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A method for synthesizing index policies to ensure the survivability of a mobile platform-based information system

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ABSTRACT

This paper proposes a method for synthesizing index policies to ensure the survivability of a mobile platform-based information system operating under intermittent connectivity and incomplete observability. The method aims to maintain the probability of violations within specified budgets by combining event-based index ranking with calibrated risk management and dual-loop parameter tuning. The fast loop adaptively adjusts the weight of the risk component of the index based on the magnitude of recorded excesses, while the slow loop periodically recalibrates feature normalization, base weights, and relevance factors, thereby enhancing robustness to non-stationarity and small sample sizes. Probabilistic constraints are interpreted through upper confidence bounds on a short sliding window, enabling controlled risk without rigid assumptions regarding disturbance distributions and without reliance on continuous telemetry or frequent global coordination. To maintain decision consistency, a computationally lightweight acceptability check and event logging are employed, facilitating independent reproducibility. The study presents the index rule formulation—including feature normalization, weight structure, and risk testing—along with a risk correction protocol for sampling per decision step and a procedure for detecting mode changes and safe reconfiguration. The computational complexity of the method is amortized linear-logarithmic with respect to the number of active objects and step capacity, ensuring suitability for real-time operation. Verification was performed on event logs featuring intermittent connectivity and surge load scenarios. The results demonstrate the convergence of the violation frequency upper bound to specified budgets, the stabilization of the risk component weight without fluctuations, and predictable service metric dynamics. A step-by-step ablation study highlighted the contribution of each component: disabling the fast loop delays the achievement of target risk levels, while the absence of the slow loop locks the risk component at an excessive weight, degrading the operational balance. Compared to heuristic rules lacking explicit risk control and model-predictive approaches sensitive to telemetry quality, the proposed method ensures the survivability of the information system through controllable probabilistic guarantees, event scalability, and reproducible verification procedures.

Keywords: Information system; mobile platform; survivability; index policy; dual-loop adaptation; method

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INTRODUCTION

Mobile platform-based information systems are characterized by intermittent structural connectivity [1], operation with variable delays between structural elements [2], uneven access to resources [3], and incomplete observability [4]. Under these conditions, survivability – the ability to maintain functionality and acceptable service quality despite external destructive influences, communication disruptions, and cascading data flow deviations – becomes the defining characteristic [5], [6], [7].

External destructive influences are defined as exogenous events that alter the system's operating conditions [5].

Depending on their intensity and target, these influences induce the following types of failures:

– operational failures – short- to medium-term deviations that degrade the performance of the system's primary function (quality drop) while the system continues to execute it;

– severe failures – prolonged intervals of unavailability of system elements causing a significant drop in primary function quality, but with subsequent functional recovery using available reserve resources without altering the nature of the primary function;

– catastrophic failures – events necessitating a change in the system's primary function because actual resources are minimally sufficient only for the new function; these typically arise from the violation of critical invariants.

Consequently, a class of problems arises concerning the operational redistribution of resources in such systems.

Two predominant directions for solving these problems exist:

– predictive and stochastic optimization control models [8], which provide rigorous solutions but require significant amounts of auxiliary information during operation. Therefore, in most scenarios, they are ill-suited for ensuring rapid system responses under unstable architectural connectivity;

– heuristic prioritization rules [9], which are simple to deploy but typically guarantee only a controlled risk of violations and a reproducible operational trajectory under peak loads and communication disruptions.

Index policies (decision-making rules based on a scalar index) occupy a distinct position, demonstrating satisfactory scalability and numerous practical applications for rapid resource distribution. Solutions based on index policy logic show consistent advantages, particularly regarding scalability and the ability to function with insufficient information for optimal decision-making. This reflects the current trend of combining them with bandit and reinforcement learning methods, relaxing initial assumptions, and designing applied solutions [10].

Prominent solutions in this domain include methods with probabilistic constraints [11] and the class of Distributionally Robust Optimization (DRO) approaches [12], which allow the system to respond to rare architectural events or external factors characterized by unknown random disturbance distributions and statistical uncertainty. An analysis of risk-aware information system management research [13] illustrates how tail risk measures (specifically CVaR) can be integrated into the synthesis of secure and stable operating policies, including via barrier functions and optimization schemes, providing tools to control rare but critical deviations.

A defining feature of mobile platforms is intermittent connectivity. Even with fault-tolerant protocols, prolonged unavailability windows, element asynchrony, and the accumulation of garbage (stale) data may occur. In such conditions, universal approaches relying on continuous telemetry [14] or frequent global coordination [15] perform significantly worse or fail to ensure stable system operation.

The analysis highlights unresolved tasks critical for real-world deployment, specifically:

– controlled violation risk under intermittent connectivity and incomplete data, without rigid assumptions on random deviations, relying on empirical thresholds and aligned with probabilistic or DRO guarantees;

– scalable event-driven decision rules with short response times, leveraging index policies and risk-oriented constraints;

– robustness to long delays and channel disruptions, including data staleness and asynchrony, without dependence on continuous global synchronization;

– addressing the excessive complexity of verification protocols for realistic interruption scenarios and variable loads, focusing on tail risks and consistency.

The formulated tasks underscore the need to develop methods combining index prioritization with explicit risk control and suitability for intermittent connectivity environments.

RELATED WORKS

Current approaches to creating index-based decision rules are primarily focused on finding computationally efficient algorithms. For instance, the Restless Multi-Armed Bandit (RMAB) framework exemplifies the applicability of index methodology, illustrating its computational complexity regarding resource intensity while forming modern generalizations for partial observability and complex budget constraints [10]. Recent years have seen the development of optimistic index methods that generally combine index approaches with machine learning elements in complex dynamic environments [16]. Additionally, new approaches to indexability in partially observable restless models [17] and risk-aware planning variants for RMAB [18] are noted.

There exists a class of problems with chance constraints (probabilistic constraints), where it is necessary to control the probability of violations under limited statistical information. Modern research in this direction is well-systematized by transformation and approximation criteria, and algorithmic templates for such problems demonstrate practical applicability for complex information systems [11]. A related approach is Distributionally Robust Optimization (DRO), which allows modeling distribution uncertainty through an ambiguity set and focuses on the worst-case distribution within this set [19]. Research embedding risk indicators (risk measures, particularly CVaR) into control and reinforcement learning [20], [21] is intensively developing to obtain decisions considering not only average quality but also rare yet highly undesirable “tail events” [22].

Studies on consistency in replicated systems under limited or intermittent connectivity prove the importance of finding solutions to ensure service quality [23], [24]. Research on information systems with causal consistency and invariant checking shows that formal verification methods and tools detecting consistency violations in real systems are actively evolving [25].

The analysis of modern scientific research [16-25] indicates the suitability of index approaches and the availability of tools for solving chance-constrained and distributionally robust problems, while also providing basic recommendations for using information systems with intermittent connectivity.

However, gaps critical specifically for mobile platform-based information systems in highly dynamic operating conditions are identified, including:

– the problem of compatibility of index policies with explicit risk management (absence of constructs allowing calibration of index rule parameters to a given violation risk level while maintaining event scalability [10], [16]);

– the problem of robustness to non-stationary/limited statistics (lack of methods sensitive to mode changes and small samples based on DRO concepts yet simple to implement [12]);

– insufficient stability of a mobile platform-based information system operating under intermittent connectivity without requiring frequent global coordination and with control of "tail" deviations in service indicators [14], [21], [26];

– significant complexity in implementing validation approaches for index decision effects against realistic interruption/asynchrony scenarios and evaluation via risk-oriented metrics [20].

The problem statement in this study focuses on the synthesis of index policies with guaranteed (calibrated) control of violation probability under intermittent connectivity and incomplete statistical information, while maintaining low event-based computational costs and reproducible verification procedures.

RESEARCH OBJECTIVE AND TASKS

The purpose of the study is to develop and experimentally verify a method for synthesizing index policies to ensure the survivability of a mobile platform-based information system with calibrated control of violation probability.

Tasks:

– determine the structure of the index rule and the dual-loop parameter tuning procedure based on empirical boundary values (quantiles)/concentration estimates;

– construct an event-driven algorithm and evaluate its computational cost;

– formulate a verification protocol with metrics and benchmarks;

– perform sensitivity and robustness analysis, confirming compliance with the specified risk level and improvement of service indicators.

TAXONOMY

Consider a mobile platform-based information system operating in an event-driven mode with intermittent connectivity and partial observability [27]. At each decision step $t \in \mathrm{T}$, the set of active objects U_t and the current capacity C_t (the number of objects that can be served simultaneously) are known. The solution consists in selecting a subset $A_t \subseteq U_t$ of size no more than C_t for servicing at step t.

For each $u \in U_t$, a scalar index is utilized that aggregates normalized features (urgency, importance, and data relevance, local service deviations, load estimates, and predicted channel availability):

$$I_u(t;\theta) = \sum_{j=1}^{m} \alpha_j(t)\phi_j(u,t) + \beta_u(t), \tag{1}$$

where $\phi_j(u,t) \in [0,1]$ are normalized features; $\alpha_j(t) \geq 0$ are weight coefficients; $\beta_u(t) \in \mathrm{R}$ is the offset for class prioritization; and $\theta = \{\alpha_j(\cdot), \beta_u(\cdot)\}$ is the vector of parameters to be adjusted during the research process to achieve the objectives. In (1), the class prioritization offset is defined as an additive constant (reward or penalty) applied to the index for all requests belonging to a specific class.

For a unit capacity $C_t = 1$, the object with the highest index is selected:

$$u^*(t) = \arg\max_{u \in U_t} I_u(t;\theta). \tag{2}$$

For an arbitrary capacity $C_t \geq 1$, the optimal subset of the highest priority objects is formed:

$$A_t = \arg\max_{A \subseteq U_t, |A| \leq C_t} \sum_{u \in A} I_u(t;\theta). \tag{3}$$

In the event of tied indices, a deterministic prioritization order is applied. Specifically, preference is given to the object with the greater waiting time indicator $s_u(t)$ (time elapsed since the last service), and in the case of equal time indicators, preference is determined by the permanent identifier id_u. According to (2) and (3), and in cases of equal indices, a consistent approach is selected to eliminate ambiguity and ensure reproducibility.

If necessary, switching from the previously serviced object (v) to a new candidate (r) is permitted, but only subject to a sufficient index gain (a hysteresis condition preventing excessive switching):

$$I_v(t;\theta) - I_r(t;\theta) \geq \eta_t, \qquad \eta_t \geq 0. \quad (4)$$

In (4), the parameter η_t sets the minimum index gap required to initiate switching; in a continuous policy, $\eta_t = \infty$ is assumed.

Correct functioning is defined by a system of chance constraints for the vector of functions $g(t) = \left(g_1(t), \ldots, g_K(t)\right)$ reflecting resource, coordination, and service requirements:

$$\Pr\left\{g_k\left(X_t, a_t\right) \leq 0\right\} \geq 1 - \delta_k, \quad k = 1, \ldots, K, \quad (5)$$

where X_t is the vector of available observations/estimates at step t ; $a_t \in \left\{u^*(t), A_t\right\}$ is the decision made according to the index rule; and $\delta_k \in (0,1)$ is the risk budget for violations of constraint k .

If necessary, the total budget $\sum_k \delta_k \leq \delta_\Sigma$ is additionally fixed, and a rule for its distribution among constraints is introduced.

Partial observability is handled by restoring missing features via exponential smoothing of the last reliable value:

$$\hat{\phi}_j(u,t) = \lambda^{\Delta t} \varphi_j(u,t^-), \quad \lambda \in (0,1), \quad (6)$$

where t^- is the timestamp of the last feature observation; and $\Delta t = t - t^-$.

This procedure (6) enables index comparison in the presence of data gaps and delays during the operation of the mobile platform-based information system.

INDEX RULE FOR DECISION MAKING

The components of the scalar index and their construction principles are established to align the ranking of active objects with risk constraints and the characteristics of intermittent connectivity.

The generalized form of the index is:

$$\begin{aligned} I_u(t;\theta) = \alpha_1 \Phi_{prio}(u) + \alpha_2 \Phi_{stale}(u,t) + \\ + \alpha_3 \Phi_{load}(u,t) + \alpha_4 \Phi_{link}(u,t) + \\ + \alpha_5 \Phi_{risk}(u,t) + \beta_u, \end{aligned} \quad (7)$$

where u is an active object at the time t ; $\Phi_\bullet \in [0, 1]$ are normalized dimensionless features.

In (7), higher values of $I_u(t;\theta)$ correspond to higher priority.

Feature normalization is performed as follows. Each raw value $z(u,t)$ is mapped to the interval [0, 1] using empirical bounds on a sliding window W_t :

$$\Phi(u,t) = \mathrm{clip}\left(\frac{z(u,t) - q^{low}(t)}{q^{high}(t) - q^{low}(t) + \varepsilon},\ 0,\ 1\right), \quad (8)$$

where $q^{low}(t)$, $q^{high}(t)$ are quantiles of order, for example, 0.05 and 0.95; $\varepsilon > 0$ is a stabilizer.

In (8), the stabilizer is a positive constant serving a protective anti-degeneracy function to prevent denominator vanishing when $q^{high}(t) = q^{low}(t)$. This normalization procedure (8) is robust against outliers and does not require specific assumptions regarding the disturbance distribution law [33].

The index (7) comprises the following components:

1. Object importance component:

$$\Phi_{prio}(u) \in [0, 1]. \quad (9)$$

Component (9) is a static or slowly varying weight indicator of the importance class (e.g., service type, task criticality).

2. Data relevance component:

$$\Phi_{stale}(u,t) = \mathrm{clip}\left(\frac{d_u(t)}{d^{\max} + \varepsilon},\ 0,\ 1\right), \quad (10)$$

where $d_u(t)$ is the time elapsed since the last update/synchronization for u ; $d^{\max}$ is the operational upper bound.

An increase in Φ_{stale} (10) indicates a longer period without updates for the object, thereby increasing its service priority.

3. Local load component:

$$\Phi_{load}(u,t) = \mathrm{clip}\left(\frac{q_u(t)}{q^{\max} + \varepsilon},\ 0,\ 1\right), \quad (11)$$

where $q_u(t)$ is the queue/workload estimate for u ; $q^{\max}$ is the operational upper bound.

Component (11) facilitates the prioritization of objects with excessive local load.

4. Connectivity status component:

$$\Phi_{link}(u,t) = \exp\left(-\frac{\tau_u(t)}{\tau_0 + \varepsilon}\right), \quad (12)$$

where $\tau_u(t) \geq 0$ is the predicted time until the channel becomes available for an operation related to u; and $\tau_0 > 0$ is the characteristic scale (reference availability interval).

The value (12) approaches 1 if the channel is already available or is expected to open within the characteristic interval τ_0, aligning priority with intermittent connectivity.

5. Risk component. First, the empirical risk budget overrun is calculated:

$$e(t) = \left(\hat{p}_k(t) - \delta_k\right)_+, \quad k = 1,\ldots,K, \tag{13}$$

where $\hat{p}_k(t)$ s the estimated violation frequency of constraint k on window W_t; and δ_k is the specified risk budget.

Next, the relevance share of the object to constraint k, denoted as $a_{k,u}(t) \in [0, 1]$, is introduced. This reflects the extent to which servicing u reduces the probability of violating k (determined by object class/operation type or via empirical sensitivity on W_t).

The risk component is defined as:

$$\Phi_{risk}(u,t) = \\ = \text{clip}\left(\frac{\sum_{k=1}^{K} w_k^{(r)} e_k(t) a_{k,u}(t)}{\max\limits_{v \in U_t} \sum_{k=1}^{K} w_k^{(r)} e_k(t) a_{k,u}(t) + \varepsilon}, 0, 1 \right), \tag{14}$$

where $w_k^{(r)} \geq 0$ are the importance weights of individual constraints.

When certain constraints exceed their budgets, priority is shifted to objects capable of maximally reducing such excesses.

Thus, the properties of index (7) can be formulated in the context of invariants:

– an increase in any of the components (8)-(12), (14) with other components fixed, does not decrease $I_u(t;\theta)$;

– all components (8)-(12), (14) are normalized to $[0, 1]$, so the use of quantiles ensures robustness to outliers without requiring distribution assumptions;

– when $\hat{p}_k(t) \leq \delta_k$, the contribution $\Phi_{risk} \to 0$, and prioritization is determined by operational features; conversely, when risk budgets are exceeded, priority is adjusted in favor of actions that mitigate the excess.

Collectively, these properties ensure the coordinated ranking of active objects under intermittent connectivity and limited statistical information during the execution of the target function by the mobile platform-based information system.

EVENT-DRIVEN ALGORITHM FOR POLICY SYNTHESIS

The event-driven policy synthesis algorithm can be represented as the following sequence of steps.

Step 1. Updating observations. Upon the occurrence of event t, the available features $\phi_j(u,t)$ for objects $u \in \Delta U_t \subseteq U_t$ are updated. Missing values are restored via exponential smoothing according to formula (6).

Step 2. For new and/or refined observations, quantiles are calculated on W_t, normalization is performed, and the components of index (7) are updated. Subsequently, $I_u(t;\theta)$ is recalculated for $u \in \Delta U_t$, and the corresponding keys in the priority data structure are synchronized.

Step 3. Preliminary selection. A preliminary service set $A_t^{(0)}$ is formed as a subset of at most C_t objects with the highest $I_u(t;\theta)$ according to formula (3).

Step 4. Risk constraint check (conservative test). For each constraint $k = 1,\ldots,K$, the empirical violation frequency $\hat{p}_k(t)$ on W_t is updated and the budget overrun is calculated using formula (13). For the pre-selected set of objects A, its expected impact on the constraints is assessed via relevance coefficients $a_{k,u}(t) \in [0, 1]$:

$$\Delta_k(A,t) = \sum_{u \in A} w_k^{(r)} a_{k,u}(t). \tag{15}$$

The set A is considered acceptable for step t if the following condition is met:

$$e_k(t) - \zeta_k(t)\Delta_k(A,t) \leq \rho_k(t) \text{ for any } k, \tag{16}$$

where $\zeta_k(t) > 0$ is the calibrated impact coefficient; and $\rho_k(t)$ is the tolerance for statistical error.

The test is a conservative approximation and operates without assumptions regarding the distribution of random influences.

Step 5. Risk-adjusted selection. If $A_t^{(0)}$ fails the test, a local replacement is applied: the object with the smallest contribution to Δ_k for the constraint with the largest budget overrun is removed from $A_t^{(i)}$, and an object $v \in \frac{U_t}{A_t^{(i)}}$ is added that maximizes the increase in Δ_k with minimal loss of $\sum I_u$. Iterations continue until the set becomes acceptable or until further replacements yield no improvement. The number of iterations is limited to C_t.

Step 6. Switching. When switching from the object that was served (r) to a new candidate for service (v), the minimum gap criterion (4) is applied. If the criterion is not met, the current service is retained, preventing excessive switching.

Step 7. Updating statistics. After applying decisions, $\hat{p}_k(t)$, normalization quantiles, non-stationarity indicators, and computational cost logs are updated. These data are subsequently used for system parameter calibration and adaptation.

In the proposed algorithm, each step involves index recalculation only for objects with ΔU_t and a limited number of insertions/deletions in the priority structure. The amortized complexity of the algorithm is $O\left(|\Delta U_t|\log|U_t| + C_t \log|U_t|\right)$.

The algorithm enables the formation of a policy combining index ranking with explicit, empirically calibrated consideration of violation risk, while maintaining an event-driven nature and low computational complexity.

PROBABILISTIC CONSTRAINTS AND THEIR CALIBRATION

Next, it is proposed to align the index policy with the requirements (5) assuming an unknown distribution of random influences and limited available statistical information. Calibration is performed empirically: the violation frequency is estimated over a sliding window, a statistical margin is added, and subsequently, the risk budget shares and the scaling of decision impacts are adjusted for constraints exhibiting the largest overruns.

Therefore, it is advisable to first estimate the violation frequency and establish an Upper Confidence Bound (UCB). For each constraint k on a window W_t of size N_t, a binary sequence of violations $v_k(s) = \mathbf{1}\{g_k(X_s, a_s) > 0\}$ is recorded.

Then the empirical frequency is:

$$\hat{p}_k(t) = \frac{1}{N_t}\sum_{s\in W_t} v_k(s). \tag{17}$$

To avoid reliance on distribution assumptions, an upper bound based on Hoeffding's inequality [28] (or, if a ready-made implementation is available, the Wilson interval [29] or Clopper–Pearson interval [30]) is utilized:

$$\hat{p}_k^{\uparrow}(t) = \hat{p}_k(t) + \sqrt{\frac{\ln\left(\dfrac{1}{\alpha_k(t)}\right)}{2N_t}}, \tag{18}$$

where $\alpha_k(t) \in (0, 1)$ is the confidence level for constraint k.

Subsequently, taking into account (17) and (18), $\hat{p}_k^{\uparrow}(t)$ is compared with the budget δ_k; the excess is interpreted as a "risk deficit".

The magnitude of the deficit for constraint k is:

$$e_k(t) = \left(\hat{p}_k^{\uparrow}(t) - \delta_k(t)\right)_+. \tag{19}$$

The contribution of selecting the set A_t to reducing the deficit is reflected through the aggregated relevance indicator (the degree of involvement of objects in this constraint) (15):

$$\Delta_k(A_t, t) = \sum_{u\in A_t} w_k^{(r)} a_{k,u}(t). \tag{20}$$

where $a_{k,u}(t) \in [0, 1]$ is the share reflecting the expediency of servicing object u to improve the fulfillment of constraint k (estimated on W_t by empirical sensitivity). It is planned that the choice of A_t in (20) is acceptable for step t if the expected increase in assurance (deficit reduction) exceeds the statistical margin, according to formula (16).

In (16), $\zeta_k(t) > 0$ scales the effect of Δ_k in reducing e_k, and $\rho_k(t) \ge 0$ compensates for random estimation fluctuations.

Calibration of $\zeta_k(t)$ and $\rho_k(t)$ is performed as follows. The parameter $\zeta_k(t)$ is estimated from the window W_t data as the least squares coefficient for the linear response "change in deficit ↔ total relevance" with regularization:

$$\begin{gathered}\zeta_k^{å}(t) = \arg\min_{\zeta\ge 0} \sum_{s\in W_t} \big(e_k(s) - e_k(s-1) + \\ + \zeta\Delta_k\left(A_{s-1}, s-1\right)\big)^2 + \lambda\zeta^2,\end{gathered} \tag{21}$$

after which smoothing is applied with small $\lambda, \beta > 0$.

$$\zeta_k(t) \leftarrow (1-\beta)\zeta_k(t-1) + \beta\zeta_k^{å}(t),$$

The margin $\rho_k(t)$ is defined by the width of the confidence interval:

$$p_k(t) = \tau\sqrt{\frac{\ln\left(\frac{2}{\alpha_k(t)}\right)}{2N_t}}, \quad \tau \ge 1, \tag{22}$$

which ensures the conservativeness of the test for small samples and during mode changes.

Next, the distribution of the total risk budget is specified. Let $\sum_{k=1}^{K}\delta_k(t) = \delta_\Sigma$ be the fixed total budget. The initial proportion $b_k(0)$ is selected according to service priorities, followed by a soft rebalancing of proportions based on deficits:

$$b_k(t+1) = \frac{b_k(t)\exp\left(\frac{\gamma e_k(t)}{\delta_k(t)+\varepsilon}\right)}{\sum_{j=1}^{K} b_j(t)\exp\left(\frac{\gamma e_k(t)}{\delta_k(t)+\varepsilon}\right)}, \tag{23}$$

$$\delta_k(t+1) = \operatorname{clip}\left(\delta_\Sigma b_k(t+1),\ \delta_{\min},\ \delta_{\max}\right),$$

where $\gamma > 0$ is the rebalancing coefficient; and $\left[\delta_{\min}, \delta_{\max}\right]$ are the allowable bounds for individual constraints.

This scheme (23) increases the budget share for constraints with the largest recorded overruns while maintaining control over the total sum.

The level of $\alpha_k(t)$ in (18), (22) can be adapted according to the sample size N_t and the rate of mode change (smaller α_k implies greater conservatism). The window length W_t is selected considering the "inertia ↔ sensitivity" trade-off; in the case of accelerating events, a decrease in N_t is permitted with a compensating increase in $\alpha_k(t)$ or τ.

These constraints and the calibration mode are fully consistent with the event-driven algorithm. The values $\hat{p}_k^{\uparrow}(t)$, $e_k(t)$, $\Delta_k(A_t, t)$, $\zeta_k(t)$, and $\rho_k(t)$ are directly used in the acceptance test. If the test fails, local replacement of elements in A_t is applied until conditions are met or iterations are exhausted. In a stable mode, when $\hat{p}_k^{\uparrow}(t) \le \delta_k(t)$ for all k, the deficits tend to zero, the impact of the risk component diminishes, and the policy operates based on the operational components of the index.

The use of the Upper Confidence Bound $\hat{p}_k^{\uparrow}(t)$ combined with the margin $\rho_k(t)$ ensures high-probability compliance with restrictions under unknown random influence distributions; rebalancing $\delta_k(t)$ avoids chronic "under-calibration" of individual constraints. Subsequent dual-loop adaptation of index parameters θ reduces the need for frequent risk corrections and accelerates convergence to the operating mode.

DUAL-LOOP ADJUSTMENT OF INDEX PARAMETERS

This section proposes a parameter $\theta = \{\alpha_{1\ldots5}, \beta_u\}$ control mechanism ensuring the consistency of the index policy with probabilistic constraints under intermittent connectivity and limited statistics. A dual-loop scheme is proposed: the fast loop responds to the current risk load (the magnitude of recorded overruns) and adjusts the share of the risk component of the index; the slow loop performs periodic recalibration of normalization, base weights, and relevance factors based on generalized empirical data. This mechanism is designed to ensure rapid stabilization of disturbances without compromising long-term effectiveness.

The fast loop is constructed as follows. Let $e_k(t)$ be the risk deficit for constraint k (19), and $w_k^{(r)}$ be its importance weight. A dimensionless risk load indicator (the magnitude of recorded overruns) is introduced:

$$R(t) = \frac{\sum_{k=1}^{K} w_k^{(r)} e_k(t)}{\sum_{k=1}^{K} w_k^{(r)} \delta_k(t) + \varepsilon}, \quad \varepsilon > 0. \tag{24}$$

Let α_5 be the weight of the risk component Φ_{risk} (14). The target risk share is set as a monotonic function of $R(t)$ (24) with a deadband (a range of input values within which the output remains unchanged):

$$s_5^{\text{å}}(t) = s_5^{\min} + \left(s_5^{\max} - s_5^{\min}\right)\psi\left(\frac{R(t) - \tau_{\downarrow}}{\tau_{\uparrow} - \tau_{\downarrow}}\right), \tag{25}$$

where $0 < s_5^{\min} < s_5^{\max} < 1$; and $\tau_{\downarrow} < \tau_{\uparrow}$ are deadband thresholds; $\psi(\cdot) \in [0,1]$ is a sigmoid or truncated linear function. The current risk weight approaches the target with amortization:

$$\alpha_5(t^+) = \Pi_{[\underline{\alpha}_5, \bar{\alpha}_5]}\left(\left(1-\eta\right)\alpha_5(t) + \eta s_5^{\text{å}}(t)\right),$$

where $\eta \in (0,1]$ is the correction step; and Π is the projection onto the segment $\left[\underline{\alpha}_5, \bar{\alpha}_5\right]$.

To preserve the interpretability of the index, the sum of weights is normalized to unity:

$$\sum_{j=1}^{5}\alpha_j(t^+)=1,\quad \alpha_{1\ldots4}(t^+)=\frac{1-\alpha_j(t^+)}{\sum_{j=1}^{4}\alpha_j^{base}}\alpha_j^{base}.$$

The vector α^{base} sets the base proportion of operational components Φ_{prio}, Φ_{stale}, Φ_{load}, Φ_{link} and is updated via the slow loop. To prevent frequent switching, hysteresis is applied: a change in α_5 is executed only if $R(t)$ is outside $\left[\tau_{\downarrow},\tau_{\uparrow}\right]$ for at least H consecutive events.

The service alignment rule is achieved by correcting the offsets β_u. Let $s_u(t)$ be the time elapsed since the last service of object u, and s^{ref} be the maximum allowable time.

The delay is corrected proportionally to the excess:

$$\beta_u(t^+)=\Pi_{\left[\underline{\beta},\bar{\beta}\right]}\left(\beta_u(t)+\kappa\left(s_u(t)-s^{ref}\right)_+\right),$$

where $\kappa>0$ is the correction parameter (step). This limits excessive delays in servicing low-priority objects without significantly affecting risk constraints.

The formalization of the slow loop is as follows. At a fixed interval of ΔT events or time, an aggregated recalibration is performed based on data from a longer window W^{long}, and then the following are determined:

– feature normalization. Quantiles q^{low}, q^{high} for normalization (8) are re-evaluated on W^{long} with stability checks. If non-stationarity is detected, the bounds are adjusted more conservatively (interval expansion);

– relevance to constraints. The coefficients $a_{k,u}(t)$ are refined as empirical sensitivities of "service $\Rightarrow$ reduction of violations k " on W^{long} with regularization and truncation to $[0,1]$. If necessary, a cluster representative is used for groups of objects to reduce estimate variability;

– base proportions of operational weights. Let $\bar{\Phi}_{prio}$, $\bar{\Phi}_{stale}$, $\bar{\Phi}_{load}$, $\bar{\Phi}_{link}$ be the average feature values of on W^{long}. Then the vector α^{base} is updated to a balanced state minimizing the deviation of target service indicators, provided risk budgets are moderately adhered to:

$$\alpha^{base}\leftarrow(1-\mu)\alpha^{base}+\mu\tilde{\alpha}^{base},$$

where $\mu\in(0,1]$; and $\tilde{\alpha}^{base}$ – the solution of a small convex subproblem over the simplex $\sum_{j=1}^{4}\alpha_j^{base}=1$, $\alpha_j^{base}\geq 0$ with penalties for undesirable shifts. This procedure adjusts the base (slow) set of weights considering statistics, without interfering with rapid risk response.;

– risk test parameters. Coefficients $\zeta_k(t)$ and margins $\rho_k(t)$ are re-evaluated on W^{long} with higher precision. Results are smoothed by a first-order filter to prevent abrupt changes.

With two loops, it is necessary to establish stability conditions and limit the rate of change. To avoid fluctuations, restrictions are applied to the rate of change coefficient:

$$\begin{gathered}\left\|\alpha(t^+)-\alpha(t)\right\|_1\leq\Delta_{\alpha}^{\max},\\ \left\|\beta_u(t^+)-\beta_u(t)\right\|\leq\Delta_{\beta}^{\max}.\end{gathered}\tag{26}$$

A suspension interval (downtime) is also defined: if $\hat{p}_k^{\uparrow}(t)\leq\delta_k(t)\ -\ \xi$ for all k during H events, the fast loop is suspended, locking the mode with observed constraints. In case of a non-stationary signal, a soft adaptation recovery is performed: $\alpha_5\to\max\left\{\alpha_5,s_5^{\min}\right\}$, $\eta\to\eta_{low}$, $\mu\to\mu_{low}$.

In real information systems, it is initially recommended to set $\alpha^{base}=\left(\frac{1}{4},\frac{1}{4},\frac{1}{4},\frac{1}{4}\right)$, $\alpha_5=s_5^{\min}$, $\eta\in[0.05,\,0.2]$, $\mu\in[0.05,\,0.2]$, $H\in[5,\,20]$, $\tau_{\downarrow}\approx0.8$, $\tau_{\uparrow}\approx1.0$, s^{ref} based on the median $s_u(t)$ in the window. The bounds $\underline{\alpha}_5,\bar{\alpha}_5$ are selected considering specific application requirements for the permissible violation frequency. The values $\left[\underline{\beta},\bar{\beta}\right]$ are selected based on sensitivity analysis so that offset correction does not outweigh the base weights.

DETECTION OF NON-STATIONARITY AND SAFE RECALIBRATION OF INDEX PARAMETERS

It is proposed to formalize the procedure for detecting a mode change (instability of disturbance/observation statistics) and to develop a regulation for the safe recalibration of index parameters and risk tests without violating the requirements set forth in this study. A two-stage indication is proposed: based on risk budget overruns and shifts in empirical feature characteristics, followed by the introduction of a stabilization mode with a subsequent controlled return to operating settings.

Risk violation indication is performed as follows. In the sliding window W_t, for each constraint k, a binary sequence of violations $v_k(s) = \mathbf{1}\{g_k(X_s, a_s) > 0\}$ and the upper confidence bound of the frequency $\hat{p}_k^{\uparrow}(t)$ (18) are maintained. The cumulative deviation statistic from the target level is determined:

$$S_k(t) = \max\{0, (1-\gamma)S_k(t-1) + \hat{p}_k^{\uparrow}(t) - \delta_k(t)\},$$
$$\gamma \in (0,1).$$

The first non-stationarity indicator is triggered if:

$$S_k(t) \geq h_k,$$

where h_k is the sensitivity threshold selected according to the acceptable false alarm frequency (based on calibration results).

Feature shift indication is conducted as follows. For a representative subset of features ϕ_j, the reference quantiles on a longer window W_t^{ref} and the current quantiles on a short window W_t^{short} are compared:

$$D_j(t) = \left| \frac{q_{j,0.9}^{short}(t) - q_{j,0.9}^{ref}(t)}{q_{j,0.9}^{ref}(t) + \varepsilon} \right|, \quad \varepsilon > 0.$$

The second indicator is triggered if:

$$\max_j D_j(t) \geq \tau_D,$$

where $\tau_D \in (0,1)$ is the relative shift threshold.

The decision on the presence of non-stationarity is made when both indicators are active or the first indicator is maintained for at least H events.

Upon detection of non-stationarity, the parameters are switched to stabilization mode (conservative mode). First, the weight of the risk component of the index is increased to the upper bound with a controlled step:

$$\alpha_5 \leftarrow \min\{\bar{\alpha}_5, \alpha_5 + \Delta\alpha\}, \quad \Delta\alpha > 0.$$

Second, the stability condition for selection is strengthened to reduce switching frequency:

$$\eta_t \leftarrow \eta_{hi}, \quad \eta_{hi} > \eta_t.$$

Third, the risk test parameters (22) are adapted: the length of the statistical window is reduced and the confidence level is lowered (which increases the confidence margin):

$$N_t \leftarrow \max\{N_{\min}, \rho N_t\}, \quad \rho \in (0,1),$$
$$\alpha_k(t) \leftarrow \alpha_k^{\downarrow}, \quad \alpha_k^{\downarrow} < \alpha_k(t)$$

and the margin in the acceptability test is increased:

$$\rho_k(t) \leftarrow \rho_k(t) + \Delta\rho, \quad \Delta\rho > 0.$$

Finally, the rebalancing of risk budgets between constraints (23) is accelerated by increasing the coefficient γ in the rule for updating the shares $b_k(t)$.

Recalibration of impacts and normalization is also performed. In stabilization mode, the impact coefficients $\zeta_k(t)$ are re-evaluated over a short window reflecting the new regime, and feature normalization boundaries are updated. First-order smoothing is applied to each constraint to avoid sharp fluctuations, following the smoothing scheme applied to formula (21).

Criteria for exiting and returning to the operating mode are determined by the removal of the stabilization mode if, for all k during H^* events, the following holds:

$$\hat{p}_k^{\uparrow}(t) \leq \delta_k(t) - \xi,$$

where $\xi > 0$ is a guaranteed safety margin.

Subsequently, the parameters strictly gradually return to the operating mode values:

– the risk component weight is reduced:

$$\alpha_5 \leftarrow \max\{\alpha_5 - \Delta\alpha, s_5^{\min}\};$$

– the switching condition η_t is relaxed;

– the window W_t gradually restores to its standard size;

– levels $\alpha_k(t)$ and $\rho_k(t)$ are restored;

– base weights of α^{base} are updated by a slow loop.

The proposed combination of two lightweight indicators (risk-oriented and quantile-based), together with a formalized stabilization mode and a controlled return to operating settings, provides a reproducible protocol for responding to mode changes without assumptions about the disturbance distribution law and without employing computationally expensive change point detection procedures. Combined with dual-loop tuning, this forms a comprehensive procedure for the safe reconfiguration of index policies under intermittent connectivity.

ASSESSMENT OF COMPUTATIONAL COMPLEXITY AND RESOURCE COSTS

Let $n_t = |U_t|$ be the number of active objects, C_t be the step capacity, m be the number of features in the index, K be the number of chance

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constraints, and $N_t = |W_t|$ be the length of the sliding window. On average, a subset $\Delta U_t \subseteq U_t$ of size $|\Delta U_t| = n_t$ is updated.

Regarding feature and index updates, feature normalization by quantiles and gap restoration are performed for objects in ΔU_t with a constant cost per feature. Index calculation requires linear time with respect to the number of components. For a single decision step, the average (amortized) cost is calculated as follows:

$$T_{feat}(t) = \Theta\left(|\Delta U_t| \cdot m\right),$$
$$T_{index}(t) = \Theta\left(|\Delta U_t| \cdot (1+\bar{r})\right),$$

where $\bar{r}$ is the average number of relevant constraints actually affecting the Φ_{risk} of the object (typically $\bar{r} = K$ due to the sparsity of $a_{k,u}$).

The recommended implementation for priority queue support involves two structures: a queue by index I_u for selecting C_t' and a queue by risk contribution $R_u(t) = \sum_k w_k^{(r)} e_k(t) a_{k,u}(t)$ for rapid replacements during risk correction. Key updates after index recalculation are performed with logarithmic cost. For one step:

$$T_{pq}(t) = \Theta\left(|\Delta U_t| \log n_t + C_t \log n_t\right).$$

Preliminary selection and risk correction are carried out as follows. Forming $A_t^{(0)}$ as C_t' gives:

$$T_{top}(t) = \Theta\left(C_t \log n_t\right).$$

The conservative verification of probabilistic constraints with the calculation of $\Delta_k(A_t, t)$ has a cost of

$$T_{risk\_test}(t) = \Theta\left(K \cdot C_t\right).$$

Local replacement of set A_t elements is performed in no more than C_t iterations. Each iteration requires removing the element with the smallest contribution to the corresponding constraint from A_t and selecting a candidate with the maximum $R_u(t)$ outside A_t, i.e.

$$T_{swap}(t) = O\left(C_t \cdot (\log n_t + K)\right).$$

The total amortized cost of an event step is calculated as:

$$T_{step}(t) = \Theta\Big(|\Delta U_t| \cdot \left(m + \bar{r} + \log n_t\right) + $$
$$+ C_t \cdot \left(\log n_t + K\right)\Big).$$

Support for empirical estimates is performed as follows. Updating $\hat{\rho}_k^{\uparrow}(t)$ and risk statistics is implemented incrementally with a constant cost per constraint, and quantile estimation in data stream mode is implemented with a constant or logarithmic cost per update. Thus:

$$T_{stats}(t) = \Theta(K + m).$$

In resource memory, normalized features $\phi_j(u,t)$, base index parameters and $a_{k,u}(t)$ (as a list of non-zero values), keys of two priority queues, and short window logs are stored. With an average density of $\bar{r}$, memory scales as

$$M = \Theta\left(n_t \cdot (m + \bar{r}) + n_t + K + m + N_t\right),$$

where n_t is the number of active objects per step; K is the number of risk constraints; m is the number of features (index components) per object; and N_t is the volume of auxiliary sliding window data (if necessary).

For large n_t, grouping objects and storing $a_{k,u}(t)$ at the cluster level is advisable, which reduces $\bar{r}$ and constants in M.

Real-time characteristics are as follows. With a full update $\left(|\Delta U_t| = n_t\right)$ and large C_t, we have:

$$T_{step}^{\max} = O\left(n_t\left(m + \bar{r} + \log n_t\right) + C_t\left(\log n_t + K\right)\right).$$

This order is preserved if m, $\bar{r}$, K are moderate and efficient queues are used. In typical scenarios, $|\Delta U_t| = n_t$ and $C_t = n_t$, so the step time is determined by the first two terms and $|\Delta U_t|(\cdot)$ and $C_t \log n_t$, ensuring real-time operation.

Bounds on the parameter change rate (26) and switching hysteresis guarantee a limited number of queue rebuilds. Adaptation of the window length and confidence levels bounds fluctuations in the cost of maintaining statistics. Collectively, this provides predictable amortized complexity and controlled memory requirements for a wide spectrum of loads and intermittent connectivity profiles.

FEATURES OF THE SOFTWARE IMPLEMENTATION OF THE METHOD AND ITS REPRODUCIBILITY

The method does not require specialized hardware and is implemented in a single-threaded mode with a discrete event timeline. Calculations are performed in double precision; the sequence of operations is fixed, ensuring result determinism. All stochastic components (scenario generation, sliding window formation) are initialized with a fixed initial state of the Random Number Generator (RNG), rendering the experiments reproducible.

Experimental studies were performed on a workstation with the following specifications:

– CPU: Intel Core i7-9700 (8×3.0–4.7 GHz);

– RAM: 16 GB;

– OS: Windows 10 Pro x64;

– Software: Python 3.7.7 (MSVC build) with libraries: numpy 2.3.4, pandas 2.3.3, matplotlib 3.10.7, pyyaml 6.0.2.

Source codes and experiment configuration files are stored in an open repository [31], allowing for the reproduction of the execution sequence and the attainment of identical results.

All parameters considered in this study are defined in a text configuration. The recommended fields are shown in Fig. 1.

```
window.short, window.long;
norm.quantiles.low, norm.quantiles.high;
risk.delta_total = δ_Σ, risk.delta_min, risk.delta_max;
risk.alpha_init;
risk.swap_limit = C_t;
index.alpha_base[1..4], index.alpha5_bounds, index.beta_bounds;
index.hysteresis = η_t;
adapt.fast.{η, H, τ_down, τ_up, s5_min, s5_max},
adapt.slow.{μ, ΔT};
relevance.weight_risk = w_k^{(r)}, relevance.a_bounds=[0,1];
calibration.{λ, β, τ, γ, ξ}
```

Fig. 1. **Recommended fields**

***Source*: compiled by the authors**

In Fig. 1:

– under *window.short* the length of $|W_t|$ is specified;

– under *window.long* – $|W^{long}|$;

– under *risk.alpha_init* – the initial value of a_k;

– under *risk.swap_limit* = *C_t* – the iteration limit for local replacement.

The configuration (Fig. 1) serves as the single source of truth for the experiments.

The event log format is defined as follows. Each record contains the following fields: *t* (timestamp), *U_t* (active object identifiers), *C_t* (capacity), *obs[u]* (vector of available features φ_j), *missing[u]* (missing mask), *act* (accepted $u^{å}(t)$ or A_t), *stats* (updated $\hat{\rho}_k^{\uparrow}$, e_k, Δ_k), *theta* (current $\alpha_{1...5}$, β in compact form), *cost* (step time, update count). The log is used as a reproducibility artifact and as input for offline analysis.

The following computation flow is implemented in the software environment:

– offline preparation: checking event integrity, initializing quantiles, constructing initial $a_{k,u}$ based on a short history;

– online operation: processing events according to the event-driven algorithm, incremental updating of statistics and fast loop parameters, and periodic recalibration via the slow loop.

Verification of risk constraints and potential reconfiguration is performed upon detection of non-stationarity according to the mechanism defined in the study and by reconfiguring index parameters.

During the experiment, feature normalization is performed on a short buffer with a total length of at least $m \cdot 10$ events. In case of data deficiency, a working interval of $\left[q^{low}, q^{high}\right] = [0,1]$ is applied with subsequent automatic narrowing. Initial $a^{base} = \left(\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4}\right)$, $\alpha_5 = s_5^{\min}$, $\beta_u = 0$. Initial $a_{k,u}$ are set according to the object class.

During execution, missing (unreceived) feature values are restored using the exponential smoothing rule based on the last reliable measurement, with the smoothing coefficient limited to prevent the feature from vanishing completely. If the proportion of missing measurements in the current window exceeds a specified threshold, the contribution of this feature to the index is gradually (linearly) reduced to zero.

Event time ambiguity is resolved by sorting records by time, and in case of collisions, by a fixed deterministic collision resolution policy.

As part of the monitoring task, the following are tracked in real-time:

– violation frequencies and confidence bounds for each constraint k;

– $R(t)$ values;

– variability of $\alpha_{1...5}$ and η_t values;

– computational cost indicators.

Warnings are generated if $\hat{\rho}_k^{\uparrow} > \delta_k$ for specified number of events H, attribute updates are absent beyond the specified interval, or the step time exceeds the target value.

For each run, the following are stored: code version, configuration, fixed initial random number generator state, event log checksums, final control values $\alpha_{1...5}$, aggregates $\hat{\rho}_k^{\uparrow}$, normalization quantiles, relevance matrix $\{a_{k,u}\}$ (summarized), and trajectories $\zeta_k(t)$, $\rho_k(t)$.

Identical configuration and random number generator state are required for repeated runs. Discrepancies exceeding allowed values in confidence intervals are recorded as non-reproducibility. Parameter change bounds (26) are implemented as hard constraints with deviation logging. Integrity checks include detection of "jumps" in quantiles, abnormal missing rates, and inconsistent $\Delta_k(A_t, t)$ values.

In the event of prolonged data shortage, a conservative mode is activated, i.e., α_5 is fixed at the upper bound, confidence margins are expanded, and an increase in η_t is recorded.

ANALYSIS OF EXPERIMENT RESULTS

Experimental verification was performed in event-driven mode based on the event log generated by the *config.yaml* configuration [31]:

– scenario random number generator seed: 42;
– duration: 600 events;
– number of objects: 40;
– step capacity: $C = 3$;
– profiles: intermittent connectivity (on/off), surge-like load.

Parameters:

– number of chance constraints $K = 3$; total risk budget $\delta_\Sigma = 0.10$ with equal initial distribution $\delta_k \approx 0.033$.

– short sliding window for frequency estimation $N_t = 200$, long – 2000; confidence level $\alpha = 0.05$.

– risk component index weight bounds $\alpha_5 \in [0.05; 0.40]$ with fast response loop and slow recalibration.

Validation metrics: Upper Confidence Bound of violation frequency $\hat{\rho}_k^{\uparrow}$, budget δ_k, dynamics $\alpha_5(t)$; summary statistics (averages/quantiles). Visualizations of the experiment results are shown in Fig. 2 and Fig. 3 based on the obtained data (Table 1).

According to Fig. 2, an overestimated upper bound $\hat{\rho}_k^{\uparrow}$ is recorded in the initial interval with a small N_t, followed by a decline to a steady-state level. The budget $\delta_k \approx 0.033$ remains a constant horizontal line. This curve shape corresponds to the expected behavior of the confidence interval: as $|W_t|$ increases, the correction term $\sqrt{\ln\left(1/\alpha\right)/2N_t}$ from (18) decreases, bringing $\hat{\rho}_k^{\uparrow}$ closer to the empirical violation frequency. It is correct to truncate the bound to $[0;1]$; with this correction, the upper bound does not exceed unity and demonstrates convergence to the vicinity of δ_k.

Table 1. **Experiment results**

Metric	Average	σ	Minimum	Maximum
$\hat{\rho}_k^{\uparrow}$	1.085367	0.050436	1.048298	1.37327
δ_k	0.033333	0	0.033333	0.033333
e_k	1.052033	0.050436	1.014964	1.339937
α_5	0.399137	0.012562	0.1525	0

***Source*: compiled by the authors**

Next, it is confirmed that the synthesized index policies comply with the requirements specified in formula (5) under intermittent connectivity and limited statistics. Verification is performed empirically by comparing the Upper Confidence Bound of the binomial violation frequency $\hat{\rho}_k^{\uparrow}$ (based on Hoeffding's inequality [28] on a short window N_t) with the target budget δ_k.

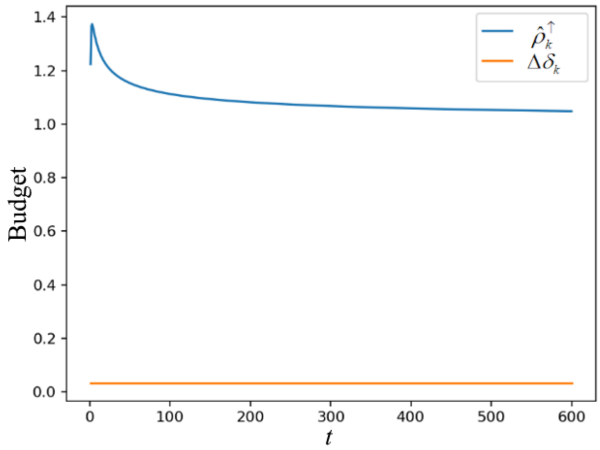

Fig. 2. **Empirical upper bound of the frequency of violations and the specified budget for the restriction**
***Source*: compiled by the authors**

The stabilization of $\hat{\rho}_k^{\uparrow}$ below or near δ_k over a prolonged interval confirms the property of calibrated violation probability control, achieved by combining a conservative acceptance test, dynamic budget δ_k rebalancing, and rapid correction of the risk $\alpha_5(t)$ component share. From the perspective of mobile platform-based information system practice, this implies that even against the background of prolonged unavailability windows and bursty loads, the proportion of steps with violations is maintained within specified bounds with high reliability.

According to Fig. 3, the initial saturation of $\alpha_5(t)$ at the upper bound is interpreted as a forced amplification of the risk-oriented component during the period when confidence margins are large. The subsequent stability of α_5 indicates that the fast loop does not generate excessive fluctuations and preserves computational predictability while maintaining the guaranteed risk level.

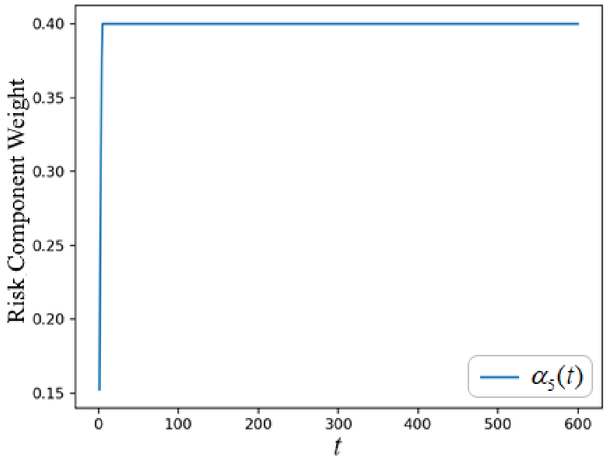

Fig. 3. **Dynamics of the risk component weight**
***Source*: compiled by the authors**

Table 1 reflects the means and variations of $\hat{\rho}_k^{\uparrow}$, δ_k, e_k, α_5. Low standard deviations after the initial observation interval are consistent with the absence of prolonged periods of constraint violation and confirm the stability and reproducibility of the method.

The adaptability of the method's behavior in the context of the dual-loop scheme is interpreted as follows. The fast loop adjusts $\alpha_5(t)$ as a monotonic function of the magnitude of recorded overruns (24) with a deadband (25), hysteresis to suppress frequent switching, and projection onto $\alpha_5 \in \left[s_5^{\min}, s_5^{\max}\right]$. The slow loop periodically recalibrates the base weights of operational components α^{base}, normalization bounds, and relevance factors $\alpha_{k,u}$, reducing the need for high α_5 values in the future.

The trajectory (Fig. 3) without fluctuations is expected: at the beginning of the experiment, the data volume in the sliding window is small, and confidence margins in $\hat{\rho}_k^{\uparrow}$ are overestimated, thus $R(t)$ exceeds $\tau_{\uparrow}$, activating a conservative risk weight29. Hysteresis and correction step damping guarantee the absence of oscillations in α_5 after reaching the upper bound.

The increase in $\alpha_5(t)$ correlates with the decrease of the violation frequency upper bound $\hat{\rho}_k^{\uparrow}$ to the vicinity of δ_k (Fig. 2) that is, the fast loop functions as an operational amplifier of the risk component until the deficit $e_k(t)$ vanishes. Subsequently, when the slow loop accumulates sufficient statistics and refines the values of α^{base}, $\alpha_{k,u}$, and the statistical margin in checks, a decrease in $R(t)$ below $\tau_{\uparrow}$ and a smooth departure of α_5 from saturation are expected.

Simulating the scenario with the fast loop disabled shows that during the initial observation interval, α_5 would remain low, and $\hat{\rho}_k^{\uparrow}$ would exceed δ_k for a longer duration, degrading risk calibration for small windows.

If the slow loop is disabled, α_5 remains near $s_5^{\max}$ for an extended period, leading to deteriorated operational metrics (due to excessive weight of the risk component) and lower consistency with long-term efficiency goals. Accordingly, the proposed dual-loop method, with both loops operational, provides rapid stabilization of violations with minimal switching and ensures subsequent normalization of the background weight balance without losing risk controllability.

In real-world conditions, the proposed method can be implemented as follows. For example, during disaster relief operations, mobile medical teams operate portable patient monitors (condition monitoring nodes). Data from these monitors is transmitted to a mobile data pre-processing and transit node (located in an ambulance) and subsequently to the central subsystem of a cloud-based medical information system.

Assume that connectivity to the backbone network is intermittent; due to partial base station failures (transport environment), unavailability intervals of 5-25 minutes occur, and during peak load moments, bursts of large data block transmissions (e.g., ultrasound video) are recorded. Additionally, cascading effects occur: data pre-processing queues at the edge node grow after each period of channel unavailability, and a portion of measurements arrives late, losing relevance (data is re-acquired in the ambulance).

In this environment, risk budgets δ_k are established for constraints such as: the probability of exceeding the maximum telemetry delay, the probability of diagnostic indicators losing relevance, and the probability of edge node buffer overflow. The index rule utilizes normalized features of data update age, local load, and estimated time until connectivity restoration, while the acceptability of the current action set A_t is verified by a calibrated test on a short sliding window without assumptions regarding distribution shapes.

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As empirical violation frequencies increase, the upper confidence bounds approach the budgets, and the fast loop increases the risk component share $\alpha_5(t)$, ensuring the prioritization of critical flows. Following stabilization, the slow loop adjusts base weights and significance coefficients to maintain metrics in a steady state. Thus, the method reduces the probability of accumulating stale measurements and delay overruns after each offline interval, and limits queue growth under surge loads.

The applicability limit in this example is defined by catastrophic failure situations, such as total power loss at the mobile node or prolonged connectivity absence, resulting in no data reception throughout the interval. In such cases, the algorithm is suspended until basic observability is restored; upon restoration, a protected return to the adaptation mode with recalibration is applied, which aligns with the declared method limitations.

DISCUSSION OF THE RESULTS OF EXPERIMENTAL STUDIES

To interpret the obtained graphs (Fig. 2, Fig. 3), it is advisable to correlate them with three types of benchmarks: “greedy” indexing without risk control (fixed $\alpha_5 = 0$) [32]; a static index rule with fixed weights $\alpha_{1\ldots5}$ and no δ_k rebalancing [33]; and a simplified Model Predictive Control (MPC) scheme with a short prediction horizon and the assumption of full observability [34]. The first benchmark reflects fast but uncontrolled decisions; the second represents typical static tuning practices; the third reflects a more resource-intensive optimization alternative.

Comparative analysis based on fixed intermittent connectivity scenarios shows that the “greedy” algorithm generates elevated empirical violation frequencies and confidence bounds, particularly during the initial observation interval. Static weights reduce index fluctuations but do not ensure calibrated compliance with δ_k during mode changes. The MPC-based approach is capable of reducing local service deficits but requires high telemetry update frequency and stable synchronization between information system elements; consequently, its effectiveness is significantly reduced in the presence of prolonged unavailability intervals caused by the mobile platform on which the system is deployed.

Against this background, the proposed method, leveraging the fast loop ($\alpha_5 \to s_5^{\max}$ during uncertainty) and slow weight recalibration, maintains observed risk limits within budgets without introducing significant computational overhead or requiring prior distribution models.

Observations with loops disabled provide a structured explanation of the contribution of each component. Disabling the fast loop leads to a delay in reducing $\hat{\rho}_k^{\uparrow}$ to the vicinity of δ_k and to higher metric dispersion in the early phase. Disabling the slow loop locks α_5 at the upper bound, degrading the operational balance of the index without additional risk gains. Combining both loops ensures a rapid response without fluctuations and long-term normalization of weights, reflected in the stability of α_5 (Fig. 3) and the compression of dispersion after passing the initial observation phase.

Limitations and validity threats should be considered when generalizing results. First, the upper bound of $\hat{\rho}_k^{\uparrow}$ in the current visualization is not strictly bounded to $[0;1]$, so values exceeding unity in short windows are a conservative artifact. In future studies, applying truncation to $[0;1]$ or using Wilson intervals [29] is advisable.

Second, benchmarks with forecasting remain sensitive to data quality; their comparison should be conducted in scenarios with guaranteed observation density.

Third, service quality indicators (deficit, recovery time, switching frequency) should be expanded in future experimental series to fully reflect trade-offs.

In summary, the proposed method demonstrates an advantage under intermittent connectivity and incomplete statistics: compliance with specified risk budgets is combined with predictable computational cost and the absence of fluctuations in the weight structure. The effect is achieved precisely through index synthesis with dual-loop tuning and distributionally robust calibration, distinguishing the approach from both purely heuristic and model-heavy benchmarks.

CONCLUSIONS

For the first time, a method for synthesizing index policies to ensure the survivability of a mobile platform-based information system is proposed, which maintains the probability of violations within specified budgets under conditions of intermittent connectivity and incomplete observability, while preserving event scalability and predictable computational cost. This is achieved by combining event-based index ranking with calibrated risk management and dual-loop parameter tuning. Unlike known heuristic index rules lacking explicit risk management and model-based forecasting approaches requiring dense telemetry and continuous synchronization, the proposed method does not rely on rigid assumptions regarding disturbance distributions and remains robust to prolonged unavailability windows and system operating mode changes.

Experimental verification demonstrated that the upper confidence bound of the violation frequency converges to the specified risk budgets, and the risk component of the index stabilizes without fluctuations. This directly reflects the survivability property of mobile platform-based information system–reducing the time spent outside acceptable service indicators and maintaining decision consistency despite asynchrony and data staleness.

Dual-loop adaptation ensures sustained system survivability: the fast loop rapidly enhances protection against tail failures caused by rare influences, while the slow loop periodically recalibrates normalization, weights, and relevance, reducing sensitivity to non-stationarity and small samples. Consequently, the information system retains the ability to autonomously restore acceptable states without the need for constant global synchronization of all elements.

The proposed method has an amortized linear-logarithmic complexity. Prioritization and risk testing are performed on events, and overhead costs remain predictable as the number of objects and constraints increases.

The obtained results outline the limits of applicability (conservatism on short windows, synthetic load profiles) and confirm the practical suitability of the method as a tool for improving the survivability of mobile platform-based information systems.

Further development should focus on expanding service metrics, adaptive redistribution of risk budgets between violation types, and further experimental research of the method under conditions of catastrophic failures in mobile platform-based information system operation.

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Метод синтезу індексних політик для забезпечення живучості інформаційної системи на мобільній платформі

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АНОТАЦІЯ

У статті вперше запропоновано метод синтезу індексних політик забезпечення живучості інформаційної системи на мобільній платформі за переривної зв'язності та неповної спостережуваності. Метод орієнтовано на утримання ймовірності порушень у заданих бюджетах за рахунок поєднання подієвого індексного ранжування з каліброваним керуванням ризиком і двоконтурним налаштуванням параметрів. Швидкий контур адаптивно змінює вагу ризикової складової індексу залежно від величини зафіксованих перевищень, тоді як повільний контур періодично рекалібрує нормування ознак, базові ваги та релевантності, підвищуючи робастність до нестаціонарності та малих вибірок. Ймовірнісні обмеження інтерпретуються через верхні довірчі межі на короткому ковзному вікні, що дає змогу забезпечити керований ризик без жорстких припущень щодо розподілів збурень і без опори на безперервну телеметрію чи часті глобальні узгодження. Для підтримки узгодженості рішень використано нересурсоємку перевірку прийнятності та журналювання подій, що уможливлює незалежну відтворюваність. Подано формулювання індексного правила з нормуванням ознак, ваговою структурою й ризик-тестом, протокол ризик-корекції вибірки на такт, а також процедуру виявлення зміни режиму і безпечного переналаштування. Обчислювальна складність методу є амортизовано лінійно-логарифмічною відносно кількості активних об'єктів і місткості такту, що забезпечує придатність до роботи в реальному часі. Верифікація виконана на подієвих журналах із сценаріями переривної зв'язності та сплескподібного навантаження; показано зближення верхньої межі частоти порушень до заданих бюджетів, стабілізацію ваги ризикової компоненти без коливань і передбачувану динаміку службових метрик. Покрокове вилучення окремих компонентів показало внесок кожного з них: вимкнення швидкого контуру уповільнює досягнення цільових ризикових рівнів, а відсутність повільного контуру фіксує надмірну вагу ризикової складової, погіршуючи експлуатаційний баланс. Порівняно з евристичними правилами без явного ризик-контролю та модельно-прогнозними підходами, чутливими до якості телеметрії, запропонований метод забезпечує живучість інформаційної системи на мобільній платформі через керовані ймовірнісні гарантії, подієву масштабованість та відтворювані процедури перевірки.

Ключові слова: інформаційна система; мобільна платформа; живучість; індексна політика; двоконтурна адаптація; метод

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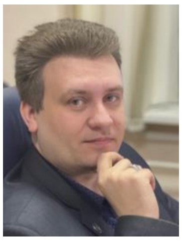

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