Multiagent Genetic Optimisation to Solve the Project Scheduling Problem

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***Abstract*—This paper considers a project scheduling problem belonging to a class of multiobjective problems of complex systems control, whose decision search time grows exponentially depending on the problem dimension. In this paper, a survey of a modified genetic algorithm application to the project scheduling problem is presented. We propose a multiagent genetic optimisation method based on evolutionary and multiagent modelling by implementing different decision searching strategies, including a simulation module. The multiagent simulation module is intended to evaluate chromosome fitness functions and describe the dynamic nature of own and subcontracted resources allocation. The proposed multiagent genetic optimisation method, the MS Project resource reallocation method, and a heuristic simulation method have been compared whilst addressing a real-world scheduling problem. The comparison has shown: firstly, the unsuitability of the MS Project planning method to solve the formulated problem; and secondly, both the advantage of the multiagent genetic optimisation method in terms of economic effect and disadvantage in terms of performance. Some techniques to reduce the impact of the method's disadvantage are proposed in the conclusion, as well as the aims of future work.**

Keywords-project scheduling; genetic algorithms; simulation; subcontract work optimisation.

I. Introduction

The scheduling problem is one of the key problems in the management of organisational and technical systems. Inefficient scheduling can lead to financial losses, quality of service losses, and loss of competitiveness for the company. Companies from various scopes are faced with the scheduling problem, e.g. industrial and project companies, shopping centres, hospitals, and call centres.

There are several scheduling problem statements depending on the application sphere: operations calendar planning [1]–[5], limited resources assignment to a set of tasks [6]–[8], and the traveling salesman problem [9].

Classical scheduling problem solving methods have a number of disadvantages. Thus the use of combinatorial methods and mathematical programming leads to high computational resources utilisation when addressing large-scale problems. In addition, these methods are applied poorly to the problem with dynamically changing constraints. Simulation takes into account the dynamic nature of the problem, but leads to a random search process, which does not guaranteed optimal decision finding. The use of genetic optimisation allows the shortcomings of the previous methods to be overcome [9]. The application of genetic optimisation to the scheduling problem with defined constraints is widely considered in the literature [1]–[9].

This paper focuses on the project scheduling problem with the use of evolutionary computation [12] and simulation. The remainder of the paper is organised as follows: Section 2 provides an overview of the application of the genetic algorithm to the scheduling problem. Section 3 formulates the project scheduling problem with time constraint. Section 4 introduces the genetic algorithm based on an annealing simulation and novelty search. Section 5 presents the algorithm of the multiagent genetic optimisation program based on the integration of evolutionary computation and multiagent simulation. Section 6 evaluates the practical implementation of the multiagent genetic optimisation program to solve the real-world scheduling problem. Section 7 concludes this paper and explores future work.

II. Related Work

In general, the scheduling problem is connected to the problem of seeking an operations sequence that satisfies the constraints and optimises the objective functions. The renewable resources (such as staff or equipment) are usually considered when studying the scheduling problem. For certain tasks (for example production planning) non-renewable resources should additionally be determined [1].

In the various scheduling problem studies different constraint sets are considered depending on the specific task. Four constraint types were identified in [3]: resource, precedence, physical layout, and information constraints. The time constraint type should be added to the constraint types list when analysing workflow inside a project development company. Time limitation is associated with a time frame for the early and late starts of the operations.

All constraints, except precedence ones, were studied by Brezuliani et al. [6]. Precedence and resource constraints were considered by Okada et al. [1], Klimek [2], Abdel-Khalek et al. [4], and Dhingra and Chandna [7]. Resource and information constraints were studied by Yang and Wu [8]. Resource, precedence, and time constraints were considered by Karova et al. [5]. Scheduling with a resource constraint to determine a public transport route was presented by Osaba et al. [9].

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The optimisation objects are also different in the studies reviewed. The classical objective function of working time (makespan) minimisation was considered by Sriprasert and Dawood [3] and Osaba et al. [9]. The objective function of constraints violation penalty minimisation was considered by Karova et al. [5], and Yang and Wu [8]. Both mentioned objective functions were considered by Okada et al. [1], Brezuliani et al. [6], and Dhingra and Chandna [7].

There are different ways of conducting an objective function evaluation: analytical methods, simulation, artificial neural networks, fuzzy systems, and component modelling. Analytical methods are the most widely used; the drawback of this approach being the lack of the analysis of the complex system dynamic behaviour. This drawback is overcome by using a simulation model to evaluate the objective function by Osaba et al. [9]. The integration of evolutionary modelling and simulation can limit the random search space and enhance heuristic optimisation by taking into account the dynamically changing constraints of the scheduling problem.

The reviewed studies do not consider subcontracted workforce optimisation, while this problem is real to developers and even to mass production enterprises. The subcontracted workforce's optimisation problem is connected to subcontracted scheduling in order to maximise the utilisation of the company's own resources. In the literature, a problem regarding the appropriate selection of subcontractors using artificial intelligence methods was studied by Chen et al. [10]. A subcontract optimisation technique based on a simulation and heuristics was suggested by Aksyonov and Antonova [11]. The current article considers new subcontract optimisation techniques with the use of a genetic algorithm.

III. PROBLEM STATEMENT

Let us consider the problem of unique projects scheduling aimed at the calendar planning of operations. All project operations have to be carried out in combination with a set of time constraints. The set of time constraints is defined through negotiations with customers. In the case of the organisation's own lack of resources, subcontracted resources have to be involved to meet the time constraints.

The objective functions of the considered problem are: 1) subcontract cost minimisation; and 2) minimisation of own resources total downtime. The second objective function is associated with the fixed labour cost in the project companies. If the salary is fixed then downtime is also paid, which is not profitable for the company.

For the project scheduling problem considered in this study, the following assumptions have been made:

1. A single project consists of a number of operations with a known processing time, early and late start dates, labour input, and labour cost.
2. The operation requires the availability of renewable resources (own or subcontracted workforces).
3. Non-renewable resources are not considered in the scheduling.
4. Operations cannot be interrupted.
5. Subcontractors can be involved to perform part of the operation.
6. Subcontractors can be interrupted and the operation can continue with the use of the company's own resources in the event of the appearance of own available resources.
7. Subcontractors are available every day on request in unlimited quantities (for example when working with different subcontractors).

Let us describe the problem of the project portfolio scheduling with the use of the following designations.

Indices:

i: project index, $i=1, 2, \ldots, P$.

j: operation index, $j=1, 2, \ldots, Op_i$.

w: department index, $w=1, 2, \ldots, V$.

t: time index, $t=0, 1, 2, \ldots, T$.

Decision variables:

$TB(i,j)$: set of start dates of operations.

Initial parameters:

$ES(i,j)$: early start date of the operation (i,j).

$LS(i,j)$: last start date of the operation (i,j).

SL_w: amount of persons in the department w.

$SLO(i,j,w)$: amount of workforces (persons) needed in department w to fulfil the operation (i,j).

$SS(i,j)$: operation (i,j) subcontract cost per day.

Parameters obtained in the decision-making process:

$Active(i,j,t)$: a sign of the operation (i,j) execution at the time t.

$$Active(i,j,t)=\begin{cases}1, & if\ \ operation\ \ (i,j)\ \ is\ \ executed\ \ at\ \ the\ \ moment\ \ t\\ 0, & otherwise\end{cases}$$

$RD(t,w)$: resources from department w demand to fulfil the active operations at the time t.

$$RD(t,w)=\sum_{i=1}^{P}\sum_{j=1}^{Op_i}\left[Active(i,j,t)\cdot SLO(i,j,w)\right]$$

$VF(t,w)$: amount of free workforces of department w at the time t.

$$VF(t,w)=\begin{cases}SL_w-RD(t,w), & if \quad RD(t,w)\le SL_w\\ 0, & otherwise\end{cases}$$

$V_{SC}(i,j)$: volume of subcontracting workforces on operation (i,j).

Problem description:

$$OF_1=\sum_{i=1}^{P}\sum_{j=1}^{Opi}(SS(i,j)\cdot V_{SC}(i,j))\rightarrow \min, \tag{1}$$

$$OF_2=\frac{\sum_{t=0}^{T}\sum_{w=1}^{V}VF(t,w)}{T\cdot V}\rightarrow \min, \tag{2}$$

$$TB(i,j)\in[ES(i,j);LS(i,j)] \quad \forall i,\forall j \tag{3}$$

Objective function (1) minimises the total subcontracting cost. Objective function (2) minimises the own resources total downtime. Constraint (3) saves the time frame of the operations start.

IV. GENETIC ALGORITHM BASED ON ANNEALING SIMULATION AND NOVELTY SEARCH

The genetic algorithms (GA) is one of the evolutionary approaches that can be used to solve complex system management problems in a short time [12]. The technique of the GA application includes the following steps: 1) selecting the method of encoding the problem decision (phenotype) into a chromosome (genotype); 2) definition of the evaluation method of the chromosome fitness function (FF); 3) the genetic operator's description; and 4) the initial population generation and GA work. The modification of the GA on the basis of an annealing simulation and novelty search is considered in the article in order to enhance the quality of the scheduling problem's decisions.

A. *Chromosome Encoding*

There are various techniques for decision encoding presented in the literature: operations sequence encoding [2][5][9], operations precedence encoding [1][3], operations start dates encoding [4][6], the resource assignments on the operation encoding [6]–[8]. We use the encoding of the operation start dates shifting because this technique supports time constraints, is not redundant, and is simple to implement.

The GA chromosome encodes the operations' start dates shifting from the initial work plan to the right or left on the time axis via binary code (0/1). The shifting range is two weeks on either side of the initial operation start date. The chromosome size is $5 \cdot r$ genes, where r – number of analysed operations, 5 – number of the genes needed to encode a single operation shifting (4 genes to encode $2^4=16$ shifting days and 1 gene to encode the shifting direction).

B. *Genetic Algorithm Modification*

A novelty concept is a major GA concept. This concept is connected with the emergence of new elements and interactions in the environment during evolution. Two novelty types are distinguished in [13]: 1) *combinatorial novelty* when the new species emerge by combining the existing species; and 2) *creative novelty* when the new species are not reproducible by a combination of the species. The validity of the fundamental feasibility of the second novelty type is still open.

Let us consider the case of a combinatorial novelty search as an adaptation mean in an open system. To implement this approach we modify a simple GA by introducing the concept of "decision originality" as a measure of the decision fitness to the environmental conditions [13]. The decision-chromosome's originality in the population is determined via the numerical transformation of the Hamming distance matrix.

Let us define the Hamming distance matrix as follows:

$$H = \left(h_{ij}\right)_{i=1,\, j=1}^{N}, \tag{4}$$

where h_{ij} – Hamming distance between the i-th and j-th chromosomes (Ch_i and Ch_j), equal to the number of positions at which the corresponding gene values are different in chromosomes Ch_i and Ch_j; N – number of chromosomes.

We associate the matrix H with the matrix of originality weights W defined as follows:

$$W = \left(w_{ij}\right)_{i=1,\, j=1}^{N}, \tag{5}$$

where w_{ii} – weight of the corresponding value of the Hamming distance determined as a quadratic function, increasing in the range from 1 to R as element h_{ij} is changed in the range 0 to L:

$$w_{ij} = \frac{R-1}{\sqrt{L}} \cdot \sqrt{h_{ij}} + 1, \tag{6}$$

where L – the chromosome size; R – the maximum weight of the chromosome in the pair, $R>0$.

The two strategies of chromosome crossing have been described using the concept of originality. The first strategy – *the originality search strategy (OSS)* [14] – focuses on the combinatorial search for the new decisions in the population by crossing chromosomes that have different encoding. The second strategy – *the maximum search strategy (MSS)* [12] – focuses on the targeted search for the best chromosomes by crossing chromosomes that are the most adapted to the environment. The fitness of the i-th chromosome to the environment is evaluated by the fitness function FF_i, $i=1..N$.

Let us define the chromosome crossing probability matrices on the basis of the proposed strategies as follows:

$$P_{OSS} = \left(p_{ij}^{OSS}\right)_{i=1,\, j=1}^{N}, \quad p_{ij}^{OSS} = \frac{w_{ij}}{\sum_{j=1}^{N} w_{ij}}, \tag{7}$$

$$P_{MSS} = \left(p_{i}^{MSS}\right)_{i=1}^{N}, \quad p_{i}^{MSS} = \frac{FF_i}{\sum_{i=1}^{N} FF_i}. \tag{8}$$

In formulas (7) and (8) the matrices cells are filled by probabilities values in accordance with the roulette law [12]. In the case of OSS strategy, the weight of the chromosome originality serves as a measure of chromosome importance. In the case of MSS strategy, the chromosome FF serves as a measure of chromosome importance.

An annealing simulation algorithm (ASA) [15] is intended to implement the proposed chromosome crossing strategies during the GA work. This algorithm is based on the analogy of the metal annealing process, which results in the appearance of new metal properties. The technique for ASA and GA integration is proposed below.

Step 1. Set the annealing simulation algorithm parameters: the initial value of the parameter t_Z; the value of the parameter α, that controls the rate of annealing temperature decrease, $0 \le \alpha \le 1$.

Step 2. Set the GA parameters: the number of generations K; the chromosome size L; the likelihood of the genetic operators being applied. Set the number of the current population Z: $Z=1$. Generate the initial population.

Step 3. Apply the genetic operators to the current population Z with a probability depending on the value of parameter t_Z. Increase the number of the current population $Z=Z+1$. Change the value of parameter t_Z [15]:

$$t_{Z+1} = t_Z + \alpha \cdot t_Z . \tag{9}$$

Step 4. Check the condition of the GA ending: $Z>K$. If the condition is satisfied then go to Step 5, otherwise return to Step 3.

Step 5. Stop.

The probability of the genetic operator's application is defined on the basis of the annealing simulation, in order to reflect the operator's dynamic nature.

C. Crossover Operator

The probability of selecting the first and second parents from the current population Z for the crossover operator (CO) is described below. The probability of selecting the first parent has to take into account both random selection and targeted selection based on the MSS strategy (8). The probability of random selection should be reduced in the population's evolution, and the probability of the MSS strategy should be increased. This fact is reflected in the probability formula of selecting the first parent i in the population Z:

$$P_i^Z(CO) = \frac{1}{N} \cdot \left(1 - \exp\left(-\frac{1}{t_Z}\right)\right) + p_i^{MSS} \cdot \exp\left(-\frac{1}{t_Z}\right). \tag{10}$$

The probability of selecting the second parent has to take into account the OSS and MSS strategies. The probability of the OSS applying (7) should be reduced in the population's evolution, and the probability of the MSS applying (8) should be increased. This circumstance is reflected in the probability formula of selecting the second parent j for the first parent i in population Z:

$$P_j^Z(CO) = p_{ij}^{OSS} \cdot \left(1 - \exp\left(-\frac{1}{t_Z}\right)\right) + p_j^{MSS} \cdot \exp\left(-\frac{1}{t_Z}\right). \tag{11}$$

D. Mutation and Inversion Operators

The applied probability of the mutation operator (MO) in population Z is described below. This formula has to take into account the probability reducing during evolution in order to save genetic material [14]:

$$P_Z(MO) = P_0(MO) \cdot \left(1 - \exp\left(-\frac{1}{t_Z}\right)\right), \tag{12}$$

where $P_0(MO)$ – the initial value of the mutation operator applied probability.

The applied probability of the inversion operator in population Z is described by an analogy with the mutation operator applied probability.

E. Fitness Function

The following fitness function considers both objective functions (1) and (2) described in Section 3:

$$FF = \omega_1 \cdot (OF_1^{Init} / OF_1) + \omega_2 \cdot (OF_2^{Init} / OF_2) \to \max , \tag{13}$$

where ω_1, ω_2 – weight coefficients, $\omega_1+\omega_2=1$; OF_1^{Init}, OF_2^{Init} – objective functions initial values obtained by expert evaluation of the operation start date.

Used FF is described with the use of the linear convolution of normalised heterogeneous criteria (1) and (2).

The multi-agent resource conversion processes (MRCP) model described in [16] is used to evaluate the chromosome FF. The MRCP model is proposed to perform the decision-making process. The decision variables and input parameters described in Section 3 are fed at the model input. The parameters obtained in the decision-making process are the model output. In the MRCP model we use agents in order to implement the resource allocation algorithm and use simulation in order to perform the operations execution. The resource allocation algorithm is described in [13] and allows executors of operations to be appointed in accordance with the assumptions made in Section 3.

V. MULTIAGENT GENETIC OPTIMISATION PROGRAM

The multiagent genetic optimisation (MGO) program has been developed on the basis of a BPsim.MAS dynamic situations modelling system and BPsim.MSN technical and economic development system [16]. The MGO program is intended to solve the problem of simulation and evolution modelling integration. BPsim.MAS supports the MRCP model description via graphical notation of the resource conversion processes. BPsim.MSN [16] ensures the development of the decision search information technology (IT) based on the UML sequence diagrams [17] and Transact-SQL database management language [18].

A genetic optimisation IT has been designed on the basis of BPsim.MSN. The genetic optimisation IT is intended to aid GA parameters setting and GA execution. The MRCP model is intended to conduct chromosomes FF evaluation by carrying out an experiment with the model. The decoded chromosome phenotype (operations calendar planning) is fed to the model input. The FF evaluation in accordance with (13) is obtained in the model output. Agents in MRCP model are used to allocate the renewable resources (both own and subcontracted).

The decision maker carries out the problem statement and solution choice among the solutions obtained by the use of the MGO program. The algorithm of interaction between the decision maker and MGO program during the decision-making process is shown in Figure 1.

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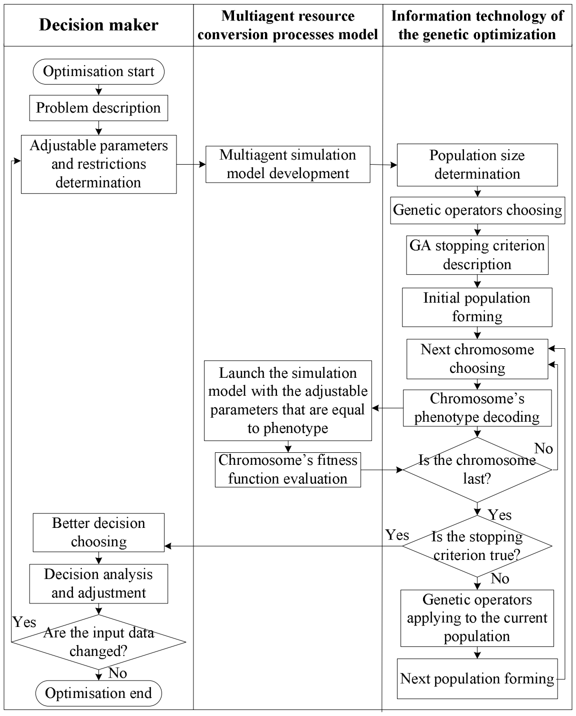


Figure 1. Interaction between decision maker and MGO program

The MGO program designed has a number of advantages compared to existing evolutionary scheduling optimisation software [2][4][8][9].

1. The integration of simulation, expert, multiagent, conceptual, and evolutionary approaches.

2. Description of the system models using MRCP and UML graphical notation.

3. The evolutionary and simulation models integration via wizard technology.

VI. Experimental Results

The application of the MGO program to solve the project scheduling problem is presented in this section. Let us consider a company «Telesystems» that consists of the project, manufacturing, and supply departments. The goal is the minimisation of the company department's total downtime and the total cost of the subcontract.

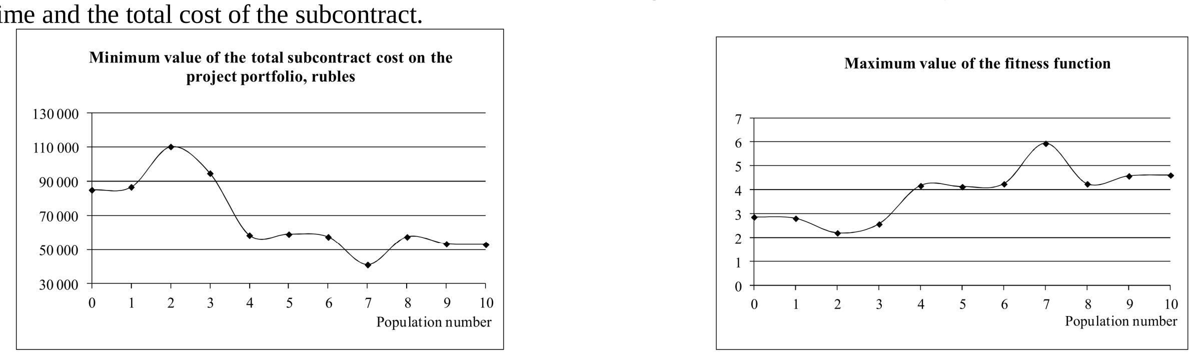
A detailed statement of the problem is given in [11]. The MRCP model has been developed in order to evaluate the chromosome FF (13). The MRCP model implements the resources allocation model, which satisfies the assumptions determined in Section 3. The model adequacy has been proven in [11] through the evaluation of 5 projects. The following input information have been used in the model: 1) number of projects – 10 with 35 operations; 2) time interval T=430 days (1 year and 3 months); and 3) time limit early and late start of the operations is determined by the shift in the provisional operations start dates for 2 weeks to the right or left along the time axis.

The following GA parameters have been determined in the course of the genetic optimisation IT work: 1) the population size – 10 chromosomes; 2) the chromosome size – 175 genes (5 genes to encode the 35 project operations); 3) the following genetic operators – reproduction based on roulette, five-point crossover with probabilities determined by (10) and (11), five-point mutation with an initial probability equal to 10% and dynamic probability determined by (12), inversion with initial probability equal to 5%; 4) algorithm stopping criterion – a change of 10 populations; 5) random initial population; and 6) following the ASA parameters values – $t_{Z0}=1$, $\alpha=0.9$, $K=10$.

The dependencies of the chromosome FF and scheduling problem objective functions values from the population number have been obtained as a result of genetic optimisation using the developed MGO program. The change in the minimum value of the objective function (1) during genetic optimisation is shown in Figure 2.a. The change in the maximum value of the fitness function (13) during genetic optimisation is shown in Figure 2.b. The best decision has been achieved in the seventh generation.

The project scheduling problem for the «Telesystems» company also has been solved by use of the MS Project 2007 resources reallocation method and heuristic-simulation (HS) method described in [11].

MS Project 2007 provides the opportunity for resource reallocation (with smoothing) in order to avoid exceeding the own renewable resources availability. The percentage utilisation of the manufacturing department for the initial work plan for the «Telesystems» company is shown in Figure 3 via means of MS Project visualisation.



a. b.

Figure 2. Dependencies of the fitness function and objective function values from the population number

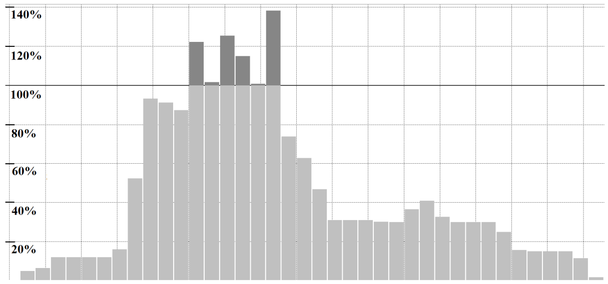


Figure 3. Percentage utilisation of the manufacturing department for initial work plan in MS Project

The initial work plan has been formed by decision making person. In the figure, the x-axis shows the time intervals (each of which lasts 12 days); the y-axis shows percentage utilisation. The resources availability overallocated (time intervals where the use of subcontract is necessary) is shown in figure as dark stripes above the horizontal line at the 100% utilisation level. The application of the MS Project resources reallocation method has allowed to reduce the total subcontract cost down to zero (that is the objective functions (1) and (2) have reached their optimal values). But the time constraints (3) have not been satisfied with the use of this method. In this way, the MS Project resources reallocation method is not suitable to considered scheduling problem.

The HS method is based on the analysis of the MRCP model output parameters. In the HS method, the following steps are performed [11]: 1) modelling results analysis – the subcontract cost and company resources utilisation; 2) search for bottlenecks associated with the operations that require high costs of subcontract; 3) shifting the start dates of operations on the period determined by HS information technology; 4) transfer the adjusted model at the experiments stage and experiments results evaluation.

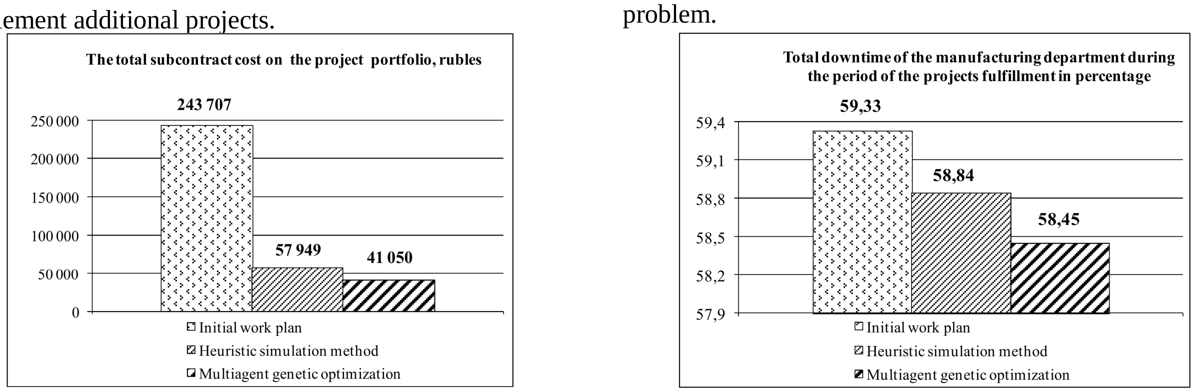
Histograms of the objective functions (1) and (2) obtained by the MGO and HS methods are shown in Figures 4.a and 4.b compared with the initial work plan. The total subcontract cost and total downtime of the manufacturing department has been consistently reduced with the use of HS and MGO methods. All time constraints have been satisfied. The total downtime indicates on a reserve of own resources to implement additional projects.

Based on the analysis of the results it was concluded that the MGO method is more effective than the HS method in addressing the project scheduling problem in terms of economic effect. The total subcontract cost of the project portfolio has been reduced by 30% and the total downtime of the manufacturing department has been reduced by 1.5% for a six month period using the MGO method compared to the HS method. The total subcontract cost has been reduced by 6 times using the MGO method compared with the initial work plan. Applying the genetic optimisation based on the simulation and evolutionary modelling integration enhances the efficiency of the decision established by taking into account the dynamic resources allocation model in the simulation model and the fulfilment of the direct search in the decisions space by GA. The economic effect of applying the MGO program to solve the scheduling problem for the «Telesystems» company will be 405000 rubles per year, which is 9% higher than the economic effect from the use of the HS method to solve the same problem.

Let us compare the HS and MGO methods in terms of performance by measuring CPU time. The CPU time for the HS method T_{HSM} consists of the sum of the HS IT runtime T_{HSIT} and the model MRCP runtime T_{MRCP}. The sum is multiplied by the number of experiments $X_{Iterations}$ conducted during the HS technology work. Thanks to the fact that $T_{HSIT} << T_{MRCP}$ we can neglect the term T_{HSIT} and define T_{HSM} time as follows: $T_{HSM} = X_{Iterations} \cdot T_{MRCP}$.

The CPU time for the MGO method T_{MGO} consists of the sum of the genetic optimisation IT runtime T_{GOIT} and model MRCP runtime T_{MRCP}, which is multiplied by the chromosome number N. The sum is multiplied by the generations number K. Thanks to the fact that $T_{GOIT} << T_{MRCP}$ we can neglect the term T_{GOIT} and define T_{MGO} time as follows: $T_{MGO} = K \cdot N \cdot T_{MRCP}$.

For the real-world scheduling problem the following parameter values have been used: $X_{Iterations}=3$, $K=10$, $N=10$. In this case the HS method is more desirable in terms of performance and consumes 33 times less CPU time than the MGO method. This fact is connected to the use of the simulation model in GA for fitness function evaluation, which performed $K \cdot N$ times. The CPU time of the MGO method is equal to 30 minutes for the real-world scheduling problem.



a. b.

Figure 4. Dependencies of the objective functions values from the decision seeking method

VII. Conclusion and Future Work

In this paper a multiagent genetic optimisation method used to solve the project scheduling problem has been described on the basis of the annealing simulation algorithm, novelty search algorithm, genetic algorithm, and multiagent simulation. The method combines three different decision seeking strategies: a random search strategy, originality search strategy, and maximum search strategy, in order to reflect the dynamic nature of the genetic operators applied. The proposed integration of evolutionary modelling and simulation limits the search space and adequately evaluates the dynamic fitness functions of the chromosomes. The method described has been implemented in a MGO program built on the basis of the BPsim.MAS multiagent modelling system and BPsim.MSN development system. The program integrates simulation, expert, multiagent, conceptual, and evolutionary modelling. The MGO method application to a real-world project scheduling problem has been compared with MS Project and HS methods. The MS project resource reallocation method has been found unsuitable for the scheduling problem considered because of the lack of constraints consideration. As a result of the comparison between MGO and HS methods, an improvement in decision quality under the constraints considered has been achieved using the MGO method.

The disadvantage of the MGO method is the high CPU time, which is 33 times higher than that of the HS method. This fact imposes constraints on the GA generation size (no more than 10 chromosomes) and GA iteration number (no more than 10 generations). Different ways to enhance the GA convergence applied should be considered in future work in order to meet the described constraints.

The aim of future research is to improve the rate of the proposed genetic algorithm convergence by applying elitism and taboo algorithms. The dependency between the decision search time and problem dimensions is assumed to be established. A comparison of the MGO method with the branch and bound method adapted to the problem considered is planned. Also consideration of non-renewable resources allocation in the simulation model is planned.

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