DOI: https://doi.org/10.15276/ict.03.2026.34
UDK 004.052:004.75

Priority recovery method for critical components of a mobile-platform-based information system using the decomposition of their contributions to the integral survivability index increment

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ABSTRACT

This paper considers the problem of determining the recovery sequence for critical components in a mobile platform-based information system under budget constraints and functional dependencies. The study aims to enhance the justification of priority recovery decisions by accounting for both direct and group recovery effects. A normalized, bounded, and monotonic set function is formulated to represent the increment in the integral survivability index. The aggregate recovery outcome is distributed utilizing the Möbius transform and component contributions derived from cooperative game theory. The proposed methodological improvement involves applying this mathematical framework to a residual increment function, which is recalculated after each completed recovery action. This approach accounts for previously implemented direct and group effects, preventing their redundant attribution. Component priority is determined based on the lower estimate of the residual contribution, along with normalized resource, time, and communication costs. To reduce the computational burden, the decomposition is localized to connected subsets of the active dependency graph by constraining the maximum interaction order and controlling the approximation error. A reproducible simulation experiment was conducted for additive, overlapping, synergistic, and mixed component-interaction scenarios across various available budget levels. The results demonstrate the superiority of utilizing residual component contributions in the presence of pronounced group interactions and confirm a substantial reduction in the number of evaluated subsets due to localization. The study identifies applicability limitations related to the completeness of the dependency graph, the accuracy of the evaluation function, the single-resource nature of the simulation experiment, and the necessity for further validation on a physical mobile platform.

Keywords: Survivability; mobile-platform-based information system; critical components; priority recovery; residual component contribution; Shapley value; dependency graph; resource constraints

For citation: **Tkachov V. M., Ruban I. V. "Priority recovery method for critical components of a mobile-platform-based information system using the decomposition of their contributions to the integral survivability index increment".** ***Informatics. Culture. Technology.*** **2026; Vol. 3 No. 1 (3): 429–443. DOI: https://doi.org/10.15276/ict.03.2026.34**

Relevance. Mobile-platform-based information systems (MPIS) operate under conditions of variable availability of computational [1], energy [2], and network resources [3], intermittent connectivity [4], and time constraints on the execution of control actions [5]. Functional impairments of individual components and variations in their interaction parameters can cause a reduction in the availability of critical services [6]. Under conditions of platform resource deficiency, the complete recovery of an MPIS is often impractical; thus, it is necessary to identify components whose recovery ensures the functional capability of the MPIS.

Research in this domain encompasses resource state prediction [7], joint optimization of service placement and computational resource allocation [8], and service instance migration [9]. A distinct area of focus includes methods for evaluating the structural importance of components in interdependent subsystems [10], detecting dependencies between microservices [11], and localizing the sources of functional anomalies [12], [13]. While these approaches enable the identification of critical nodes, dependencies, and potential anomaly sources, they fail to distribute the aggregate recovery outcome among interdependent components.

When establishing a recovery sequence, merely accounting for local deficits, structural significance, or the isolated outcome of a single action is insufficient. The recovery outcomes of components may mutually amplify, substitute for one another, or partially overlap. In such cases, the independent evaluation of each component leads to the redundant attribution of the shared outcome or the underestimation of group effects. Shapley values and interaction indices [14] provide the mathematical foundation for distributing the aggregate outcome; however, their application to the priority recovery of information system components requires specific formalization.Consequently, the relevance of this study is driven by the need to rigorously determine the recovery sequence for interdependent critical MPIS components under resource and time deficits, where local evaluations fail to reflect their aggregate impact on system survivability.

Aim of the Study. The aim of this study is to develop a priority recovery method for critical MPIS components by decomposing the integral survivability index increment into direct and group components, determining the residual contribution of each component after preceding recovery actions, and formulating a recovery sequence under constrained resource and time budgets.

To achieve this aim, the following tasks must be completed: formulate a conditional recovery outcome function and perform its balanced decomposition; determine the average marginal and residual contributions of critical components; develop a prioritization rule with computational localization and error estimation; and experimentally demonstrate the efficacy of the proposed method in comparison to baseline recovery sequencing approaches.

Baseline Provisions and System State Formalization. Consider an MPIS whose component structure is defined by a finite set:

$$C = \{c_1, c_2, \dots, c_n\}, \tag{1}$$

where c represents components – which can encompass software modules, processes, services, data elements, and resource provision facilities – the state of which directly affects the execution of critical MPIS functions.

The set of critical components is defined as $C^{\xi} \subseteq C$. The current state of the MPIS at time t is specified by the vector:

$$\vec{x}(t) = (x_1(t), x_2(t), \dots, x_n(t)), \quad x_i(t) \in X_i, \tag{2}$$

where X_i is the set of admissible states for component c_i.

For each component (1), a normalized functional capability indicator $q_i(x_i) \in [0,1]$ is introduced, characterizing the degree to which it performs its designated functions in state x_i (2). The value $q_i = 1$ corresponds to the nominal state of the component. A decrease in this indicator reflects a partial degradation or loss of component operability.

The set of critical components requiring recovery in the current state is defined as:

$$F(x) = \{c_i \in C^{\xi} : q_i(x_i) < q_i^{\wp}\}, \tag{3}$$

where $q_i^{\wp}$ is the minimum admissible level of the component's functional capability. Set (3) may include completely inoperable components, as well as components whose state fails to meet the established requirements.

The functional dependencies of the MPIS are defined by an active directed graph $G_x = (C, E_x)$, where the presence of a directed edge $(c_i, c_j) \in E_x$ signifies that the functional capability of component c_j depends on the state of component c_i. The composition of set E_x may change due to failures, reconfiguration, the execution of recovery actions, and similar factors.

The survivability of the MPIS is evaluated using the integral index $S(x) \in [0,1]$. Its value increases as the MPIS's capacity to perform critical functions improves. The integral index serves as the baseline evaluation function, formulated by accounting for the state of data, processes, services, and resource provision. The method for constructing this index for an MPIS is provided in [15].

For each component $c_i \in F(x)$, a recovery action R_i, is specified; its execution transitions the component into an admissible or nominal state. The action is characterized by resource costs r_i, duration τ_i, and the data volume g_i, required to synchronize the recovered state of the component. The admissibility of an action is determined by the available MPIS resources, the time budget, connectivity parameters, and the conditions for correct recovery completion.

Let $A \subseteq F(x)$ be an arbitrary set of components subject to recovery. Let x^A denote the conditional state of the MPIS following the recovery of the components in set A, assuming the states of the components in $F(x) \setminus A$ remain unchanged. This representation serves as the foundation for evaluating the outcomes of individual and joint recovery actions, as well as for the decomposition of the integral survivability index increment.

Formulation of the Integral Survivability Index Increment Function. To quantitatively evaluate the impact of recovery actions on MPIS survivability, an integral survivability index increment function is introduced, defined on the power set of impaired critical components:

$$\upsilon: 2^{F(x)} \to \mathbb{R}. \tag{4}$$

For an arbitrary set $A \subseteq F(x)$, its value is defined as the increment of the integral survivability index following the completed recovery of the components in set A:

$$\upsilon(A) = S(x^A) - S(x). \tag{5}$$

State x^A is established after the execution of the respective recovery actions, the completion of the necessary data synchronization, and the transition of the recovered components into a functionally admissible state. Intermediate states during action execution are not accounted for in the value of $\upsilon(A)$. For an empty set, it is assumed that $\upsilon(\emptyset) = 0$.

The function $\upsilon(A)$ (5) characterizes the system-wide recovery outcome driven by state changes in critical services, processes, data, and resource provision. Subsequent formalization relies on the assumption that the completion of an admissible recovery action neither degrades the functional capability of the recovered component nor impairs the state of other components, and that the integral index $S(x)$ is non-decreasing with respect to the indicators $q_i(x_i)$.

Therefore, for arbitrary sets $A \subseteq B \subseteq F(x)$, the following holds:

$$S(x) \leq S(x^A) \leq S(x^B) \leq 1,$$

whence

$$0 = \upsilon(\emptyset) \leq \upsilon(A) \leq \upsilon(B) \leq 1 - S(x).$$

Consequently, the increment function $\upsilon(A)$ (5) is a normalized, bounded, and monotonic set function. These properties validate its domain-specific interpretation as the integral survivability index increment resulting from completed recovery actions.

The outcome of the individual recovery of component c_i is determined by the value:

$$\upsilon(\{c_i\}) = S\left(x^{\{c_i\}}\right) - S(x), \tag{6}$$

which characterizes the integral survivability index increment (4) provided that solely component c_i is recovered. This evaluation excludes the influence of recovering other components.

To determine the outcome for component c_i given the prior recovery of the components in set A, a marginal increment is introduced:

$$\Delta_i(A) = \upsilon(A \cup \{c_i\}) - \upsilon(A) = S\left(x^{A\cup\{c_i\}}\right) - S(x^A). \tag{7}$$

According to (7), the value $\Delta_i(A)$ depends on the composition of set A. Therefore, a component may yield a substantial outcome during individual recovery, yet provide only a minor increment following the recovery of a functionally similar component. Conversely, its recovery may establish a prerequisite for the functioning of dependent components.

For components c_i and c_j, the pairwise interaction component is defined as follows:

$$I_{ij} = \upsilon\left(\{c_i, c_j\}\right) - \upsilon(\{c_i\}) - \upsilon\left(\{c_j\}\right). \tag{8}$$

According to (8), $I_{ij} > 0$ indicates that the outcome of the joint recovery of the components exceeds the sum of their individual recovery outcomes. For $I_{ij} < 0$, the joint outcome is less than the sum of the individual outcomes, a condition potentially caused by functional overlap or component interchangeability. For $I_{ij} = 0$, pairwise interaction is absent.

Consequently, function (5) enables the comparison of individual and joint recovery outcomes; however, it does not delineate the specific contribution of each component to the aggregate increment.

Decomposition of the Integral Survivability Index Increment. To distribute the aggregate recovery outcome among individual components and the results of their interactions, the Möbius transform of the set function $\upsilon(A)$ is utilized, the components of which correspond to Harsanyi dividends in cooperative game theory [14].

For each non-empty subset $B \subseteq F(x)$, the increment component is defined as follows:

$$m(B) = \sum_{A \subseteq B} (-1)^{|B|-|A|} \upsilon(A). \tag{9}$$

Within the proposed method, this mathematical framework is applied to the recovery outcomes of interdependent critical components and, subsequently, to the residual increment function, which is recalculated after each executed recovery action.

According to (9), the value $m(B)$ defines the irreducible component of the integral survivability index increment driven by the joint recovery of the components in set B and not accounted for by the components of its proper subsets.

For a singleton set, the following holds:

$$m(\{c_i\}) = \upsilon(\{c_i\}),$$

thus, the component $m(\{c_i\})$ corresponds to the integral survivability index increment resulting from the individual recovery of component c_i.

For a pair of components, the pairwise component takes the form:

$$m(\{c_i, c_j\}) = \upsilon(\{c_i, c_j\}) - \upsilon(\{c_i\}) - \upsilon(\{c_j\}),$$

which aligns with the joint outcome evaluation introduced in formula (8).

For three components, the group component is defined as:

$$m(\{c_i, c_j, c_\ell\}) = \upsilon(\{c_i, c_j, c_\ell\}) - \upsilon(\{c_i, c_j\}) - \upsilon(\{c_i, c_\ell\}) - \upsilon(\{c_j, c_\ell\}) + \upsilon(\{c_i\}) + \upsilon(\{c_j\}) + \upsilon(\{c_\ell\}),$$

enabling the isolation of the outcome generated by the joint recovery of three components that cannot be reduced to direct and pairwise components.

The sign of the value $m(B)$ characterizes the direction of the irreducible interaction of the components in set B relative to the outcomes already accounted for by its proper subsets. The value $m(B) > 0$ signifies that the increment from the joint recovery of the components exceeds the sum of lower-order components, which corresponds to a positive group interaction. The value $m(B) < 0$ denotes that the joint increment is less than the outcome formulated by lower-order components, which may be caused by functional overlap, component interchangeability, or the utilization of a shared reserve. When $m(B) = 0$, an additional interaction of order $|B|$ is absent.

A positive value of $\upsilon(A)$ does not necessitate that all components *m(B)* be positive. The recovery of a set of components may increase the integral survivability index despite the partial overlap of local outcomes. Therefore, ranking solely by the values of $\upsilon(\{c_i\})$ can overestimate the expected recovery increment.

For set $A \subseteq F(x)$, the increment function is reconstructed using the introduced components:

$$\upsilon(A) = \sum_{\emptyset \neq B \subseteq A} m(B). \tag{10}$$

For the complete set of impaired critical components, the following identity holds:

$$\upsilon(F(x)) = \sum_{\emptyset \neq B \subseteq F(x)} m(B). \tag{11}$$

The balance identity (11), taking (10) into account, ensures the exact alignment of the aggregate integral survivability index increment with the sum of direct and group components, preventing both the loss and redundant attribution of the outcome.

Determination of Component and Residual Contributions. The components $m(B)$ characterize both direct and group recovery outcomes. To establish priorities, the share of the aggregate integral survivability index increment attributable to each component is determined. The group component *m(B)* is distributed equally among the components of set *B*.

The component contribution of component $c_i \in F(x)$ is defined as follows:

$$\phi_i(F) = \sum_{\substack{B\subseteq F(x)\\ c_i\in B}} \frac{m(B)}{|B|}. \quad (12)$$

According to (12), the contribution $\phi_i(F(x))$ encompasses the direct outcome $m(\{c_i\})$ and the shares of all group components that include component c_i.

An equivalent representation corresponds to the average marginal contribution of the component across all possible recovery sequences:

$$\phi_i(F(x)) = \sum_{A\subseteq F(x)\setminus\{c_i\}} \frac{|A|!(|F(x)|-|A|-1)!}{|F(x)|!}[v(A\cup\{c_i\}) - v(A)]. \quad (13)$$

The weighting coefficient in formula (13) equals the proportion of recovery sequences in which the components of set A precede component c_i. Therefore, $\phi_i(F(x))\, c_i$ accounts for the dependency of the component's outcome on the composition of the previously recovered set.

For component contributions, the property of allocation completeness holds:

$$\sum_{c_i\subseteq F(x)} \phi_i(F(x)) = v(F(x)). \quad (14)$$

Relationship (14) indicates that the aggregate integral survivability index increment is thoroughly distributed among the components without loss or redundant attribution of group outcomes.

If $\phi_i(F(x)) > v(\{c_i\})$, the amplification of the component's outcome due to interactions with other components prevails. If $\phi_i(F(x)) < v(\{c_i\})$, a portion of its individual outcome overlaps with the outcomes of other components.

Following the execution of the first recovery action, the initial contributions lose their relevance, as a segment of the direct and group outcomes has already been implemented. Let$R \subseteq F(x)$ denote the set of recovered components. For the remaining components, a residual function is introduced:

$$v_R(A) = S(x^{R\cup A}) - S(x^R), \quad A \subseteq F(x)\setminus R. \quad (15)$$

Here, $v_R(\emptyset) = 0$. Given the conditions introduced for the function $v(A)$, where$A \subseteq B \subseteq F(x)\setminus R$, the inequality $S(x^R) \le S(x^{R\cup A}) \le S(x^{R\cup B})$ holds, yielding:

$$0 = v_R(\emptyset) \le v_R(A) \le v_R(B) \le 1 - S(x^R).$$

Thus, the residual function (15) preserves the normalization, boundedness, and monotonicity of the initial increment function, identifying the outcome that remains attainable following the recovery of set R.

The residual group components are defined as:

$$m_R(B) = \sum_{A\subseteq B}(-1)^{|B|-|A|} v_R(A), \quad \emptyset \ne B \subseteq F(x)\setminus R. \quad (16)$$

The residual contribution of an unrecovered component c_i takes the form

$$\phi_i^R = \sum_{\substack{B\subseteq F(x)\setminus R\\ c_i\in B}} \frac{m_R(B)}{|B|}. \quad (17)$$

For the residual contributions (16) – (17), the balance equality also holds:

$$\sum_{c_i\in F(x)\setminus R} \phi_i^R = S\left(x^{F(x)}\right) - S(x^R). \quad (18)$$

Consequently, ϕ_i^R characterizes the portion of the integral survivability index increment accessible post-recovery of set R. Recalculating the residual contributions accounts for previously implemented outcomes, preventing their redundant attribution when formulating the subsequent recovery sequence (18).

Priority Recovery Rule. Let $R_k \subseteq F(x)$ denote the set of recovered components at the k-th step, with $R_0 = \emptyset$. The remaining resource, time, and communication budgets are denoted by Ξ_k, T_k and Υ_k, respectively.

The set of components whose recovery is feasible in the current MPIS state is defined as:

$$\Gamma_k = \{c_i \in F(x)\backslash R_k : r_i \le \Xi_k, \tau_i \le T_k, g_i \le \Upsilon_k, \chi_i(x^{R_k}) = 1\}, \quad (19)$$

where $\chi_i(x^{R_k})$ is the indicator of compliance with the prerequisites and stable conditions for completing the recovery action.

In (19), the value $\chi_i = 1$ signifies that the action can be executed in the current state of the MPIS.

Since resource costs, action duration, and data synchronization volumes utilize differing units of measurement, a normalized cost evaluation is introduced for the recovery of each component $c_i \in \Gamma_k$:

$$d_i^{(k)} = \lambda_r \frac{r_i}{\Xi_k} + \lambda_\tau \frac{\tau_i}{T_k} + \lambda_g \frac{g_i}{\Upsilon_k}, \quad (20)$$

where $\lambda_r, \lambda_\tau, \lambda_g > 0$ are weighting coefficients satisfying $\lambda_r + \lambda_\tau + \lambda_g = 1$.

The coefficient values in (20) are established based on the prioritization of resource, time, and communication costs within the current MPIS operating mode.

In the presence of state or integral index evaluation errors, the lower bound of the residual contribution is employed:

$$\underline{\phi}_i^{R_k} = \hat{\phi}_i^{R_k} - \eta_i^{(k)}, \quad (21)$$

where $\hat{\phi}_i^{R_k}$ is the calculated estimate of the residual contribution, and $\eta_i^{(k)} \ge 0$ is the upper bound of the absolute error of $\hat{\phi}_i^{R_k}$ (for exact evaluation, $\eta_i^{(k)} = 0$ is assumed).

The priority index for the component's recovery is determined as follows:

$$P_i^{(k)} = \frac{max\{0, \underline{\phi}_i^{R_k}\}}{d_i^{(k)}}, \quad c_i \in \Gamma_k. \quad (22)$$

The value $P_i^{(k)}$ serves as a local estimate of the viability of recovering the component at the k-th step and does not predetermine the outcome of the entire sequence. The priority index (22) is defined as the ratio of the component's residual contribution lower estimate (21) to its normalized recovery costs. Since every recovery action entails resource, time, or communication costs, $d_i^{(k)} > 0$ holds for all admissible actions. A higher value of $P_i^{(k)}$ corresponds to a component offering a greater residual contribution at lower normalized costs.

The target component for priority recovery is identified by the rule:

$$i_k = arg \max_{i:c_i \in \Gamma_k} P_i^{(k)}. \quad (23)$$

The rule (22)-(23) implements the sequential selection of the component with the maximal ratio of the residual contribution lower estimate to normalized costs within the current MPIS state. This ensures the feasibility of each selected recovery action, as the ranking is restricted to the set Γ_k. However, it does not guarantee the global optimality of the generated sequence for an arbitrary non-additive increment function and multi-dimensional budget constraints. The degree of proximity of the achieved outcome to the exact optimum is evaluated experimentally.

In cases of identical priority values, preference is assigned to the component with the higher $\underline{\phi}_i^{R_k}$ value. If these values also match, the action demanding the shortest execution duration is selected.

Following the completion of the recovery action, the set of recovered components is updated:

$$R_{k+1} = R_k \cup \{c_{i_k}\}, \quad (24)$$

and the remaining budgets are updated as:

$$\Xi_{k+1} = \Xi_k - r_{i_k}, \quad T_{k+1} = T_k - \tau_{i_k}, \quad \Upsilon_{k+1} = \Upsilon_k - g_{i_k}.$$

For the new state $x^{R_{k+1}}$, the active dependency graph, the residual function $v_{R_{k+1}}(A)$, the group components, and the component contributions are recalculated. As a result of this update (24), the outcome achieved after the recovery of component c_{i_k} is not redundantly attributed when calculating the priorities for subsequent actions.

The procedure terminates upon fulfilling one of the following conditions:

$$S(x^{R_k}) \geq S^{\wp}, \quad \Gamma_k = \emptyset, \quad \max_{c_i \in \Gamma_k} P_i^{(k)} = 0. \tag{25}$$

In conditions (25), $S^{\wp}$ denotes the required level of the integral survivability index. Under localized decomposition, termination based on zero priorities is permissible only after verifying the sufficiency of the adopted depth for accounting for group interactions.

Localization of Decomposition and Error Estimation. A complete decomposition of the residual function requires evaluating the recovery outcomes across all subsets of unrecovered components. For q unrecovered components, the number of non-empty subsets equals $2^q - 1$, which restricts the application of exhaustive computation in real-time operations. To curtail computational costs, the decomposition is localized using the active dependency structure and the maximum order of accounted interactions.

At the k-th step, the set of unrecovered components is defined as $U_k = F(x) \setminus R_k$, while the active dependencies among them are specified by the induced graph $G_k = G_x[U_k]$.

Group components are considered for components structurally linked within the active graph. If G_k accurately reflects all functionally significant dependencies, for an unconnected set $B \subseteq U_k$, it is assumed that $m_{R_k}(B) = 0$.

For a stipulated decomposition order h, a collection of connected subsets is introduced:

$$\Psi_h^{(k)} = \{B \subseteq U_k : G_k[B] \text{ is connected}, 1 \leq |B| \leq h\}. \tag{26}$$

According to (26), at h=1, direct recovery outcomes are accounted for, whereas at h=2, both direct and pairwise interactions are considered. Augmenting h facilitates the inclusion of higher-order group components.

The approximate value of the residual function for set $A \subseteq U_k$ is determined as:

$$\tilde{v}_{R_k,h}(A) = \sum_{\substack{B \in \Psi_h^{(k)} \\ B \subseteq A}} m_{R_k}(B). \tag{27}$$

Based on (27), the approximate residual contribution of component $c_i \in U_k$ is formulated as:

$$\tilde{\phi}_{i,h}^{R_k} = \sum_{\substack{B \in \Psi_h^{(k)} \\ c_i \subseteq B}} \frac{m_{R_k}(B)}{|B|}. \tag{28}$$

The error in reproducing the aggregate residual outcome is determined by the formula:

$$\varepsilon_h^{(k)} = \left| v_{R_k}(U_k) - \tilde{v}_{R_k,h}(U_k) \right|. \tag{29}$$

The relationship (29) quantifies the segment of the aggregate survivability increment neglected at the assigned decomposition order h.

To prevent the underestimation of error due to the mutual compensation of positive and negative components, a theoretical upper bound is applied:

$$E_h^{(k)} = \sum_{\substack{B \subseteq U_k \\ G_k|B| \text{ is connected} \\ |B| > h}} \left| m_{R_k}(B) \right|, \quad \varepsilon_h^{(k)} \leq E_h^{(k)}. \tag{30}$$

To estimate the bound (30), the total absolute magnitude of components of order s is defined as:

$$M_s^{(k)} = \sum_{\substack{B \subseteq U_k \\ G_k|B| \text{ is connected} \\ |B| = s}} \left| m_{R_k}(B) \right|. \tag{31}$$

If the condition $M_{s+1}^{(k)} \le \rho M_s^{(k)}$ (where $0 \le \rho < 1$) is satisfied for higher-order components, the upper bound of the residual error (30) is evaluated as:

$$E_h^{(k)} \le \frac{M_{s+1}^{(k)}}{1-\rho}.$$

In (31), the value ρ is specified as the upper bound of the ratios $M_{s+1}^{(k)}/M_s^{(k)}$, established for the corresponding MPIS class based on the outcomes of preliminary cycles or simulation research. If the decay condition is not satisfied, the value of h is incremented.

The error of the approximate component contribution is constrained by the relationship:

$$\left|\phi_i^{R_k} - \tilde{\phi}_{i,h}^{R_k}\right| \le \frac{E_h^{(k)}}{h+1}, \tag{32}$$

given that every unaccounted component is distributed among at least h+1 components.

The estimate on the right side of (32) is incorporated into the value $\eta_i^{(k)}$ when computing the lower estimate of the residual contribution utilizing formula (21).

The maximum interaction order h is selected subject to the condition $E_h^{(k)} \le \vartheta$, where ϑ denotes the admissible localization error. If the discrepancy between the two highest approximate contributions fails to exceed $2E_h^{(k)}/(h+1)$, the value h is incrementally elevated until the priority component is unambiguously identified.

In the worst-case scenario, the number of evaluated subsets does not exceed:

$$\sum_{s=1}^{h} \binom{|U_k|}{s},$$

which, for a fixed modest h, is substantially less than $2^{|U_k|} - 1$. For sparse graphs, the quantity of connected subsets is curtailed even further. Consequently, localization mitigates the computational burden while maintaining a controlled error bound for component contributions.

Implementation Features and Properties of the Method. The input data for the method encompass the current MPIS state x, the set of impaired critical components $F(x)$, the active dependency graph G_x, the integral survivability index $S(x)$, recovery action parameters, initial budgets Ξ_0, T_0, Υ_0, the required level $S^{\wp}$, and the admissible error ϑ. The output is an ordered sequence of component recoveries and the set of actions whose execution is feasible within the existing constraints.

The method's implementation entails the following stages:

1. Assume $R_0 \neq \emptyset$, identify the set of unrecovered components $U_0 = F(x)$, and set the initial maximum interaction order to h=1.

2. At the k-th step, using state x^{R_k}, refine the active graph G_k, remaining budgets, and the set of admissible components Γ_k (19).

3. For subsets $B \in \Psi_h^{(k)}$, compute the values of the residual function and group components:

$$m_{R_k}(B) = v_{R_k}(B) - \sum_{\emptyset \neq A \subset B} m_{R_k}(A).$$

Using formula (28), the approximate residual contributions are determined. The lower estimate of the contribution is formed via (21), ensuring that $\eta_i^{(k)}$ encompasses both the state evaluation error and the localization error bound $E_h^{(k)}/(h+1)$.

4. If the condition $E_h^{(k)} \le \vartheta$ remains unmet or the error obscures the unambiguous identification of the priority component, increment h. Otherwise, employ formulas (22) and (23) to select the component with the highest priority and execute the corresponding recovery action.

5. Following action completion, update set R_{k+1}, remaining budgets, system state, and the active dependency graph. Residual contributions are recurrently calculated for the new state, preventing the redundant attribution of previously implemented outcomes.

6. The computation terminates upon fulfilling any condition in (25). The finalized sequence takes the form:

$$\Pi = \left(c_{i_0}, c_{i_1}, \dots, c_{i_{K-1}}\right), K \le |F(x)|.$$

The proposed method inherently possesses the property of balance consistency. Under localized decomposition, the deviation of the sum of approximate component contributions from the aggregate residual outcome is confined by the magnitude:

$$\left|v_{R_k}(U_k) - \sum_{c_i \in U_k} \tilde{\phi}_{i,h}^{R_k}\right| \le E_h^{(k)}.$$

The feasibility of the resultant sequence is guaranteed by restricting component selection strictly to the set Γ_k. The operational finiteness follows from the expansion of set R_k by exactly one component after each executed action; thus, the total step count never exceeds $|F(x)|$.

Through localization, the volume of evaluated subsets equates to:

$$N_h^{(k)} = \left|B_h^{(k)}\right| \le \sum_{s=1}^{h} \binom{|U_k|}{s},$$

which, for a fixed small h, is substantially less than $2^{|U_k|} - 1$. For a sparse graph, the computational load is additionally reduced by excluding disconnected subsets.

Experimental Evaluation of Method Efficacy and Computational Complexity. To validate the proposed method, a reproducible simulation experiment featuring nine critical components was conducted. An additive scenario, a functional overlap scenario, a mutual synergy scenario, and a mixed scenario were investigated. For each scenario, 100 independent implementations were generated. The variability sources included the weights of critical services, the mapping between services and components, the composition of functional interaction groups, and component recovery costs. The pseudo-random number generator was initialized with the seed 20260715.

In the additive scenario, each component corresponded to an isolated service, with no group outcomes present. In the overlap scenario, each component provided between two and four services shared with the outcomes of other components. In the synergy scenario, groups of two or three components were assembled, whose joint recovery generated a supplementary increment in the integral survivability index. The mixed scenario simultaneously incorporated service overlap and positive group interactions. Edges in the dependency graph were established between components that delivered a shared service or belonged to an identical synergy group.

Recovery costs were assigned integer values ranging from 1 to 10. The analyzed budgets equaled 25 %, 40 %, and 55 % of the cumulative recovery costs for all components. Consequently, the simulation experiment verified a single-resource specific case of the generalized rule (20), where resource, time, and communication costs were represented by an aggregated surrogate cost a_i.

For each implementation and specified budget D, the exact benchmark outcome was extracted via an exhaustive search of admissible subsets:

$$A^* = arg \max_{\substack{A \subseteq F(x) \\ \sum_{c_i \in A} a_i \le D}} v(A).$$

For the set A_Π generated by the proposed algorithm, normalized efficacy was evaluated as:

$$\eta_\Pi = \frac{v(A_\Pi)}{v(A^*)},$$

while the relative deviation from the exact benchmark outcome was defined as: $gap_\Pi = 1 - \eta_\Pi$.

Values of $\eta_\Pi = 1$ and $gap_\Pi = 0$ denote the attainment of the exact maximum under the imposed budget.

Four ranking methodologies were compared. Under fixed criticality, priority was dictated by the ratio of the component's local functional significance – adjusted for its degree in the dependency graph – to recovery costs. The second method employed the ratio of the isolated increment $v(\{c_i\})$ to costs.

The third utilized the ratio of the current marginal increment $v(\{c_i\})$ to costs:

$$\frac{\upsilon(R_k \cup \{c_i\}) - \upsilon(R_k)}{a_i}.$$

The proposed approach leveraged the ratio of the exact residual component contribution $\phi_i^{R_k}$ to costs a_i. All baseline methods were implemented by the authors within a unified software environment, utilizing identical input data, budget constraints, and termination rules.

In total, 4800 execution runs were completed: four scenarios, 100 implementations, three budget tiers, and four methods. For each data cluster, the mean normalized efficacy, standard deviation, and mean deviation from the benchmark outcome were ascertained. Paired comparisons between the proposed method and the current marginal increment approach were executed for identical model implementations and budgets. The bounds of the 95 % confidence interval for the mean paired difference were calculated via bootstrap estimation over 2000 resamples.

Table 1. **Mean Normalized Efficacy of the Evaluated Methods**

Scenario	Current Marginal Increment, %	Proposed Method, %	Difference, p.p.
Additive	97.86 ±2.71	97.86±2.71	0,00
Overlapping	98.89±3.05	98.95±3.27	+0,06
Synergistic	92.33±12.59	95.12±10.28	+2,79
Mixed	94.95±8.04	95.71±7.08	+0,76

Source: **compiled by the authors**

Table 1 also reports the standard deviation. In the additive scenario, all methods delivered identical mean efficacy, aligning perfectly with the absence of group interactions. In the overlap scenario, the mean divergence between the proposed method and the current marginal increment was a trivial 0.06 percentage points, lacking consistency across all budget tiers.

The most significant advantage was observed in the mutual synergy scenario. Under a 40% budget, the mean paired difference registered at 2.74 percentage points, carrying a 95 % confidence interval of 0.36 to 5.20 percentage points. At a 55 % budget, the gap widened to 3.45 percentage points, with a confidence interval spanning 1.70 to 5.34 percentage points. Averaged across the three budget classifications, the proposed method surpassed the current marginal increment approach by 2.79 percentage points and outperformed the fixed criticality method by 19.65 percentage points.

In the mixed scenario, a robust advantage was corroborated at the 55 % budget: the mean paired difference stood at 2.57 percentage points, with the 95 % confidence interval anchored between 1.19 and 4.08 percentage points. At the 25 % and 40% budget tiers, the confidence intervals of the paired difference contained zero. Consequently, these findings validate the superiority of residual component contributions over the current marginal increment, predominantly under pronounced mutual synergy and adequate budget provisions within the mixed scenario (Fig. 1 and Fig. 2).

The reduction in the quantity of subsets resulting from the localization of decomposition was evaluated separately (Fig. 3). The pool of unrecovered components fluctuated from 6 to 16, while the maximum accounted interaction order adopted values of h=1, h=2 and h=3. For each configuration, the aggregate number of non-empty subsets, the number of subsets up to order h, and the volume of connected subsets within the active graph were precisely quantified.

For 16 components, an exhaustive search necessitated the evaluation of 65535 non-empty subsets. At h=2, only 47 connected subsets were included in the calculation, equating to a reduction in search volume by a factor of approximately 1394. At h=3, 134 connected subsets were assessed, translating to a reduction by a factor of roughly 489.

These results empirically demonstrate the constriction of combinatorial computational overhead. The raw outputs of all execution runs, aggregated tables, paired bootstrap estimates, simulation scenario parameters, source code, and figures are publicly deposited in strict accordance with FAIR principles in the Zenodo repository [16], facilitating independent verification and result reproduction.

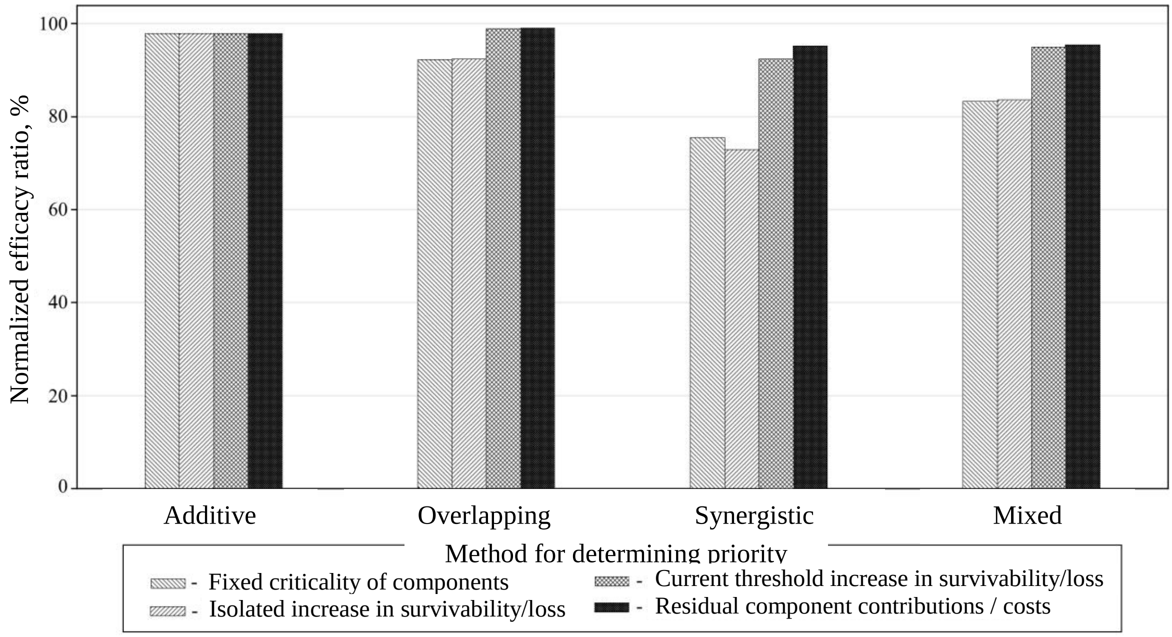

Fig. 1. **Mean normalized efficacy of the methods across test scenarios**

Source: **compiled by the authors**

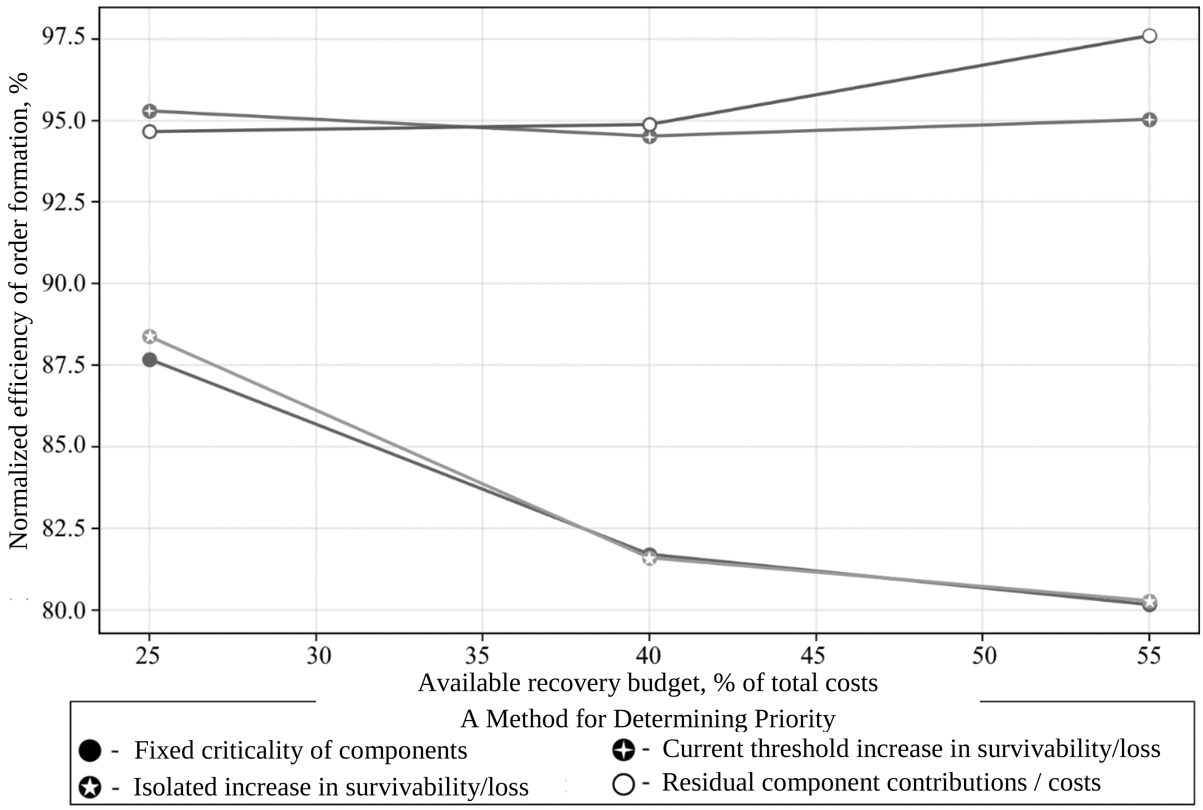

Fig. 2. **Dependence of normalized efficacy on the available budget in the mixed scenario**

Source: **compiled by the authors**

Discussion of Results and Applicability Limitations. The efficacy of the proposed method relies heavily on the structural validity of the integral survivability index $S(x)$, the topological completeness of the active dependency graph G_x , and the exactitude of recovery action parameters. The domain-specific interpretation of the increment function presupposes that completed, admissible recovery actions inherently avoid degrading collateral components and that the integral index is strictly non-decreasing relative to functional capability indicators. Should these criteria remain unfulfilled, or if the dependency graph omits functionally pivotal links, the computed component contributions may inaccurately mirror the pragmatic recovery outcome.

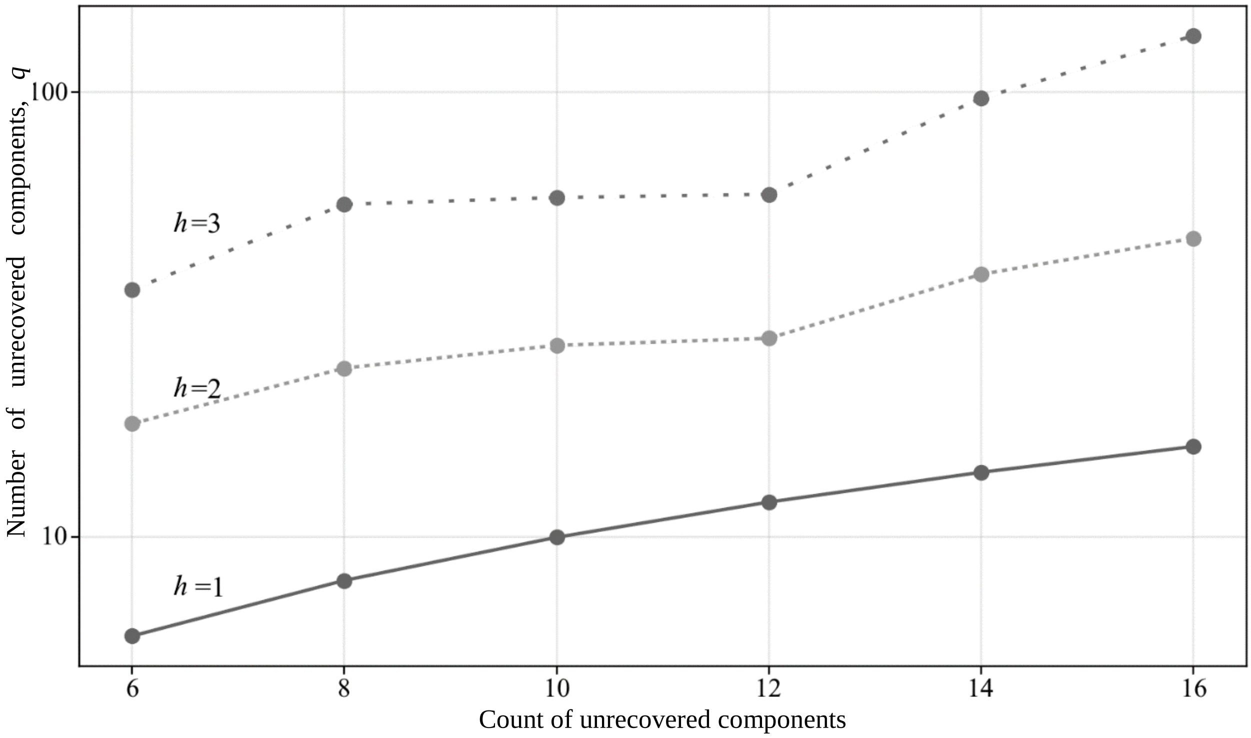

Fig. 3. **Number of connected subsets as a function of the unrecovered component count and the decomposition order**
Source: **compiled by the authors**

The priority selection rule generates a feasible finite recovery sequence based on the current system state, residual contributions, and the available budget. For an arbitrary non-additive increment function intertwined with multidimensional constraints, the global optimality of the derived sequence is theoretically unguaranteed. Its merit is appraised via normalized efficacy and deviations from exact benchmark outcomes, delineated by exhaustive searches in the simulation experiments.

The conducted experiments encompassed synthetic scenarios featuring surrogate aggregate recovery costs and flawless residual contributions. Therefore, the obtained results confirm the properties of the method for a single-resource special case, but do not fully characterize the impact of simultaneous resource, time, and communication constraints. The localization protocol was validated solely by the mathematical contraction of evaluated subsets; the empirical error of localized contributions and the deterministic fidelity of the resultant rankings across fluctuating h values mandate extended empirical scrutiny.

Evaluations of execution latency, peak memory allocation, and battery energy depletion on physical mobile platforms were deliberately excluded from this study. Consequently, the achieved reduction in computational volume establishes the prerequisites for the real-time application of the method, while its practical applicability for a specific class of mobile devices can be confirmed by a separate experiment.

Conclusions. The strict conditions governing the correct application of the integral survivability index increment function have been established. Under the assumption that completed admissible recovery actions do not degrade component states and that the integral index is non-decreasing relative to functional capability metrics, the formulated function remains normalized, bounded, and monotonic. These traits validate its strict domain interpretation as the system-wide recovery outcome for any arbitrary subset of critical components.

To distribute the aggregate increment, the Möbius transform of the set function – whose components correspond strictly to Harsanyi dividends – and component contributions equivalent to Shapley values were employed. The primary scientific advancement lies in the extension of this mathematical framework to a residual increment function iteratively reconstructed following each completed action. The residual contribution characterizes the portion of the survivability increment available in the current system state, preventing the redundant attribution of previously implemented direct and group outcomes.

An enhanced method for the priority recovery of critical components has been formalized, wherein the subsequent action is selected based on the mathematical ratio of the lower estimate of the residual contribution to normalized resource, time, and communication costs. The method programmatically assembles a feasible, finite sequence strictly within the bounds of available budgets; however, it does not mathematically guarantee global optimality for an arbitrary non-additive function subjected to multidimensional constraints. The quality of the generated sequence is evaluated using normalized efficacy and its deviation from an exact benchmark.

A reproducible simulation experiment comprising 4800 execution cycles spanned additive, overlapping, synergistic, and mixed interaction scenarios. In the mutual synergy scenario, the proposed method achieved a mean normalized efficacy of 95.12 %, outperforming the 92.33 % delivered by the current marginal increment algorithm. The mean algorithmic advantage equated to 2.79 percentage points; at 40 % and 55 % budgets, the confidence intervals of the paired differences strictly excluded zero. In the mixed scenario, a statistically robust advantage was confirmed under a 55 % budget constraint, recording a mean divergence of 2.57 percentage points.

To suppress the combinatorial explosion of computational demands, a decomposition localization strategy confined to connected subsets of the active dependency graph was instituted. For 16 unrecovered components, the number of evaluated subsets decreased from 65535 to 47 at h=2 and to 134 at h=3, which corresponds to a reduction by a factor of approximately 1394 and 489, respectively.

The derived findings strictly pertain to a synthetic single-resource paradigm utilizing surrogate recovery costs and idealized residual contributions. Future research vectors must target the rigorous validation of this method against synchronized, multidimensional resource, temporal, and connectivity constraints; the quantification of actual errors injected by localized contributions; and the physical measurement of execution latency, memory taxation, and energy drain on authentic mobile hardware architectures.

Conflict of Interest: The authors declare that they have no known competing financial interests, personal relationships, copyright conflicts, or any other conflicts that could have appeared to influence the work reported in this paper

Funding: This research received no external funding

Use of Artificial Intelligence (AI) Tools: The authors confirm that they did not use artificial intelligence tools to write this work

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Received 08.07.2026
Revised after revision 20.08.2026
Accepted 28.08.2026

DOI: https://doi.org/10.15276/ict.03.2026.34
UDC 004.451:502/504

Метод пріоритетного відновлення критичних компонентів інформаційної системи на мобільній платформі за декомпозицією їх внесків у приріст інтегрального індексу живучості

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АНОТАЦІЯ

Розглянуто задачу формування черговості відновлення критичних компонентів інформаційної системи на мобільній платформі за обмеженого бюджету та наявності функціональних залежностей між компонентами. Метою дослідження є підвищення обґрунтованості вибору першочергових відновлювальних дій з урахуванням прямих і групових результатів відновлення. Сформовано нормовану, обмежену та монотонну множинну функцію приросту інтегрального індексу живучості. Для розподілу сукупного результату використано перетворення Мебіуса та компонентні внески, що відповідають положенням теорії кооперативних ігор. Удосконалення методу полягає у застосуванні зазначеного математичного апарату до залишкової функції приросту, яка повторно формується після кожної завершеної відновлювальної дії. Це забезпечує врахування вже реалізованих прямих і групових результатів та запобігає їх повторному зарахуванню. Пріоритет компонента визначається з урахуванням нижньої оцінки залишкового внеску та нормованих ресурсних, часових і комунікаційних витрат. Для скорочення обчислень декомпозиція локалізується на зв’язних підмножинах активного графа залежностей із обмеженням максимального порядку взаємодії та контролем похибки. Проведено відтворюваний модельний експеримент для адитивного сценарію, сценаріїв перекриття, взаємного підсилення та змішаної взаємодії компонентів за різних рівнів доступного бюджету. Результати засвідчили перевагу використання залишкових компонентних внесків за виражених групових взаємодій і підтвердили істотне скорочення кількості оцінюваних підмножин унаслідок локалізації. Визначено межі застосовності методу, пов’язані з повнотою графа залежностей, точністю оцінної функції, одноресурсним характером модельного експерименту та потребою подальшої перевірки на реальній мобільній платформі.

Ключові слова: живучість; інформаційна система на мобільній платформі; критичні компоненти; пріоритетне відновлення; залишковий компонентний внесок; значення Шеплі; граф залежностей; ресурсні обмеження

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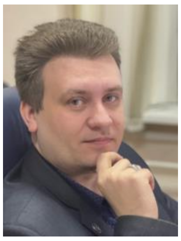

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