Formalizing the Survivability Target Function of Information System on Mobile Platform

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Abstract. *The purpose of the work is to formalize the survivability target function of an information system based on a mobile platform for selecting information system operating policies under disturbances. A multi-level model of an information system on a mobile platform is considered, which includes SLO requirements and causal-temporal consistency invariants. The target function combines the mean service shortfall, the CVaR tail risk measure, the penalty for approaching the survivability region, and the cost of reconfigurations, making it suitable for minimization on a sliding horizon under partial observability. Simulations with intermittent channels show a reduction in tail losses and time spent outside the acceptable region at moderate resource costs. The approach provides a consistent trade-off between risk, safety, as well as resources and serves as a single operational criterion for real-time survivability management.*

Keywords: *information system; survivability; target function; mobile platform; survivability core; partial observability.*

I. Introduction and Problem statement

Current information systems on a mobile platform operate under conditions of intermittent connectivity, partial observability, limited time- and other resources, as well as under disturbances (component failures, channel losses, attacks) [1-2]. To make control decisions (data rerouting, controlled service quality degradation, migration/replication, reserve activation), an operational criterion is required that aligns the target functionality with resource-time and causal-temporal constraints. Analysis of existing approaches often focuses on partial metrics (availability, reliability, average delay) and does not provide a single way to rank policies and optimize them in real time [3-5].

The paper sets the task of formalizing the target function of survivability for a multi-level model of an information system that combines:

– service requirements in the form of a target towards which the system is directed (SLO) and invariants of casual-temporal consistency;

– the acceptable area and survivability core $K \subseteq X$ as a set of states in which there is a policy that keeps the trajectory of the information system's functioning within the permissible area despite channel “availability windows”;

– partial observability (working with approximation/probabilistic state estimation) and the resource cost of reconfiguration.

Let us introduce the following system of definitions:

– state of the information system – $x_t \in X$;

– actions in the system – $u_t \in U$, disturbance – w_t ;

– telemetry (information about the values of measured parameters of controlled and managed elements in the information system and its processes) – y_t , which forms an a posteriori assessment of the state b_t ;

– service level (the function of an information system with a known interface and predictable behavior used by other elements of this system) $S(t)$ is compared with a requirement (a formalized target constraint specified by a threshold and a time window) $\mathrm{SLO}(t)$;

– service shortfall (the inherent difference between the specified requirement and the actual level of service in a selected time window) – $\Delta\mathrm{SLO}^{+}(t) = \max\{0, \mathrm{SLO}(t) - S(t)\}$;

– distance to the core (an inherent measure of how close the current state of the system is to the “core of survivability” (a set of states from which the system can remain in the acceptable region), which equals to zero inside the core and increases as it approaches the boundary) – $d(x_t, K)$;

– cost of actions (generalized “price” of applying control influence or reconfiguration) – $C(u_t)$.

Available time/resource constraints and invariants determine the class of allowable trajectories.

Then the goal of the work is to construct a target function J that reflects the policy π in a numerical assessment of survivability and is suitable for “on-the-fly” decision making where the target function is not minimized just once in advance, but is recalculated at each step based on new telemetry and current constraints (online optimization). Requirements for J :

– prioritization of critical services through penalties (a fixed contribution that increases when the service does not meet SLO) according to $\Delta\mathrm{SLO}^{+}$;

– consideration of tail risks for rare but destructive events;

– penalty for proximity to the acceptable region boundary via $d(x_t, K)$;

– resource awareness through understanding the cost of management impact and reconfigurations;

– suitability for sliding horizon/online computing;

– aggregation by services/flows with agreed weights;

– comparability between scenarios, weight selection based on telemetry;

– ability to evaluate using streaming data under partial observability.

II. Problem solution and Results

Target function and its equivalent representations. Let us consider a set of services S . For an $i \in S$ service at a step t : level $S_i(t)$, requirement $\mathrm{SLO}_i(t)$, shortfall

$$\delta_i(t) = \max\{0, \mathrm{SLO}_i(t) - S_i(t)\}. \tag{1}$$

Then, the aggregated shortfall (with priority weights $\lambda_i > 0$):

$$D(t)=\sum_{i\in S}\lambda_i\delta_i(t). \quad (2)$$

Let $d(x_t,K)\geq 0$ be the "soft" distance/barrier to $\partial K, C(u_t)$ – the cost of actions/reconfigurations. For discount $\gamma\in(0,1)$ (the coefficient of discount factor for future losses: shortfalls closer in time weigh more, distant ones weigh less) and horizon H cumulative shortfall (the sum of instantaneous shortfalls in the planning interval from t to $(t+H)$) is calculated as

$$\Theta_{t:H}=\sum_{\tau=t}^{t+H-1}\gamma^{\tau-t}D(\tau). \quad (3)$$

Considering (1)-(3), the risk-aware target function of survivability has the following form:

$$J(\pi)=\alpha\mathbb{E}[\Theta_{t:H}]+b\mathrm{CVaR}_\beta(\Theta_{t:H})+ +c\mathbb{E}\sum_{\tau=t}^{t+H-1}\gamma^{\tau-t}d(x_t,K)+d\mathbb{E}\sum_{\tau=t}^{t+H-1}\gamma^{\tau-t}C(u_\tau) \quad (4)$$

at dynamics $x_{\tau+1}=f(x_\tau,u_\tau,w_\tau)$ and invariants of casual-temporal consistency and resource constraints. In (4) $a,b,c,d>0$ are calibrated weights, $\beta\in(0,1)$.

For online computability, an equivalent convex representation of CVaR in the form of Rockefeller-Uryasev [6] is used, which reduces the tail risk assessment to minimization below an auxiliary threshold η.

$$\mathrm{CVaR}_\beta(\Theta)=\min_{\eta\in\mathbb{R}}\eta+\frac{1}{1-\beta}\mathbb{E}\left[(\Theta-\eta)^+\right], \quad (5)$$

The representation (5) is a coherent risk measure, it preserves convexity with respect to the distribution Θ, and induces asymmetric pinball loss, which allows stochastic subgradient updates of η and policy parameters to be performed on streaming samples. Due to this, the CVaR component is directly integrated into online optimization on a sliding horizon without massive batch calculations of metrics on a large dataset.

Thus, representation (5) induces a stochastic surrogate (pinball) loss function suitable for online CVaR minimization:

$$\Im_\eta(\pi)=a\Theta_{t:H}+b\left(\eta+\frac{1}{1-\beta}(\Theta_{t:H}-\eta)^+\right)+ +c\sum_\tau\gamma^{\tau-t}d(x_\tau,K)+d\sum_\tau\gamma^{\tau-t}C(u_\tau), \quad (6)$$

where η is updated along with policy parameters π.

Optimization procedure (sliding horizon). The algorithm runs cyclically for $t=0,1,\ldots$ – at each cycle t the steps are performed sequentially.

Step 1. State assessment. It is necessary to obtain telemetry y_t and update the posterior state b_t.

Step 2. Forecasting. Based on b_t, it is necessary to generate N scenarios of disturbances, "availability windows," and resource fluctuations on the horizon H.

Step 3. Metric evaluation. For each scenario, it is necessary to calculate the instantaneous shortfall (2), cumulative shortfall (3), and stochastic surrogate loss function (6).

Step 4. CVaR threshold update. It is necessary to perform a subgradient step for η:

$$\eta\leftarrow\eta-\alpha_\eta\left(1-\frac{1}{1-\beta}\mathbf{1}(\Theta_{t:H}>\eta)\right).$$

Step 5. Selecting an action. It is necessary to minimize empirical $\hat{\mathbb{E}}[\Im_\eta]$ on the horizon H and take the first action from the optimal sequence by gradient steps according to a parameterized policy or by searching in a discrete space of tactics (rerouting, replication, activation of reserves, etc.).

Step 6. Horizon shift. It is necessary to apply u_t, collect y_{t+1}, update b_{t+1} and proceed to step 1 for $t+1$.

The algorithm is characterized by risk sensitivity (CVaR), safety regularization with respect to the core K, monotonicity with respect to weights, decomposability by services, and suitability for stream computing. The algorithm is a continuous regulator – stopping occurs under event conditions (end of scenario, stable achievement of goals, lack of quality improvement, or emergency restrictions).

Demonstration results (simulation). Let there be a mobile platform with an "on-off" channel (probability of the off-mode $p=0.3$, average length of the "availability window" – 5 steps); two services with weights $\lambda_1=1$, $\lambda_2=2$; range limitation; and executable actions: rerouting, replication, quality degradation. Horizon $H=30$, $\gamma=0.98$, $\beta=0.95$. The evaluation is performed across over 1000 episodes.

Three configurations of weights (a,b,c,d) are compared (scaled so that $a=1$):

- mean-only configuration: $b=0$, $c=0.1$, $d=0.1$ – focus on mean shortfall;
- risk-aware configuration: $b=0.6$, $c=0.1$, $d=0.12$ – tails consideration;
- barrier-heavy configuration: $b=0.4$, $c=0.25$, $d=0.12$ – with proximity to K.

The following metrics are used: $\mathbb{E}[D]$ – mean per-step shortfall; $\mathrm{CVaR}_{0.95}(\Theta_{t:H})$ – tail risk of cumulative shortfall; $T_{\notin K}$ – proportion of steps outside the acceptable region; E – average percentage of the mobile platform's reserve budget used.

The quantitative results are summarized in Table 1 and visualized in Figure 1.

Table 1. Comparison of survivability optimization configurations

Configuration	$\mathbb{E}[D]$	$\mathrm{CVaR}_{0.95}(\Theta_{t:H})$	$T_{\notin K}$, %	E, %
Mean-only	0.38	1.21	12.5	63
Risk-aware	**0.34**	**0.77**	5.1	68
Barrier-heavy	0.36	0.83	**3.4**	72

The risk-aware configuration reduces the tail risk $\mathrm{CVaR}_{0.95}$ of the cumulative shortfall by approximately 36% and lowers the mean shortfall by ~10% compared to the mean-only configuration, with a moderate increase in resource costs (+5 units). In contrast, the barrier-heavy configuration minimizes the time outside the core K to 3.4% (compared to 12.5% in the mean-only configuration), demonstrating better safety at an acceptable cost for such a scenario. In Fig. 1, the mean per-step shortfall is shown in hatched lines, and $\mathrm{CVaR}_{0.95}(\Theta)$ – in grid lines. In both cases, critical services are prioritized (via λ_i) and causal-temporal consistency invariants are maintained.

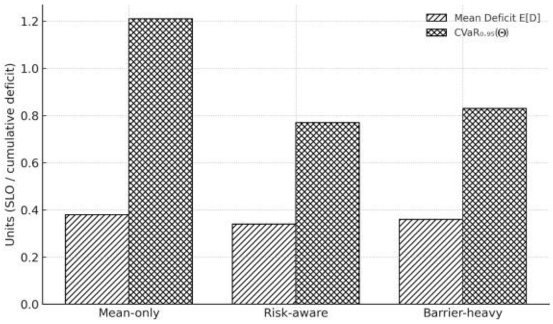

Fig. 1 – Demo Results: Tail-Risk vs Mean Shortfall

Practical recommendations for calibration and implementation:

– weights a,b,c,d,λ_i are normalized to comparable scales: δ_i – in "SLO units", $d(\bullet,K)$ – through the barrier function $h(x)$ with normalization, C – in time/traffic with subsequent normalization;

– the parameter β is selected according to the task class: for critical services – 0.95-0.99, for non-critical services – 0.9-0.949;

– for incomplete measurements, the posterior state is maintained using a Bayesian/ensemble estimator, after which a forecast is made at each step for the horizon H with a set of disturbance scenarios and "availability windows." The action must be selected by minimizing empirical loss (6) through a quick search in a finite library of tactics (rerouting, replication, activation of reserves, etc.) or through a differential policy with gradient parameter updates.

As a result, the proposed form J ensures operational optimization of survivability on a sliding horizon with explicit consideration of tail risks, security constraints (proximity to K) and the cost of management interventions, as confirmed by simulation on scenarios with intermittent connectivity (Fig. 1).

III. CONCLUSIONS

The paper formalizes the operational target function of survivability for a multi-level model of an information system on a mobile platform, taking into account SLO requirements, causal-temporal consistency invariants, partial observability, and resource-time constraints. The function J combines the mean service shortfall, tail risk CVaR_β, cumulative shortfall, safety barrier based on the distance to the survivability core K, and the cost of control actions, and is applicable for minimization on a sliding horizon.

Simulation examples demonstrate a reduction in 95% CVaR of cumulative shortfall and time spent outside the acceptable region at moderate resource costs, as well as transparent trade-offs between risk sensitivity and safety regularization (penalty for approaching the survivability limit).

The proposed target function J is the only configurable integrated criterion that combines tail risk optimization with safety regularization regarding the survivability core K. Unlike fragmented reliability/availability metrics, J provides a consistent scale for online ranking and policy selection (rerouting, replication, quality degradation) under "availability windows" and the stringent energy constraints of the mobile platform.

As further research, we propose to investigate the possibility of automatic calibration for a,b,c,d,λ_i using telemetry, integrate built-in state estimators for mobile platforms at the model level, analyze the consequences of scaling barrier functions $d(\bullet,K)$ in the case of multicore K, and perform hardware validation of the proposed solutions in real-world scenarios, such as UAV swarm.

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