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DEVELOPMENT OF A PREDICTIVE ADAPTIVE RESOURCE REALLOCATION METHOD WITH CRITICAL PROCESS DISPATCHING IN INFORMATION SYSTEMS ON MOBILE PLATFORMS

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This work investigates the process of real-time resource management of an information system on a mobile platform under intermittent connectivity, destructive influences, and nonstationary resource availability.

The scientific task relates to the fact that forecast errors and the inertia of platform reconfiguration can induce oscillatory resource redistribution, causing critical processes to intermittently lose the minimum required resource at each control time-step.

A time-step-based predictive adaptive redistribution method with dynamic reservation has been devised in this study. The method introduces an operational survivability constraint. It is formulated as a requirement to maintain a minimum guaranteed resource profile for critical processes. The method adapts the reservation volume according to the assessed reliability of the current forecast. It also constrains the frequency of reconfigurations within a sliding window. These constraints are combined with dispatching of critical processes by urgency and allowable delay. By combining forecast-adaptive reservation with inertia-consistent reconfiguration constraints, the control loop reduces the amplitude and the cumulative intensity of reconfigurations. In particular, under bursty critical workload, the maximum reconfiguration step decreases by about 52%, while the cumulative magnitude of profile changes decreases by about 14%. These effects are explained by the fact that reserved resources compensate for forecast degradation, whereas reconfiguration constraints prevent abrupt control actions and stabilize time-step allocation.

The results could be implemented to build resource management information systems for robotic platforms, sensor networks, as well as mobile systems under intermittent connectivity and real-time resource degradation

Keywords: information system, predictive-adaptive control, critical process survivability, dynamic resource reservation

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1. Introduction

In modern mobile robotic systems, distributed sensor networks, and mobile complexes, information systems perform monitoring and status assessment functions. They also perform forecasting and planning. In addition, such systems provide operational redistribution of computing, network, and other resources of the mobile platform. Management decisions are formed on the basis of current data on the state of the platform [1, 2]. The effectiveness of a given information system is determined by the ability to provide target quality indicators in the presence of resource constraints and external environmental influences, including destructive ones.

The class of information systems on mobile platforms (ISMPs) is characterized by strict resource constraints, non-stationarity of external destructive influences, discontinuous connectivity of system elements, and partial observability of platform states [3]. Under such conditions, survivability becomes the defining integrated property of ISMP. Within the framework of this study, survivability is interpreted as the ability of the system to maintain and/or restore the performance of critical functions in real time under resource shortages, connectivity disruptions, and uncertainty about the current state [4, 5]. Accordingly, the requirements for the functioning of ISMPs are formed in two interrelated directions – maintaining acceptable average quality indicators over a long operating interval and ensuring the operability of critical functions over short intervals of operational control (with a limited forecast interval). In these intervals, management decisions are obtained in real time, taking into account rapid changes in available resources, structural variability of exchange channels, and indicators of uncertainty about the current state of ISMP.

The need for scientific research in this subject area is due to the lack of a holistic methodological apparatus for dynamic backup and adaptive recovery for ISMPs. First of all, this concerns the operational support of the implementation of critical functions of the information system within each interval of resource management of critical processes of ISMPs. There are a number of approaches to building multi-level models of information systems of increased survivability [6], risk-oriented predictive resource management [7], index methods [8], and two-level policy coordination schemes [9, 10]. However, they do not fully solve the problem of forming management decisions and dispatching critical processes under conditions of forecast uncertainty and the dynamics of access of the information system to the resources of the mobile platform. In real ISMPs, this is manifested in cases where the forecast error or excessive intensity of reallocations of resources of the mobile platform causes oscillatory modes of resource allocation. Such modes cause local denials of access to resources for critical processes of the ISMP and form short-term, but the most dangerous episodes of disruption of the main function of ISMP [11, 12].

The practical significance of the study is determined by the possibility to devise a method that provides a minimum guaranteed level of resource provision for critical functions of ISMP in real time by combining predictive-oriented resource redistribution with dynamic reservation.

The criterion for the applied suitability of the study results is the formalization of restrictions on the intensity and frequency of ISMP reconfigurations. This makes it possible to reduce destabilizing effects in the resource management loop and increase the number of control intervals. Within these intervals, critical functions are performed without violating the operational requirements for the survivability of ISMP.

Thus, the combination of time constraints of the real-time regime, the need for guaranteed performance of critical functions of ISMPs, forecast uncertainty and inertia of the redistribution of mobile platform resources, form the current scientific agenda for the development of methods of dynamic backup and adaptive recovery for ISMPs. In this context, it is a relevant task to devise a method of predictive-adaptive real-time resource redistribution with dispatching of critical processes, for which a violation of resource support directly leads to the degradation of target indicators of ISMP survivability.

2. Literature review and problem statement

The evolution of mobile platforms has updated the direction of finding solutions for operational resource management, reservation, and task scheduling in edge and hybrid architectures. In [13], resource management models and methods are systematized, in particular optimization, game, and training settings. It is shown that a significant part of the approaches is evaluated by averaged indicators of latency, throughput, and energy consumption. However, the operational verification of critical functions under forecast uncertainty in real time remains unresolved. The reason is that the requirements of critical processes are mostly not set as hard constraints but are included in the objective functions. This justifies the need to devise methods that combine the tasks of forecasting, reservation, and operational verification of the fulfillment of the minimum resource profile for critical processes.

In [14], a generalization of the application of machine and deep learning methods for resource allocation in edge computing with multipoint access is provided. It is shown that such methods are used to select solutions during task offloading, execution planning, and joint resource allocation under dynamic network and load conditions. However, the issues of transforming these approaches into rules that guarantee the minimum necessary resource for critical processes in each interval of system resource management remain unresolved. The reason for this may be the orientation of the considered statements on the optimization of efficiency indicators and the absence of explicit survivability requirements as constraints for each interval. The solution may be to introduce a minimum guaranteed resource profile for each interval and combine it with predictive-adaptive reservation and reconfiguration constraints.

In [15], a review of resource planning approaches in edge computing with multipoint access is given, with a focus on deep reinforcement learning. Classes of tasks for content caching, computational offloading, and resource management are shown, as well as comparative centralized and distributed approaches. Unresolved issues include the presence of constraints on the speed and frequency of system reconfigurations, which is important for resource nonstationarity. The reason for this may be the orientation of the solution to the quality of service indicators during the operation of the entire system, rather than to the strict conditions of a separate interval of the entire system life cycle. A possible solution may be the introduction of a minimum guaranteed resource profile for critical processes in each interval and constraints on the intensity of rearrangements in a sliding window. However, this approach should be evaluated under the forecast uncertainty and inertia of reconfigurations.

In [16, 17], the task of managing the execution of tasks in edge computing for vehicles through the choice of local execution or transfer to a border node is considered. The problem is represented as a Markov decision process. The rule for selecting control actions is determined by deep reinforcement learning. The optimization goal is formulated as the minimization of the aggregate indicator that aggregates delay, energy costs, and constraints on available computational resources. However, the issue of a guaranteed minimum resource for critical processes in each control interval remains unresolved. This may be due to the initial conditions of the problem statement, which are oriented towards average service quality indicators, where the criticality of tasks is not introduced as an explicit condition. A solution may be to supplement the learning policy with the requirement of a minimum resource profile and constraints on the intensity of rearrangements in a sliding window.

In [18], the results of coordinated data processing planning in transport edge computing using deep reinforcement learning are reported. It is shown that the unified scheme takes into account data exchange, computation, caching, and cooperation between nodes, as well as compliance with service latency constraints. At the same time, the issue of guaranteeing the minimum resource for critical processes in each system control interval remains unresolved. The reason for this is the rigidity of the formalization of constraints, where the total costs are minimized, and the criticality of processes is not specified as a mandatory condition. A potential solution is to introduce an operational survivability requirement as a mandatory requirement for ensuring critical processes.

In [19], the results of research on task translation in the edge-cloud environment using deep meta- and reinforcement learning are given. It is shown that the introduction of meta-learning increases the portability of the model and accelerates the convergence of the decision rule after changing environmental conditions. But the issues of guaranteed resource support of critical processes at short intervals of system operation in case of destructive influences of the external environment remained unresolved. The reason for this is the specificity of the formation of target control tasks, where efficiency is assessed by integrated indicators of service quality. At the same time, the minimum required level of support of critical processes is not set as a mandatory condition for each interval. A possible solution may be the introduction of an operational requirement for system survivability as a guaranteed profile of critical processes at each interval and restrictions on the intensity of resource allocation rearrangements in a sliding window.

In [20], the results of the distribution of users between border nodes under limited resources and overlapping service areas are reported. It is shown that the assignment rule forms a model that assigns different weights to the features of the user and node states. The model directly estimates the probability of the "user-node" correspondence and selects a suitable node for each user. However, an unresolved issue is the organization of support for priority services during a sudden decrease in the available resource or the loss of some nodes. The reason for this may be the goals aimed at the overall efficiency of the distribution, without operational rules for maintaining critical processes at each interval. An option to overcome this is to introduce an operational requirement for survivability and restrictions on the intensity of user reassignments between nodes, consistent with the inertia of system restructuring.

In [21], the results of research on the transfer of computational tasks from vehicles to network computational nodes are described. It is shown that the rule for selecting the place of execution reduces the delay and energy costs, taking into account the bandwidth and available resource. To refine the solutions, particle swarm optimization with adaptive inertia was applied. However, the issues of the stability of these solutions during communication breaks and rapid losses of available resources in the network remained unresolved. The reason for this may be unformalized failure scenarios and recovery procedures. An option to overcome this is to introduce an operational survivability requirement for critical calculations and restrictions on the intensity of resource allocation rearrangements in a sliding window.

In [22], the results of optimization of offloading computations in a three-level system "device – border – cloud" based on the theory of potential games are given. It is shown that individual solutions are coordinated through a potential function, and the optimization is aimed at reducing the delay and energy costs. However, the issues of stability of solutions remain unresolved when communication channels and computing power change their characteristics faster than the coordination of strategies is completed. The reason for this may be the iterative search for equilibrium and the need to exchange telemetric information, which adds delays and overhead to coordination. A solution option is to introduce a priority support mode for critical processes and limit the intensity of strategy changes in a sliding window. It is this game approach that was used in [23] for decentralized task transfer between nodes and distribution of computing resources with an orientation towards the perceived quality of service. However, the main emphasis is on achieving equilibrium and convergence estimates, rather than on guarantees of minimal support for critical computations in each interval of system resource management.

In [24], the results of risk-based energy planning for boundary computing under unstable node power supply are reported. It is shown that the risk of undesirable operating modes is estimated by a special risk measure and used together with multi-agent learning. However, the issues of maintaining critical services during short-term node power failures and sharp spikes in computational load remain unresolved. The reason for this may be the peculiarities of planning, when the risk describes the average behavior, and not the conditions of each interval. An option for overcoming this is the mandatory requirement of providing an energy-allowable resource for critical processes in each interval.

In [25], a mechanism for risk-oriented task translation in the industrial Internet of Things involving edge nodes is described. It is shown that when choosing solutions, the average delay and the risk of large delays are taken into account for uncertain channel and computing resource characteristics. The uncertainty of the parameters is represented by fuzzy estimates, and the problem is reduced to a stable optimization. However, the question of how to transform risk estimates into operational rules for supporting critical processes in each control interval remains unresolved. The reason for this may be the orientation on the risk of delay as a generalized metric and the absence of dispatching procedures by criticality. A potential solution is to establish a logical connection between the increase in risk and the transition to a conservative control mode, where the resource reserve increases and the intensity of resource usage scenario restructuring decreases.

In [26], a method for optimizing the position of a mobile platform (UAV) and planning communication and computing resources in the space-air-ground network is proposed. It is shown that the goal is to reduce the maximum delay of task processing through the joint choice of association, task distribution and UAV computational resource. Block-by-coordinate descent and successive convex approximation were used for the solution. However, the issues of maintaining critical processes during a sharp deterioration in connectivity or a sudden decrease in the available resource remained unresolved. The reason for this may be the focus on delay optimization and the lack of an explicit division of tasks by priority. An option for solving the problem is to introduce an operational survivability requirement for critical processes and rules for changing resource distribution, taking into account the inertia of their restructuring.

In [27], a model of a "space-air-ground" network is proposed. The network includes satellites, UAVs, as well as ground terminals, where satellites and UAVs perform specified computational procedures. It is shown that the joint use of data transmission channels, the use of calculation distribution methods, caching solutions, and UAV position minimize the total delay in the execution of system tasks. However, the issues of ensuring the functioning of critical calculations when connectivity and available resources change according to unpredictable scenarios remain unresolved. The reason for this may be the assumption of known state parameters and the need to coordinate many variables in a large optimization problem over a significant time period. A possible solution is to add priority dispatching and a conservative reservation mode, which is used when the predictive estimate of network resource usage deteriorates.

In [28], the results of planning the flow of interdependent tasks in a joint environment of edge nodes and the cloud are reported, taking into account several criteria. But the question of how to transform the reliability indicator into mandatory actions for maintaining critical computations in the event of a sudden loss of nodes remains unresolved. The reason for this may be the focus on finding compromises between criteria and the use of probabilistic reliability estimates without interpretation in control intervals. An option to overcome this is to introduce an explicit profile for ensuring critical processes and policies for its use.

In [29], an approach to scheduling multiple task flows in a multilayer environment "devices – edge nodes – intermediate layer – cloud" is described, taking into account the deadlines for plan execution and security requirements. Two heuristic scheduling algorithms are proposed that improve the relationship between costs, energy consumption, and reliability of task execution in a heterogeneous environment. But the question of how to guarantee the execution of priority computations in such schemes when network and resource parameters change unpredictably remains unresolved. This may be due to the assumption of sufficient completeness of the environment state and the reliance on heuristic decision making without a separate recovery loop after connectivity failures. An option to overcome this is to supplement the planning with predictive-adaptive reservation procedures to maintain the operability of priority processes even in the event of a sudden deterioration in the connection between nodes or loss of an available resource.

Existing approaches to resource management in edge-cloud and hybrid environments mainly optimize generalized indicators. Most often, these are latency, energy consumption, and bandwidth. With such guidelines, maintaining critical processes is usually not formalized as a mandatory requirement in each control interval – it is represented as a contribution to the objective function. As a result, short-term failures in resource availability for priority calculations cannot be eliminated and are considered an acceptable compromise in favor of integrated efficiency.

An additional reason is the mismatch of time scales. Reconfiguration of resource allocation has inertia and overhead, while the state of the environment and resource availability can change faster than the system reconfiguration is completed. In the presence of prediction error and restructuring delays, this leads to oscillatory control modes. Then the system often changes its configuration but fragmentarily does not provide the minimum required resource for critical processes. On mobile platforms, these problems are exacerbated by intermittent connectivity, partial observability of the state, and non-stationarity of the available resource. Because of this, the rules of the system operation, tuned to averaged indicators, lose the ability to guarantee the performance of critical functions in each control cycle.

All this allows us to argue that it is advisable to conduct research on investigating a predictive-adaptive real-time resource redistribution for information systems on a mobile platform. The approach should provide operational requirements for the survivability of critical processes through a combination of three components:

– forecasting of the available resource in a short operating interval;

– dynamic reservation of the minimum permissible profile for priority calculations;

– dispatching processes taking into account criticality.

In this case, it is necessary to formalize restrictions on the step and frequency of reconfigurations in the sliding window in order to coordinate control actions with the inertia of restructuring and reduce oscillatory modes of resource allocation.

Thus, our study focuses on the transition to procedures that guarantee the minimum required resource to critical processes in each control interval under conditions of forecast uncertainty and resource availability dynamics.

3. The aim and objectives of the study

The purpose of our study is to devise a method for predictive-adaptive real-time resource redistribution with dispatching of critical processes of ISMP. This will make it possible to ensure the performance of critical functions in each control interval with intermittent connectivity and partial observability. This will also make it possible to reduce the destabilization of resource distribution by taking into account inertia and resource costs for restructuring the ISMP operating scheme.

To achieve the goal, the following tasks were set:

– to formalize operational survivability constraints for critical processes and set the resource profile necessary for their implementation in each control interval;

– to devise a procedure for assessing the ISMP state in the forecast interval and a forecast reliability indicator for intermittent connectivity;

– to construct a dynamic reservation rule for critical processes in scenarios of degradation of the available resource;

– to justify restrictions on the step and frequency of restructuring of the system resource distribution and assess their impact on the dynamics of operational distribution;

– to design a mechanism for dispatching critical processes in combined resource and load change scenarios and coordinate it with resource reservation processes for critical processes.

4. The study materials and methods

4. 1. Object of study, working hypothesis, and starting points

The object of our study is the process of operational management of information system resources on a mobile platform under conditions of intermittent connectivity, destructive influences, and non-stationary resource availability. The functioning of ISMP is considered as a sequence of short intervals (cycles) of operational management, within which decisions are formed on the redistribution of resources and maintaining the availability of reserve resources to support critical processes.

Our study's principal hypothesis assumes that the combination of a short-term forecast of the state of ISMP resource level and a quantitative assessment of the reliability of this forecast makes it possible to form an operational resource management mechanism. Additionally, restrictions are introduced that reflect delays and operational resource costs for reconfigurations. The mechanism in each cycle should support the minimum required level of resource provision for critical ISMP processes and at the same time reduce the risk of destabilization of resource distribution due to too frequent or abrupt ISMP reconfigurations.

Assumptions adopted:

– the resource state of the mobile platform is represented by a discrete sequence of estimates formed at each resource management cycle;

– critical processes are determined by functional significance (priorities) and time requirements for their execution in the operational resource management loop;

– telemetry data may be incomplete/uneven, but are sufficient to build a short-term forecast and an indicator of its reliability;

– ISMP reconfigurations are characterized by finite duration and non-zero overhead costs (resource and time), which use part of the mobile platform resources;

– the speed and frequency of ISMP reconfigurations are taken into account as constraints in the operational resource management loop of the mobile platform.

The accepted simplifications are to use an aggregated description of resources and loads without detailing hardware components and application implementations of processes. Destructive impacts are represented by a limited set of typical scenarios: deterioration of connectivity, reduction of available resources, and increase in the intensity of critical load, which is sufficient for reproducible modeling of operational management procedures of ISMP. As a result, within the framework of this study, state forecasting, assessment of its reliability, dynamic reservation for critical processes, as well as constraints that take into account reconfiguration delays, are considered as mutually agreed elements of a single operational mechanism for managing mobile platform resources.

4. 2. Operational model of resource management of an information system on a mobile platform

The process of operational resource management of an ISMP is given by a discrete-time model, in which the moments of making management decisions correspond to the sequence of control cycles $t = 1, 2, \ldots$. For ISMP, the heterogeneity of resources (computing, network, etc.) that change unevenly and can affect the execution of critical processes in different ways is fundamental. Accordingly, it is advisable to formalize the model in vector form. This will provide a single notation for a set of resources and will enable the formulation of cycle constraints for the survivability of ISMP as multidimensional (by resource types) requirements.

Let the resource state of ISMP at cycle t be given in the form of a vector

$$\vec{r}_t \in \mathbb{R}_+^m,\ \vec{r}_t = \left[r_t^{(1)},\ldots,r_t^{(m)}\right]. \quad (1)$$

In formula (1): m is the number of aggregated resource types (for example, if $m = 3$, then there may be, for example, the following resources: computing, network, memory resource); $\mathbb{R}_+^m$ – a set of non-negative vectors.

Information system processes are divided into critical and non-critical. Within each cycle, the need for resources is aggregated through the vectors of the total resource need

$$\vec{d}_t^{\zeta} \in \mathbb{R}_+^m,\ \vec{d}_t^{\xi} \in \mathbb{R}_+^m. \quad (2)$$

In formula (2): $\vec{d}_t^{\zeta}$ is the total resource requirement of critical processes in cycle t; $\vec{d}_t^{\xi}$ – the total resource requirement of non-critical processes in cycle t. The components of the vectors correspond to the same resource types as in $\vec{r}_t$ (1).

In cycle t, the distribution of available resources between three components is formed: a resource for critical processes, a resource for non-critical processes, and a reserve resource block (reserve). This is, accordingly, described by vectors $\vec{a}_t^{\zeta}$, $\vec{a}_t^{\xi}$, $\vec{a}_t^{\varsigma} \in \mathbb{R}_+^m$ and a budget constraint on resource allocation (balance condition)

$$\vec{a}_t^{\zeta} + \vec{a}_t^{\xi} + \vec{a}_t^{\varsigma} \preceq \vec{r}_t. \quad (3)$$

In formula (3), the component-wise inequality (for each type of resource separately) takes into account that part of the resource may remain unused due to limitations in connectivity, access modes, or internal costs of the mobile platform.

Survivability requirements for critical processes in the control cycle are set as a strict operational constraint on the minimum allowable level of resource support for processes

$$\vec{a}_t^{\zeta} \preceq \vec{r}_{\min}^{\zeta},\ \vec{r}_{\min}^{\zeta} \in \mathbb{R}_+^m. \quad (4)$$

In formula (4), $\vec{r}_{\min}^{\zeta}$ is the minimum guaranteed resource profile (resource provision configuration) for critical processes. Constraint (4) is a formalized reflection of the cycle requirements for survivability – in each cycle critical processes must receive resource provision not lower than the specified minimum.

Since resource profile reconfigurations are accompanied by delays and operational costs, constraints are introduced into the model that regulate the intensity of resource allocation changes between neighboring cycles. For this purpose, a constraint is set on the norm of the reconfiguration step, i.e., on the norm of the difference between resource allocations in neighboring cycles:

$$\left\|\vec{a}_t^{\zeta} - \vec{a}_{t-1}^{\zeta}\right\|_1 \le \Delta_{\zeta},\ \Delta_{\zeta} \ge 0,$$

$$\left\|\vec{a}_t^{\varsigma} - \vec{a}_{t-1}^{\varsigma}\right\|_1 \le \Delta_{\varsigma},\ \Delta_{\varsigma} \ge 0. \quad (5)$$

In formula (5): $\|\cdot\|_1$ – L_1-norm (sum of component modules); $\Delta_{\zeta}, \Delta_{\varsigma}$ – permissible steps of changing the resource allocation for critical processes and the reserve, respectively. Constraint (5) sets the maximum permissible total change in the resource profile in one cycle, which reflects the impact of delays and resource costs of reconfigurations on the operational management of ISMP.

The operational costs of reconfiguration can be reflected through the adjusted (residual) available resource, which is reduced by the amount of costs associated with performing the reconfiguration

$$\vec{r}_t^{\psi} = \vec{r}_t - \vec{\varphi}\left(\vec{a}_t - \vec{a}_{t-1}\right),\ \vec{\varphi}\left(\cdot\right) \succeq \vec{0}. \quad (6)$$

In formula (6): $\vec{r}_t^{\psi}$ – adjusted (residual) available resource in cycle t after taking into account operational costs; $\vec{\varphi}\left(\cdot\right)$ – vector function of operational costs of reconfiguration (in terms of resource types); $\vec{a}_t = \vec{a}_t^{\zeta} + \vec{a}_t^{\xi} + \vec{a}_t^{\varsigma}$ – total resource distribution profile. If necessary, the balance condition (3) should be further interpreted in relation to $\vec{r}_t^{\psi}$ (6) if it is necessary to explicitly take into account the required amount of resources for performing ISMP reconfigurations.

Thus, relations (1)–(6) set the formal basis for the operational description of resource management in ISMP. It includes the vector state of the resource (1), the aggregated need of processes (2) and the structure of resource distribution, including reserve ones (3). The cycle requirements for the survivability of critical processes (4), the limitation of the reconfiguration step (5) and, if necessary, the resource costs for reconfiguration (6) are determined.

4. 3. Forecasting the state of the resource level of an information system on a mobile platform and introducing a forecast reliability indicator

Taking into account (1)–(6), short-term forecasting of the vector of available resources $\vec{r}_t$ (1) is considered as an information basis for forming a control action, in particular for choosing the reserve value $\vec{a}_t^{\varsigma}$ and the permissible intensity of reconfigurations, limited by relations (5), (6). Since the telemetry of a mobile platform may be incomplete and non-stationary, the forecast is given in a generalized form – without being tied to a specific algorithm, which ensures the reproducibility of the approach for different classes of platforms. In particular, the choice of algorithm (ARIMA [30], filtering methods [31] or learning models [32]) is not specified.

Let an estimate of the available resource $\vec{a}_t^{\varsigma}$ be formed at each time step t based on telemetry data. Next, a forecast is determined for a predetermined depth L (the number of subsequent times), which can be formalized as a sequence of vectors

$$\hat{\vec{r}}_{t+1:t+L} = \left(\hat{\vec{r}}_{t+1|t}, \hat{\vec{r}}_{t+2|t}, \ldots, \hat{\vec{r}}_{t+L|t}\right),\ \hat{\vec{r}}_{t+\ell|t} \in \mathbb{R}_+^m. \quad (7)$$

In formula (7), $\hat{\tilde{r}}_{t+\ell|t}$ is the forecast of the available resource for the cycle $t+\ell$, built in cycle t.

The forecasting procedure can be interpreted as a forecasting function that uses a sliding window of observations of length W

$$\hat{\tilde{r}}_{t+1:t+L|t} = F\left(\tilde{\vec{r}}_{t-W+1:t}\right),\ \tilde{\vec{r}}_{t-W+1:t} = \left(\tilde{\vec{r}}_{t-W+1},\ldots,\tilde{\vec{r}}_t\right). \quad (8)$$

In formula (8), $F(\cdot)$ is a generalized forecast operator, the parameters and structure of which are determined by the selected forecasting method.

For the operational control loop, the quantitative assessment of the reliability of the forecast is fundamental, which is used as an internal regulator during the formation of the control action. Reliability is assessed a posteriori by the quality of the one-step forecast, since it is the one-step error that is most consistent with the current mode of operation of ISMP and adequately reflects local non-stationarity.

The error vector of the one-step forecast is formalized in the form

$$\vec{\varepsilon}_t = \tilde{\vec{r}}_t - \hat{\tilde{r}}_{t|t-1},\ \vec{\varepsilon}_t \in \mathbb{R}_+^m. \quad (9)$$

In formula (9), $\hat{\tilde{r}}_{t|t-1}$ is the forecast of the available resource at cycle t, built at time $(t-1)$.

To reconcile the error for different resource scales and ensure correct comparison over time, a normalized scalar measure of the posterior error on the sliding window is introduced

$$E_t = \frac{1}{W}\sum_{i=0}^{W-1}\frac{\left\|\vec{\varepsilon}_{t-i}\right\|_1}{\left\|\tilde{\vec{r}}_{t-i}\right\|_1 + \wp},\ E_t \ge 0,\ \wp > 0. \quad (10)$$

In formula (10): $\|\cdot\|_1$ – L_1-norm (component-wise aggregate measure), consistent in form with the use of $\|\cdot\|_1$ in the reconfiguration constraints (5); $\wp$ – positive numerical stabilization parameter introduced to prevent division by zero.

The forecast reliability indicator $\rho_t \in [0, 1]$ is given as a monotonically decreasing function of E_t, which converts the normalized forecast error into a forecast reliability scale suitable for use in the control loop

$$\rho_t = \exp\left(-\frac{E_t}{\kappa}\right),\ \kappa > 0. \quad (11)$$

In formula (11), κ is a scale parameter that specifies the rate of decrease of ρ_t with increasing E_t: for smaller κ, the decrease of ρ_t occurs faster.

Introduction of ρ_t (11) provides a formal basis for adaptation of the control mode. In cycles where ρ_t decreases, the control action will subsequently be formed under the control mode with an increased level of reservation and a restriction on the intensity of reconfigurations. That is, in fact, the prioritization of reservation is carried out and a restriction on the intensity of reconfigurations is introduced in accordance with (5), (6). For this purpose, the threshold interpretation of the reliability indicator is used

$$\rho_t \ge \rho_{\min} \Rightarrow o_1,\ \rho_t < \rho_{\min} \Rightarrow o_2. \quad (12)$$

In formula (12): o_1 – forecast-oriented redistribution mode; o_2 – enhanced redundancy mode; $\rho_{\min} \in (0, 1)$ – threshold value separating control modes.

Thus, relations (7)–(12) form an integrated information block of operational control, which includes the resource state forecast $\hat{\tilde{r}}_{t+1:t+L|t}$ according to (7), (8), and the reliability indicator ρ_t according to (11), (12). These values are used to form (adapt) control decisions regarding redundancy and reconfigurations within the operational resource management cycle, provided that the cycle requirements for the survivability of critical processes (4) and restrictions on reconfiguration (5), (6) are met.

4. 4. Predictive-adaptive reserve and reconfigurations management

Here, the procedure for forming a control action in the cycle t in the form of a resource profile $\vec{a}_t^{\zeta}$, $\vec{a}_t^{\xi}$, $\vec{a}_t^{\varsigma}$ is given. This profile must provide the cycle requirements for the survivability of critical processes according to constraint (4) and satisfy the resource balance (3), taking into account the possible operational costs of reconfigurations (6). The profile must comply with the reconfiguration restrictions given by the relation (5). The adaptability of the procedure is ensured by using the forecast reliability indicator ρ_t, determined from relation (11), as well as by the regime interpretation according to rule (12).

The basic resource profile of critical processes is formed as follows. At each control cycle, the minimum guaranteed resource profile of critical processes $\vec{r}_{\min}^{\zeta}$, is first fixed, which determines the lower limit $\vec{a}_t^{\zeta}$ in the form of (4). To ensure a margin of stability against short-term deteriorations in resource availability, an additional (over the minimum guaranteed) component is introduced, which depends on the forecast (7), (8) and the reliability ρ_t (11).

Let the forecast of the minimum available resource on the forecast interval of length L be defined as the component-wise minimum

$$\hat{\tilde{r}}_t^{\min} = \min_{\ell=1,\ldots,L}\hat{\tilde{r}}_{t+\ell|t},\ \hat{\tilde{r}}_t^{\min} \in \mathbb{R}_+^m. \quad (13)$$

Formula (13) is used as a conservative estimate relevant to tact control to determine the reserve in the presence of a risk of a decrease in the available resource within the forecast interval.

Then the dynamic reserve $\vec{a}_t^{\varsigma}$ is formed as a vector, the value of which increases with a decrease in ρ_t (11), i.e. with an increase in forecast uncertainty. For this purpose, the reservation coefficient $\gamma(\rho_t)$ is introduced, which determines the level of reservation depending on the reliability indicator:

$$\gamma\left(\rho_t\right) = \gamma_{\min} + \left(\gamma_{\max} - \gamma_{\min}\right)\left(1-\rho_t\right),$$

$$0 \le \gamma_{\min} \le \gamma_{\max},\ \gamma\left(\rho_t\right) \in \left[\gamma_{\min}, \gamma_{\max}\right]. \quad (14)$$

In formula (14): $\gamma_{\min}$ – minimum level of reservation for high values of the forecast reliability indicator ρ_t; $\gamma_{\max}$ – maximum level of reservation for low values of the forecast reliability indicator ρ_t.

The reserve is defined as proportional to the vector of the minimum guaranteed resource profile of critical processes with an adjustment for the minimum forecast estimate of the available resource (13)

$$\vec{a}_t^{\varsigma} = \gamma\left(\rho_t\right)\vec{r}_{\min}^{\zeta} \oplus \left[\vec{r}_{\min}^{\zeta} - \hat{\tilde{r}}_t^{\min}\right]_+. \quad (15)$$

In formula (15), $[x]_+ = \max(x, 0)$ is component-wise cutoff of negative values (ReLU-like operator [33]). The first component (15) specifies the reserve regulated by the forecast reliability indicator ρ_t, which increases with decreasing ρ_t

according to (14). The second component compensates for the resource deficit when the forecasted minimum resource in the forecast interval is lower than the minimum required resource profile of critical processes.

The formation of a control action taking into account the reconfiguration constraints is carried out according to the following procedure. In cycle t, the basic resource allocation to critical processes is given as the sum of the minimum guaranteed profile and the part of the reserve that is directly assigned to critical processes. Let us introduce the coefficient $\eta \in [0, 1]$, which determines which part of the reserve is held in an unsecured form (in a common resource pool), and which is allocated to critical processes

$$\vec{a}_t^{\zeta,*} = \vec{r}_{\min}^{\zeta} + (1-\eta)\vec{a}_t^{\varsigma}. \quad (16)$$

In formula (16), $\vec{a}_t^{\zeta,*}$ – target (preliminary) resource profile for critical processes. From (16) it is obvious that for larger η most of the reserve remains in the form $\vec{a}_t^{\varsigma}$, and for smaller – the reserve is fixed (reserved) to a greater extent for critical processes.

Next, the pre-formed profile (16) is coordinated with the reconfiguration regulation. For this purpose, the projection operator onto the set of admissible reconfigurations is used, which ensures the fulfillment of constraint (5). For critical processes

$$\vec{a}_t^{\zeta} = \Pi_{\Delta_\zeta}\left(\vec{a}_{t-1}^{\zeta}, \vec{a}_t^{\zeta,*}\right). \quad (17)$$

In formula (17), Π_{Δ_ζ} is defined as the solution to the projection problem

$$\Pi_{\Delta_\zeta}\left(\vec{a}_{t-1}^{\zeta}, \vec{a}_t^{\zeta,*}\right) = \arg\min_{\vec{x}} \left\| \vec{x} - \vec{a}_t^{\zeta,*} \right\|_2^2, \quad (18)$$

subject to

$$\left\| x - \vec{a}_{t-1}^{\zeta} \right\|_1 \le \Delta_\zeta, \ \vec{x} \succeq \vec{r}_{\min}^{\zeta}.$$

The projection (18) ensures that the generated $\vec{a}_t^{\zeta}$ is as close as possible to the profile (16) but does not violate either the tact survivability constraint (4) or the reconfiguration step constraint (5).

Similarly, the reserve is formed taking into account the constraint on its change

$$\vec{a}_t^{\varsigma} = \Pi_{\Delta_\varsigma}\left(\vec{a}_{t-1}^{\varsigma}, \vec{a}_t^{\varsigma}\right). \quad (19)$$

In formula (19), Π_{Δ_ς} is determined by analogy with (18) with the replacement of Δ_ζ by Δ_ς and without the condition $\vec{x} \succeq \vec{r}_{\min}^{\zeta}$, since the profile (4) is superimposed precisely on $\vec{a}_t^{\zeta}$.

After the formation of $\vec{a}_t^{\zeta}$ and $\vec{a}_t^{\varsigma}$, the resource available for non-critical processes is determined, based on (3). If the operating costs for reconfiguration (6) are taken into account, then the balance condition is formulated relative to $\vec{r}_t^{\psi}$

$$\vec{a}_t^{\xi} = \left[\vec{r}_t^{\psi} - \vec{a}_t^{\zeta} - \vec{a}_t^{\varsigma} \right]_+. \quad (20)$$

Formula (20) automatically ensures the fulfillment of balance conditions (3) and guarantees the non-negligibility of the resource for non-critical processes.

The regime interpretation by the reliability indicator can be formalized as follows. The control mode in cycle t is determined by the threshold rule (12). For the case $\rho_t < \rho_{\min}$ in (12), a conservative reserve mode is applied, which is implemented by increasing $\gamma(\rho_t)$ through (14) and, if necessary, strengthening the restrictions on reconfiguration by reducing Δ_ζ and Δ_ς in (5), (18)–(19). For the case $\rho_t \ge \rho_{\min}$ in (12), a more active use of predictive information (13)–(15) is allowed while maintaining the cycle guarantees (4) and the restrictions on reconfiguration (5), (6).

Relations (13)–(20) determine the procedure for forming a reserve and control action in each cycle of operational control. This ensures the following:

– fulfillment of the cycle requirements for the survivability of critical processes (4);

– compliance with reconfiguration constraints (5) through operators (17)–(19);

– matching the resource profile with effective availability, taking into account resource costs for reconfigurations (6), (20).

4. 5. Dispatching of critical processes in the operational control cycle

Dispatching plays the role of an internal operational control mechanism, which in each cycle t transforms the formed resource profile for critical processes $\vec{a}_t^{\zeta}$ (defined by (17), (18)) into a specific solution for the functioning of critical processes and resource distribution between them. In this case, dispatching does not change the resource profile, but works within the already allocated resource budget, ensuring the fulfillment of the cycle requirements for survivability (4) and consistency with the reconfiguration regulations (5), (6), since the profile $\vec{a}_t^{\zeta}$ is already formed taking into account these restrictions.

First, a model of critical processes in a cycle is formalized. Let $C_t = \{1, \ldots, N_t\}$ be the set of critical processes (active or ready to execute) in cycle t. For each process $i \in C_t$, an aggregated vector of the resource requirements profile for one cycle is introduced

$$\vec{q}_{i,t} \in \mathbb{R}_+^m. \quad (21)$$

In formula (21), $\vec{q}_{i,t}$ – resource requirements of the i-th process during cycle t by resource types (the same m components as in $\vec{r}_t$ (1)). The index t allows the dependence of resource requirements on the platform operating mode and the parameters of ISMP objective function.

To describe the dynamics of process execution, the variable of the residual work volume is used, which is measured in discrete (normalized) units of work, consistent with the control cycle

$$s_{i,t} \ge 0, \quad (22)$$

where the transition of the process between states is given by the equation

$$s_{i,t+1} = \left[s_{i,t} - u_{i,t} \right]_+, \ u_{i,t} \in [0,1]. \quad (23)$$

In formulas (22), (23), $0 \le \gamma_{\min} \le \gamma_{\max}$, (23) $u_{i,t}$ is the fraction of process execution in cycle t (for $u_{i,t} = 1$ the process executes one normalized unit of work in cycle t, for $u_{i,t} = 0$ – it is not executed). The operational time requirements of critical processes are given through the time reserve, which is interpreted as the number of cycles during which the process can be delayed without violating the time requirement for execution

$$\delta_{i,t} \in \{0,1,2,\ldots\}. \quad (24)$$

In formula (24), $\delta_{i,t} = 0$ is interpreted as the need for execution in the current cycle. The method of forming $\delta_{i,t}$ is determined by the adopted time requirements model and the ISMP dispatching rules.

It is advisable to introduce a cycle dispatching constraint. For this purpose, it is assumed that in cycle t the dispatcher forms a vector of dispatching decisions $\vec{u}_{i,t} = \left[u_{1,t},\ldots u_{N_t,t}\right]^{\top}$, which must be resource-acceptable with respect to the budget $\vec{a}_t^{\zeta}$, obtained in (17), (18). The generalized resource-acceptability condition takes the form

$$\sum_{i\in C_t} u_{1,t}\vec{q}_{i,t} \preceq \vec{a}_t^{\zeta}. \tag{25}$$

If necessary, in real ISMPs, it is allowed to use part of the reserve $\vec{a}_t^{\varsigma}$ as an emergency resource within a cycle (this is not a reconfiguration, since it does not change $\vec{a}_t^{\zeta}$, but only clarifies the internal distribution of the already available resource). Then an additional vector of intra-cycle reserve engagement is introduced

$$\vec{b}_t \preceq \vec{a}_t^{\varsigma}, \tag{26}$$

and the condition of resource acceptability of dispatching is given as

$$\sum_{i\in C_t} u_{1,t}\vec{q}_{i,t} \preceq \vec{a}_t^{\zeta} + \vec{b}_t. \tag{27}$$

In formulas (26), (27): $\vec{b}_t$ – part of the reserve that is actually used within the cycle to support the execution of critical processes; $\vec{a}_t^{\varsigma}$ – reserve formed according to (15) and limited according to (19).

To ensure computational feasibility in real time, dispatching is implemented as a priority procedure with ranking of processes by an index that combines functional criticality and urgency of execution [34]. A criticality weight coefficient $\omega_i > 0$ (set at the ISMP configuration stage) and an urgency amplification function dependent on the forecast reliability indicator ρ_t from (11) are introduced. The priority index is defined as follows

$$\pi_{i,t} = \omega_i \cdot \frac{1+\lambda\left(1-\rho_t\right)}{\delta_{i,t}+1}, \ \lambda \geq 0. \tag{28}$$

In formula (28): $\pi_{i,t}$ – priority index of process i in cycle t; ω_i – functional criticality coefficient (static priority weight) of process i; λ – conservativeness coefficient, which determines the degree of influence of decreasing forecast reliability ρ_t on priority. With such definition (28), decreasing ρ_t leads to an increase in the multiplier $(1 + \lambda(1 - \rho_t))$, i.e., dispatching becomes more conservative – with an increase in the priority of urgent critical processes under modes when the forecast is less reliable.

Therefore, the dispatching procedure in cycle t is determined by the following steps:

Step 1. Formation of a priority list. Processes $i \in C_t$ are ordered in descending order of $\pi_{i,t}$ from (28). This order ensures the coordination of dispatching with the regime interpretation of control, which is determined by the forecast reliability indicator ρ_t according to (11), (12).

Step 2. Assignment of control variables under the resource admissibility condition. Sequentially, in rank order, process i is assigned the $u_{i,t}$ value. The $\pi_{i,t}$ value is chosen so that after the process is turned on, the resource admissibility condition (25) (or (27) with consideration $\vec{b}_t$ according to (26)) is fulfilled. If the requirements (25), (27) are violated, the process is not executed ($u_{i,t} = 0$) or is partially executed $u_{i,t} \in (0, 1)$ for a minimally sufficient value that preserves resource admissibility, in accordance with the adopted policy.

Step 3. Updating the states of processes. After determining vector $\vec{u}_t$ according to (23), the unfulfilled volume of work of processes $s_{i,t}$ is specified. Thus, in the next cycle $(t + 1)$ dispatching uses the updated values $s_{i,t+1}$ from (23) and the time reserve $\delta_{i,t+1}$ from (24), which ensures the closure of the operational cycle.

Step 4. Fulfilling the conditions for using the reserve within the cycle. If the experiment allows intra-cycle involvement of reserve $\vec{b}_t$ (26), then its use is activated only if there is a risk of violating the operational time requirements of critical processes (for example, when there is a process with $\delta_{i,t} = 0$, which cannot be included without $\vec{b}_t$). In this case, $\vec{b}_t$ is chosen as the minimum required (in component-wise order) vector that ensures the fulfillment of the resource admissibility condition (27) for the set of processes with the highest $\pi_{i,t}$ values, determined from (28). The proposed rule ensures the use of the reserve as a mechanism for maintaining critical processes, without turning the reserve into a constantly used resource.

Thus, relations (21)–(28) define a formalized methodology for tact dispatching of critical processes: a description of the resource needs of processes (21), the dynamics of execution (22), (23), operational time requirements in the form of a time reserve (24), resource admissibility conditions (25)–(27), and the priority index (28). The indicator of reliability of the forecast ρ_t (11) acts as a control parameter of the regime interpretation (12), determining the degree of conservatism of decisions in the operational control loop.

4. 6. Conditions of simulation research and experimental setup

The simulation research is aimed at reproducing the conditions of functioning and evaluating the effectiveness of the proposed operational resource management mechanism. The experiments are built as a discrete-cycle simulation, in which at each cycle t the resource state $\vec{r}_t$ (1) is formed, the resource state forecast $\vec{r}_{t+1:t+L|t}$ (7), (8) is built, the reliability indicator ρ_t (11), (12) is estimated. After that, the control action is formed in the form of resource distribution profiles $\vec{a}_t^{\zeta}$, $\vec{a}_t^{\xi}$, $\vec{a}_t^{\varsigma}$ according to (13)–(20) and the dispatching of critical processes is performed according to (21)–(28). Such an organization of the experiment ensures compliance with the real-time regime since each cycle contains a full cycle of "assessment – forecast – control – dispatching".

The duration of the simulation is given by the number of cycles T, and all variables are determined in discrete time. For the vector resource model (1), the dimensionality m is fixed as the number of aggregated resource types, which include at least the computational and network components, and if necessary, other ISMP resources. The sliding window length W and the forecast depth L are defined as the parameters of the forecast block (8)–(10) and remain constant within a series of experiments.

For the forecast reliability indicator, the parameter κ (11) and the threshold value $\rho_{\min}$ (12) are used, which determine the control mode. The reconfiguration constraints are given by the allowable steps Δ_{ζ}, Δ_{ς} according to (5) and are used in the projection procedures (18), (19). The reservation coefficients $\gamma_{\min}$, $\gamma_{\max}$ set the limits for function $\gamma(\rho_t)$ (14), and the parameter η determines the reserve structure in the critical profile according to (16).

The formation of the resource state and telemetry observations is carried out as follows. Since the basic resource state of ISMP at time t is given by vector $\vec{r}_t$ (1), then to reproduce intermittent connectivity and the influence of external factors, a random or vector of availability coefficients is introduced, which acts component-wise by resource types

$$\vec{r}_t = \vec{r}_t^{\,\mu} \odot \vec{\alpha}_t,\ \vec{r}_t^{\,\mu} \in \mathbb{R}_+^m,\ \vec{\alpha}_t \in \left[0,1\right]^m. \tag{29}$$

In formula (29): $\vec{r}_t^{\,\mu}$ – nominal resource profile of the platform; $\vec{\alpha}_t$ – vector of availability coefficients (connectivity, access to network channels, degradation of computing elements, etc.).

The state assessment by telemetry $\tilde{\vec{r}}_t$ is formed as follows

$$\tilde{\vec{r}}_t = M_t \vec{r}_t + \vec{\upsilon}_t,\ M_t \in \mathbb{R}^{m\times m}. \tag{30}$$

In formula (30): M_t – diagonal observability matrix (elements 0/1 or values in [0, 1] for modeling losses/reductions in telemetry quality by resource types); $\vec{\upsilon}_t$ – measurement error vector. Using (30) provides controlled reproduction of situations when telemetry data are incomplete or uneven, which is necessary for estimating ρ_t (11).

In the simulation study, the generation of load and states of critical processes is simulated. For this purpose, the aggregate demand of critical and non-critical processes is given by vectors $\vec{d}_t^{\,\zeta}$, $\vec{d}_t^{\,\xi}$ (2) and is formed as a result of generating sets of processes in a cycle. Critical processes are modeled by the set C_t and parameters $\vec{q}_{i,t}$ (21), $s_{i,t}$ (22), $\delta_{i,t}$ (24). To test the method in different load and time requirements scenarios, three classes of critical processes are introduced:

– processes with low resource requirements and strict time requirements;

– processes with high resource requirements and moderate time requirements;

– processes with a variable resource demand profile $\vec{q}_{i,t}$, which depends on the impact of the environment on ISMP.

The functional criticality of processes is given by coefficient ω_i in the priority index (28).

The non-critical load is given as a background process or batch task flow that uses the remaining resource according to the rule (20). If necessary, a change in load intensity over time is assumed, which forms short-term peak episodes of critical load, necessary to check the fulfillment of tact requirements (4) and the effectiveness of the reservation mechanism (15).

For a reproducible comparison of experimental modes, a reference set of scenarios is given, which are implemented through $\vec{\alpha}_t$ (29) and the load parameters:

1. The base scenario, characterized by the absence of additional destructive influences, the resource state is formed according to (29) under the standard mode.

2. The scenario of deterioration of connectivity, characterized by a periodic or random decrease in the availability of the network component of the resource, which is modeled by a decrease in the corresponding component $\alpha_t^{(net)}$ in (29).

3. The scenario of a decrease in the available platform resource, characterized by a stepwise or monotonous decrease in the volume of the resource (for example, degradation or failure of the module), reproduced through $\vec{r}_t^{\,\mu}$ or $\vec{\alpha}_t$ in (29).

4. The scenario of an increase in the intensity of the critical load, characterized by short-term intervals of increased intensity of the arrival of critical processes or an increase in their resource requirements in (21).

5. A combined scenario characterized by a simultaneous change in resource availability (29) and load to check the consistency of the reservation (15) and reconfiguration constraints (5) under conditions of increased non-stationarity.

In each scenario, the variability of the conditions is given by a controlled change in the parameters that determine: the level of incompleteness of observations (M_t (30)), the variance of the measurement error $\vec{\upsilon}_t$ (30), the parameters of the forecast block (W, L, κ (8), (11)) and the parameters of the reconfiguration constraints given by the permissible steps (Δ_ζ, Δ_ς (5)).

For the correct interpretation of the results, comparable control modes are set in the simulation study, differing only in the presence or absence of key elements of the methodology:

– mode without adaptation according to the forecast reliability indicator: the forecast (7), (8) is used, however, ρ_t does not affect the reservation; the reservation coefficient $\gamma(\rho_t)$ (14) is fixed at a constant level;

– mode without reconfiguration restrictions: resource profiles are formed without taking into account the restrictions (5), i.e., without using projection procedures (18), (19), which makes it possible to assess the impact of reconfiguration restrictions on the stabilization of the operational contour;

– full mode of the proposed method (*M_full*): ρ_t according to (11), (12) is used in the reservation rules (14), (15), and the reconfiguration restrictions (5) are implemented through procedures (18), (19) during the formation of the control action.

Each mode is evaluated in a series of experimental repetitions with fixed scenario parameters and different implementations of random components (additive telemetry error $\vec{\upsilon}_t$, random perturbations $\vec{\alpha}_t$, process arrivals). This ensures statistical reproducibility without specifying numerical results.

The simulation model is implemented in a software environment [35], which provides step-by-step reproduction of the tact cycle and storage of service execution logs. For reproducibility, the following are fixed: the values of all model parameters (m, T, W, L, κ, $\rho_{\min}$, Δ_ζ, Δ_ς, $\gamma_{\min}$, $\gamma_{\max}$, η, λ) initial conditions $\vec{r}_0$, generation rules $\vec{\alpha}_t$ in (29) and process generation rules C_t, $\vec{q}_{i,t}$, $s_{i,t}$, $\delta_{i,t}$ in (21)–(24). The structure of logging trajectories of variables $\vec{r}_t$, $\tilde{\vec{r}}_t$, $\hat{\vec{r}}_{t+\ell|t}$, ρ_t, $\vec{a}_t^{\,\zeta}$, $\vec{a}_t^{\,\varsigma}$ and control actions $\vec{u}_t$ is recorded separately, which provides the possibility of checking the correctness of the implementation of constraints (3)–(6), (25)–(27) and rule (12) during further analysis.

4. 7. Replication package and ensuring reproducibility of experiments

A complete set of primary time series, summary tables and generated figures for all simulation scenarios is placed in the replication package, which is publicly available [35]. The package contains input data, scenario settings, and software scripts for reproducing calculations and constructing graphical materials. This ensures the verifiability and reproducibility of the experiments performed under the same simulation conditions.

In the replication package, the results are arranged by simulation scenarios and control modes. At the top level, there are directories *S1_baseline, S2_link_instability, S3_resource_degradation, S4_critical_bursts, S5_combined*, which correspond to the five scenarios described in our study. In each scenario catalog, a complete set of artifacts is formed for the compared control modes: *M_full* (full configuration of the method using the reliability indicator ρ_t and reconfiguration constraints), *M_no_inertia* (mode without reconfiguration constraints), and *M_no_rho* (mode without adaptation of the reservation by ρ_t, i.e., with fixed γ).

Three groups of data were generated for each scenario: primary time series, summary tables, and visualizations. Primary time series are provided by the files *timeseries_M_full.csv*, *timeseries_M_no_inertia.csv*, *timeseries_M_no_rho.csv*, which contain trajectories of key model variables in discrete time (resource state, estimates/forecast values, ρ_t indicator, resource allocation parameters, control actions and dispatching variables). Summary indicators are provided by the files *summary_M_full.csv*, *summary_M_no_inertia.csv*, *summary_M_no_rho.csv*, which aggregate the results over the simulation interval (the proportion of cycles fulfilling operational constraints, characteristics of deviation values from the guaranteed limit, intensity of reconfigurations, dispatching indicators, etc.). Additionally, integrated *summary_all.csv* and *summary_all_wide.csv* are provided at the top level of the package, which provide a comparison of modes between all scenarios.

The visualizations in each scenario directory have a unified naming scheme *Fig_5_k_<type>_M_<mode>.png*, where the index $k \in \{1,\ldots,5\}$ corresponds to the figure number in our study, *<mode>* to the control mode, and *<type>* to the thematic block of results. In particular:

– *Fig_5_1_survivability_...* – indicators of compliance with operational requirements/integral performance metrics;

– *Fig_5_2_forecast_...* – characteristics of the forecast block and the confidence indicator ρ_t;

– *Fig_5_3_reserve_...* – formation/use of the reserve and related values;

– *Fig_5_4_reconf_...* – characteristics of reconfigurations (intensity, frequency or amplitude of changes in the distribution profile);

– *Fig_5_5_dispatch_...* – results of dispatching critical processes.

A separate figure *Fig_5_6_methods_comparison.png* presents a summary comparison of modes by key metrics within the corresponding scenario.

Thus, any figure or table can be uniquely identified by the pair (scenario, mode), as well as by the thematic index of the results block (*survivability/forecast/reserve/reconf/dispatch*), which ensures the reproducibility and verifiability of the experimental conclusions reported in our study.

5. Results of investigating the operational resource management of a mobile platform to ensure the survivability of an information system

5. 1. Operational survivability requirements and the resource profile of critical processes

Within the framework of the vector model built, the operational requirement for the survivability of critical processes on the control cycle is formalized as the non-negativity of the minimum reserve between the resource provision of critical processes and the minimum guaranteed profile. To quantitatively fix this requirement, a scalar indicator of the minimum reserve is introduced:

$$s(t) = \min_{i \in \{1,\ldots,m\}} \left(a_i^{\zeta}(t) - r_i^{\zeta,\min} \right),$$

$$\vec{a}^{\zeta}(t) = \left[a_1^{\zeta}(t), \ldots, a_m^{\zeta}(t) \right]^{\top},$$

$$\vec{r}^{\,\zeta,\min}(t) = \left[r_1^{\zeta,\min}(t), \ldots, r_m^{\zeta,\min}(t) \right]^{\top}. \quad (31)$$

In formula (31): $\vec{a}^{\zeta}(t)$ – resource distribution vector for critical processes in cycle t; $\vec{r}^{\,\zeta}(t)$ – minimum guaranteed resource profile of critical processes; m – number of aggregated resource types. All components in (31) are given in a consistent (normalized) scale of aggregated resources, which ensures comparability of components.

The operational survivability constraint in discrete time takes the form

$$s(t) \geq 0, \ t = 0, 1, \ldots, T-1. \quad (32)$$

That is, at each tact cycle, critical processes receive a resource not lower than $\vec{r}^{\,\zeta,\min}$ for each type of resource.

To experimentally confirm the implementation of (32) in the simulation scenarios, the fraction of tact cycles at which the constraint is met was used

$$p_{ok} = \frac{1}{T} \sum_{t=0}^{T-1} \Im\left(s(t) \geq 0\right), \quad (33)$$

as well as distribution indicators $s(t)$, characterizing the degree of exceeding the minimum guaranteed limit (average value and 1%-quantile as an indicator of the approximate lower level $s(t)$, less dependent on single extreme values).

Table 1 shows the implementation of the operational constraint (32) for the proposed method (*M_full* mode) in five typical scenarios. In all scenarios, $p_{ok} = 1.000$ is obtained, i.e., the minimum guaranteed profile of critical processes is maintained at each control cycle. At the same time, the value of indicator $s(t)$, reflecting the minimum exceeding of the minimum guaranteed profile, varies depending on the nature of the destructive effects. The scenario with critical load surges (S4) is closest to the limit (32), in which the 1%-quantile $s(t)$ decreases to 0.105, which indicates a reduction in the minimum exceeding while simultaneously observing the constraint (32).

Table 1

Performance indicators of operational survivability limit (32) for critical processes (*M_full* mode, $T = 600$)

Scenario	p_{ok} (share of tacts with $s(t) \geq 0$)	$\bar{s}$ (mean)	$s_{0.01}$ (1%-quantile)
S1_baseline	1.000	0.181	0.118
S2_link_instability	1.000	0.195	0.120
S3_resource_degradation	1.000	0.183	0.117
S4_critical_bursts	1.000	0.169	0.105
S5_combined	1.000	0.201	0.126

The graphical interpretation of the execution of the constraint (32) for the baseline scenario S1. is shown in Fig. 1.

In Fig. 1, the curve $s(t)$ is defined from (31). Throughout the entire simulation interval, the curve is positive, i.e., it does not cross the zero limit, which meets the requirements of (32). For *S1_baseline* we obtained: $\min_t s(t) = 0.115$, $\bar{s} = 0.181$, $s_{0.01} = 0.118$, which is consistent with the tabular estimates and confirms the presence of a positive deviation from the minimum guaranteed profile $\vec{r}^{\,\zeta,\min}$ during tact control. The dotted line indicates the limit $s(t) = 0$, which corresponds to the operational survivability limit (32).

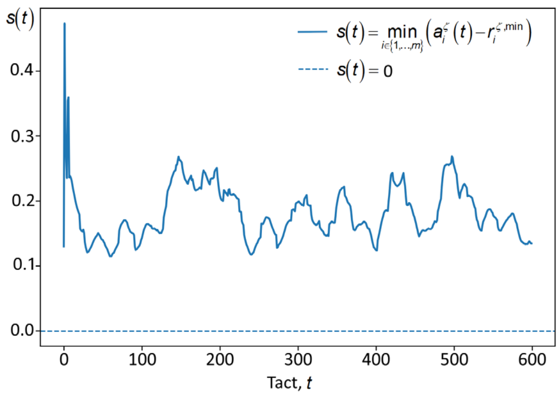

Fig. 1. Minimum resource surplus relative to the minimum guaranteed critical process profile $s(t)$ in the *S1_baseline* scenario (*M_full* mode)

Thus, our results ((31)–(33), Table 1, Fig. 1) formalize the operational survivability requirements and the resource profile of critical processes.

5. 2. Forecast of the resource state of an information system on a mobile platform and assessment of the reliability of the forecast

To assess the impact of intermittent network connectivity on the quality of short-term forecasting, the *S2_link_instability* scenario was considered, in which the resource state of ISMP changes unevenly, in particular with sharp transitions caused by the degradation and restoration of exchange channels. Under these conditions, the forecast is formed one tact cycle ahead and is used as an information component of the operational decision on resource allocation. For quantitative analysis, the error vector of the one-step forecast is introduced

$$\vec{e}(t)=\vec{r}(t)-\hat{\vec{r}}^{(1)}(t),\; t=0,1,\ldots,T-1. \quad (34)$$

To quantify the forecasting accuracy, the mean absolute error (MAE) [36] and root mean square error (RMSE) [37] indicators were used, calculated over all resource components and all cycles:

$$\text{MAE}=\frac{1}{Tm}\sum_{t=0}^{T-1}\sum_{i=1}^{m}\left|e_{t,i}\right|, \quad (35)$$

$$\text{RMSE}=\sqrt{\frac{1}{Tm}\sum_{t=0}^{T-1}\sum_{i=1}^{m}e_{t,i}^{2}}. \quad (36)$$

In the $S2$ scenario, MAE = 0.443 and RMSE = 0.719 were obtained. The increased values of these indicators are due to cycles in which they undergo sharp changes due to breaks and restoration of network connectivity, i.e., it has pronounced non-stationarity.

The key element of the proposed method is an explicit assessment of the reliability of forecast $\rho_t \in [0, 1]$, which is interpreted as a scalar indicator of the reliability of forecast information in the current cycle and is used to select the resource management mode. In the implementation of the experimental package, ρ_t is directly reflected in the control parameter $\gamma(t)$, which determines the level of reservation (the share of the resource reserved for supporting critical processes), according to the linear rule

$$\gamma(t)=0.55-0.45\rho(t). \quad (37)$$

Thus, a decrease in ρ_t leads to an increase in $\gamma(t)$, i.e., to increased redundancy, while an increase in ρ_t reduces $\gamma(t)$ and shifts control to a less conservative mode.

For the *S2_link_instability* scenario, the following average and low-level characteristics of ρ_t were obtained: $\bar{\rho}=0.666$, $\rho_{0.10}=0.543$, $\rho_{0.01}=0.489$, $\min\rho=0.445$. Within the simulation, approximately 11.2% of cycles are characterized by $\rho_t<0.55$, and 3.8% of cycles are characterized by $\rho_t<0.50$. These intervals correspond to episodes of reduced reliability of forecast information, for which it is advisable to apply more conservative settings for resource redistribution.

Fig. 2 shows a typical implementation of a one-step forecast for one resource component ($r_0(t)$ and $\hat{r}_0^{(1)}(t)$, as well as the ρ_t trajectory, are shown).

During sharp changes in the actual state (jumpy resource transitions), the forecast shows a systematic deviation, while ρ_t simultaneously decreases, which serves as a formalized basis for switching to a regime with enhanced redundancy according to rule (37). Unlike approaches in which uncertainty is taken into account indirectly through the randomness of the environment, in this formulation the reliability of the forecast is given by an explicit scalar indicator ρ_t, included in the operational control mechanism as a formal regulator.

Thus, the forecast of the resource state of ISMP and quantitative estimates of the reliability of the forecast, suitable for use in operational resource management rules, have been obtained.

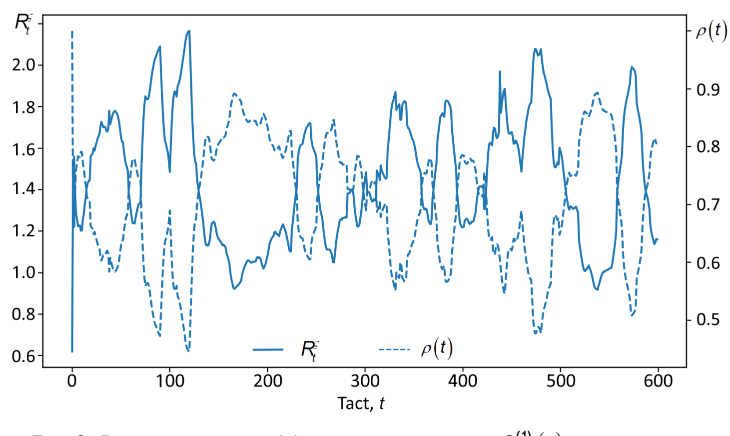

Fig. 2. Resource state $r_0(t)$, one-step forecast $\hat{r}_0^{(1)}(t)$, and forecast confidence factor ρ_t in the *S2_link_instability* scenario (*M_full* mode)

5. 3. Dynamic resource reservation for critical processes support

To test the dynamic reservation rule, the *S3_resource_degradation* scenario was considered, in which the available resource of the mobile platform degrades over time, which leads to episodes of decreasing deviation $s(t)$ from the minimum guaranteed profile of critical processes. Under these conditions, the reserve $\vec{a}_t^{\varsigma}$ is interpreted as a buffer resource component that is maintained available within the control cycle and adjusted depending on the predicted state of the resource and the reliability indicator. To match the reservation level with the reliability of the forecast information, a weighted combination of two components was used – nominal and conservative

$$\vec{a}_t^{\varsigma} = \left(1-\gamma(t)\right)\vec{a}_t'^{\varsigma}(t) + \gamma(t)\vec{a}_t''^{\varsigma}(t). \quad (38)$$

In formula (38), $\vec{a}_t'^{\varsigma}$, $\vec{a}_t''^{\varsigma}$ are the vectors of budget shares (by resource types) that are held as a reserve, where $\vec{a}_t'^{\varsigma}$ is obtained from the nominal (expected) assessment of the resource state, and $\vec{a}_t''^{\varsigma}$ is oriented towards a conservative (pessimistic) assessment of the state.

For quantitative analysis of the dynamics of reservation, a scalar characteristic of the total volume of the reserve is introduced as the L_1-norm of the reserve vector

$$R_t^{\varsigma} = \left\|a_t^{\varsigma}\right\|_1 = \sum_{i=1}^{m} a_t^{\varsigma,i}, \quad (39)$$

which provides a generalized estimate of the level of reservation regardless of its distribution between the resource components.

According to the simulation results for *M_full* in the *S*3 scenario, $\bar{R}_{\varsigma} = 1.458$, $R_{\varsigma}^{0.95} = 1.983$, $\max R_{\varsigma} = 2.165$, $\min R_{\varsigma} = 0.620$ were obtained. The average value of the forecast reliability indicator is $\bar{\rho} = 0.700$, and the minimum ρ_t values reach 0.446. The dependence of $R_{\varsigma}(t)$ on ρ_t has a pronounced inverse character (correlation coefficient – 0.999), which is consistent with rules (37)–(39): with a decrease in ρ_t, $\lambda(t)$ increases, and the total volume of the reserve increases.

The reaction of the reservation rule to episodes of reduced forecast reliability was separately tested. For cycles in which $\rho_t < 0.55$ (about 9% of the interval), we obtain $\bar{R}_{\varsigma} = 2.001$, and for the remaining cycles – $\bar{R}_{\varsigma} = 1.404$. This means that the reservation is adaptive – in cycles with low ρ_t) the total volume of the reserve increases, while in cycles with high ρ_t – it decreases. Comparison with the mode without using ρ_t (where $\rho_t \equiv 1$ and fixed $\lambda(t)$) shows that in 59.3% of cycles $R_{\varsigma}(t)$ under the *M_full* mode is lower than the fixed reserve level, and in 40.7% of cycles – higher. Therefore, the proposed mechanism provides a temporary concentration of the reserve in intervals of increased forecast uncertainty.

Fig. 3 shows a typical implementation of trajectories $R_{\varsigma}(t)$ and ρ_t in the resource degradation scenario.

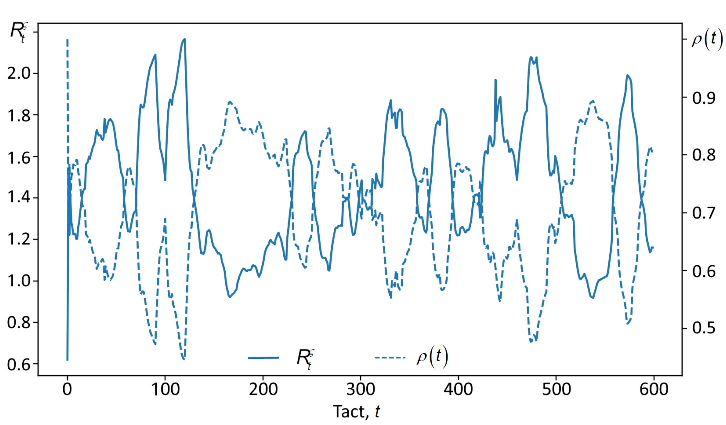

Fig. 3. Total reserve volume $R_{\varsigma}(t)$ and forecast confidence factor $\rho(t)$ in the *S3_resource_degradation* scenario (*M_full* mode)

In Fig. 3 it is seen that the decrease in ρ_t is accompanied by the increase in $R_{\varsigma}(t)$, i.e., rules (38), (39) ensure the coordination of the level of reservation with the reliability of the forecast information. Such a dependence is important for combining reservation with reconfiguration procedures and tact dispatching in the operational resource management loop.

Thus, a procedure for dynamic resource reservation has been formed, which specifies the volume and structure of the reserve for critical processes when the available resource changes.

5. 4. Limiting the intensity and frequency of resource allocation reconfigurations

To verify the role of reconfiguration regulation, the *S4_critical_bursts* scenario was considered, in which the critical load has an impulse character (bursts), which initiates sharp changes in the target resource profile. Under these conditions, the reconfiguration intensity at cycle *t* is quantitatively characterized by the rate of increase of the control action vector (resource profile) relative to the previous cycle

$$I_{\chi}(t) = \left\|\Delta\vec{a}_t\right\|_1 = \left\|\vec{a}_t - \vec{a}_{t-1}\right\|_1. \quad (40)$$

The reconfiguration constraints proposed in the method are set in the form of a restriction on the permissible step of changing the resource profile in one cycle and a restriction on the frequency (intensity) of rearrangements in the sliding window

$$I_{\chi}(t) \le I_{\max}. \quad (41)$$

In formula (41), $I_{\max}$ is the maximum permissible value of the change in the resource profile, taking into account restructuring delays and overhead costs

$$\sum_{\tau=t-W+1}^{t} \Im\left(I_{\chi}(\tau) > \varepsilon\right) \le N_{\max}. \quad (42)$$

In formula (42), W is the window length (in cycles); $N_{\max}$ is the allowable number of cycles with significant reconfiguration within this window; ε is the insensitivity threshold that cuts off insignificant changes in $I_{\chi}(t)$ due to numerical errors and small fluctuations; $\Im(\cdot)$ is the indicator function.

Fig. 4 shows the implementation of $I_{\chi}(t)$ for the *M_full* mode, subject to constraints (5.11), (5.12). The selection of the upper 5% $I_{\chi}(t)$ values allows us to identify cycles in which the control loop initiates the largest amplitude changes in the resource profile in response to pulsed load surges.

Quantitative assessment [35] shows that the introduction of reconfiguration constraints reduces the total amount of resource profile changes over the entire simulation interval – for the *M_full* mode $I_{\chi} = 0.0600$ versus 0.0700 in the *M_no_inertia* variant, which corresponds to a reduction of ≈14%. Additionally, a significant limitation of the extreme values of the reconfiguration step is observed – the maximum $I_{\chi}(t)$ value decreases from 4.323 (without corresponding constraints) to 2.084, i.e., by approximately 52%. This result is consistent with the content of constraint (41) – large amplitude profile changes in one cycle are replaced by a sequence of smaller adjustments, which is consistent with the assumption of inertial reconfigurations and the presence of overhead costs for their implementation on a mobile platform.

At the same time, in scenario *S4*, the minimum guaranteed resource profile for critical processes is maintained in all cycles. Therefore, the differences between the methods are manifested in the nature of the control actions, that is, in the ability of the control loop to stabilize the change in the resource profile in the presence of pulse bursts of critical load.

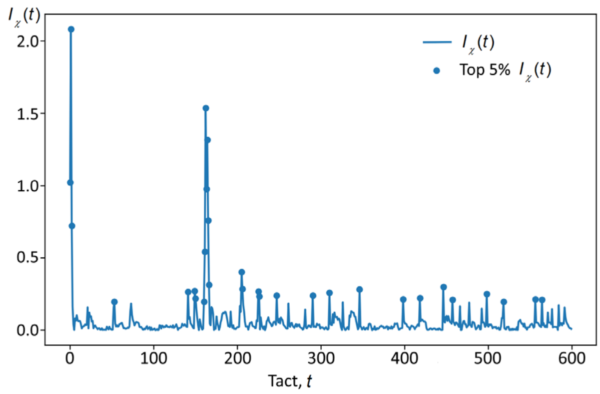

Fig. 4. Intensity of reconfiguration of the distribution profile $I_\chi(t)$ in the *S4_critical_bursts* scenario – comparison of the *M_full* and *M_no_inertia* modes

Thus, formalized constraints on the intensity and frequency of resource allocation reconfigurations are given and their parameters are given for the scenarios under study.

5. 5. Dispatching of critical processes in real time taking into account priorities and permissible delay

The dispatching task considers a combined scenario *S5_combined*, in which intermittent connectivity, degradation of the available resource, pulse bursts of critical load, delays and overhead costs of reconfigurations simultaneously operate. The operation of the dispatching mechanism is considered under conditions when in individual cycles the proportion of processes approaching the limit time requirements increases, while the available resource and permissible intensity of reconfigurations change unevenly.

To quantify the cycles in which critical processes require immediate start, an indicator is introduced

$$n_u(t)=|U(t)|. \quad (43)$$

In formula (43), $U(t)$ is a subset of critical processes with zero allowable delay in cycle t. Thus, $n_u(t)$ reflects the number of processes for which the time allowance for postponing execution has been exhausted, i.e., execution must be started in the current cycle.

The fact of non-fulfillment of the start requirement in the current cycle for processes with zero allowable delay is recorded by a counter

$$m_u(t)=\sum_{p\in U(t)} \mathbf{1}\{p\notin E(t)\}. \quad (44)$$

In formula (44): $E(t)$ is the set of critical processes allowed by the dispatcher to execute in cycle t; $\mathbf{1}\{\cdot\}$ is the indicator function (takes the value 1 if the condition in brackets is true, and 0 otherwise). The accumulated number of such cases in the simulation interval is defined as

$$M_u(t)=\sum_{\tau=1}^{t} m_u(\tau), \quad (45)$$

which corresponds to the solid curve in Fig. 5.

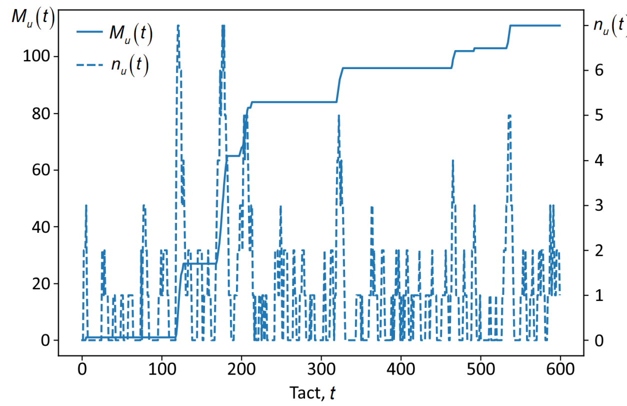

Fig. 5. The tact rate of critical processes with zero allowable delay $n_u(t)$ and the cumulative number of their non-tolerances $M_u(t)$ in the *S5_combined* scenario (*M_full* mode)

According to the simulation results for the *M_full* mode in the *S5_combined* scenario, the following generalized dispatching characteristics were obtained. At the interval $T=600$ cycles, the total number of processes with zero permissible delay (i.e., those that should be allowed to execute in the current cycle) is $\sum_t n_u(t)=647$. The total number of cases of non-admission of such processes in the cycle of the requirement occurrence is equal to $\sum_t m_u(t)=111$, which corresponds to the relative frequency of non-admissions $111/647\approx 0.1716$. The fraction of cycles without non-admissions for processes with zero permissible delay is determined as 0.9067. The operational limitation of the minimum guaranteed resource profile for critical processes is performed in each cycle (the fraction of cycles is 1.0), which confirms the operability of the combination of reservation and dispatching precisely in terms of ensuring a guaranteed level of resource support for critical processes.

Analysis of the plots in Fig. 5 reveals that the cumulative number of non-admissions of urgent processes $M_u(t)$ has a stepwise nature and is formed mainly in short intervals of increased concentration of urgent requirements. The most intensive intervals of accumulation of omissions are observed in groups of cycles 118–127, 169–182, 198–213, 320–327, which correlates with local maxima of $n_u(t)$ (up to 7 urgent processes in a cycle). This means that in the absence of sharp surges of urgent requirements, the dispatching procedure ensures timely admission of such processes to execution. Cases of refusal of admission occur primarily in short episodes of sharp growth of $n_u(t)$, when the total volume of urgent resource requirements exceeds the resource budget available in the cycle, taking into account the inertia of reconfigurations.

The mode of intra-cycle reserve involvement (redistribution of part of the reserve resource in favor of critical processes without changing the profile by reconfiguration) is separately evaluated. Under the *M_full* mode, the use of this mechanism was recorded in approximately 6.67% of cycles, and the maximum value of the intra-cycle additional allocation (by L_1-measure by resource components) reached 1.56. The obtained values indicate that the reserve is used selectively, that is, only in cycles with peak urgent requirements. The reserve does not go into systematic use, which could worsen the consistency of resource distribution between cycles and enhance oscillatory modes in the operational circuit.

Thus, a dispatching procedure has been formed that determines the order of servicing critical processes by priorities and the maximum permissible delay in each control interval.

6. Discussion of the results of devising a method of predictive-adaptive resource redistribution with dispatching of critical processes

The results obtained within the framework of our research are explained by the fact that the proposed operational resource management circuit combines three complementary mechanisms:

– explicit parameterization of forecast uncertainty through the forecast reliability indicator ρ_t and the associated reservation mode parameter $\gamma(t)$ ((34)–(37), Fig. 2);

– adaptive dynamic reservation with the transition between the nominal and conservative components depending on ρ_t ((38), (39), Fig. 3);

– formalization of profile reconfigurations restrictions by the magnitude of the change between cycles and the frequency of reconfigurations ((40)–(42), Fig. 4) with subsequent dispatching ((43)–(45), Fig. 5).

This circuit architecture explains why, in episodes of sharp non-stationarity, the ISMP changes the control mode within each operational control cycle. This maintains the resource profile of critical processes and reduces the risk of oscillatory resource allocation modes.

The results of solving the problem of predicting the resource state of an information system on a mobile platform and assessing the reliability of the forecast in a scenario of unstable connectivity are explained by the fact that the breaks in the exchange channels change the structure of available information and cause jump-like transitions in the resource state r_t, which increases the error of the one-step forecast $e(t)$ ((34)–(36) and Table 2). In such episodes, the forecast reliability indicator ρ_t naturally decreases (Fig. 2), therefore, the threshold rule (37) increases $\gamma(t)$ and transfers the operational circuit to a conservative control mode. In fact, ρ_t acts as a measure of the consistency of the forecast under the current mode. That is, when the forecast reliability indicator decreases, the control mechanism reduces the dependence of the control decision on the forecast component and increases the reservation, which is critical for cyclic dispatching and resource allocation.

The results of solving the problem of dynamic resource reservation for maintaining critical processes in a resource degradation scenario are explained by the direct dependence of the reserve resource on $\gamma(t)$ in (38). As a result, a controlled inverse relationship is observed between ρ_t and the scale of reservation $R_\varsigma(t)$ ((39), Fig. 3). In cycles with a reduced ρ_t, the reserve increases, and in cycles with a high ρ_t, it decreases, without forming a stable excessive conservatism. In essence, this means that the reserve is used as a cycle mechanism for compensating for forecast uncertainty, and not as a statically fixed reserve block that equally limits available resources regardless of the current resource state r_t.

The results of solving the problem of introducing restrictions on the intensity and frequency of resource allocation reconfigurations in the scenario of critical load surges are explained by the fact that in the absence of profile reconfigurations restrictions, surge compensation is implemented through significant changes in $\vec{a}(t)$. This increases the peak values of the reconfiguration intensity $I_\chi(t)$ according to (40) and creates conditions for oscillatory modes. The introduction of restrictions (41), (42) reduces the instantaneous value of the profile change and, accordingly, the peak values of the restructuring (Fig. 4), stabilizing the operational circuit by taking into account the inertia of the reconfiguration and overhead costs. The reduction in the average and maximum $I_\varsigma(t)$ values is a direct consequence of the fact that the reconfiguration is modeled as a process limited in speed and frequency, and not as an instantaneous action with zero resource costs.

The results of solving the problem of dispatching critical processes in real time, taking into account priorities and permissible delay in the combined scenario are explained by the fact that dispatching functions as a tact mechanism for coordinating the available resource, reserve, and current time requirements of critical processes. This is manifested in the stepwise accumulation of $M_u(t)$ according to (45) – violations of the time requirements for the execution of critical processes are concentrated in short episodes of peak $n_u(t)$ according to (43) (Fig. 5). That is, they have a causal relationship with pulse loads and reconfiguration constraints.

The execution of the minimum guaranteed profile for critical processes is ensured in each simulation cycle, which is a fundamental difference of the cycle approach. The operational requirement is formulated in a cycle form and checked in each control cycle. The execution control is carried out by cycle values, without switching to averaging over a long interval.

Compared with the known approaches to resource management in MEC/edge-cloud, where approaches to optimization of delays, energy consumption or aggregated functionalities on average are widespread ([13–18, 28]), a different class of properties is formed in our study. The proposed operational circuit introduces operationally-oriented requirements for survivability as an integrated control element and reflects them in the reserve construction structure (38), (39) and in the profile reconfigurations constraints (41), (42). Experimental verification of these provisions is shown in Fig. 3, 4.

In learning-based approaches to offload computation, uncertainty is typically accounted for statistically through environmental data [16–18] or through mechanisms for rapid policy adaptation between scenarios [19–21]. In this paper, forecast uncertainty is parameterized by a forecast confidence indicator ρ_t and incorporated into a threshold control mode selection rule (37), which provides adaptive adjustment of the reservation scales according to the current ρ_t value (Fig. 3).

In game models of strategy coordination [22], the main properties are determined by the equilibrium and interactions of participants at longer intervals. In the proposed approach, the problem is formulated in a tact form: stabilization of the resource allocation profile is performed in each operational control cycle due to profile and dispatching reconfigurations constraints (40)–(45), which is consistent with the requirements of the operational resource management loop.

Risk-oriented resource management schemes, in particular based on conditional value at risk (CVaR) and uncertainty models [24, 25], usually relate risk to optimization criteria defined at long intervals. In the proposed operational loop, the forecast reliability indicator ρ_t is used for tact adjustment of the reservation and resource allocation profile, due to which the risk of forecast error is consistent with the specific management decision within each tact cycle.

From the perspective of the issues formulated in this study, our results are summarized in the form of three key provisions:

– it is shown that guaranteed maintenance of the resource profile of critical processes in each cycle can be integrated into the operational circuit without reduction to averaged indicators. This is implemented through the mechanisms of reservation and dispatching (38), (39), (43)–(45) and is confirmed graphically (Fig. 5).

– an explicit consideration of the reliability of the forecast is demonstrated – the indicator ρ_t is not considered as a hidden parameter of the mode, which is formed "on average" by the statistics of the environment, but directly determines the choice of the control mode through $\gamma(t)$ (37). This explains the change in the scale of reservation and the reaction of the operational circuit under conditions of unstable connectivity (Fig. 2, 3);

– the constraints on the intensity and frequency of reconfigurations (41), (42) are formalized and their stabilizing effect is shown in scenarios where, without such constraints, oscillatory modes of resource allocation arise (Fig. 4).

The results reported here are expedient to be applied in the tasks of operational management of ISMP resources in distributed border-cloud environments. Typical areas are:

– transport border computing (support of services on board vehicles with the transfer of tasks to border nodes);

– robotic complexes and unmanned platforms;

– mobile measuring and monitoring information systems;

– industrial Internet of Things systems with mobile gateways;

– as well as hybrid infrastructures, in which part of the processing process is performed locally and part in the cloud environment.

The results are applicable to information systems in which critical functions must be guaranteed to be performed in each control interval under conditions of rapid changes in computational load and resource availability.

The limitations of the study, important for practical application, include aggregated description of resources and loads (without detailing hardware components), discretization of time by control cycles, and use of typical scenarios. The prediction reliability indicator ρ_t and the parameters of profile reconfigurations constraints ($I_{\max}$, $N_{\max}$, W, ε) require adjustment for the class of mobile platform and telemetry channels.

A necessary condition for the application of the devised method is the operational determination of the set of critical processes of the system, their functional tasks and minimum permissible resource profiles for each control interval. It is also assumed that there is a predictive assessment of resource availability in a short interval with parameterized reliability, and resource profile reconfigurations must be technically possible.

Insufficient accuracy of telemetric observations reduces the informativeness of the ρ_t indicator. At the same time, at small limit values of $I_{\max}$ and $N_{\max}$, the speed of adaptation of the operational circuit to pulsed load changes may decrease. Under peak load modes, dispatching may lead to the fact that some critical processes do not receive resource provision for execution within the current cycle. This should be interpreted as an operational compromise between meeting time requirements and limited resource profile reconfigurability.

The disadvantages of this study are related to the fact that the experimental verification was performed in a simulation environment and is based on generalized metrics. For full technological validation of the results, a prototype test is required, taking into account real-world reconfiguration delays, telemetry limitations, and resource heterogeneity. An additional limitation is that the communication rule $\rho_t \mapsto \gamma(t)$ is given by a simple function (37). This form increases interpretability but may be suboptimal for certain classes of platforms and require adaptive tuning.

In real ISMPs, the expected effect is to reduce the frequency of short-term performance failures of critical processes during communication breaks between ISMP components or changes in channel bandwidth. This is explained by the fact that in cycles with reduced forecast reliability, the scale of redundancy will increase, and the intensity of reconfigurations will decrease.

In mobile robotic and unmanned platforms, more stable resource provision of navigation and control processes during degradation of mobile platform resources is expected. Under pulsed loads, restrictions on reconfigurations reduce the risk of oscillatory modes that arise in the absence of requirements for the frequency of resource profile reconstruction.

In the industrial Internet of Things systems with mobile gateways, an increase in overall system survivability is expected due to priority collection and primary processing of data during connectivity losses. Dispatching coordinates the available resource, redundancy, and time requirements in each control interval, which reduces the risk of disruption of priority procedures.

Therefore, the use of the devised method at the stage of organizing the ISMP provides for an increase in the proportion of control intervals in which the minimum permissible resource profile of critical processes is fulfilled without averaging. Limitations on the step and frequency of reconfigurations reduce the peak intensity of restructuring, reduce oscillatory modes, and increase the survivability of ISMP under the action of destructive influences.

Further development of our research should focus on three areas:

– the first direction is associated with the expansion of the ρ_t formation methodology for partial observability modes and heterogeneous telemetry channels, in particular with the use of adaptive tuning of the parameters for assessing the reliability of the forecast without losing the interpretability of the threshold control rule;

– the second direction is to reconcile the tact operational requirements with risk-oriented measures through the quantitative assessment of the forecast error for critical processes and the subsequent reflection of this risk in the reservation parameters and in the profile reconfigurations constraints;

– the third direction involves the transition from an aggregated resource model to a multi-resource formulation with formalized inter-resource dispatching rules, which is necessary for practical implementation on actual mobile platforms.

7. Conclusions

1. To ensure the requirements for the survivability of the information system on the mobile platform with respect to critical processes, a system of vector constraints in the form of inequalities has been formed. The input values are the minimum required resource profile of critical processes for each type of resource and the current resource distribution. The output value is the resource reserve relative to the minimum profile, and the condition for operability is its non-negativity in each control interval. The influence of individual input components is determined by the smallest reserve – the scarce resource component is decisive for fulfilling the constraints. The average value of the minimum resource surplus relative to the minimum guaranteed profile is 0.169–0.201, and the lower level of this surplus is 0.105–0.126. The smallest deviation from the limit is recorded in the scenario with critical load surges, where the lower level is 0.105. In the base scenario, the minimum value of the minimum surplus over the entire modeling interval is 0.115. The result is the introduction

of a mandatory minimum resource limit for the provision of critical processes. This is explained by the fact that the specified limit fixes the minimum permissible level of provision regardless of fluctuations in the load on the information system.

2. For short-term forecasting of the resource state, dependences were obtained that connect the predicted state vector with the forecast error vector and the scalar indicator of the reliability of the forecast information in the control interval. The input values are the predicted and actual resource states. The output values are the generalized error and the reliability indicator, which takes values in the range [0; 1]. The increase in the generalized error corresponds to a decrease in the reliability indicator, and the contribution of individual components is determined by their relative error. A feature of the solution is the use of the reliability indicator as a control value in the operational loop. The average absolute generalized forecast error is 0.443, and the root-mean-square generalized error is 0.719. The reliability indicator of forecast information in 90% of control intervals is not less than 0.543, in 99% of control intervals it is not less than 0.489, and the minimum value is 0.445. At the same time, 11.2% of control intervals are characterized by reliability below 0.55 and 3.8% of control intervals are characterized by reliability below 0.50. This is due to the fact that under destructive influences on ISMP, the reliability of the forecast determines the choice of a more conservative resource management mode.

3. For dynamic resource reservation, a rule for reserve formation as a weighted combination of two components – nominal and conservative – has been constructed. The input values are estimates of the expected and pessimistic resource status and the forecast reliability indicator, and the output values are the reserve vector by resource types and its generalized volume. When the available resource decreases and the forecast reliability decreases, the share of the conservative component increases and the reserve volume increases. The contribution of individual reserve components is determined by those resource types for which the reserve relative to the minimum profile is the smallest. Under the conditions of degradation of the available resource, the generalized reserve volume varies within 0.620–2.165. The minimum value of the forecast reliability indicator is 0.446. The result obtained consists in combining the reserve with the forecast reliability indicator in real time. The relationship between the forecast reliability indicator and the generalized reserve volume has a pronounced inverse character, which is confirmed by the correlation coefficient of –0.999. At the same time, for reliability indicators below 0.55 (approximately 9% of the control intervals), an increased reserve is formed. This is explained by the need to take into account the risk of forecast error at short control intervals.

4. To take into account the inertia of reconfigurations, constraints are formed that specify permissible changes in the resource allocation profile by two parameters – the change step size and the frequency of reconfigurations in a sliding window. The input values are the current and target resource allocation profiles and the parameters of the permissible step and frequency. The output value is the permissible trajectory of profile reconfigurations. Reducing the permissible step and frequency limits the amplitude and repeatability of the configuration, while the changes in those resource components for which the resource costs of reconfigurations are the greatest become decisive. That is, the introduction of constraints reduces the total value of resource profile changes for the entire modeling interval. The obtained value is 0.0600, which corresponds to a decrease of approximately 14% compared to the option without corresponding constraints. A feature of the solution is the introduction of reconfigurations constraints as a component of the resource management method. This is because the delays and overhead of reconfigurations affect the stability of the operational control loop.

5. For dispatching critical processes, a rule for forming an execution plan within the control interval is formed, taking into account the priority of the process and the allowable delay of its execution. The input values are the set of critical processes with specified priorities and the remaining allowable delay, as well as the available resource taking into account the reserve. The output values are subsets of processes assigned to execution in the current control interval and processes transferred to subsequent intervals. The influence of the allowable delay is decisive: processes with the minimum remaining allowable delay receive service priority compared to processes with a larger time tolerance for close priority values. The simulation results show that the total number of cases when a process with zero allowable delay is not assigned to execution in the cycle of the requirement is 111. The total number of processes with zero allowable delay is 647, therefore, the relative frequency of such cases is 0.1716. The proportion of cycles without such cases is 0.9067. The result is a combination of dispatching with operational survivability requirements and redundancy within a single resource management loop. This is explained by the fact that during short-term overloads, the coordinated assignment of processes, prior to their execution, ensures the stability of critical functions.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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The study was conducted without financial support.

Data availability

The manuscript has linked data in the Zenodo data repository. The full set of simulation results (input scenario parameters, time series, summary tables of metrics, and generated primary graphics) is publicly available [35].

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

Authors' contributions

Vitalii Tkachov: Methodology; Software; Validation; Formal analysis; Investigation; Data Curation; Writing – original draft; Visualization; Supervision; Project administration; Corresponding author; **Igor Ruban**: Conceptualization; Writing – review & editing.

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