

INTEGRATED PLANNING OF ACTIVE MOBILE OBJECTS CONTROL SYSTEM WITH ALLOWANCE OF UNCERTAINTY FACTORS

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KEYWORDS

Integrated planning and scheduling, active mobile objects, combined methods of modeling and optimization.

ABSTRACT

The Active Mobile Objects Control System (AMO CS) is the main object of an investigation in the proposed paper. An integrated structure and dynamic models of AMO CS functioning, and combined methods and algorithms of planning and scheduling in the system, are developed. The general advantage of suggested models methods and algorithms is related with comprehensive consideration main constraints of investigation area on the base of integrated approach.

INTRODUCTION

Analysis of the main trends for modern complex organizational-technical systems (COTS) indicates their peculiarities such as: multiple aspects and uncertainty of behavior, hierarchy, structure similarity and surplus for main elements and subsystems of COTS, interrelations, variety of control functions relevant to each COTS level, territory distribution of COTS components.

The preliminary investigations confirm that the most convenient concept for the formalization of COTS control processes is the concept of an active mobile objects (AMO). In general case, it is an artificial object (a complex of devices) moving in space and interacting (by means of information, energy, or material flows) with other AMO and objects-in service [7, 8].

At the conceptual level, the process of AMO functioning can be described as a process of operation execution, while each operation can be regarded as a transition from one state to another one. Meanwhile, it is convenient to characterize the AMO state by the parameters of operations.

The particular control models are based on the dynamic and structural interpretation of operations and the

previously developed particular dynamic models of AMO functioning.

In accordance with the proposed conceptual model of AMO control system (AMO CS), let us introduce the following basic sets and structures.

VERBAL DESCRIPTION OF A SCHEDULING AND RESOURCE ALLOCATION PROBLEM

Let $A = \{A_i, i \in N\}$, $N = \{1, \dots, n\}$ be a set of active mobile objects, elements of COTS. Let us introduce a set $B = \{B_j, j \in M\}$, $M = \{1, \dots, m\}$ of resources and two more sets: a set of interaction operations $D^{(i)} = \{D_{\kappa}^{(i)}, \kappa \in \Phi\}$, $\Phi = \{1, \dots, s_i\}$ and a set of flows $E^{(i)} = \{E_{\rho}^{(i)}, \rho \in \tilde{R}\}$, $\tilde{R} = \{1, \dots, \pi_i\}$. These sets will be used in formal statement of the considered scheduling problem.

The presented considerations permit the following verbal description of the scheduling problem: it is necessary to find such allowable program (a plan of functioning) for activities of AMO that all operations of AMO technological control cycles (TCC) are executed in time and completely, and the quality of support meets the requirements. In addition, if several allowable programs of AMO control are available, the best one would be selected according to the optimality criteria.

DYNAMIC MODELS OF OPERATIONS PLANNING FOR AMO

The formal statement of the scheduling problem will be produced, as it was noted in the introduction, via dynamic interpretation of operation execution processes (Athans, and Falb, 1966; Sokolov, and Kalinin, 1985; Zimin, and Ivanilov, 1971).

Models for program control of interaction operations and channels

a) Models of processes:

$$\dot{x}_{ik}^{(o)} = \sum_{j=1}^m \varepsilon_{ij}(t) \cdot \Theta_{ikj} \cdot u_{ikj}^{(o)}, \quad (1)$$

$$\dot{x}_j^{(k,1)} = \sum_{i=1}^n \sum_{\kappa=1}^{s_j} u_{ikj}^{(o)}, \quad (2)$$

$$\dot{x}_{ikj}^{(\pi)} = u_{ikj}^{(\pi)}(t), i=1, \dots, n; \kappa=1, \dots, s_i. \quad (3)$$

b) Constraints

$$\sum_{j=1}^n u_{ikj}^{(o)} \cdot (a_{i(\kappa-1)}^{(o)} - x_{i(\kappa-1)}^{(o)}) = 0, \quad (4)$$

$$\sum_{j=1}^n u_{ikj}^{(o)}(t) \leq 1, u_{ikj}^{(o)}(t) \in \{0,1\}, \quad (5)$$

$$\sum_{i=1}^n \sum_{\kappa=1}^{s_i} u_{ikj}^{(\pi)}(t) \leq R_j^{(\pi)}, \quad (6)$$

$$i=1, \dots, n; \kappa=1, \dots, s_i; j=1, \dots, m.$$

c) End conditions

For the initial time $t = t_0$:

$$x_{ik}^{(o)}(t_0) = a_{ik}^{(o)}; x_{ik}^{(\pi)}(t_0) = d_{ik}^{(\pi)}; x_j^{(k)}(t_0) = d_j^{(k)}. \quad (7)$$

For the end point $t = t_f$:

$$x_{ik}^{(o)}(t_f) = a_{ik}^{(o)}; x_{ik}^{(\pi)}(t_f) = a_{ik}^{(\pi)}; x_j^{(k)}(t_f) \in \mathbf{R}^1. \quad (8)$$

d) Quality measures of schedule for AMO operation

$$J_1^{(o)} = \frac{1}{2} \sum_{i=1}^n \sum_{\kappa=1}^{s_i} \left(a_{ik}^{(o)} - x_{ik}^{(o)} \right) \Bigg|_{t=t_f}; \quad (9)$$

$$J_2^{(o)} = \sum_{i=1}^n \sum_{j=1}^m \sum_{\kappa=1}^{s_i} \int_{t_0}^{t_f} \alpha_{ik}(\tau) u_{ikj}^{(o)}(\tau) d\tau; \quad (10)$$

$$J_3^{(k)} = \frac{1}{2} \sum_{j=1}^m (T - x_j^{(k)}(t_f))^2, \quad (11)$$

$$J_4^{(\pi)} = \frac{1}{2} \sum_{i=1}^n \sum_{\kappa=1}^{s_i} \left(a_{ik}^{(\pi)} - x_{ik}^{(\pi)} \right) \Bigg|_{t=t_f}, \quad (12)$$

where $x_{ik}^{(o)}$ is a variable characterizing the state of operation $D_{\kappa}^{(i)}$. Here we interpret the state of operation as an actual amount of work done by a specified time; $\varepsilon_{ij}(t)$ is a preset matrix time function of time-spatial constraints for interaction between AMO A_i and resource B_j , here $\varepsilon_{ij}(t)=1$ if A_i falls within the interaction zone of B_j , $\varepsilon_{ij}(t)=0$ if not; Θ_{ikj} is a preset matrix that characterizes structure of operation execution, here $\Theta_{ikj}=1$ if the interaction operation $D_{\kappa}^{(i)}$ can be executed on resource B_j and $\Theta_{ikj}=0$ if not; $x_j^{(k)}$ is a variable equal to joint activity duration of resource B_j by the time t ; $u_{ikj}^{(o)}(t)$ is a control input that is equal to 1 if the operation $D_{\kappa}^{(i)}$ involving AMO

A_i is being executed on resource B_j and equal to 0 if not.

The constraints (4) set a sequence of operations of AMO CS. These equations prohibit the execution of operation $D_{\kappa}^{(i)}$ until the previous operation $D_{(\kappa-1)}^{(i)}$ is completed, i.e., $x_{i(\kappa-1)}^{(o)} = a_{i(\kappa-1)}^{(o)}$. Here $a_{i(\kappa-1)}^{(o)}$ is known (preset) value. $x_{ikj}^{(\pi)}$ is a variable that is equal to actual amount of information was processed (transmitted) during the operation $D_{\kappa}^{(i)}$ on resource B_j .

To simplify the expressions describing AMO TCC it was assumed that the operations of TCC are strictly ordered and are executed one after another. The expression (5) is actual for non-separable operations. These constraints mean that at a fixed time each resource B_j can execute at most one operation $D_{\kappa}^{(i)}$.

The constraint (6) sets maximum total intensity of process execution by resource B_j .

End conditions (7), (8) specify the values of variables at the beginning and the end of scheduling period. Here $d_{ik}^{(o)}$, $d_{j\kappa}^{(k,1)}$, $d_j^{(k)}$, $a_{ik}^{(o)}$ are given values, $\mathbf{R}^1 = [0, \infty)$.

The measure (9) of program control quality characterizes the accuracy of end conditions accomplishment or expresses extent of losses caused by disparity. The functional (10) lets specify preferable time gaps for execution of operation $D_{\kappa}^{(i)}$. The quality measure (11) helps to estimate the uniformity of channels use by the end point $t = t_f$ of planning period.

Now the scheduling problem can be formulated as a following problem of dynamic system (1)–(3), program control: it is necessary to find an allowable control $\bar{u}(t), t \in (t_0, t_f]$, that meets the requirements (4)–(6) and guides the dynamic system (1)–(3) from the initial state (7) to the specified final state (8). If there are several allowable control (schedules) then the best one (optimal) should be selected in order to maximize (minimize) the quality measures of program control (9)–(12). The components of the program-control vector $\bar{u}(t)$ possess Boolean values and specify time intervals for works of the appropriate AMO.

Formal problem statement

Also we can present the multiple-model multi-criteria description of AMO program control problem:

$$\begin{aligned} \bar{J}(\bar{x}(t), \bar{u}(t), \bar{\beta}, t) \rightarrow \text{extr}_{\bar{u}(t) \in \Delta}, \quad (13) \\ \Delta = \left\{ \begin{aligned} &\bar{u}(t) \mid \bar{x}(t) = \bar{\varphi}(t_0, \bar{x}(t_0), \bar{x}(t), \bar{u}(t), \bar{\beta}, \bar{\xi}(t), t), \\ &\bar{y}(t) = \bar{\psi}(\bar{x}(t), \bar{u}(t), \bar{\beta}, \bar{\xi}(t), t), \\ &\bar{x}(t_0) \in X_0(\bar{\beta}), \bar{x}(t_f) \in X_f(\bar{\beta}) \end{aligned} \right\}, \end{aligned}$$

The formulas define a dynamic system describing AMO control processes. Here $\vec{x}(t)$ is a general state vector of the AMO CS, $\vec{y}(t)$ is a general vector of output characteristics. $\vec{u}(t)$, control vector, represents AMO control programs (plans of AMO CS functioning). The vector $\vec{\beta}$ is a general vector of AMO CS parameters. The vector $\vec{\xi}(t)$ is a general vector of uncertainty factors. The vector of AMO CS effectiveness measures is described:

$$\vec{J}(\vec{x}(t), \vec{u}(t), \vec{\beta}, t) = \|\vec{J}^{(o)T}, \vec{J}^{(k)T}, \vec{J}^{(\pi)T}\|^T. \quad (14)$$

The indices «o», «k», «π» corresponds to the following models: models of operations control; models of resources control; models of flows control. Expression (16) determines end conditions for the AMO state vector $\vec{x}(t)$ at time $t = t_0$ and $t = t_f$ (t_0 is the initial time of a time interval the AMO CS is being investigated at, and t_f is the final time of the interval).

STRUCTURAL MODEL OF AMO WITH ALLOWANCE OF INCERTANT ENVIRONMENT

Structural representation of AMO can explicitly define the sequence of operations and determine the spatial relationships, technical and technological limitations of various elements of the AMO CS. The structural model has a different interpretation of the dynamic model parameters. The processes are interpreted as a finite set of predefined orders of different types in the sense of queueing theory (QT); \vec{p} are parameters of the distribution of productivity of the resource, which is of stochastic nature, not deterministic as in case of dynamic models; Θ_{ikj} determines the structure of operations, as described in (1); ζ_{ik} corresponds to static priorities of processes: $\zeta_{ik} = \psi_{ik}(t_0), i = 1, \dots, n; \kappa = 1, \dots, s_i$, where $\vec{\psi}(t)$ has been defined in (13). The higher ζ_{ik} the higher the priority of a process; all other parameters are interpreted the same way as in dynamic model.

The simulation of structural model allows approximate the quality measures of schedule for AMO operations (Kokorin, Sokolov 2010, 2011) defined, as a means of values of multiple realization of a process, which will be defined as $\vec{f}(q_0(\vec{\zeta}, \vec{p}))$.

THE METHOD OF RESOLVING THE PLANNING AND RESOURCE ALLOCATION TASKS

We pose the problem of optimizing $J_G = \sum_{i=1}^4 \lambda_i J_i, \lambda_i \geq 0, \sum_{i=1}^4 \lambda_i = 1$ as a function of static

priorities of operations and the maximum limit of resources productivity rates: $J_G = f(q_0(\vec{\zeta}, \vec{p})) \rightarrow \min_{Z, \Omega}$, where $q_0(\cdot)$ determines the all other fixed parameters of the formal model, Z is a set of possible priorities, and Ω is a set of possible rates or resources productivity. In this formulation, the use of unlimited resources allow arbitrarily close to the global optimum J_G . Therefore, it is proposed to add constraints of the form:

$$\begin{aligned} \vec{p} &= (R_1^{(\pi)}, \dots, R_m^{(\pi)})^T, \\ \vec{c}^T \vec{p} &\leq C, \end{aligned} \quad (1)$$

where $\vec{c} = (c_j)^T, j \in M$ – factors determining the cost of one unit of resources productivity maintenance and C is a limit to the total cost of resource maintenance. The uncertainty of dynamic mode $\vec{\xi}(t)$ is included in structural model as a stochastic model of resource allocation, set as an exponential distribution function with a variable parameters \vec{p} .

Priorities $\vec{\zeta}$ represent ordinal values, while the maximum intensity of the resources \vec{p} are continuous and nonnegative. The mixed optimization problems are difficult to solve. We propose to consider the scheme of ν successive iterations in this paper, where iteration consists of two steps and it starts with $\nu = 0$ and $\vec{\zeta}^{(0)} = \vec{\zeta}_g$, where $\vec{\zeta}_g$ – fixed vector of initial priorities, e.g. equal values consider the FIFO discipline.

Phase 1. Optimization of resource allocation for data transmission and processing using a structural model:

$$\vec{f}(q_0(\vec{\zeta}^{(\nu)}, \vec{p})) \rightarrow \min_{\vec{p} \in \Omega}, \quad (2)$$

Phase 2. Dynamic scheduling with fixed vector of resources productivity distribution \vec{p}_ν obtained from previous step:

$$f(q_0(\vec{\zeta}, \vec{p}_\nu)) \rightarrow \min_{\vec{\zeta} \in Z}. \quad (3)$$

For the stopping criteria of the iteration procedure we propose to use one of the following approaches:

- any time algorithm;
- achievement of level $\tilde{\epsilon}$ of a difference values of successive iterations, that is, $\min\{\nu : |f(q_0(\vec{\zeta}^{(\nu)}, \vec{p}_\nu)) - f(q_0(\vec{\zeta}^{(\nu-1)}, \vec{p}_\nu))| < \tilde{\epsilon}\}$
- the value is close (vicinity $\tilde{\epsilon}$) to the global extreme, for the case then convergence could not be met: $\min\{\nu : f(q_0(\vec{\zeta}^{(\nu)}, \vec{p}_\nu)) < \tilde{\epsilon}\}$.

RESOURCE ALLOCATION OPTIMIZATION ALGORITHM

We are going to investigate the influence of the structure of a CTS network.

Two methods are used for optimization of the target function, described earlier in the paper: global search method – the method of psi-transform (CHichinadze 1983), and a method of numerical optimization without calculating derivatives – the method of principal axes of Brent (Brent 1973).

The method of psi-conversion is a method for searching the global extremum of the objective function. It is not critical to the choice of an initial approximation, but requires of significant computational resources in the case when the dimension of parameters to be optimized is increasing. We chose a probability measure on the set of modifiable parameters which the value of a given objective function above a predetermined levels as a psi-function at. Thus, the problem of optimization reduces to finding a solution to the equation with many variables (parameters to be optimized). Using this method as an independent method of optimization often yields results of the very low accuracy.

The algorithm of the global optimization (Algorithm #1):

Step 1.1. The estimation of the spread of values of the objective function by the random test.

Step 1.2. Choose of the value levels $f(q(\bar{\zeta}^*, \bar{p}^{(\pi)})) \geq \sigma_l$, $l \in \{1, \dots, L\}$.

Step 1.3. Define the $\Delta_l = \{\bar{p}: \bar{f}(q(\bar{\zeta}^*, \bar{p})) \geq \sigma_l\}$

Step 1.4. Calculation of mean values of the objective function for each level by the means of the random test.

$$\Psi_l = 1/S \sum_{\Delta_l} (\bar{f}(q(\bar{\zeta}^*, \bar{p})) - \sigma_l), \quad (21)$$

S – number of random generations, \bar{p}_k – parameters of the k -th iteration, $l \in \{1, \dots, L\}$.

Step 1.5. Calculation of the mean values for optimizing parameters for each level.

$$\bar{p}_{il} = S / \Psi_l \sum_{\Delta_l} \bar{p}_i (\bar{f}(q(\bar{\zeta}^*, \bar{p})) - \sigma_l)^\alpha. \quad (22)$$

Step 1.6. The parabolic approximation of Ψ_l and the extrapolation to the level 0 and search for optimal parameters.

Because of the high computational complexity of the method of psi-transformation and its lack of the precision while solving problems of large dimensions are proposed the method of principal axes of Brent. This method focuses on local optimization of functions of several variables without calculating derivatives. In practice, the method proved effective in the solving problems of optimization of network structure, including, for the case when the parameters' space has a large dimension and fairly tight restrictions, the introduction of possible restrictions will be described below. The main drawback of the algorithm, it implements, is the need to specify the initial approximations, which should be calculated for an each task separately. In this case, the algorithm is characterized by two main parameters: the index of

accuracy of the target function and the magnitude of step changes in parameters to be optimized. The first of these determines the moment to stop the iterative process; the second determines the rate of convergence of the algorithm.

The algorithm of the local optimization (Algorithm #2):

Step 2.1. Calculation of initial approximation \bar{p}_0 , which is the final solution of the global optimization algorithm (see the step 5 of previous algorithm).

Step 2.2. The initial directions is defining $U^{(0)} = \{u_i\}_{i=1}^m = I$, where I – the identity matrix of the given dimension.

Step 2.3. Alternately, the optimal value is searched along each direction.

Step 2.4. The direction vector with minimal index is dropped and new vector is substituted in the end of direction matrix $\bar{p}_m - \bar{p}_0$.

Step 2.5. After a complete change of a set of directional vectors U^m , a set of directional vectors is replacing with the orthogonal matrix that approximates the Hessian of the objective function in the point of current value.

Step 2.6. Steps 2.3 – 2.5 is repeating till the achieving the given factor of preciseness: $|\bar{f}_r(q(\bar{\zeta}, \bar{p})) - \bar{f}_{r-1}(q(\bar{\zeta}, \bar{p}))| \leq \hat{e}$, where r is index of successive iterations and \hat{e} – parameter for convergence level.

It proposed to use global optimization method for initial estimation of a local one. Such combination allows achieve a fast convergence for a given task.

The method is proven to converge in case of double continuously differentiable functions, and numerical experiments shows good convergence for wider class of target functions. Same time the method of a global optimization could be adopted to define the maximal possible distance from checked points to the global optimum by setting its parameters.

DYNAMIC SCHEDULING ALGORITHM

Computational scheme of the scheduling algorithm (Algorithm #3) is as follows.

Step 3.1. Setting the rough decision (any valid plan) $\bar{u}_g(t), t \in (t_0, t_f]$. In the special case empty plan ($\bar{u}_g(t) \equiv \bar{0}$) can be selected.

Step 3.2. Integrating basic system of equations (1)–(3) with initial conditions (7) and the $\bar{u} = \bar{u}_g(t)$. Vector $\bar{x}_{(0)}(t)$ obtained as a result of integration. In addition, determine $\bar{J} = \|J_1, J_2, J_3, J_4\|$ at $t = t_f$, which is taken as a record. Calculating the transversality condition which could be found in [...].

Step 3.3. Integrating the conjugate system of equations

$$\begin{aligned} \dot{\psi}_l = & -\frac{\partial H}{\partial x_l} + \sum_{\alpha=1}^{I_1} \eta_{\alpha}(t) \frac{\partial q_{\alpha}^{(1)}(\bar{x}(t), \bar{u}(t))}{\partial x_l} + \\ & + \sum_{\beta=1}^{I_2} \rho_{\beta}(t) \frac{\partial q_{\beta}^{(2)}(\bar{x}(t), \bar{u}(t))}{\partial x_l}, l = 1, \dots, \bar{n} \end{aligned} \quad (18)$$

where H – Hamiltonian [...], η_{α} and ρ_{β} could be found from

$$\begin{aligned} \rho_{\beta}(t) q_{\beta}^{(2)}(\bar{x}(t), \bar{u}(t)) & \equiv 0, \beta = 1, \dots, I_2, \\ \text{grad}_{\bar{u}} H(\bar{x}(t), \bar{u}(t), \bar{\psi}(t)) & = \\ \sum_{\alpha=1}^{I_1} \eta_{\alpha}(t) \text{grad}_{\bar{u}} q_{\alpha}^{(1)}(\bar{x}(t), \bar{u}(t)) & + \\ \sum_{\beta=1}^{I_2} \rho_{\beta}(t) \text{grad}_{\bar{u}} q_{\beta}^{(2)}(\bar{x}(t), \bar{u}(t)), & \end{aligned}$$

where $\bar{\psi}(t)$ is a general vector of the conjugate system of equations, $q_{\alpha}^{(1)}(\bar{x}(t), \bar{u}(t))$ and $q_{\beta}^{(2)}(\bar{x}(t), \bar{u}(t))$ – components of given system of constraints, from $t = t_f$ to $t = t_0$ with $\bar{u} = \bar{u}_g(t)$. At $t = t_0$ we get a first approximation of $\bar{\psi}_i(t_0)$. This completes the iteration $r = 0$.

Step 3.4. From the moment t_0 control $\bar{u}^{(r+1)}(t)$ is sought ($r = 0, 1, 2, \dots$ – number of iterations) based on the maximization of the Hamiltonian $H(\bar{x}^*(t), \bar{u}^*(t), \bar{\psi}^*(t))$ [...]. Simultaneously the main system of equations is integrated. Thus at any given time there is a dynamic decomposition of the main tasks for several mathematical programming problems: linear programming, assignment problems.

The iterative optimization process ends when the following conditions are satisfied: $|J^{(r+1)} - J^{(r)}| \leq \varepsilon$.

Thus $\bar{\psi}(t_0)$ defines vector of associative values of static priority $\bar{\zeta}$ for each operation $D_k^{(i)}$.

CONCLUSION

As a result of the research, the multi-stage procedure for an integrated planning of the AMO CS has been developed. One of its main advantages is a combination of different types of restrictions related to the operation of AMO CS and uncertainties affecting the stability of worked-out plans. The originality of the developed models of planning bases on the fact that each of them takes into accounts the limitations and characteristics of planning procedures that are within each of these structurally formalized. Studies have shown that the basic space-time, technical and technological constraints related to the operation of AMO CS best described by using a previously developed by the authors, models, software operations management and resources. Uncertainty and structural factors were taken into account in the static model. It is shown (Krasnoshokov) that the proposed resource allocation

algorithms provide theoretical and practical convergence and obtaining the planning results in a finite number of steps. The results of computer experiments have confirmed this convergence.

ACKNOWLEDGMENTS

This research is supported by project 2.1/ELRI - 184/2011/14:

«Integrated Intelligent Platform for Monitoring the Cross-Border Natural-Technological Systems» as a part of «Estonia-Latvia-Russia cross border cooperation Programme within European Neighborhood and Partnership instrument 2007-2013».

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