COMPUTER-AIDED DESIGN SYSTEMS

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OPTIMAL CHOICE OF THE TECHNICAL MEANS OF RATE, PITCH AND ROLL CHANNELS SUBSYSTEMS OF NAVIGATION EQUIPMENT SIMULATION TABLE

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Abstract**—***Design of complex large-scale systems has been surveyed. In this article it is proposed multi-level multiobjective optimization methodology that can be implemented in the computer-aided design software for technical means optimal choice.*

Index Terms—Multiobjective optimization; hierarchical multilevel systems; simulation table; genetic algorithm.

I. INTRODUCTION

With the rapid development of unmanned aerial vehicles (UAV) there was necessary to create an integrated navigation systems (INS) that improve accuracy of navigation parameters through the use of UAV navigation systems running on different physical principles (complexing). To solve this problem in the INS are included: inertial navigation systems, which consist of accelerometers and gyroscopes, satellite navigation systems, magnetometers, air signals system, navigation system, odometer system, etc.

During the flight INS are subject to various influences that may adversely affect their accuracy and indicators of reliability, so there is a need for a means of providing technical testing navigation equipment in conditions close to the real flight.

In this paper, to solve this problem there is proposed to use the simulation table (ST), the structure of which is shown in Fig. 1. Simulation table must ensure tests on the parameters close to real, namely the angular positions, overload, angular velocity and acceleration of all control channels. To ensure these parameters on the technical design stage it is necessary to solve the task of developing assembly units, functional task, the task of developing algorithms and software, the task of selecting a set of technical means.

Indicator of efficiency when designing ST are criteria are accuracy, reliability and cost.

$$F = (F_1(x),..., F_i(x),..., F_l(x)), (i = 1,.., l)$$

Optimization problem is proposed to address with these criteria on the basis of a systematic approach when there are three levels of tasks: lower-lower-level goals, coordinating - objectives for the upper (coordinator) and the global – the goal of a whole system. In this regard, there are four different problems [1]: synthesis of coordinating element, methods (procedures) of coordination, problem of modification, decomposition.

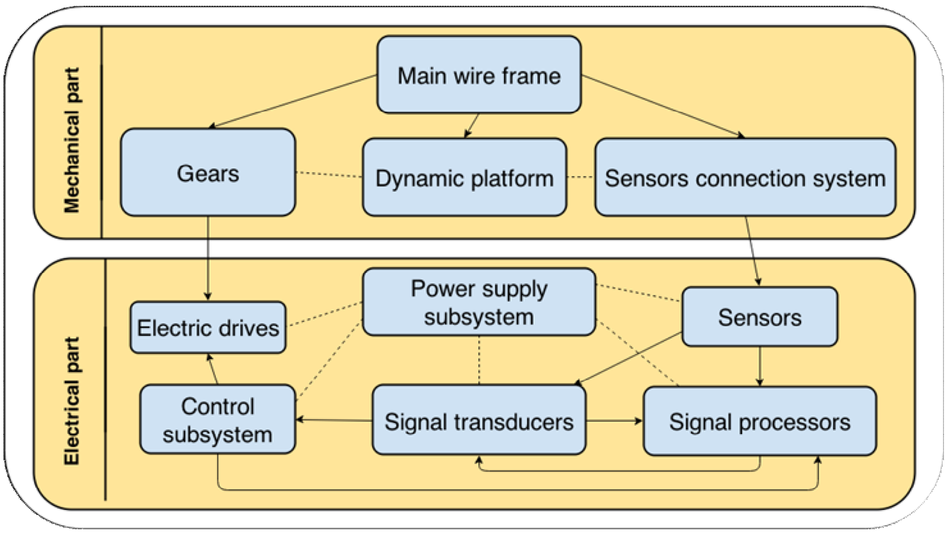

Fig. 1. Structure scheme of the simulation table for navigation equipment testing

It will allow to divide a complex optimization problem into several low-level subtasks. Solution to the global optimization problem is a vector solutions of coordinated lower-level subtasks. Methodology of this decomposition into subtasks and coordination for various models of hierarchical systems is considered in detail by M. Mesarovic, J. Takahara et al [1], [2].

To improve the efficiency of ST design there is proposed computer-aided design (CAD) system, the block diagram of which is shown in Fig. 2.

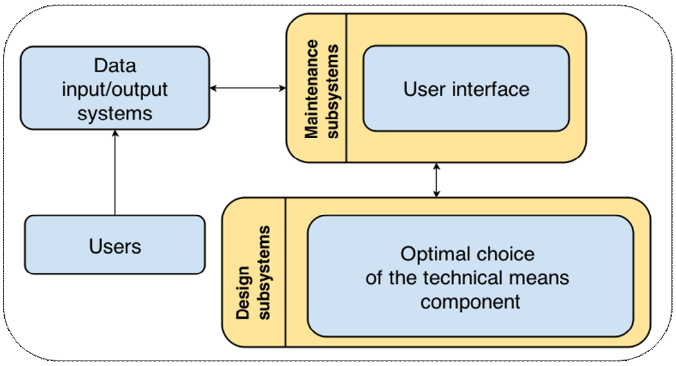

Fig. 2. Structure scheme of CAD software

II. TASK STATEMENT

Consider the problem of multicriteria optimization of complex system consisting of subsystems, which has a two-level hierarchy with the criteria of the upper F and lower layer f. Top-level criteria are essential for all subsystems – performance, accuracy, reliability and cost (F_1, F_2, F_3). On the upper level there are limitations associated with the technical specifications for the entire system, which directly affect the optimization of the subsystems. That are such restrictions as providing predetermined angular positions, velocities, accelerations, mass of equipment under the test, dimensions ($G = \{G_1, G_2, G_3, G_4, G_5\}$).On the lower level design parameters of each subsystem are determined based on their own restrictions (g_j). These values should be defined in an array of variables that would have increased the maximum efficiency of the system, while providing optimality of each subsystem and satisfying all the constraints. Thus, the task has two types of objective functions for the criteria of the upper level and lower-level criteria that are linked through coordinating variables.

We assume that the performance of each subsystem can be expressed in terms of the criteria of technological quality indices f such as:

1. Indices of destination:

a) Classificational (voltage, power).

b) Functional (performance, precision, limits of measurement).

c) Design (weight, dimensions).

d) Maintenance (electric power consumption).

2. Reliability indices:

a) Reliability (mean time to first failure, the probability of failure-free operation for a certain period, the failure rate).

b) Durability.

c) Repairability.

3. Economical use of resources (energy conversion efficiency, energy consumption).

4. Standardization and unification.

5. Security.

6. Resilience to external influences.

7. Economic.

Let us consider the main technological parameters of quality for ST subsystems.

For dynamic platform this is carrying capacity depending on the class of UAV, dimensions.

For gear units this is reliability, dimensions, accuracy, gear ratio, load indices.

For electric drives and control subsystem it is the weight, size, reliability, speed, control equipment, electric performance, stiffness of mechanical characteristics of the drive, smoothness of motion, accuracy of control.

For subsystems of information acquisition and transmission this is accuracy, sample rate, noise immunity.

For power subsystem – it is energy conversion efficiency, dimensions and weight, fault tolerance.

Moreover, all subsystems have their economic indices, such as fair cost.

As it can be seen, technological criteria of quality are comparable and in many cases conflicting.

Simulation table design problem can be represented as a multi-level multi-criteria optimization problem formal statement of which is as follows.

$$\min_{\lambda} F(\lambda, y) = (F_1(\lambda, y), \ldots, F_i(\lambda, y), \ldots, F_l(\lambda, y)),$$

$(i = 1,..,l)$, subject to: $G(\lambda, y) \le 0$, where (λ, y) are Pareto optimal for

$$\min_{x_j} f = \left(f_1(\lambda, x_1), \ldots, f_j(\lambda, x_j)\right),\ (j = 1, \ldots, k)$$

subject to: $g_1(\lambda, x_1), \ldots, g_j(\lambda, x_j) \le 0.$

$$\lambda \in X\ ,\ x, y \in Y\ ,$$

where $G(\lambda, y)$ is the vector of system constraints; $g_j(\lambda, x_j)$ is the vector of subsystems constraints; $F_i(i = 1,.., l)$ are top-level goal functions; $f_j(j = 1, \ldots, k)$ are goal functions of the lower level; x_j is the vector of subsystems variables; λ is the vector of coordinating variables.

The task is to optimize the lower level for a tight budget for each subsystem λ_j coordinated so as to achieve the best solution of entire system as a whole (Fig. 3).

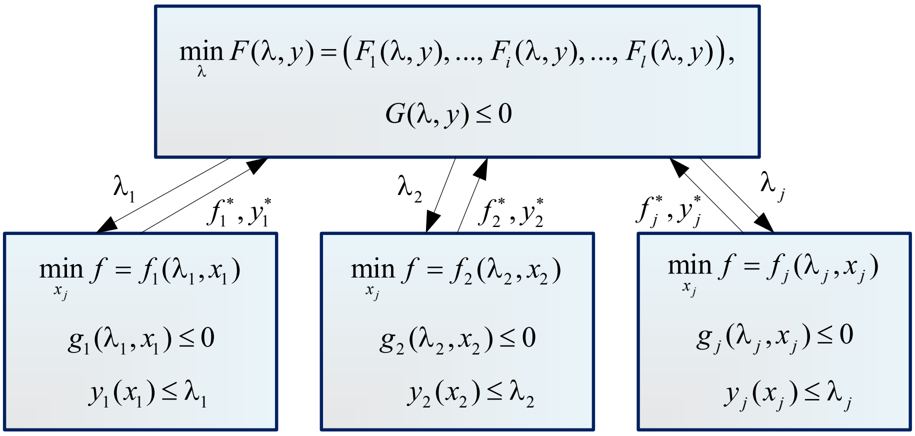

Fig. 3. The hierarchical structure of the problem of multicriteria optimization

III. PROBLEM SOLUTION

A lot of traditional optimization techniques have been proposed for solving multiobjective optimization, such as the method of global criterion, the weighted sum of [3], [4], ε is constraints [5], weighted metrics [4], the method of goal programming [6], lexicographic ordering method [7], [8], [4], a variety of interactive methods, etc. Most of these methods are based on the transformation of the problem into single criterion, and often have several disadvantages, such as the constant need for different adjustments of the method and receiving only a single solution at the end of each iteration.

For solving multiobjective problems there was proposed to use genetic algorithms (GAs) using a population approach and the concept of Pareto dominance in the process of finding solutions, where each iteration has more than one solution, and with each iteration, a new array of data is formed to find the optimal solutions. Genetic algorithm is often divided into two main groups: the dominated and nondominated sorting [9]. Among modern methods one can distinguish genetic algorithm nondominant sort NSGA-II developed by Kalyanmoy Deb, Samir Agrawal, Amrit Pratap, and T Meyarivan [10], [11], the algorithm with the archive, using the concept of force SPEA2 developed by Eckart Zitzler, Marco Laumanns and Lothar Thiele [12], the algorithm of particle swarm MOPSO [13] and GA based on the evaluation of the entropy [14], [15].

Let us consider the last GA [14] for solving multiobjective optimization of two-level hierarchical system. The main idea consists in finding the optimal solution for each subsystem by systematically using the entropy value of intermediate solutions. To optimize the subsystems GA developed by Carlos Fonseca and Peter Fleming [16] are used. In addition the system level is converted, the top-level constraints and coordinating variables are introduced in the optimization problem of subsystems.Below are shown the transformed optimization problem of subsystem j.

$$\min F_i(\lambda, y)\ ,\ (i = 1,.., l);$$

$$\min f_j(\lambda, x_j)\ ,\ (j = 1, \ldots, k);$$

$$\text{subject to} \begin{Bmatrix} G(\lambda, y) \\ g_j(\lambda, x_j) \end{Bmatrix} \le 0.$$

Figure 4 shows a flowchart. GA for each subtask works with its own population (λ, x_j).

The population size P to optimize each task is the same. In addition there are two external populations: the global population and the overall gene pool that contain global variables vector (λ, x_j, y). Global population is an estimate solutions to the global problem, which has a size P, as in the subsystems.

Common gene pool is the archive of mergers of subtasks solutions, in this population the computation of the entropy metric is performed. Common gene pool is K times more than P. Initially, the global population is randomly generated, and the total gene pool is empty. Chromosomes of global population are used as initial data for each subsystem GA, while using only the corresponding chromosome (λ, x_j) with their constraints. After mutation of all chromosomes in K populations and obtaining a complete vector variables of the system, they are added to a common gene pool. This operation represents one iteration. Before the start of the next iteration the global population is replenished from the common gene pool. Each chromosome in the gene determines the point in the vector space of solutions of the optimization problem. The task of the GA is to obtain the most diverse solutions in this space. To do this from $K \times P$ chromosomes of common gene pool GA picks P chromosomes that maximize the entropy metric and replace P chromosomes in global population with these new P chromosomes.

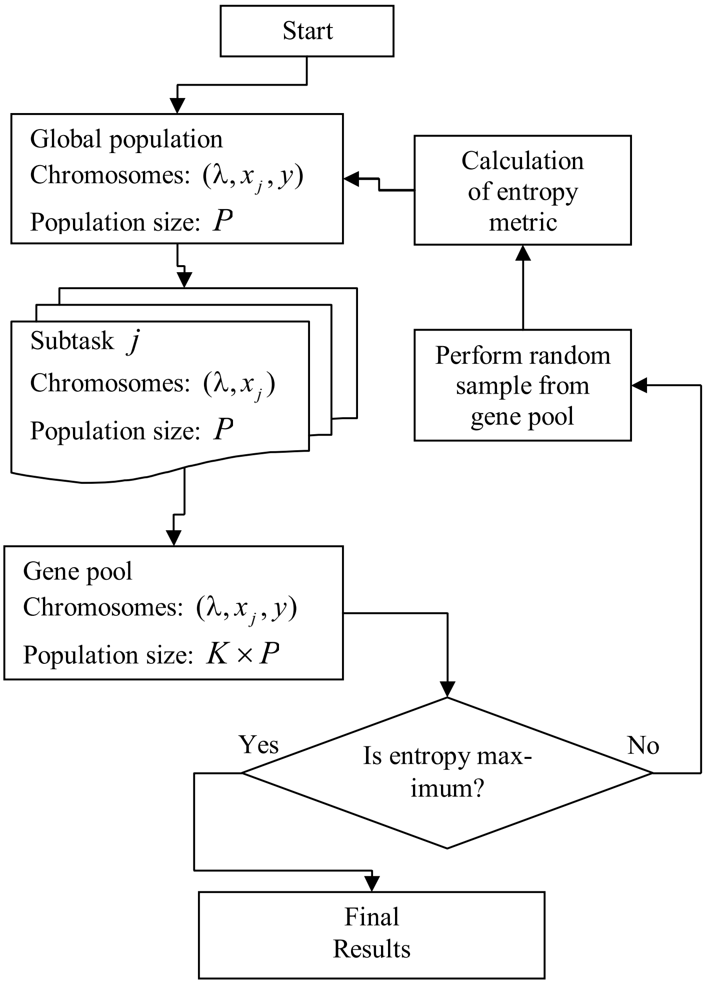

Fig. 3. Flowchart of the GA with the evaluation of entropy

Selection problem of P chromosomes that maximize the metric of entropy can be considered as a separate optimization problem. However, because size of the search space for this optimization problem is large enough $\begin{pmatrix} K \times P \\ P \end{pmatrix}$, it is recommended to perform regular random sample $10P$ times for selection of P chromosomes that maximize the metric of entropy.

New chromosomes of global population are used as a new offspring and continues iteration of GA until no further improvement in the metric of entropy (i.e., the maximization of the entropy).Then sorting algorithm stops. Solution of the optimization problem is non dominating front of points of the common gene pool in the latest iteration of the GA.

Step by step GA representation is shown below.

1. Enter the initial values of the variables: global iteration counter $I = 0$, the metric of entropy $E = 0$.

2. Create an empty common gene pool and the initial global population of P random chromosomes of global vector of variables (λ, x_j, y).

3. Use chromosomes (λ, x_j) from the global population for the initial population of subtasks j. Do N iterations of GA algorithm for each task j.

4. Re-sequence evolved chromosomes (λ, x_j) of subtasks j with the chromosomes of the global population.

5. Delete all the chromosomes of the common gene pool and add all of the chromosomes mutated from all subtasks to common gene pool.

6. If there is no improvement of the entropy metric E for the last T iterations stop GA. Take non dominated front of points from common gene pool. Otherwise, continue GA to the next iteration.

7. From $K \times P$ of the common gene pool produce $10P$ random samples (each containing P chromosomes). Calculate the metric of entropy for each sample in the search space of the optimization problem. Determine $B_{\max}$ sample with maximal entropy.

8. Remove the chromosomes in the global population. Add P chromosomes from the sample B the global population.

9. Set a global iteration counter $I = I + 1$, the entropy value $E = E(B_{\max})$.

Go to step 3.

Genetic algorithm uses five stopping criteria:

The number of iterations – the algorithm reached the set number of iterations.

Time – the algorithm is run during a specific time interval (in seconds).

Limit of the fitness function (FF) – the best value is less than or equal to a certain value.

Stop by iterations – the algorithm computes a certain number of iterations, and stops if there is no improvement of the metric of entropy.

Stop by time – algorithm is executed during some time interval and stops if there is no improvement in the FF.

The efficiency of this GA is shown in [14] for solving optimal design problem for light aircraft engine gear [17]. Ceteris paribus GA based on the evaluation of the entropy gives more different Pareto solutions compared with the results of traditional GA (Fig. 5).

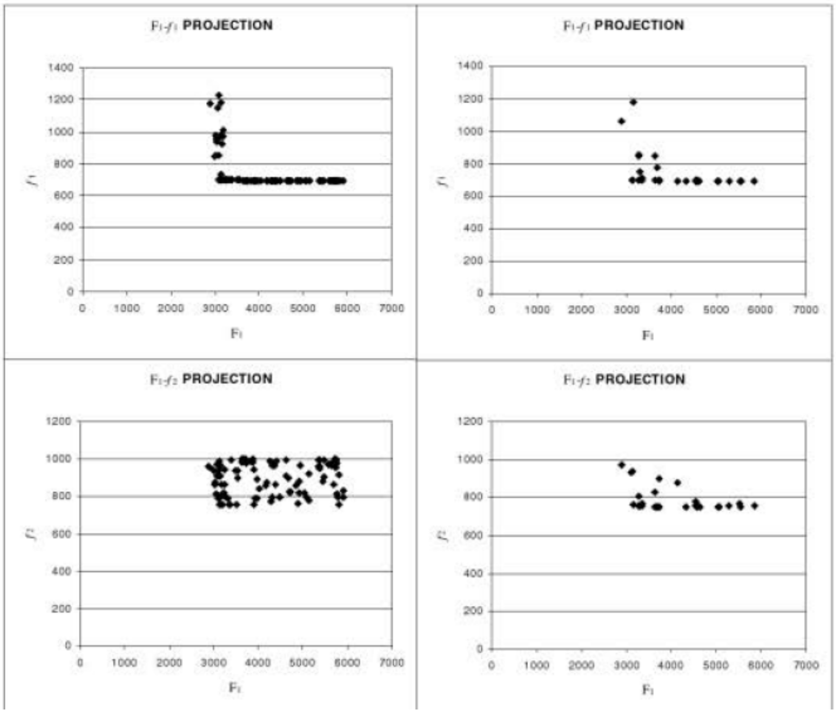

Fig. 4. Pareto front of example optimization problem

On the left there are shown the results obtained using the GA based on the evaluation of entropy.

IV. Conclusions

There was proposed the solution of simulation table design problem by means of milti-level multicriteria optimization. Genetic algorithm approach is the modern and promising tool proven by variety of publications worldwide. It has undergo rapid growth during the last decade. The development of the CAD software on the basis of the described framework will be the goal of the future developments in this realm.

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В. М. Синєглазов, С. О. Долгоруков. Оптимальний вибір комплексу технічних засобів підсистем керування каналів курсу, тангажу та крену випробувального стенду навігаційного обладнання

Розглянуто задачу проектування великомасштабних систем. Запропоновано методологію багаторівневої багатокритеріальної оптимізації, яку можна використовувати для розробки програмного забезпечення системи автоматизованого оптимального вибору комплексу технічних засобів випробувального стенда навігаційного обладнання.

Ключові слова: багатокритеріальна оптимізація; ієрархічні багаторівневі системи; випробувальний стенд навігаційного обладнання; генетичний алгоритм.

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В. М. Синєглазов, С. О. Долгоруков. Оптимальный выбор комплекса технических средств подсистем управления каналов курса, тангажа и крена испытательного стенда навигационного оборудования

Рассмотрена задача проектирования крупномасштабных систем. Предложена методология многоуровневой многокритериальной оптимизации, которая может быть использована для разработки программного обеспечения системы автоматизированного оптимального выбора комплекса технических средств испытательного стенда навигационного оборудования.

Ключевые слова: многокритериальная оптимизация; иерархические многоуровневые системы; испытательный стенд навигационного оборудования**;** генетический алгоритм**.**

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