local kinematic disturbances characterized by abrupt increases in velocity, discontinuities in orientation angle, or anomalous increases in angular velocity. The position jump is interpreted as a spatial discontinuity of the trajectory, defined as a sudden displacement of coordinates inconsistent with prior kinematic evolution.

Reference labels are generated via controlled injection of such perturbations into nominal trajectories. The proportion of anomalous observations is approximately 2–3% of the total sample, corresponding to a rare-event detection setting and justifying the use of metrics sensitive to class imbalance.

Fig. 1 shows the spatiotemporal evolution of agent trajectories in the A-BAS scenario, exhibiting nonlinear motion dynamics with frequent intersections and directional changes that hinder visual identification of deviations. This configuration indicates the absence of trivial spatial anomaly patterns and motivates the use of statistical and entropy-based indicators for reliable detection.

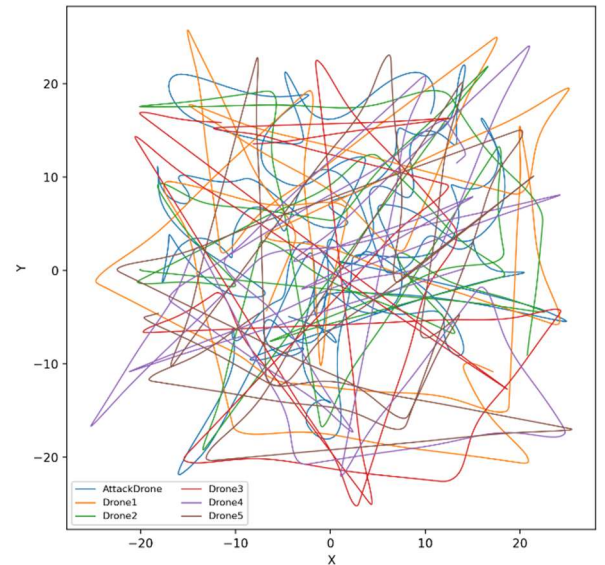


Figure 1. Horizontal trajectories: Scenario A-BAS.

Fig. 2 shows the temporal profile of the combined statistic $Q(t)$ for the Drone3 agent in the A-BAS scenario, illustrating the separation between nominal and anomalous dynamics. The values of $Q(t)$ lie within $(-2.5, 2.2)$, while the majority of observations in the quasi-nominal regime are concentrated in the interval $[-1.0, 0.5]$. Anomalous episodes correspond to local deviations of the statistic beyond this concentration region, predominantly in the range of positive extremes with $Q \gtrsim 1.0$, indicating sufficient contrast of the entropy-based indicator relative to background fluctuations.

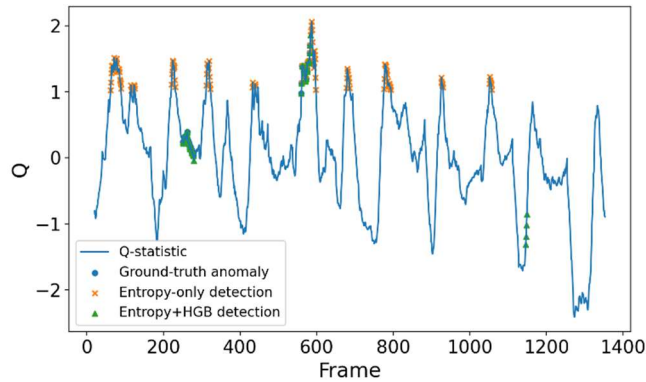


Figure 2. Temporal dynamics of Q-statistic: Scenario A-BAS (Drone3).

The *Entropy-only* thresholding scheme exhibits elevated sensitivity to moderate variations in $Q(t)$, resulting in a spatiotemporal expansion of detections relative to the reference anomalous segments. In contrast, the calibrated *Entropy+HGB* variant performs nonlinear selection of entropy-derived and auxiliary features, retaining detections localized in the vicinity of true anomalies.

Thus, Fig. 2 indicates that ML-based calibration preserves the informative structure of $Q(t)$ while improving classification accuracy by reducing false positives and more precise temporal localization of anomalous events.

Fig. 3 shows the spatial distribution of anomalous segments along the trajectory of the Drone3 agent in the XY plane for the A-BAS scenario. The trajectory occupies the region $[-25, 25] \times [-25, 25]$ and is characterized by self-intersections and segments with varying curvature, which complicate localization. Anomalous events form compact segments of limited length (tens of points), predominantly located in regions with abrupt changes in direction or velocity.

The *Entropy-only* approach without calibration produces spatially extended detections that cover not only these segments but also adjacent trajectory regions, leading to increased coverage and a higher false-positive rate. In contrast, the calibrated *Entropy+HGB* variant produces more compact detection regions aligned with the geometry of anomalous segments: detections concentrate along the corresponding trajectory fragments and remain confined within their boundaries. Figure 3 indicates that ML-based calibration performs nonlinear filtering of entropy-derived features, reducing spatial overextension of detections and improving localization accuracy in complex trajectory configurations.

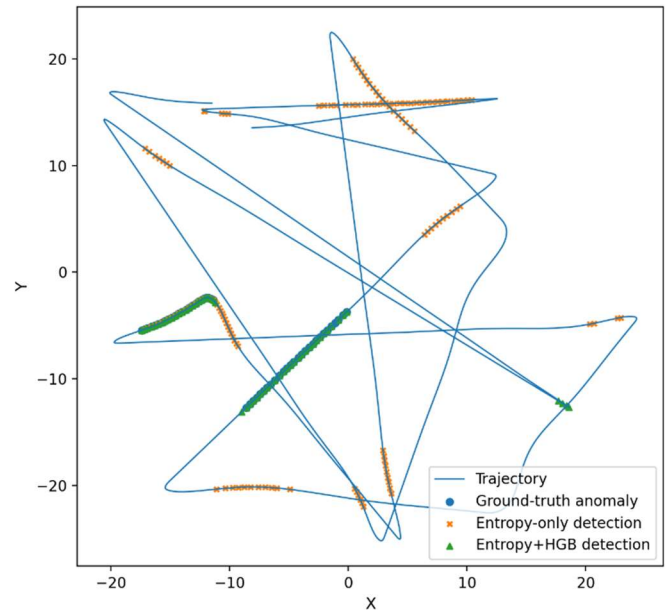


Figure 3. Spatial anomaly localization: Scenario A-BAS (Drone3).

Fig. 4 shows the matrix representation of the statistic $Q_i(t)$ in the agent–time space for six drones in the A-BAS scenario and supports analysis of the coherence of anomalous perturbations across the system levels. The indicator values lie within $[-2.5, 2.8]$, while the background regime is characterized by a concentration of observations in a narrow neighborhood of zero, $|Q_i(t)| \lesssim 0.5$.

Localized high-amplitude structures appear as vertically oriented bands over time intervals $t \approx 50-80, 340-370, 540-580$, and $980-1060$, where $Q_i(t) \gtrsim 1.5$ or $Q_i(t) \lesssim -1.5$. The geometry of these structures reflects their nature: vertical coherence, defined by the simultaneous occurrence of extrema across multiple agents, indicates coordinated inter-agent perturbations, whereas isolated pixels or short segments correspond to local fluctuations of individual trajectories.

The heatmap thus reveals that the statistic $Q_i(t)$ separates independent and collective anomalous regimes and enables their identification through analysis of spatiotemporal coherence, without explicit use of structural interaction models.

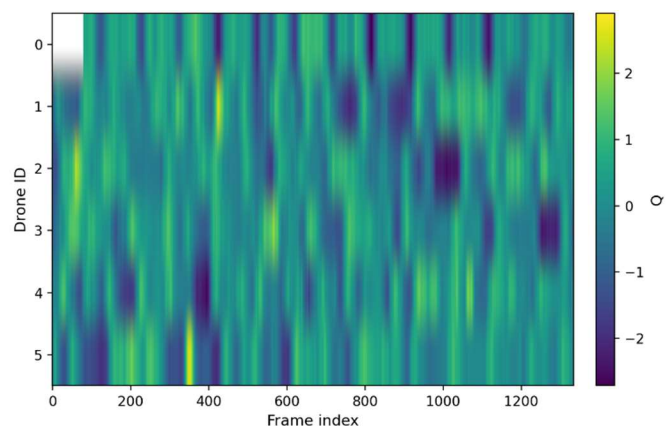


Figure 4. Q-statistic heatmap across drones: Scenario A-BAS.

Fig. 5 shows the ROC curves for the two approaches and demonstrates a clear change in class separation after ML-based calibration. The *Entropy+HGB* curve strictly dominates the

Entropy-only curve over the entire range $FPR \in [0,1]$, with the area under the curve increasing from 0.748 to 0.915 ($\Delta AUC = 0.167$).

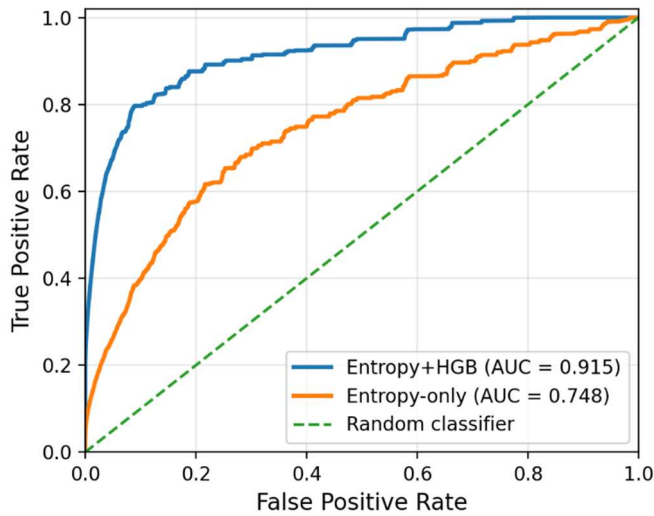


Figure 5. ROC-based comparison of anomaly detection models.

In the low false-positive regime ($FPR \leq 0.1$), *Entropy+HGB* achieves $TPR \approx 0.8$, whereas the *Entropy-only* criterion yields $TPR \approx 0.4$, indicating a twofold improvement in sensitivity at the same Type I error level. A similar advantage is observed around $FPR \approx 0.2$, where the gain in sensitivity is approximately 0.3 in absolute terms.

The *Entropy+HGB* curve rapidly approaches the upper boundary of the ROC space, indicating a stronger concentration of scores for anomalous states and improved class separation, whereas the *Entropy-only* approach exhibits a more gradual transition between classes. Thus, Fig. 5 shows that HGB-based calibration modifies not only performance metrics but also the decision structure, providing a more favorable trade-off between sensitivity and false-positive rate.

Fig. 6 shows the Precision–Recall curves for the two approaches under class imbalance. The *Entropy+HGB* curve strictly dominates the *Entropy-only* curve over the entire range $Recall \in [0,1]$, with the area under the curve increasing from 0.768 to 0.924 ($\Delta = 0.156$).

The curve shapes differ substantially. For *Entropy+HGB*, precision remains close to unity at low recall levels and decreases gradually. In contrast, the *Entropy-only* approach exhibits an approximately linear decrease in precision as recall increases, indicating weaker separation between classes in the score space.

In the high-recall regime ($Recall \approx 0.8–0.9$), the difference is most pronounced: the hybrid model maintains Precision $\approx 0.80–0.90$, whereas the entropy-based approach decreases to Precision $\approx 0.50–0.60$, corresponding to a higher false-positive rate. These results indicate that ML-based calibration redistributes scores by concentrating probability mass for anomalous states at higher values, thereby maintaining high precision even at elevated recall levels.

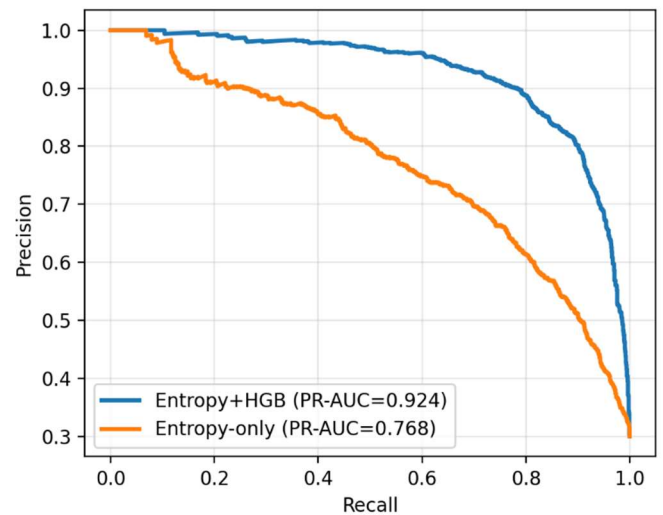


Figure 6. Precision–Recall comparison of anomaly detection models.

Fig. 7 shows the variability of model performance under five-fold cross-validation and assesses the stability of estimates with respect to sample partitioning. The ROC-AUC values lie within a narrow interval of 0.900–0.940, with a mean of 0.924, corresponding to a relative deviation within $\pm 2.2\%$. Similarly, the F1-score ranges from 0.810 to 0.850 with a mean of 0.834, with fluctuations within $\pm 2.9\%$.

For all folds, $ROC - AUC > 0.90$, indicating stability of ranking quality with respect to the choice of training and test subsets. The discrepancy between ROC-AUC and F1-score observed on individual folds, in particular a decrease in F1 at nearly constant ROC-AUC, indicates sensitivity of threshold-based decisions to local properties of score distributions rather than a degradation of the model.

These results indicate a concentration of performance metrics within a narrow range and stability of the ranking function, supporting robust generalization under variations in training subsets.

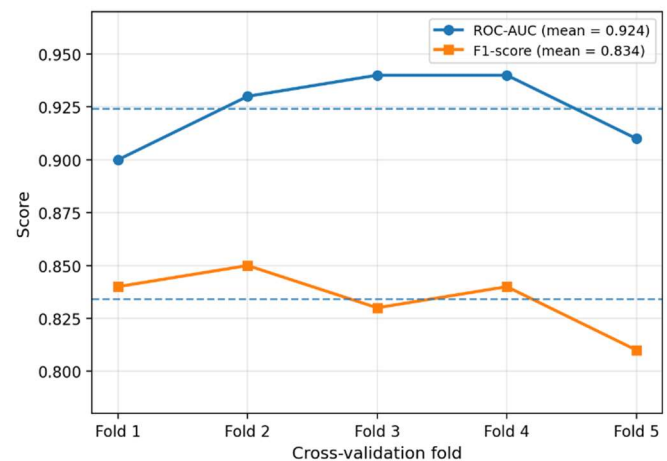


Figure 7. Cross-validation stability of the proposed anomaly detection model.

Overall, the experimental evaluation demonstrates that the proposed detector achieves consistent and quantitatively significant improvements across all considered representations. In particular, ML-based calibration increases the ROC-AUC

from 0.748 to 0.915 ($\Delta = 0.167$) and the PR-AUC from 0.768 to 0.924 ($\Delta = 0.156$), with the most pronounced gains observed in the low-FPR regime ($\text{FPR} \leq 0.1$), where the true positive rate approximately doubles. At the structural level, this improvement is reflected in the transition from spatially diffuse detections to compact segments aligned with ground-truth anomalies, as well as in the suppression of spurious responses in quasi-nominal regions, where $|Q_i(t)| \lesssim 0.5$. The heatmap analysis further reveals that the statistic $Q_i(t)$ preserves sensitivity to both isolated and coordinated perturbations, enabling discrimination between local and system-level anomalies without explicit modeling of interaction dynamics. Cross-validation results confirm the robustness of the approach, with ROC-AUC confined to the interval 0.90–0.94 (mean 0.924) and F1-score varying within 0.81–0.85 (mean 0.834), indicating low sensitivity to sample partitioning. Collectively, these results show that HGB calibration not only improves metric values but also restructures the decision space, concentrating anomaly scores and ensuring stable detection performance under realistic conditions of noise, nonlinearity, and class imbalance.

VIII. PROSPECTS FOR FURTHER RESEARCH AND IMPLEMENTATION

The developed entropy-based approach to anomaly detection in multi-component UAV systems opens up a number of promising directions for further research and practical implementation. Further development may include the expansion of the mathematical model for heterogeneous fleets of agents with different types of sensors and movement characteristics, as well as integrating interaction models with other transport systems within complex logistics chains. Special attention should be given to the study of adaptive strategies for optimizing hyperparameters in real time, as well as the development of attack-resistant models to improve the cybersecurity of UAV control systems. The implementation of the obtained results can be carried out in regional situational centers to increase the level of monitoring automation, minimize risks, and ensure an operational response to critical events in complex dynamic environments.

IX. CONCLUSIONS

The study proposes a comprehensive approach to detecting anomalies in the trajectories of multi-component unmanned aerial vehicle (UAV) systems based on entropy analysis and machine learning methods. The developed mathematical model takes into account the kinematic parameters of agents, the structure of interactions, as well as stochastic environmental influences. Combined entropy statistics, based on local and structural information measures, demonstrate high sensitivity to complex anomalous events, such as short-term kinematic perturbations and structural changes in agent interactions.

The experimental evaluation indicates that the integration of ML-based calibration (*Entropy+HGB*) improves detection performance. Specifically, ROC-AUC increases from 0.748 to 0.915 and PR-AUC increases from 0.768 to 0.924, indicating improved discriminative capability under class imbalance. The effect is most pronounced in the low false-positive regime ($\text{FPR} \leq 0.1$), where the true positive rate is approximately twice higher than that of the entropy-only baseline. At the structural level, the method transforms spatially diffuse detections into

compact segments aligned with ground-truth anomalies and reduces spurious responses in quasi-nominal regions.

Robustness is supported by cross-validation results: ROC-AUC remains within 0.90–0.94 (mean 0.924), and F1-score remains within 0.81–0.85 (mean 0.834), indicating low sensitivity to sample partitioning. From a computational perspective, the pipeline exhibits near-linear complexity in the number of agent–time observations, supporting scalability to large multi-agent systems.

These results indicate that the proposed entropy–ML framework supports operational monitoring of coordinated UAV behavior, capturing both local kinematic anomalies and higher-order interaction effects under noise, nonlinearity, and dynamic structural variation.

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