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INTEGRAL SURVIVABILITY METRIC OF AN INFORMATION SYSTEM ON A MOBILE PLATFORM UNDER FUNCTIONAL CASCADING AND SECONDARY FAILURES

The subject of the study is an integral metric of the survivability of an information system on a mobile platform under intermittent connectivity, partial observability, and cascading and secondary failures. The system is presented as a multilevel "data–processes–resources" structure. **The goal of the work** is to develop an integrated survivability metric that takes into account time deviations from requirements, their propagation through a dependency graph, and hidden violations; to propose a single-pass algorithm and prove its properties on scenarios. The article solves the following **tasks**: to formalize service requirements and structure projection; to build a metric with risk-oriented aggregation of deficits, cascading correction, and systematic consideration of secondary failures; to develop single-pass calculations in "availability windows"; to prove monotonicity, scale invariance, and resistance to omissions; to define rules for parameter tuning and configuration comparison; to perform experimental verification and comparison with baseline indicators. The following **methods** are used: projection of services at the level of data, processes, and resources; use of conditional average excess as risk-oriented aggregation; cascading correction by depth and width; organization of secondary failures and desynchronization fixation; normalization in "availability windows"; single-pass updates close to linear complexity. The following **results** were obtained: an integrated metric of survivability was proposed and formally defined; its monotonicity in terms of parameters, boundedness, invariance to scaling, and resistance to omissions were proven; the difference from the average deficit was shown – the proposed metric amplifies the contribution of rare deep failures and responds to cascading, while the average values are almost constant; in the absence of service deficits, a positive level is maintained due to the detection of latent secondary failures; scenarios yield consistent families of curves and a three-dimensional surface that demonstrate controllable sensitivity tuning and stable ranking of configurations for industrial mobile platform operating conditions. **Conclusions:** The proposed metric provides a service-consistent assessment of the state of the information system, while taking into account time deficits, cascading propagation, and secondary failures. It is suitable for sequential computing in resource-constrained environments, enhances early risk detection, and supports monitoring, localization, and survivability.

Keywords: integrated metric; survivability; information system; cascading fault; risk-oriented monitoring.

Introduction

Over the past years, information systems on mobile platforms have increasingly found functional applications in industry – autonomous mobile robots in manufacturing, inspection drones for oil, gas, and energy infrastructure, and field service teams with onboard computing – operate in a changing environment with intermittent connectivity, partial observability, and severe constraints on computing and energy resources [1–3]. Data exchange takes place within the windows of availability of information system elements, processing queues and routing are reorganized in dynamic conditions of a rapidly changing external environment, and data and process synchronization is complicated by the absence of stable data transmission channels. Under such conditions, the failure of a single element of the information system rarely remains local: the disruption spreads through chains of dependencies "data–processes–resources", changing the quality of services at adjacent nodes and levels [4]. The complex interaction of individual elements of an information system or entire subsystems amplifies cascading effects and generates new requirements for risk management. Therefore, there is a need to develop a service-semantic survivability metric that aggregates time deficits from the service level objective (SLO) while taking into account rare deviations and inter-level dependencies in the information system architecture.

In addition to primary failures (hardware or channel), cascade effects often occur when the unavailability or quality degradation of one element of the information system induces degradation in other elements due to structural dependencies [5]. Additionally, secondary functional failures are observed – situations when the service deteriorates without physical failure of the mobile platform components, for example, due to violations of the cause-time consistency of data, accumulation of outdated information, shifts in priorities, or breaks in service chains. The cumulative effect of such phenomena manifests itself at the level of service

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indicators and directly affects the system's ability to perform its target functions within the allotted time limits.

Well-known indicators of reliability [6], availability [7], average downtime of an information system [8], and average quality deficits [9] are classic approaches to forming the concept of information system survivability, but they do not reflect the integral picture in the presence of cascading and secondary effects. Thus, average values "smooth out" short but critical failures, and binary assessments of "function performed/not performed" do not take into account the depth and duration of failures. Graph models of fault propagation are usually not combined with service level requirements due to the excessive complexity of working with them in the process of solving more complex failure prediction problems. In addition, given the mobility of the platform, these limitations are exacerbated by interruptions in internal system connections in horizontal or vertical planes (fragmentary observations, confirmation delays) and system resource constraints.

In this regard, there is a scientific challenge to develop and study an integrated metric of information system survivability on a mobile platform that is applicable at the service level and takes into account the temporal structure of deviations from specified requirements, quantitatively accounts for the spread of violations along the dependency graph and induced (secondary) degradations, is capable of identifying rare but significantly harmful deviations, and is suitable for calculation on a stream of events in a mode of limited resources and unstable communication between internal elements.

In general terms, the task can be interpreted as follows. There is a set of services with specified quality requirements. For each service, time-based quality values are observed and events are recorded that reflect the structure of dependencies between elements of the information system. It is necessary to determine a coordinated integral assessment that aggregates temporally weighted deficits relative to requirements, adjusts them to account for the depth and breadth of the spread of violations, and amplifies the contribution of peak failures. The resulting assessment should be used to compare configurations, select localization/recovery policies, and monitor the status of information system services in dynamic conditions.

Statement of the problem

An information system on a mobile platform with a multi-level structure of "data–processes–resources" is considered. In this representation, services are an observable cross-section of this structure. SLOs are set for services, and disruptions propagate through chains of dependencies within the "data–processes–resources" structure. An information system on a mobile platform is characterized by unstable connections between elements, partial observability, and tight resource budgets for processing, storage, and data exchange channels. Local disruptions cause cascading effects (spreading through the dependency structure) and secondary functional failures (induced degradation, such as data desynchronization, priority shifts, and service chain breaks). In addition, information system indicators may malfunction when typical averaged or binary indicators do not reflect the integral impact of the situations described above.

Therefore, an integrated service-level survivability metric is needed that aggregates temporally weighted deviations from SLOs, corrects them for the spread of failures in the "data–processes–resources" model and the contribution of secondary failures, amplifies the impact of rare but critical episodes through conditional value at risk (CVaR), and is calculated sequentially in real time with incomplete observability.

The task can be solved by decomposing it into subtasks and solving each of them step by step:

– formalization of service indicators, SLO, time weights, and service projection at the data, process, and resource levels;

– description of dependencies in the "data–processes–resources" model and event classes (cascades, secondary failures) with signs of their detection;

– design of risk-sensitive aggregation of deviations (conditional value at risk) with normalization and prioritization of services;

– development of a tool for correcting the spread of violations, reflecting the depth/width of the cascade and marking secondary effects;

– development of a single-pass algorithm for calculating metrics on the event stream, resistant to data omissions and/ing the peculiarities of availability windows.

– research of metric properties and its differences from baseline indicators in representative scenarios.

Analysis of recent studies and publications

Recent years have seen the emergence of new approaches to solving this problem in four areas: developing metrics and approaches to the survivability of information systems in cyberspace, modeling cascading

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failures in dependency networks, ensuring SLO-level requirements in cloud, microservice, and fog computing environments, and ensuring the survivability of information systems with unstable connections between elements.

Thus, in [10], a fault tolerance metric for UAV swarms is proposed, based on the relationship between the speed of reaching a new coordinated state and the spectral characteristics of the graph connectivity (algebraic connectivity) that describes the information system. The approach focuses primarily on the control dynamics and topology of the UAV swarm, rather than on system service deficits, and does not model secondary failures at the data or process level. Thus, the work [10] lacks integration with SLO requirements and risk-sensitive aggregation of deviations.

Studies devoted to the analysis of cascading failures in interdependent information systems [11], using the example of data exchange networks, describe the mechanisms of failure propagation in directed and undirected interdependent graphs and systematically classify system vulnerabilities at different levels. In study [11], the model correctly describes the structural propagation of failures. At the same time, the connection with service semantics and a unified numerical metric of service status, which simultaneously takes into account the depth, duration, and cascading amplification of deviations from SLO, is not considered in study [11].

The approach to building the architecture of distributed systems that are tolerant to delays and frequent communication interruptions in environments with unstable data transmission channels (relevant to mobile platforms) is analyzed [12]. The advantages and limitations of such architectures for processing and transmitting data with high delays and significant losses are shown. At the same time, the indicators used remain transport-network-based, and the single service metric of survivability, which integrates cascade/secondary effects and the risk of "heavy tails", is considered superficially in [12] and does not provide a complete picture of its applicability.

An overview of the principles of cyber resilience of information systems systematizes organizational and technical strategies, tools, and approaches to building and evaluating indicators [13]. The need for operationally viable quantitative characteristics that link service level with system behavior during failures and attacks is emphasized. At the same time, the results are generalized and difficult to apply in applied systems.

An analysis of studies related to the use of SLA/SLO indicators for cloud environments, in particular in [14], shows the generality of approaches to formalizing the semantics of service requirements. The main focus is on centralized cloud scenarios and binary availability/unavailability indicators. Risk-sensitive tail allocation (in particular, through conditional value at risk, CVaR) and the connection with cascade effects in complex dependencies are considered superficially.

An integrated quantitative framework for assessing the stability of multi-level cyber-physical systems is presented in [15]: the cyber level is described by probabilistic anomalies (Markov chains), and the physical level is described by models of degradation and recovery of performance. The approach [15] includes parameter normalization and coordination of cyber-physical subsystems with the construction of stability curves (time profiles of performance changes under the influence of disturbances) for different scenarios. The framework demonstrates a consistent quantitative assessment procedure with clear steps and output in the form of an interpreted curve/index; However, direct modeling of SLO deficits, communication interruptions, and secondary failures in service-oriented information systems in [15] is not the main goal, although the results are interpreted from the perspective of service semantics.

The analysis [10–15] made it possible to identify systemic gaps – the lack of a single service-oriented integrated metric that takes into account temporally weighted deviations from SLO, cascading propagation, and secondary failures under conditions of intermittent communication; to clarify the requirements for the desired assessment (normality, sensitivity to deviation "tails", resistance to incomplete observations); make a formal definition of an integrated survivability metric, introduce the concept of a corrective rule for the propagation of failures, a procedure for evaluating the flow of events, and a set of representative scenarios for comparison with baseline indicators. Taken together, this justifies the feasibility of building an integral metric of information system survivability on a mobile platform, taking into account cascading and secondary functional failures.

Terminological basis and formalization of the system of level quality indicators and interlevel invariants

The study will use the presentation of an information system on a mobile platform as a multi-level structure of "data–processes–resources" [16]. To construct an integrated survivability metric, we propose to establish the following set of tools: an oriented

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graph of logical dependencies between objects of three levels, which determines the paths of propagation of violations and the contexts of secondary failures; event logs of failures and recoveries and time series of quality indicators aggregated in availability windows; a service slice as a reflection of each service on a subset of data, processes, and resources with SLO requirements assigned to services; inter-level invariants of cause-time consistency, the violation of which is marked as a secondary failure; weighting coefficients for the importance of services and levels, and normalization rules that enable configuration comparisons. These tools are used as input ports for metrics, i.e., level indicators form the basic contributions, graphs and event data form the corrective component, and the service view forms the interpretation of the result in relation to the requirements imposed on the information system or its individual elements. Subsequently, these tools simultaneously serve as inputs for an integrated assessment – level measurements and invariant violations form its basic and corrective parts.

Next, it is necessary to determine the observed indicators at the "data–processes–resources" levels and inter-level invariants that mark secondary failures and set the context for cascading propagation. It is assumed that the triad "data–processes–resources" records observable temporal indicators and conditional event logs. Then the service slice is a reflection of each service on subsets of data, processes, and resources, and SLOs are used as reference boundaries when causal dependencies and violations occur at all levels of the information system. The assessment is carried out in availability windows (intervals where data is guaranteed to be consistent), between which observation gaps are allowed.

Data level indicators include: timeliness (the time the data exists within the window), causal-temporal consistency (no "jumping" of events and conflicting timestamps), completeness (the proportion of useful data), and version stability (no collisions in the presence of duplicates). In real-world conditions, acceptability thresholds are also set, which, for example, determine the maximum allowable lifetime of data for a single version and tolerances for time shifts between related events.

Process level indicators include: timeliness of execution (proportion of operations completed within the acceptable time), delay (quantiles of execution time), goal achievability (proportion of successfully completed transactions), queue status (average length and spikes), routing stability (frequency of process chain reorganization between information system elements).

Resource level indicators include: quota utilization (proportion of allocated budgets), overload level (budget overruns within the window), availability fluctuations (short dips or anomalies).

Using groups of triad indicators, it is possible to form conditions of correctness (invariants), the violation of which we interpret as secondary functional failures in the information system:

Inv_T – time consistency invariant (Inv_T). The point is that if a process uses data with a timestamp t_d, the completion of the associated operation with the timestamp t_s must satisfy the logic t_s and t_d, and $t_s - t_d \le \Delta_{\max}$ in critical intervals. Otherwise, we have a synchronization violation;

– resource load preservation invariant ( ), based on the logic that in each time window, the volume of incoming requests is equal to the sum of processed, irretrievably lost, and in critical intervals. Otherwise, we have a synchronization violation;

– resource load preservation invariant (Inv_R), based on the logic that in each time window, the volume of incoming requests is equal to the sum of processed, irretrievably lost, and queue growth requests. A systematic deviation from this balance indicates either telemetry errors or hidden failures that are not recorded;

– resource budget invariant (Inv_B), which uses logic whereby all process requests within the window do not exceed the available resource (taking into account reserves), and their regular exceeding is an indicator of induced degradation;

– invariance of dependency continuity (Inv_I), when deviations in the "parent" element or level of the information system must be reflected in the dependent element (level) with no more than a specified delay, therefore the absence of reflection indicates a break in the process chain;

– recovery invariant Inv_{rec}, when, after a recovery event, the level indicators return to the acceptable range no later than a predetermined time. Exceeding this time is an indicator of a hidden secondary problem in the information system.

Violation of any of the invariants $(\mathrm{Inv}_T$, Inv_R, Inv_B, Inv_I, $\mathrm{Inv}_{rec})$ is recorded as a secondary failure event with reference to the level and dependencies within which it was detected. The set of level indicators and invariants forms the observable basis for the further

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introduction of an integral metric of system survivability: level indicators determine basic deviations, invariants form signs of induced degradation, and the dependency diagram provides the context for taking into account cascading propagation.

Development of an integrated survivability metric

Let us assume that a multi-level information system operates on the observation horizon $[t_0, t_1]$. Let us introduce the notation of a set of services $S' = \{S_i\}_{i=1}^{m}$, time windows of availability $\{W'_r\}_{r=1}^{R}$ (intervals within which observations are consistent), and an oriented graph of dependencies $G = (V, E)$ between levels of the information system (nodes V – abstractions of "data/processes/resources", edges E – causal/technological connections). For each service S_i, a service level requirement (SLO) is specified – a threshold function $\theta_i(t)$ and a quality indicator $q_i(t)$ (both values are normalized in the interval $[0,1]$).

Let's formalize the basic deviations in the process of performing the main function by the information system. The service deficit can be presented as:

$$d_i(t) := [\theta_i(t) - q_i(t)]_+ = \max\{0, \theta_i(t) - q_i(t)\} \in [0,1]. \quad (1)$$

At (1) $d_i(t) = 0$ – if SLO are satisfied, and $d_i(t) > 0$ – if there are deviations.

Next, we formalize the representation of temporal weighting. Let $w(t) \geq 0$ be a time priority profile (a penalty multiplier for a deficit at time t). It will be greater in critical intervals $w(t)$ and smaller outside them. To suppress short-term fluctuations, we will apply a linear smoothing filter W with a non-negative and normalized kernel $k(\tau)$:

$$\begin{aligned} &(W * x)(t) = \int_0^{\infty} k(\tau)\, x(t-\tau)\, d\tau, \\ &k(\tau) \geq 0, \quad \int_0^{\infty} k(\tau)\, d\tau = 1. \end{aligned} \quad (2)$$

Based on (2), a temporally weighted deficit is formed:

$$x_i(t) := w(t)(W * d_i)(t). \quad (3)$$

Next, the concepts of a cascade corrector and a secondary failure indicator are introduced. Since the previously specified oriented dependency graph G defines the paths of propagation of failures between levels of the information system, it is advisable to formalize the adjacency matrix, which describes the non-negative weights on the arcs, in the form $A \in \mathbb{R}_+^{|V| \times |V|}$, and the service projection in the form of a binary vector $\Pi_i \in [0,1]^{|V|}$, which marks the elements V involved in the service S_i.

To formalize the cascade corrector, it is first necessary to formulate the logic of cascade amplification. Let $\lambda \in (0,1]$ be the propagation depth parameter, then we define the cascade operator as:

$$\Phi_\lambda := \sum_{\ell=0}^{\infty} \lambda^\ell A^\ell = (I - \lambda A)^{-1}, \quad \rho(\lambda A) < 1, \quad (4)$$

where $\rho(\bullet)$ is the spectral radius; A is the adjacency matrix of the dependency graph.

In (4), the operator Φ_λ accumulates the contributions of all oriented paths in G with attenuation along the length (depth of the cascade).

Next, we form a cascade-corrected deviation vector (corrector). Let $z(t) \in \mathbb{R}_+^{|V|}$ be the level-localized deficits (matched to $[0,1]$) on the elements V originating from service deviations $d_i(t)$ through a known matching mechanism (for example, distribution of service deficit across the involved nodes [17]). Then the corrector is set as:

$$\tilde{z}(t) := \min\{\Phi_\lambda z(t), \mathbf{1}\}. \quad (5)$$

After correction via Φ_λ, some components may exceed $\mathbf{1}$. Therefore, in (5) we apply a component-wise upper bound of one (projection onto the hypercube $[0,1]^{|V|}$) using the unit vector $\mathbf{1}$ to ensure that all components belong to the interval $[0,1]$.

We form the secondary failure indicator as follows. Let $I' = \{I_u\}_{u=1}^{U}$ be a set of inter-level invariants Inv_T, Inv_R, Inv_B, Inv_I, Inv_{rec}. Then the degree of violation of the invariant I_u is denoted as:

$$\sigma_u(t) \in [0,1] \quad (6)$$

If $\sigma_u(t) = 0$, then no violation is detected. Therefore, taking into account the interval (6), the secondary failure indicator is as follows:

$$\sigma(t) = (\sigma_u(t))_{u=1}^{U}. \quad (7)$$

Next, we move from level-localized deficits to risk-oriented systemic aggregation with time weighting and CVaR. For the service S_i, we will highlight the

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part of the cascading corrected deviations that falls on the nodes of its projection:

$$\tilde{d}_i(t) := \frac{\langle \Pi_i, \tilde{z}(t) \rangle}{\max\{1, \langle \Pi_i, \mathbf{1} \rangle\}} \in [0,1], \qquad (8)$$

where $\langle \bullet, \bullet \rangle$ is a scalar product; Π_i is the projection of the service onto the elements V .

To highlight rare cases, such as "heavy tails," it is necessary to consider discretization by availability windows $\{W_r'\}_{r=1}^{R}$. Let:

$$Y_{i,r} := \int_{W_r'} w(t)\left(W * \tilde{d}_i\right)(t)\,dt \in \left[0, |W_r'|\right], \qquad (9)$$

and the distribution on $\{Y_{i,r}\}$ will be determined by specific weights $\omega_r := |W_r'| \Big/ \sum_{q=1}^{R} |W_q'|$ or another agreed rule (for example, proportionally to the number of events). Then $\{Y_{i,r}\}$, taking into account (9), form a sample for risk-oriented aggregation.

For risk-oriented allocation of "tails" in the sample $\{Y_{i,r}\}$, we further introduce the metric of conditional average excess (CVaR) at the confidence level $\alpha \in (0,1)$, which estimates the average value from the largest $(1-\alpha)\%$ observations:

$$\text{CVaR}_\alpha(Y_i) = \min_{u \in \mathbb{R}} \left\{ u + \frac{1}{1-\alpha} \sum_{r=1}^{R} \omega_r \left[Y_{i,r} - u \right]_+ \right\}. \qquad (10)$$

In the context of system integration, the vectors $\sigma(t)$ indicate secondary failures, and their integral effect in the window W' can be estimated by:

$$\Sigma_r = \int_{W_r'} \langle \eta, \sigma(t) \rangle\,dt, \quad \eta \in \mathbb{R}_+^{U}, \qquad (11)$$

where η are the weights of the significance of the invariants Inv_T , Inv_R , Inv_B , Inv_I , Inv_{rec} .

Therefore, taking into account (5, 8, 9, 11), the following formalization of the integral metric of survivability ISM_α is proposed:

$$\text{ISM}_\alpha = \sum_{i=1}^{m} \beta_i\, \text{CVaR}_\alpha\left(\{Y_{i,r}\}_{r=1}^{R}\right) + \gamma \underbrace{\sum_{r=1}^{R} \omega_r \Sigma_r}_{\text{secondary crops}}, \qquad (12)$$

where $\beta_i \geq 0$ is the weight of service importance; $\lambda \in [0,1)$ is the cascade depth parameter in the graph G ; γ is the weight of secondary failures (contribution of invariant violations).

In (12) $\sum_{i=1}^{m}(\bullet)$ – risk-oriented service component (through CVaR from temporally weighted deficits (3), already corrected by a cascade operator). $\sum_{r=1}^{R}(\bullet)$ – system penalty for secondary failures, independent of a specific service (because secondary nature is an inter-level phenomenon). Accordingly, we assume that the lower the value of ISM_α , the higher the survivability of the information system.

Next, the study considers the formalization of the main properties of ISM_α (12) with a demonstration of their applicability. As a basis for constructing proofs of properties, it is advisable to first introduce our own statements, which will be used as an evidence base.

Lemma 1 on the monotonicity of non-negative operators. If $x(t) \leq y(t)$ for all t , then:

– $w(t)x(t) \leq w(t)y(t)$;

– $(W * x)(t) \leq (W * y)(t)$;

– for $u, v \geq 0$ and the matrix $M \geq 0$, we have $M\,u \leq M\,v$;

– for $\Phi_\lambda = \sum_{\ell \geq 0} \lambda^\ell A^\ell$, $A \geq 0 : \Phi_\lambda u \leq \Phi_\lambda v$.

Each point of Lemma 1 follows from the fact that all operations with non-negative coefficients preserve order: multiplication by a non-negative function does not reduce the smaller part relative to the larger one; smoothing with a non-negative kernel is averaging with non-negative weights, which also preserves order; multiplication by a matrix with non-negative elements is a non-negative linear combination of components and therefore does not reduce values; and the sum of such monotonic mappings with non-negative coefficients remains monotonic.

Lemma 2 formalizes the basic properties of CVaR for a finite weighted sample:

– monotonicity: if $y_r \leq \hat{y}_r$ for all r , then $\text{CVaR}_\alpha(\{y_r\}) \leq \text{CVaR}_\alpha(\{\hat{y}_r\})$;

– shift: $\text{CVaR}_\alpha(\{y_r + c\}) = \text{CVaR}_\alpha(\{y_r\}) + c$ for any stable c ;

– homogeneity: for

$$c \geq 0,\ \text{CVaR}_\alpha(\{c\,y_r\}) = c\,\text{CVaR}_\alpha(\{y_r\});$$

– resistance to small changes: if $|y_r - \hat{y}_r| \leq \varepsilon$ for all r , then $|\text{CVaR}_\alpha(\{y_r\}) - \text{CVaR}_\alpha(\{\hat{y}_r\})| \leq \varepsilon.$

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The known properties follow from the equivalent representation (10) and the monotonicity/convexity of the mapping $y \mapsto [y-u]_+$.

Taking into account the introduced lemmas, the following properties of ISM_α are formulated:

1. Zero normalization property. If $d_i(t) \equiv 0$ for all i, t and $\sigma_i(t) \equiv 0$, then $\mathrm{ISM}_\alpha = 0$. The base level without deviations gives a zero metric.

Proof: For $d_i(t) \equiv 0$, for all i, each element of the construction is zero $z(t) \equiv 0 \Rightarrow \Phi_\lambda z(t) \equiv 0 \Rightarrow \tilde{z}(t) \equiv 0 \Rightarrow \tilde{d}_i(t) \equiv 0 \Rightarrow Y_{i,r} \equiv 0 \Rightarrow \mathrm{CVaR}_\alpha = 0$. The second component is also zero $\sigma(t) \equiv 0 \Rightarrow \Sigma_r = 0$. Therefore, $\mathrm{ISM}_\alpha = 0$.

2. Monotonicity property for temporal deviations. If, over a certain period of time, the deviations $d_i(t)$ increase by at least $\varepsilon > 0$ (for fixed values λ, β_i, w, W), then ISM_α does not decrease $\left(\mathrm{ISM}_\alpha \geq \mathrm{ISM}_\alpha\right)$. Larger deviations at any interval do not decrease the metric.

Proof: First, Lemma 1 gives the monotonicity of all links: $d_i(t)\uparrow \Rightarrow z\uparrow \Rightarrow \Phi_\lambda z\uparrow \Rightarrow \tilde{z}\uparrow \Rightarrow \tilde{d}_i\uparrow \Rightarrow Y_{i,r}\uparrow$; second, Lemma 2 gives $\mathrm{CVaR}_\alpha\left(\{Y_{i,r}\}\right)\uparrow$ for each i; third, adding non-negative weights β_i and a fixed penalty for secondary failures (the same failure), we obtain $\mathrm{ISM}_\alpha \geq \mathrm{ISM}_\alpha$.

3. Cascade sensitivity property. For $\lambda \in [0,1]$ and non-negative A and $z(t)$, we have $\partial \mathrm{ISM}_\alpha / \partial\lambda \geq 0$. Amplifying cascade propagation does not reduce the risk estimate.

Proof: First, (4) has a derivative:

$$\frac{d\Phi_\lambda}{d\lambda} = (I-\lambda A)^{-1} A (I-\lambda A)^{-1} = \Phi_\lambda A \Phi_\lambda \geq 0, \qquad (13)$$

where all elements are non-negative, because $A \geq 0$; secondly, since $\Phi_\lambda z(t)$ increases component-wise according to λ, then after applying the component-wise upper bound by one (operations $v \mapsto \min\{v,1\}$), the obtained values also do not decrease with the increase of λ; and thirdly, the monotonicity chain, as in the second property, gives an increase in each $\{Y_{i,r}\}$ and service component; the penalty for secondary failures does not depend on λ. Therefore, ISM_α does not decrease with λ.

4. Sensitivity to the appearance of "tails." For the same "area" of deviations, the metric is higher when they are more concentrated in large peaks (CVaR's value is higher). The metric emphasizes rare but large violations.

Proof: since CVaR_α is the average value in the upper part of the sample (by weight $1-\alpha$), the redistribution of the population from the average values to the largest ones increases the upper $(1-\alpha)$ quantile and the average value in the "tail." Formally, this is a well-known fact of "dominance by increasing convex functionals" (Hardy–Littlewood–Polya logic [18–19]): if the sample $\{Y_{i,r}\}$ has no less partial sums after sorting in descending order than $\{Y_{i,r}\}$ (majorization), then for all convex and increasing φ (in particular, $\varphi(y) = [y-u]_+$ in the representation CVaR we have $\sum \omega_r \varphi(Y_{i,r}) \geq \sum \omega_r \varphi(Y_{i,r})$. By minimizing u the inequality will be achieved for any $\alpha \in (0,1)$.

5. Property of large-scale consistency of measurement units. Linear change of units $q_i(t) \mapsto a q_i(t) + b$, $\theta_i(t) \mapsto a\theta_i(t) + b$ at $a > 0$ does not change the ranking of configurations if the normalization $d_i(t)$ and $z(t)$ are consistent. The transition between measurement units does not affect the comparison.

Proof: with a linear change in units, the difference between the plan and actual values scales identically – the new difference is equal to a (previous difference). Therefore, the "deficit to normalization" at each moment is simply multiplied by the same positive coefficient. Accordingly, the entire subsequent path (smoothing over time, weighting factors, projection onto service, cascading propagation onto the graph, etc.) is linear with non-negative coefficients, so it also simply multiplies the time series of values by the same coefficient a up to the normalization stage.

According to the assumption of "coordinated normalization" $d_i(t)$ and $z(t)$ are strictly increasing transformations that remove the global scale (for example, by dividing by the corresponding normalization factor and truncating to $[0,1]$). Therefore, applying this same normalization to two time series of

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values that differ only by a common positive factor preserves the component order and returns the same (or equivalent for comparison) normalized values. Thus, all subsequent time integrations/aggregations (including CVaR) receive the same normalized inputs, and the final value for each configuration remains unchanged. Accordingly, the ranking of configurations remains the same.

6. Property of stability to small perturbations. For any $\varepsilon > 0$ there exists $\delta > 0$ such that if $\sup_t \|q_i(t) - \hat{q}_i(t)\| \le \delta$ and $\sup_t \|\theta_i(t) - \theta_i(t)\| \le \delta$ for all i, then $\left|\mathrm{ISM}_\alpha(q,\theta) - \mathrm{ISM}_\alpha(\hat{q},\hat{\theta})\right| < \varepsilon$.

Proof:

– changing (q_i, θ_i) within the limits of δ changes $d_i(t) = [\theta_i - q_i]_+$ by no more than δ;

– Lemma 1 and the boundedness of kernels/weights give $\left|(W * d_i)(t) - (W * \hat{d}_i)(t)\right| \le \delta$, $|w(t)(\bullet) - w(t)(\bullet)| \le \|w\|_\infty \delta$;

– since $\Phi_\lambda = \sum_{\ell \ge 0} \lambda^\ell A^\ell$ has a finite norm over $\rho(\lambda A) < 1$, the difference $(\tilde{z} - \hat{\tilde{z}})$ is bounded by a constant multiple of δ;

– Integration in windows W_r' scales the error by no more than their length; as a result, there exists $C > 0$ (a constant independent of the data, which estimates the increase in integrals in windows), such that $\left|Y_{i,r} - \hat{Y}_{i,r}\right| \le C\delta$ for all i and r;

– applying Lemma 2 to each service and linearity by weight β_i, we have:

$$\left|\mathrm{ISM}_\alpha - \mathrm{ISM}_\alpha\right| \le \left(\sum_i \beta_i\right) C\delta + \left|\sum_i \omega_r \left(\Sigma_r - \hat{\Sigma}_r\right)\right|. \quad (14)$$

Since $\sigma_u(t)$ are determined from invariants as functions of the same observations, they change by no more than $C'\delta$, and therefore the penalty is no more than $C''\delta$. By choosing $\delta = \dfrac{\varepsilon}{\left(C'' + \sum_i \beta_i C\right)}$, this property is proven.

7. Additivity property by services. ISM_α is the weighted sum of service components and penalties for secondary failures, which allows changing β_i according to the weight of services without losing comparability. The result is formed as a weighted aggregation of services.

Proof: At the system aggregation step for each service S_i, its own risk component R_i is first calculated (by constructing $\{Y_{i,r}\}$ and CVaR on this sample). The final metric is defined as a linear combination of these components with non-negative weights β_i (usually normalized to $\sum_i \beta_i = 1$). Therefore, ISM_α is the weighted sum of service components. Changing β_i only reorients the priorities between services; if we fix the same vector β for all compared configurations, we obtain a well-defined scalar value, so comparability is preserved (the scale is unified by normalizing the weights).

If, in some scenarios, certain components of $\Phi_\lambda z(t)$ reach 1 and are "truncated," all proofs are preserved in a weak form: monotonicity and sensitivity to λ become non-strict (13) (the metric does not decrease and may not increase with small changes (14)), which is consistent with the logic: after reaching the "maximum" local degradation, further strengthening does not affect the evaluation beyond the established limit.

If necessary, a structural penalty for an overly connected graph (for overly connected configurations) can be added using the regularizer $\rho\left((I - \lambda A)^{-1}\right)$ or $-\log\det(I - \lambda A)$ with a coefficient, but the basic definition is already sufficiently sensitive due to the cascade operator (4).

Procedure for calculating integral metrics in real time

The organization of real-time integral metric calculations consists of dividing the calculation process into four modules that operate in an event stream and are synchronized outside the availability windows:

– module A (localization of deficits at graph nodes): $d_i(t) \to z(t)$;

– module B (cascade correction (graph broadcast)): $d_i(t) \to \tilde{z}(t)$ via local transmissions along graph edges with decay λ;

– module C (temporally weighted aggregation at the service level): $\tilde{d}_i(t) \to \tilde{z}(t) \to Y_{i,r}$ (exponential convolution followed by integration in a window);

– module D (risk-oriented aggregation and secondary failures): online evaluation CVaR_α in sequence $\{Y_{i,r}\}$; and accumulation Σ_r.

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Let us first consider module A. The main goal of the module is to convert service deficits $d_i(t)$ into a node vector $z(t)$.

The distribution rule is formed as follows. For node $v \in V$, we determine its localized deficit:

$$z_v(t) = \min\left\{1, \sum_{i=1}^{m} \underbrace{\frac{\Pi_i(v)\beta_i}{\sum_{u\in V}\Pi_i(u)}}_{\text{service share } S_i \text{ at the node } v} \cdot d_i(t)\right\}. \quad (15)$$

In (15): $\Pi_i(v) \in \{0,1\}$ – a sign of belonging to the service node S_i; normalization divides the service deficit between the involved nodes; β_i allows you to strengthen important services. Other schemes agreed upon with the subject area (for example, taking into account the local weights of the nodes) are also acceptable – the algorithm below does not change.

When the event "d_i updated at t" occurs, we enumerate only those components z_v where $\Pi_i(v) = 1$.

Next, let us consider module B. Since direct calculation of $\tilde{z}(t) = (I - \lambda A)^{-1} z$ in an information system is excessively resource-intensive, it is proposed to use local message propagation along the arcs of the graph instead (analogous to the Neumann series with truncation of small terms [20]).

Formalization of the propagation rule (B1). Let us assume that at time t, an increment Δz_v is recorded at node v of the graph. We create a message queue Q with initialization $Q \leftarrow \{(v, \Delta z_v, 1)\}$, where the third argument is the path coefficient c (initially 1). Next, iteratively:

– extract $(u, \Delta, c) \in Q$. Add to the accumulated cascade deviation of the node u according to the scheme $\tilde{z}_u(t) \leftarrow \{1, \tilde{z}_u + \Delta\}$;

– for the outgoing edge $(u \to w) \in E$ with weight A_{uw}, we form a new message $(w, \lambda c A_{uw}\Delta, c' = \lambda c A_{uw})$ and add it to Q only if $c' \geq \varepsilon$ and $\hat{z}_w < 1$.

Heuristic explanation B1: the contribution along paths of length ℓ has weight $\lambda^{\ell} \prod A$; the threshold ε cuts off paths in the graph that are too long or too weak.

Formalization of the computational complexity limits of module B when processing a single event (B2). Let $\Delta_{\max}$ be the maximum change in component z per event. The number of messages generated per event is geometrically limited (geometric series logic):

$$N_{msg} \lesssim \sum_{\ell \geq 0} \left(\bar{d}\lambda\bar{A}\right)^{\ell} = \frac{1}{1 - \bar{d}\lambda\bar{A}}, \quad (16)$$

where $\bar{d}$ is the average outgoing degree of a node; $\bar{A}$ is the average weight of an arc (after scaling) under the condition $\bar{d}\lambda\bar{A} < 1$.

In (16), geometricity is understood as the construction of a geometric series from the contributions of all edge lengths.

In practice, ε further restricts ℓ, ensuring quasi-linear cost with respect to the number of tangent edges.

Next, we consider the C module, whose purpose is to convert the current normalized deficits $\tilde{d}_i(e)$ into representative time statistics $Y_{i,r}$ in the availability windows W_r for further risk-oriented aggregation.

Next, in submodule C1, we consider recursive smoothing with an exponential kernel. We use a one-sided exponential convolution with a kernel $k(\tau) = \rho e^{-\rho\tau} (\rho > 0)$, which gives greater weight to previous values and ensures causality and normalization $\left(\int k = 1\right)$. For each service S_i, we maintain a state $s_i(t) \approx \left(W * \tilde{d}_i\right)(t)$, which evolves according to

$$\dot{s}_i(t) = \rho\left(\tilde{d}_i(t) - s_i(t)\right), \quad (17)$$

and is updated recursively in discrete time

$$s_i \leftarrow e^{-\rho\Delta t} s_i + \left(1 - e^{-\rho\Delta t}\right)\tilde{d}_i. \quad (18)$$

In (17–18), the parameter ρ determines the "memory" of the filter $1/\rho$. The update is stable, non-negative, and does not change the scale of the time series of values, because the kernel is normalized.

Next, in submodule C2, we determine the integration in the availability window. At the same time, we sum up the time-averaged values, multiplying each by the importance coefficient for the corresponding moment in time:

$$S_i \leftarrow S_i + w(t)s_i(t)\Delta t. \quad (19)$$

When the window W_r closes, we record $Y_{i,r} := S_i$, after which $S_i \leftarrow 0$ (if necessary, normalized to the window duration. The rule (taking into account (19)) is the same for all services). Thus, $Y_{i,r}$ forms a sample of deficit episodes taking into account previous values

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(via s_i) and calendar priority (via w), which is further used in CVaR aggregation.

Next, let's look at module D. Submodule D1 provides two evaluation options: CVaR_α.

In option D1.1, we use a stochastic gradient (without a buffer). To do this, we enter a threshold estimate u_i (analogous to VaR_α) and an estimate CVaR c_i for the service S_i. Then, for each new $Y_{i,r}$, we perform

$$u_i \leftarrow u_i - \eta_r \left(1 - \frac{1}{1-\alpha}\mathbf{1}\{Y_{i,r} \ge u_i\}\right), \quad c_i \leftarrow (1-\zeta_r)c_i + \zeta_r \left(u_i + \frac{1}{1-\alpha}\left[Y_{i,r} - u_i\right]_+\right), \tag{20}$$

where $\eta_r, \zeta_r > 0$ and ζ_r are small, decreasing (decaying) steps; for example, $\eta_r = \eta_0 / (1+r)^\kappa$.

Current estimate $\mathrm{CVaR}_\alpha \approx c_i$. Advantage: no buffer required (zero memory). Disadvantage: careful selection of the step schedule is required.

In option D1.2, we use a quantile buffer (fixed memory M) – we maintain a buffer of the latest values $B_i := \{Y_{i,r}\}$ of size M (discarding the oldest ones) and keep an approximate α quantile $\hat{q}_\alpha$. Then:

$$\mathrm{CVaR}_\alpha = \frac{1}{(1-\alpha)} \cdot \frac{1}{|T_i'|} \sum_{y \in |T_i'|} y, \quad T_i' = \{y \in B_i' : y \ge \hat{q}_\alpha\}. \tag{21}$$

The advantage of (21) over (20) is stability and controlled memory, while the disadvantage is a slight delay due to the buffer. Both modes are consistent with the definition CVaR (10) and preserve single-passability.

In submodule D2, we aggregate secondary failures within the window W_r. First, we integrate

$$\Sigma_r \leftarrow \Sigma_r + \langle \eta, \sigma(t) \rangle \Delta t, \tag{22}$$

where $\sigma(t)$ is the degree of violation of invariants (7) with weights $\eta \ge 0$.

After closing the window W_τ, add the contribution $\omega_r \Sigma_r$ to ISM_α and reset $\Sigma_r \leftarrow 0$ (22).

Before moving on to evaluating the cost and settings, let's record how the structure behaves when observations are missing and when working with availability windows:

– between windows, we do not update the value $s[i]$ (or we update only the decrease $e^{-\rho\Delta t}$ without new observations); we do not increase the integral $S[i]$ – the absence of data is not considered zero quality;

– when opening a new window, we initiate the time weight $\omega(t)$ according to the mission schedule, and it is advisable to reduce the parameter s η_r and ζ_r for CVaR for small samples (short windows).

Since the practical applicability of the method is determined not only by accuracy but also by resource cost, we formulate the asymptotic complexity per event/step and the corresponding memory costs for each module (Table 1).

Table 1 uses the following symbols: m – number of services; $|V|$ – number of nodes; $|E|$ – number of edges; $|\mathrm{supp}\ \Pi_i|$ – number of service nodes; N_{msg} – number of messages in a cascade per event; M – buffer capacity.

Table 1. *Asymptotic complexity and memory consumption for each module*

Module	Complexity	Memory
A	$O\left(\sum_i \lvert\mathrm{supp}\ \Pi_i\rvert\right)$ per deficit change event	$O(1)$ – additional; $O(\lvert V\rvert)$ – shared
B	$O(N_{msg})$ on the event	$O(\lvert V\rvert + \lvert E\rvert)$
C	$O(m)$ per event	$O(m)$
D (gradient mode)	$O(m)$	$O(m)$
D (buffer mode)	$O(m \log M)$	$O(m \cdot M)$

The complexity limits obtained (Table 1) define the working ranges of parameters. Below are practical guidelines for selecting them in real conditions:

– tail sensitivity (α) determines what proportion of the largest observations to take into account CVaR. For severe peak risks, it is advisable to use $\alpha = 0.9...0.99$; for more balanced scenarios, use $\alpha = 0.7...0.9$. Higher values shift the metric toward rare large episodes.

– λ (cascade depth) – selected so that the stability condition is met $\bar{d}\lambda\bar{A} < 1$ (in practice, it is necessary to calibrate based on historical cascade episodes and keep a reserve to the limit so as not to distort long graph paths);

– ε (cutoff threshold) – a regulator of the compromise between accuracy and speed in the propagation module; accordingly, we cut off very weak/long contributions that have almost no effect on the result. Typical values are $10^{-3} \ldots 10^{-2}$;

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– ρ (smoothing rate) – corresponds to the filter's "memory time" $\tau \approx 1/\rho$, respectively: the higher the ρ, the shorter the memory and sensitivity to recent changes; the lower the ρ, the stronger the averaging. In real conditions, it is necessary to match τ with the characteristic duration of episodes in the given data;

– β, η, γ are weight parameters extracted from the priorities of the information system's objective function: β_i is the importance of services in the final aggregation; η is the weight of secondary failures; γ is the structural penalty coefficient (if necessary). Changing these weights does not destroy the properties of metric (12), but orders the configurations according to the selected priorities.

CVaR mode is selected as follows: under severe memory constraints, we use the gradient option (D1.1) – single-pass, without a buffer. When additional stability and reproducibility of reports are required, we use the buffer option (D1.2) with a fixed capacity M.

Configuring parameters and practical modes of use of the integrated survivability metric

The following protocol for applying the metric is proposed (12).

Step 1. Ensure that "local" deviations $(z(t)$ components) lie within $[0,1]$. This fixes the scale and makes comparisons between configurations correct.

Step 2. We divide the event stream into intervals where data consistency is guaranteed. If the target function of the information system has critical phases, we set a higher $w(t)$ during these periods (for example, stepwise or bell-shaped [21]).

Step 3. Determine the "response horizon" for subsidence. For short peaks, take a smaller $\tau_{1/2}$ (i.e., a larger ρ) so as not to stretch the peaks. For slow drifts, take a larger $\tau_{1/2}$. Typical recommendations:

– reactive mode $\tau_{1/2} = 10...30$ s;

– balanced monitoring $\tau_{1/2} = 60...300$ s;

– background monitoring $\tau_{1/2} = 600...1800$ s.

Step 4. We reproduce the empirical reachability of the cascade. From event logs, we estimate the average "length" of the effect by calibrating λ so that the simulated propagation matches this length (with a margin to the stability limit $\rho(\lambda A) \le 1$), i.e., we essentially work with $\lambda \in (0, 0.9]$. We select the threshold ε according to the calculation budget using the cutoff scheme for contributions that change $\tilde{z}$ by less than $10^{-3}...10^{-2}$. And we check the impact on (12) – the difference should be within the selected reporting accuracy.

Step 5. Based on practical guidelines for selecting parameter values α, we link α to the frequency of acceptable failures. If significant deviations are allowed in no more than 5% of windows, we take $\alpha = 0.95$. For supercritical services, we take $\alpha = 0.99$; for ordinary services, we take $\alpha = 0.8...0.9$.

Step 6. We build a "priority budget" $\sum_i \beta_i = 1$. By β_i, we mean the proportional values of the service in the target function of the information system or the expected losses from its degradation. A simple way is to standardize ξ points p_i according to the selected scheme.

Step 7. First, we normalize η so that $\sum_u \eta_u = 1$. Next, we select a reference scenario: "one complete violation of the invariant I_u within T_{ref} seconds in 1 window". We select γ so that the contribution $\gamma \omega_r \Sigma_r$ in this scenario is equal to, say, the median CVaR_α for the base service. This level curve makes the scales comparable.

Step 8. Perform sensitivity analysis. Change each parameter to $\pm 10\%$ and check whether the configuration ranking remains the same. If the ranking "jumps", reduce α (reduce peak dominance) or λ (reduce cascade amplification), or increase $\tau_{1/2}$ (for greater stability).

Step 9. Perform a backtest on previously recorded incidents. We expect (12) to rise to the peak of the incident, remain there during the incident, and decrease after recovery to the baseline level. This is the criterion for the correctness of the settings.

In this protocol, ξ points are understood as preliminary numerical assessments of service priority, which are then converted into weights β by simple normalization:

$$\beta_i = \xi_i \Big/ \sum_j \xi_j . \qquad (23)$$

Such ξ_i can be set in several complementary ways:

1. Uniform a priori method:

$$\xi_i \equiv 1 \quad \Rightarrow \quad \beta_i = 1/m , \qquad (24)$$

where m is the number of services. This sets the initial priority.

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2. Method based on service load level:

$$\tilde{\xi}_i = \overline{\text{req}}_i \cdot v_i, \quad \xi_i = \tilde{\xi}_i \Big/ \sum_j \tilde{\xi}_j . \qquad (25)$$

where $\overline{\text{req}}_i$ is the average intensity of requests to S_i; v_i is the "usefulness" coefficient (if absent, then $v_i = 1$).

3. Risk-oriented method based on observation history:

$$\tilde{\xi}_i = \wp_i \cdot \text{CVaR}_\alpha\left(\{Y_{i,r}\}_r\right), \quad \xi_i = \tilde{\xi}_i \Big/ \sum_j \tilde{\xi}_j , \qquad (26)$$

where $\wp_i$ – frequency of "problematic" windows for S_i; $\text{CVaR}_\alpha\left(\{Y_{i,r}\}_r\right)$ – conditional average of the largest $(1-\alpha)\%$ values $Y_{i,r}$.

In (26), frequent and "heavy" availability windows increase W_r.

4. Method based on structural influence in the graph component:

$$s_i = \frac{\langle \Pi_i, \Phi_\lambda \mathbf{1} \rangle}{\langle \Pi_i, \mathbf{1} \rangle}, \quad \tilde{\xi}_i = s_i, \quad \xi_i = \frac{\tilde{\xi}_i}{\sum_j \tilde{\xi}_j}, \qquad (27)$$

where $\Pi_i \in \{0,1\}^{|V|}$ – indicator vector of service nodes S_i.

The value of s_i (27) is the average "reachable influence" of service nodes and reflects its potential cascading.

5. SLO method:

$$\tilde{\xi}_i = 1/E_i, \quad \xi_i = \tilde{\xi}_i \Big/ \sum_j \tilde{\xi}_j , \qquad (28)$$

where E_i – acceptable budget for failures/deficits for S_i (a smaller budget gives higher priority).

If necessary, several methods (24–28) can be combined for a single assessment. An example of such a combination:

$$\tilde{\xi}_i = a \cdot \text{req}_i + b \cdot \text{CVaR}_\alpha(Y_i) + c \cdot \hat{s}_i, \quad a + b + c = 1,$$

where the circumflex sign means the preliminary scaling of each indicator to $[0,1]$. After that, the usual normalization of $\xi_i = \tilde{\xi}_i \Big/ \sum_j \tilde{\xi}_j$ is performed and the weights β_i (23) are calculated.

To facilitate initial setup, we provide practical profiles – ready-made sets of coordinated parameters for typical operating modes. They do not replace calibration, but they provide the correct "entry point" and explain why these particular values work.

1. "Fast-moving critical target functions" profile. In this profile, it is important to catch rare peak deviations in time. Therefore, we take a high "tail" $\alpha = 0.95$ (the metric focuses on the upper tail), short memory $\tau_{1/2} = 10...30$ c (large ρ; peaks are not "blurred"), moderate cascade depth $\lambda = 0.3...0.6$ (the cascade is taken into account, but does not "overheat"), low cutoff threshold $\varepsilon \approx 10^{-3}$ (more precisely, if the resource allows). We make the time weight $w(t)$ pulsed during critical phases, and increase the weight of secondary failures γ – during maneuvers, secondary failures often become decisive.

"Overheating" of the cascade refers to a situation where propagation parameters (large λ and/or dense graph A) overly amplify cascade paths, causing minor local deviations to spread throughout the information system and artificially causing an unjustified increase in metrics (12).

2. Profile "Continuous service flows." The balance between peaks and averages is more important than "chasing tails." Therefore, $\alpha = 0.8...0.9$ (compromise), memory is longer $\tau_{1/2} = 60...300$ c (less sensitivity to small fluctuations), the cascade is deeper $\lambda = 0.4...0.7$, and the cutoff can be made coarser $\varepsilon \approx 10^{-2}$ to save resources. $w(t)$ is almost uniform with slight amplifications according to the schedule; γ is average, i.e., secondary failures have an impact but do not dominate.

3. Profile "Environments with dense dependencies (dense graphs)". The main risk is cascade amplification. This occurs when the network is so dense or the λ is so large that even a small local deviation quickly amplifies along many paths of the graph. Therefore, we first scale A so that $\rho(A) \le 1$, and keep λ restrained $(0.2...0.5)$ to avoid overcounting long paths. We make the threshold ε slightly higher, controlling the error ISM (12); we set $w(t)$ according to the parameters of the target function of the information system. If necessary, you can increase the structural penalty γ to add a penalty for excessive graph connectivity to the metric.

4. Profile "Intermittent connection and long 'dead zones'". When telemetry comes in fragments, the first thing to do is to extend or adapt W_r (so as not to merge short bursts into noise (short, irregular metric deviations caused not by service degradation, but by side effects of measurement and information system functioning)) and increase $\tau_{1/2}$ – this reduces random jumps between windows. In $w(t)$, we underestimate the weight of periods without confirmed data. We leave other parameters (λ, ε, α) from the base profile and adjust them after a quick check of the existing historical data.

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After selecting the start profile, it is recommended to perform a short calibration on previous metric runs – specify (λ , ρ , ε , α) under the graph provided by the information system, data rhythm (telemetry every second, logs every minute, spikes under load, downtime, time peaks) and the computing budget, and then check the stability of the ranking and the limits of the system resources.

After fixing the parameters and profiles, we move on to the presentation of the methodological principles of interpreting the integrated survivability metric, which regulate the rules for reading the metric in a production environment and the procedures for making decisions based on it.

Thus, when determining the scales and thresholds of the integral survivability metric, it is advisable to set two levels – warning and critical – with numerical values established either by empirical percentiles (e.g., 80th and 95th) or by target risk budgets (probability of exceeding the limit). When ensuring the stability of the metric indicator, it is recommended to adjust only the filtration parameters: if the metric is "noisy," it is necessary to slightly increase $\tau_{1/2}$ or decrease α ; if the metric is inertial, it is necessary to decrease $\tau_{1/2}$ or strengthen $w(t)$ in critical intervals (if necessary, slightly adjust ε), while preserving the semantics of the metric.

Below is a summary of typical errors in configuring the integrated survivability metric, with an analysis of the causes and practical steps to resolve them.

1. Error: too high λ in dense graphs (cascade "overheating" effect).

Problem analysis: when $\rho(\lambda A)$ or $\bar{d}\lambda\bar{A}$ approaches 1, the contribution of long paths increases sharply: the number of messages increases exponentially, most $\hat{z}_v$ are cut to 1, and the metric is artificially inflated.

Solution: scale A so that $\rho(A)\le 1$; reduce λ; increase the cutoff threshold ε if necessary, limit the path length ℓ or add a structural penalty to γ .

2. Error: too large α with a poor sample (few windows).

Problem analysis: the tail estimate becomes unstable: CVaR_α is very volatile because only a few observations remain in the upper $(1-\alpha)\%$.

Solution: reduce α (more tail averaging) or switch to buffer mode D1.1 with a larger M (stabilizes the tail).

3. Error: abnormally small or abnormally large ρ (smoothing rate).

Problem analysis: too small ρ approximates peaks – the system lags behind in performing the function; too large ρ makes the metric abnormally active – the reaction occurs to noise fluctuations.

Solution: focus on the required response time of the target function of the information system: select $\tau_{1/2}\sim 1/\rho$ so that you can see relevant peaks, but not noise; for "noisy" metrics, slightly increase $\tau_{1/2}$, and for "inertial" metrics, decrease it.

4. Error: β_i and γ are not comparable (dominance of one indicator).

Problem analysis: if the weights of services β_i or the weight of secondary failures γ are set without coordination, one component (service or secondary) begins to dominate regardless of the data.

Solution: apply a link to the level curve (sixth step of the metric application protocol), in particular, select γ so that in the reference scenario, the contribution of $\gamma\omega_r\Sigma_r$ is equal to, for example, the median CVaR_α of the base service; normalize β_i $\left(\sum_i \beta_i = 1\right)$ and check the sensitivity (±10%) – the ranking should be preserved.

The relationship between the integral metric of survivability and the operational area and the rules for comparing configurations

Next, it is necessary to formalize when the integral survivability metric certifies that the information system is in the operational zone and how to correctly compare architectural configurations and recovery policies based on it.

Taking the above into account, let us summarize some concepts:

– $\mathcal{I}_i := \mathrm{CVaR}_\alpha\left(\{Y_{i,r}\}\right)$ – service "tail" assessment for the service S_i ;

– $\mathcal{J} := \sum_{r=1}^{R}\omega_r\Sigma_r$ – the integral contribution of secondary failures.

Next, we set the reference limits:

– $\kappa_i > 0$ – acceptable tail degradation of the S_i service (at the level of CVaR_α);

– $\tau > 0$ – acceptable integral level of secondary failures;

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– $\Gamma > 0$ – global limit of the integral survivability metric.

Therefore, the trajectory of the information system lies within the operational range if three budget conditions are met simultaneously:

$$\mathcal{I}_i \le \kappa_i \ \forall i, \quad \mathcal{J} \le \tau, \quad \mathrm{ISM}_\alpha \le \Gamma. \qquad (29)$$

Condition (29) is explained by the fact that local service "tails" and the aggregate contribution of secondary failures fit within their budgets, and their weighted sum does not exceed the global risk budget.

A simple sufficient condition for operability follows from the linear structure of ISM :

$$\sum_{i=1}^{m} \beta_i \kappa_i + \gamma \cdot \tau \le \Gamma \Rightarrow \left(\mathcal{I}_i \le \kappa_i \ \ \forall i \ \wedge \ \mathcal{J} \le \tau \right) \Rightarrow \mathrm{ISM}_\alpha \le \Gamma. \qquad (30)$$

Condition (30) provides a mechanism for reconciling local limits (κ_i, τ) with global limits Γ. Accordingly, if local budgets are chosen so that their weighted sum does not exceed the global limit, then the fulfillment of local constraints guarantees the fulfillment of the global constraint.

The algebraic difference between the limit and the current value of the metric (margin to limit) allows you to conveniently track the margin to threshold:

$$\Delta := \Gamma - \mathrm{ISM}_\alpha. \qquad (31)$$

Then, at $\Delta > 0$ (31) shows that the system is within the operating range (there is a reserve); $\Delta = 0$ – at the limit; $\Delta < 0$ – outside the range (exceeding $|\Delta|$). For operational control, it is also convenient to use a normalized reserve:

$$\zeta := 1 - \frac{\mathrm{ISM}_\alpha}{\Gamma} \in (-\infty, 1], \quad (31) \textit{ shows that the system is within the operating range } (\textit{there is a reserve}); \qquad (32)$$

which is a dimensionless indicator: $\zeta = 1$ means zero risk, $\zeta = 0$ – threshold point, $\zeta < 0$ – shows the percentage of "exceeding" the global limit.

To calibrate the limits (κ_i, τ, Γ), we first calculate empirical values $\mathcal{I}_i$ for each service and $\mathcal{J}$ for secondary failures at stable intervals; then we set local thresholds as high percentiles: $\kappa_i := q_p(\mathcal{I}_i)$, $\tau_i := q_p(\mathcal{J}_i)$ from $p \in [0.90, 0.95]$. After that, we reconcile them with weights and set a global limit so that with a given margin $\Delta_{\min} > 0$ the sufficient condition is satisfied:

$$\sum_{i=1}^{m} \beta_i \kappa_i + \gamma \cdot \tau \le \Gamma - \Delta_{\min} \qquad (33)$$

Any Γ from the interval $\left[\sum_{i=1}^{m} \beta_i \kappa_i + \gamma \cdot \tau + \Delta_{\min}, \infty \right)$ satisfies condition (33). To fix a specific value, it is convenient to take the minimum allowable:

$$\Gamma := \sum_{i=1}^{m} \beta_i \kappa_i + \gamma \cdot \tau + \Delta_{\min}. \qquad (34)$$

If necessary, the reserve can be specified in relative form $\zeta_{\min} > 0$, then from (34) we have:

$$\Gamma = \frac{\sum_i \beta_i \kappa_i + \gamma \cdot \tau}{1 - \zeta_{\min}}. \qquad (35)$$

When the mission priorities change (weights β_i; if necessary, κ_i), we check the higher condition with the new values and rebind Γ (35) or $\Delta_{\min}$ to maintain the target reserve.

Next, we can formalize the rules for comparing configurations. We assume that the configurations/policies Ψ_1 and Ψ_2 are evaluated using the same weights (β_i, γ), limits (κ_i, τ, Γ) and windows W_r. Then:

Rule R1. A configuration is acceptable if and only if conditions (29) are satisfied. Configurations that do not satisfy these conditions are discarded without further ranking.

Rule R2. Among acceptable configurations, preference is given to the one with less ISM_α. For practical stability of comparison, the dominance margin $\delta > 0$ is used: if $\mathrm{ISM}_\alpha(\Psi_1) \le \mathrm{ISM}_\alpha(\Psi_2) - \delta$, then Ψ_1 dominates Ψ_2.

Rule R3. If $\left| \mathrm{ISM}_\alpha(\Psi_1) - \mathrm{ISM}_\alpha(\Psi_2) \right| < \delta$ (tie according to R2), preference is given to the configuration with a smaller $\mathcal{J}$ (fewer invariant violations), because secondary failures increase the structural risk of cascades.

Rule R4. If the previous criteria are equal, compare the vector $\mathcal{I}_i$ in descending order β_i. The configuration with lower $\mathcal{I}_i$ for the highest priority services wins.

Rule R5. For strategic planning (before selecting β_i, γ), it is useful to construct a Pareto front [22] along two coordinates: $\left(\sum_i \beta_i \mathcal{I}_i, \mathcal{J} \right)$. Alternatives that lie

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above/to the right of the front (worse on both criteria) are rejected as dominated (alternatives for which there is another alternative that is not worse on all criteria and is better on at least one).

To make the comparison of configurations resistant to estimation errors (since $\mathcal{I}_i$ and $\mathcal{J}$ are calculated based on a finite number of windows W_r), we take a confidence interval for each value: $\mathcal{I}_i \in \left[\underline{\mathcal{I}}_i, \overline{\mathcal{I}}_i\right]$, $\mathcal{J} \in \left[\underline{\mathcal{J}}, \overline{\mathcal{J}}\right]$.

Then we formulate the rules:

Rule 1. The configuration is considered acceptable if, even under the worst-case scenario, the budget system is fulfilled (robust acceptance):

$$\overline{\mathcal{I}}_i \le \kappa_i \ \forall i, \quad \overline{\mathcal{J}} \le \tau, \quad \sum_i \beta_i \overline{\mathcal{I}}_i + \gamma \overline{\mathcal{J}} \le \Gamma. \qquad (36)$$

Those who do not satisfy condition (36) are cut off without further ranking.

Rule 2. Let us compare two admissible configurations Ψ_1 and Ψ_2. Suppose that Ψ_1 dominates Ψ_2 if its worst generalized indicator is less than the best indicator of Ψ_2:

$$\sum_i \beta_i \overline{\mathcal{I}}_i^{\Psi_1} + \gamma \overline{\mathcal{J}}^{\Psi_1} < \sum_i \beta_i \underline{\mathcal{I}}_i^{\Psi_2} + \gamma \underline{\mathcal{J}}^{\Psi_2}. \qquad (37)$$

This guarantees an advantage even in the "worst case for Ψ_1" versus the "best case for Ψ_2". If necessary, we add a small margin of $\delta > 0$ to the right side of (37) as a tolerance for rounding.

In practice, if the intervals overlap and the inequality is not satisfied with a margin, and the conclusion is "undetermined," then we either increase the number of windows (more data), or use the buffer mode CVaR with a larger M, or transfer the decision to the profile level (rules R3–R5).

To transform the integrated survivability metric from a simple diagnostic figure into an operational tool, two aspects need to be fixed: how to act for different values of the indicator, and how to make correct comparisons between different target functions of the information system.

To this end, an algorithm of actions for the operational zone is proposed. For this purpose, a standardized indicator (32) will be used as a single "traffic light":

– emerald zone: $\zeta \ge 0.2$ – normal operation of the information system;

– yellow zone: $0 < \zeta < 0.2$ – warning mode: limit non-critical loads, increase the weight of $w(t)$ in critical intervals, activate preventive localization policies;

– red zone: $\zeta \le 0$ – information system outside the operational zone: cascade cut-off policies must be applied immediately – reduce λ and/or increase ε; forcibly align invariants, increase resource reserves.

At the same time, we monitor the contribution structure. If the share of secondary failures in ISM_α exceeds ~ 40–50%, this is an indicator of the secondary nature of the degradation. In this case, the priority should be to restore invariants $\left(\mathrm{Inv}_T, \mathrm{Inv}_R, \mathrm{Inv}_B\right)$.

To correctly compare configurations for different target functions of the same information system (different critical interval schedules, different W_r'), it is necessary to ensure the invariance of settings: maintain the same weights $\left(\beta_i, \gamma\right)$ and the same level of α; normalize $w(t)$ so that $\int_{W_r} w(t)dt = 1$ in each target function of the information system (then $Y_{i,r}$ – comparable in scale); ensure the same $\tau_{1/2}$.

Under these conditions, ISM_α becomes comparable in terms of the results of performing different target functions by the same information system.

Analytical comparison of the integral metric of survivability with basic indicators

Next, we will demonstrate through analytical examples (scenarios) how ISM_α provides a more informative and stable assessment than common basic indicators such as the proportion of time out of demand (binary indicator), average deficit, information system availability, average downtime, etc.

First, let's look at the basic indicators that will be compared with ISM_α. So, let's say that for the service S_i, the quality indicator $q_i(t) \in [0,1]$ and the requirement $\theta_i(t) \in [0,1]$ are observed on the horizon $[t_0, t_1]$. The deficit is determined by formula (1). Then:

1. Binary indicator of violations (the proportion of time when $d_i(t) > 0$):

$$\Upsilon_i := \frac{1}{T}\mu\left(\left\{t \in [t_0, t_1] : d_i(t) > 0\right\}\right), \quad T = t_1 - t_0, \qquad (38)$$

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where $\mu(\bullet)$ is the Lebesgue metric (the proportion of time during which the deficit $d_i(t)$ was positive) [23].

2. Average deficit indicator:

$$\vartheta_i := \frac{1}{T}\int_{t_0}^{t_1} d_i(t)dt. \quad (39)$$

3. Availability indicator:

$$o_i := 1 - \Upsilon_i. \quad (40)$$

These indicators (38–40) do not see either the topology of dependencies or the tail structure of the distribution of deviations, and therefore may give the same values for significantly different risks.

Next, let's move on to the scenarios themselves.

Scenario S1 ("heavy tails"). Let's construct two deficit trajectories for a single service at $[0,1]$:

– trajectory $\mho_1$ with rare but significant declines in service quality: $d_i(t)=1$ in the range of ε, and in the rest of the interval $d_i(t)=0$;

– trajectory $\mho_2$ with frequent but minor dips in service quality: $d_i(t)=\varepsilon$ throughout the entire interval.

Both trajectories have the same average deficit:

$\vartheta_i^{(\mho_1)} = \varepsilon\cdot 1 + (1-\varepsilon)\cdot 0 = \varepsilon, \quad \vartheta_i^{(\mho_2)} = (1)\cdot\varepsilon, \quad \vartheta_i^{(\mho_1)} = \vartheta_i^{(\mho_2)}.$

Similarly, $\Upsilon_i^{(\mho_1)} = \varepsilon$, $\Upsilon_i^{(\mho_2)} = 1$ (for any $\varepsilon > 0$), i.e., the binary indicator even ranks them in reverse: in $\mho_2$, the indicator records constant violations, while in $\mho_1$, they are rare. However, in terms of peak risk (operational loss, emergency shutdowns), the $\mho_1$ scenario is worse.

Let $w(t)\equiv 1$ and $\lambda=\gamma=0$ (i.e., ignore cascading and secondary). Then $Y_{i,r} = \int_0^1 (W * d_i)(t)\,dt$ equals (by unit convolution) ϑ_i. But CVaR_α acts on a sample of windows, and for $\alpha > (1-\varepsilon)$ we will have:

$$\mathrm{CVaR}_\alpha^{(\mho_1)} \approx 1, \quad \mathrm{CVaR}_\alpha^{(\mho_2)} \approx \varepsilon.$$

Therefore, $\mathrm{ISM}_\alpha^{(\mho_1)} > \mathrm{ISM}_\alpha^{(\mho_2)}$ for any α in the tail $(\alpha > (1-\varepsilon))$. Thus, the average indicators do not distinguish $\mho_1$ from $\mho_2$, and the binary ones are misleading; ISM_α correctly reflects the danger of short critical peaks.

Scenario S2 (cascading). Consider a graph with two nodes $V=\{1,2\}$ and an arc $1\to 2$, $A_{12}=1$, the rest of the values are 0. The service S is projected onto both nodes: $\Pi = e_1 + e_2$.

Let's compare two patterns of localized deficits $z(t)$ (5) of equal amplitude $\delta > 0$ (at equal time intervals):

– pattern ι_1 ("deficit at the top" (the primary node pulls the dependent node)): $z = [\delta, 0]^\top$;

– pattern ι_2 ("deficit down" (final node)): $z = [0, \delta]^\top$.

Cascading correction gives:

$$\tilde{z}^{\iota_1} = (I - \lambda A)^{-1} z = \begin{bmatrix} 1 & \lambda \\ 0 & 1 \end{bmatrix}\begin{bmatrix} \delta \\ 0 \end{bmatrix} = \begin{bmatrix} \delta \\ \lambda\delta \end{bmatrix},$$

$$\tilde{z}^{\iota_2} = \begin{bmatrix} 1 & \lambda \\ 0 & 1 \end{bmatrix}\begin{bmatrix} 0 \\ \delta \end{bmatrix} = \begin{bmatrix} \lambda\delta \\ \delta \end{bmatrix}.$$

Service deficit in each pattern:

$$\tilde{z}^{\iota_1} = \frac{\delta + \lambda\delta}{2}, \quad \tilde{z}^{\iota_2} = \frac{\lambda\delta + \delta}{2}.$$

That is, at the level of instantaneous values, they are the same. However, the reason is different: in ι_1, the violation "pulls" the dependent node (cascade), and in ι_2, the primary node is "at the end." When secondary violations (violations of interlevel invariants) are marked in event logs for ι_1, then $\sigma(t)$ takes on a positive value, while for ι_2, it does not. Thus, with the same $\tilde{d}$ ISM_α, ι_1 is greater due to the addition of $\gamma\sum_r \omega_r \Sigma_r$. The basic indicators ϑ, Υ, o do not distinguish between these structurally different cases, while ISM_α separates configurations through the component of secondary failures.

Scenario S3 (hidden desynchronization). Let $q_i(t)$ perform the requirement $q_i(t) \geq \theta_i(t) \Rightarrow d_i(t) \equiv 0$ over the entire interval. At the same time, the invariant Inv_T is violated on a large scale, so $\sigma_{u^*}(t) \approx 1$ on a significant portion of the windows. Then:

$$\vartheta_i = 0,\ \Upsilon_i = 0,\ o_i = 1,$$

but

$$\mathrm{ISM}_\alpha = \underbrace{0}_{\text{service part}} + \gamma\sum_r \omega_r \Sigma_r > 0.$$

That is, ISM_α warns of a hidden systemic risk (high probability of secondary failures and cascades when dependent processes are activated), which basic indicators do not notice.

Scenario S4 (observation gaps and availability windows). With intermittent communication, part of the telemetry is missing from the information system. Basic

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indicators either exclude these intervals (overestimating "availability") or consider the deficit to be zero (underestimating the problem). In the approach proposed in this work, aggregation is performed only within the agreed windows $\{W_r'\}_{r=1}^{R}$ and integrals are normalized by definition – the metric becomes resistant to gaps and comparable between target functions of information systems with different observation "densities."

Thus, the scenarios presented show that ISM_α is the basis for achieving increased survivability of an information system on a mobile platform with multi-level dependencies, while basic indicators remain useful only as simple diagnostic overviews without a guarantee of correct configuration ranking.

Experimental verification of the integral survivability metric

As part of this study, a reproducible Python testbed [24] was developed that implements ISM_α and demonstrates its behavior on synthetic but representative scenarios. The experiment was conducted in a software environment using Python 3.11.8, NumPy 1.24.0, Pandas 1.5.3, and Matplotlib 3.6.3.

Initial data:

– dependency graph $A \in \mathbb{R}_+^{|V|\times|V|}$: random sparse directed graph $(|V| = 30)$ without loops, edge weights in $[0.2;0.8]$;

– services $m = 3$ with projections onto nodes via matrices B (distribution of deficit onto nodes) and C (reverse service cut). Each service covers a subset of nodes, normalization guarantees $[0;1]$;

– time: $T = 300$ steps (discretization in 1 s). Availability windows: mostly 30 s each; in scenario S4, every third window is missing (interrupted connection);

– parameter values: $\alpha \in \{0.8, 0.9, 0.95, 0.99\}$, $\lambda \in \{0, 0.2, 0.5, 0.8\}$, exponential smoothing with half-life $\tau_{1/2} \approx \ln 2/\rho$, service weights $\beta \in (0.5, 0.3, 0.2)$. The penalty for secondary failures is implemented as $\sum_r \omega_r \Sigma_r$ with a weight vector of invariants $\eta = (0.05, 0.02, 0.01)$, i.e. γ absorbed in η for ease of comparison);

– cascade correction: approximation of the Neumann series $\tilde{z} = \min\left\{\sum_{\ell=0}^{L} (\lambda A)^\ell z, \mathbf{1}\right\}$ with $L = 6$ (fast convergence for selected λ;

– CVaR: empirical weighted calculation over sets $Y_{i,r}$, where weights are proportional to window duration.

Scenarios:

– S1: S_0 service – rare but deep failures; S_1 – constant minor failures; S_2 – nominal;

– S2: two spikes (the first one is at the top of the chain with a secondary marking (invariance violation), the second one is more local);

– S3: $q_i(t) \ge \theta_i(t)$ always, but three intervals violate the invariants $(\mathrm{Inv}_T, \mathrm{Inv}_R)$, so $\Sigma_r > 0$;

– S4: similar to S1, but every third window is unavailable; time weights are amplified in available windows.

For analytical validation, along with ISM_α, basic indicators were collected on the services: average deficit ϑ and proportion of time outside demand Υ.

The dataset of the experiment results is available in the Zenodo repository [25]. Below are graphs showing the results obtained by (Figs. 1–5).

Fig. 1 shows the family of dependencies of the integral survivability metric ISM_α on the tail sensitivity parameter α for a fixed cascading depth $\lambda = 0.5$ for four scenarios: S1 – rare deep failures versus frequent minor failures; S2 – cascading failures with marked secondary nature; S3 – only secondary failures without service deficits; S4 – operation with intermittent connection, taking into account availability windows. The curves demonstrate three typical modes: monotonous growth followed by saturation at large α when CVaR focuses on the worst windows; increased metrics in the presence of cascades and secondary failures; practically α – invariant behavior in the absence of a service component ($\mathcal{J}$ dominates).

Fig. 1, *a*) shows that as the parameter α increases from 0.8 to ≈ 0.95, the metric value increases significantly and then levels off; this is due to the fact that at higher α, CVaR gives greater weight to rare but deep service failures – a manifestation of "tail" sensitivity.

In Fig. 1, *b*), the steepest growth is to $\alpha \approx 0.95$, followed by a plateau; tail sensitivity amplifies the contribution of windows with cascading/secondary disturbances.

In Fig. 1, *c*) growth to $\alpha \approx 0.9$ and subsequent saturation; missing windows do not distort the estimate, since aggregation is performed only on available intervals.

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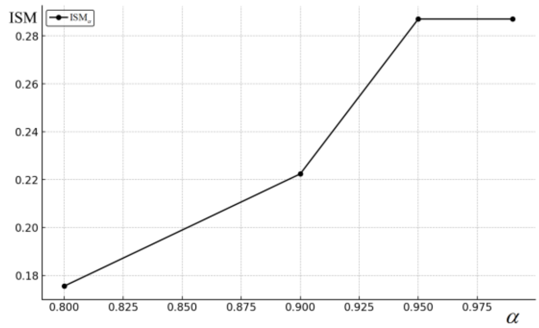
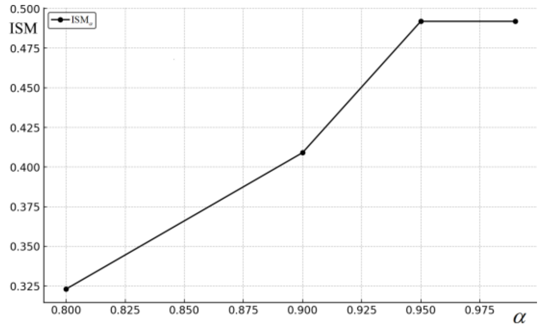
It should be noted that when α increases above the threshold that "covers" the worst windows, CVaR_{α} averages the same tail of the distribution, so ISM_{α} stops growing. At $\vartheta \approx 0$, the curve is practically horizontal – the service part has no effect, and the system penalty $\mathcal{J}$ does not depend on α; the metric remains positive, fixing the latent risk.



a)



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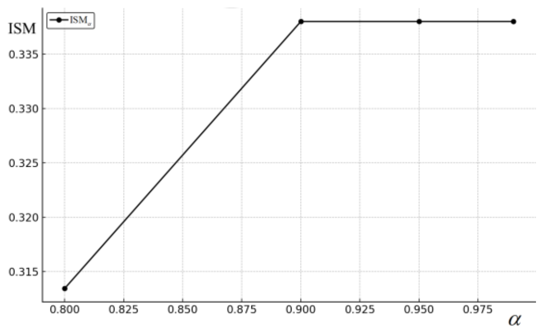
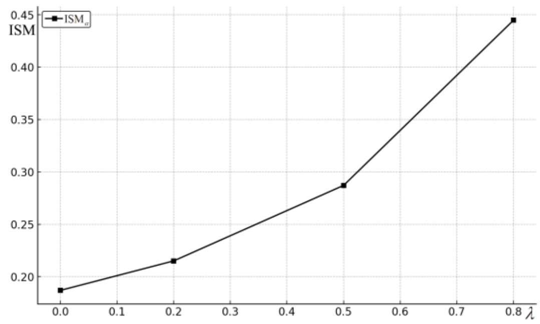


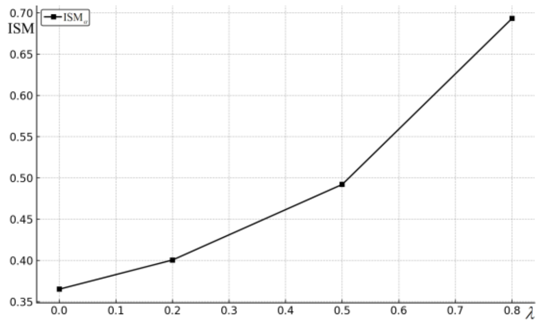
c)

Fig. 1. Dependence of the integral metric on the level of "tail" sensitivity (ISM_{α}) from α for a fixed $\lambda = 0.5$: a) scenario S1; b) scenario S2; c) scenario S4

Fig. 2 shows the dependence of the integral metric on the depth of cascade correction (ISM_{α}) from λ for a fixed $\lambda = 0.95$ for four scenarios. The parameter $\lambda = [0,\ 0.8]$ scales the impact of propagation of failures along the dependency graph $(I - \lambda A)^{-1}$; thus, an increase in λ amplifies the contribution of cascades, while secondary failures are accounted for through $\mathcal{J}$. The curves show the structural sensitivity of the metric: in the presence of cascades/secondary failures, the slope increases, and in the absence of service deficits, the curve remains almost unchanged.



a)



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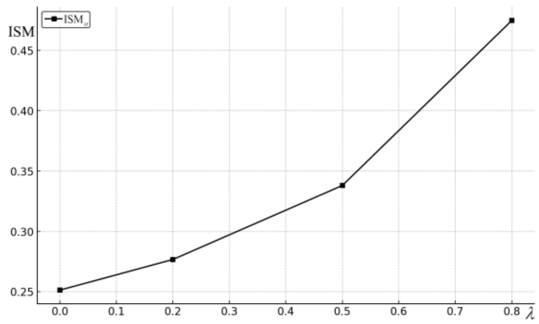

c)

Fig. 2. Dependence of the integral metric on the depth of cascade correction (ISM_{α} on λ) for a fixed $\lambda = 0.95$: a) scenario S1; b) scenario S2; c) scenario S4

Fig. 2, *a*) shows that the curve increases monotonically and is convex at the top; the largest increase is observed in the interval $\lambda = [0.5,\ 0.8]$, where cascade correction "pulls up" the influence of rare deep drops in dependent nodes.

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Fig. 2, *b*) shows that the steepest gradient among all scenarios: an increase in λ sharply increases ISM_{α} due to the combined action of cascade amplification and $\mathcal{J}$ from violated invariants.

Fig. 2, *c*) shows a steady, smooth curve growth without jumps; the largest increase is at high λ. Working exclusively in accessible windows makes the assessment robust to telemetry omissions, so cascading manifests itself without artificial artifacts.

If the service component is zero and $\mathcal{J}$ does not depend on λ, then ISM_{α} remains almost constant.

The example of scenario S1 (rare deep troughs S0 versus frequent small troughs S1) (Fig. 3) shows the discrepancy between the integral metric and the average deficit. With a fixed $\alpha = 0.95$ and an increase in the cascade parameter λ, the value of ISM_{α} monotonically increases (from approximately 0.19 to 0.45), while ϑ for services remains almost unchanged $(S_0 \approx 0.012$, $S_1 \approx 0.005)$. This illustrates that ϑ does not respond to either the depth of the cascade or the "tails" of the distribution, and therefore may misrank situations. Instead, ISM_{α} correctly increases the risk assessment with the growth of λ, accumulating the cascade amplification of rare but critical episodes.

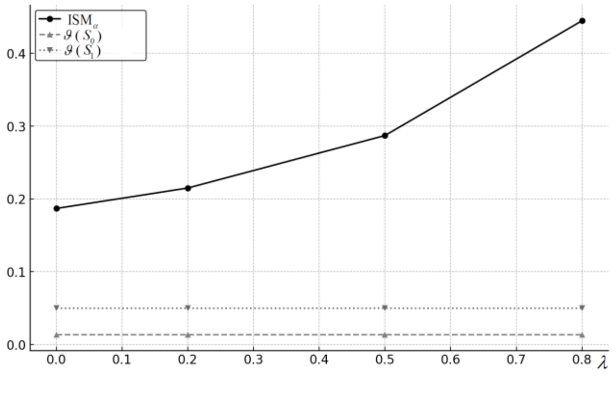

Fig. 3. Discrepancy between ISM_{α} and ϑ in scenario S1 – dependence on the cascade parameter λ $(\alpha = 0.95)$

Fig. 4 shows that in scenario S3, the average deficit ϑ is practically zero for all α, since $q_i(t) \geq \theta_i(t)$ (there are no service deviations). At the same time, ISM_{α} maintains a stable level (~0.166) and is almost independent of α, because the value of the metric is determined by $\mathcal{J}$, which accumulates invariant violations (secondary failures) and is not included in CVaR – aggregation of service deficits. Thus, the metric signals a latent risk when the SLO is in the emerald zone, which remains invisible to basic indicators such as ϑ.

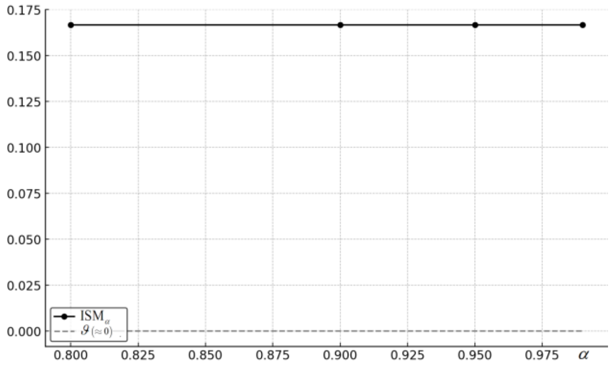

Fig. 4. Detection of secondary failures in the absence of service deficits $(\lambda = 0.5)$

Fig. 5 demonstrates the coordinated growth of ISM_{α} with both an increase in "tail" sensitivity α and a deepening of the cascade λ. The largest increase occurs in the direction of λ (the cascade component "pulls up" the deficits from the upper levels), while the increase in α amplifies the contribution of the worst windows; in the $\alpha \gtrsim 0.95$ zone, a plateau is observed, since CVaR averages the same tail of the distribution. The surface ridge in the area of large α and λ reflects the combined effect of cascading and secondary failures and sets the working parameter range for the target functions of an information system on a mobile platform with increased risk and survivability requirements.

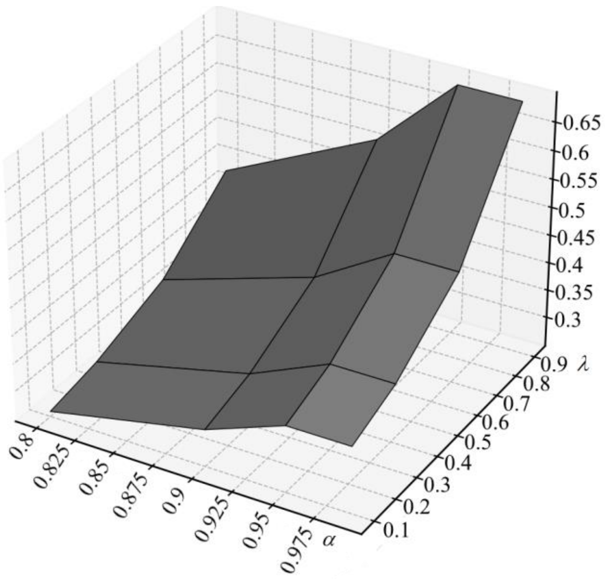

Fig. 5. Three-dimensional surface – $\mathrm{ISM}_{\alpha}(\alpha,\lambda)$ s for cascade disturbances with secondary markers

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The stand confirmed the key properties of the metric: monotonicity in cascade depth, tail sensitivity to rare critical episodes, structural informativeness (distinction between primary and secondary degradations), and robustness to observation gaps due to availability windows. Thanks to the developed procedure for calculating the integral metric in real time, the calculations are lightweight and suitable for on-board applications when the information system is deployed on a mobile platform, and the parameters considered earlier in the study are interpreted and controlled under the target function of the information system.

Scope of application of the integrated survivability metric

The proposed integrated survivability metric is designed for information systems on a mobile platform and reflects their specific conditions (availability windows, partial observability, cascades of "data–processes–resources"). Outside this class of information systems, the metric can be applied by reconfiguring SLO thresholds, dependency graph topology, and aggregation parameters, but empirical validation of such transfers is not the subject of this study.

Conclusions

The paper develops an integrated metric of information system survivability on a mobile platform (ISM_{α}) as a single scalar functional operating across the entire multilevel structure of "data–processes–resources" and reconciles temporally weighted deficits in relation to service requirements with cascading propagation of failures and the contribution of secondary functional failures. A single-pass real-time calculation procedure is proposed based on the localization of deficits at nodes, cascade correction with messages according to the dependency graph, exponential time convolution in availability windows, and risk-sensitive aggregation through conditional average excess (CVaR), which makes the metric suitable for use with intermittent connectivity and limited resources. The limitations, monotonicity, and resistance – ISM_{α} s to small parameter perturbations and incomplete observations are analytically justified; the concept of an operability zone with agreed thresholds and configuration comparison rules is introduced, which ensures controllability in decision-making. Experimental scenarios confirmed the correct ranking of configurations in cases where basic indicators (proportion of time outside demand, average deficit) are uninformative, and also demonstrated tail sensitivity to rare critical episodes and the ability to distinguish primary disturbances from induced secondary ones. A method for adjusting parameters is proposed separately, and the reproducibility of the results is demonstrated (all related FAIR/O data are added).

The scientific novelty lies in the fact that the paper proposes for the first time an integral metric of the survivability of an information system on a mobile platform, which simultaneously aggregates temporally weighted service deficits, corrects them taking into account their cascading propagation in the "data–processes–resources" graph, introduces a system penalty for secondary failures due to consistency invariants, and amplifies the contribution of rare but critical episodes using CVaR, with the entire procedure implemented in a single pass with an operation on availability windows. For the first time in such a coordinated format, service semantics, structural cascading, and secondary nature are combined in a single functionality suitable for comparing configurations and managing a viable area, as well as for working with intermittent communication; Additionally, robust comparison rules are proposed, taking into account the uncertainty of evaluation, which ensures the stability of conclusions with a finite sample of windows.

The proposed metric provides researchers with a single indicator of the state of the information system with a decomposition of the contribution of services and secondary failures, serves as an early warning tool and allows prioritizing recovery actions – reducing cascading through redistribution of dependencies and loads or eliminating secondary failures through restoration of time, integrity, and queue invariants. ISM_{α} It supports the selection and validation of configurations according to agreed survivability thresholds, ensures comparability between the target functions of the information system through weight normalization, and can be used in a mode of minimal use of additional information system resources without heavy matrix operations, which facilitates integration into industrial and embedded information systems. Working with availability windows makes the assessment resistant to intermittent communication and telemetry gaps, ensuring support for the mobility conditions of the platform on which the information system can be deployed.

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Further work involves identifying the structure of dependencies and weight parameters of telemetry metrics, developing adaptive schemes for selecting levels α and time weights $w(t)$ in real time, integratingт ISM_{α} with predictive and control strategies for selecting localization and recovery policies, deepening the dictionary of invariants for more accurate detection of secondary failures and reduction of false positives, studying robustness to shifts in environment distributions (in highly mobile platforms), scaling the approach to groups of information systems (megasystems) with shared risk budgeting [26–27], as well as verification on real event logs of operation with calibration of survivability thresholds and assessment of the effect of changes in architectural and operational decisions in load balancing tasks of multiprocessor computer systems [28] and virtual heterogeneous data centers [29].

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ІНТЕГРАЛЬНА МЕТРИКА ЖИВУЧОСТІ ІНФОРМАЦІЙНОЇ СИСТЕМИ НА МОБІЛЬНІЙ ПЛАТФОРМІ В УМОВАХ КАСКАДНИХ І ВТОРИННИХ ФУНКЦІОНАЛЬНИХ ЗБОЇВ

Предметом дослідження є інтегральна метрика живучості інформаційної системи на мобільній платформі за переривного зв’язку, часткової спостережуваності та каскадних і вторинних збоїв. Систему подано як багаторівневу структуру "дані – процеси – ресурси". **Мета роботи** – розробити інтегральну метрику живучості, яка бере до уваги часові відхилення від вимог, їх поширення графом залежностей і приховані порушення; запропонувати однопрохідний алгоритм і довести його властивості на сценаріях. Для досягнення окресленої мети необхідно виконати так **завдання**: формалізувати сервісні вимоги й проєкцію структури; побудувати метрику з ризик-орієнтованим агрегуванням дефіцитів, каскадною корекцією та системним урахуванням вторинних збоїв; розробити однопрохідні обчислення у "вікнах доступності"; довести монотонність, інваріантність масштабу й стійкість до пропусків; визначити правила налаштування параметрів і порівняння конфігурацій; експериментально перевірити й зіставити з базовими індикаторами. Упроваджено такі **методи:** проєкція сервісів на рівні даних, процесів і ресурсів; використання умовного середнього перевищення як ризик-орієнтованої агрегації; каскадна корекція за глибиною та шириною; організація фіксації вторинних збоїв і розсинхронізації; нормування у "вікнах доступності"; однопрохідні оновлення близької до лінійної складності. **Досягнуті результати:** запропоновано й формально визначено інтегральну метрику живучості; доведено її монотонність за параметрами, обмеженість, інваріантність до масштабування й стійкість до пропусків; продемонстровано відмінність від середнього дефіциту – розроблена метрика підсилює внесок рідкісних глибоких провалів і реагує на каскадність, тоді як середні значення майже сталі; за відсутності сервісних дефіцитів зберігається додатний рівень завдяки виявленню латентних вторинних збоїв; на сценаріях отримано узгоджені сімейства кривих і тривимірну поверхню, які демонструють кероване налаштування чутливості та стійке ранжування конфігурацій для промислових умов експлуатації мобільних платформ. **Висновки:** запропонована метрика забезпечує сервісно узгоджену оцінку стану інформаційної системи, одночасно зважаючи на часові дефіцити, каскадне поширення та вторинні збої; інтегральна метрика придатна для послідовних обчислень у ресурсно обмежених умовах, підсилює раннє виявлення ризиків і підтримує моніторинг, локалізацію, забезпечує живучість.

Ключові слова: інтегральна метрика; живучість; інформаційна система; каскадний збій; ризик-орієнтований моніторинг.

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