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Optimization with the Help of Genetic Algorithms for Solving Practical Problems

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I. Introduction

Recent years are marked by rapid development of the investigations in the area of evolutionary and Genetic Approaches (GA) and their wider application in solving optimization problems of practical use.

Genetic algorithms are a search method based on the selection of the best species in a population in analogy to the evolution theory of Charles Darwin.

Their origin is based on the model of biological evolution and the methods of random search. From different bibliographical sources [1-4] it is evident that random search appeared as a realization of the simplest evolutionary model when the random mutations are modeled during random phases of searching for the optimal solution and the selection is modeled as "removal" of the unfeasible versions.

The main goal of GA-s is twofold:

• abstract and formal explanation of the adaptation processes in evolutionary systems;

• modeling of natural evolutionary processes for efficient solution of a determined class of optimization and other problems.

During the last years a new paradigm is applied to solve GA-based optimization problems and modifications of GA. GA realize searching for a balance between efficiency and quality of solutions at the expense of selecting the strongest alternative solution [5, 6].

The continuously growing number of publications and also of practical implementations during the last years is a stable proof of the growing expansion of the scientific and application research in GA domain.

In order to give a general idea about the type of applications, they could be classified in four main directions [2]:

- science – to increase the level of various scientific research [1, 2, 7-12];
- engineering – to solve specific engineering problems [12-16];
- industry – to increase the quality and the amount of production for some industrial processes [4, 13, 15, 17-19];
- various other directions (miscellaneous applications) [1, 7, 20, 21].

In the rest of the paper we propose the usage of GA in the problem of effective cutting of plastic panels.

II. Theoretical background

An often met problem in practice is the one for rational cutting out of used materials with minimal residuals (waste). The unceasing growth of demands for materials and power supply require minimization of expenses for the production of any product.

The criteria of efficiency are presented by the coefficient of usage K_u. There have been offered given sets of mathematical methods, that solve similar problems, but they are oriented to solving statistical problems when the original information is apriori completely known and it does not change during the production process.

We shall examine the solution of a problem for cutting plastic panels in the production of windows, shop windows or screens, doors, roofs, etc. The dimensions of plastic sheets are with different parameters depending on the specific case. The original blocks for cutting are with different standard dimensions (up to six types) and each dimension has several gauges with different designs.

Different initial blocks for cutting are used depending on the dimensions, gauges and shapes. So the portfolio of the orders is divided into groups depending on the specific features of the initial blocks.

If we ignore the organizational specifics of this production, the problem for cutting may be formulated in the following way: choose the number of products (door, window, screen elements, etc.) from the portfolio of the orders and according to the dimension and the type of the initial block perform rational cutting with minimal losses of the original material. These losses must be minimal, so we must maximize K_u according to the formula

$$K_u = \frac{\sum_{r=1}^{n} S_r}{S_{eb}}, \tag{1}$$

where the numerator is the sum of the surfaces for the orders from the portfolio of the orders and S_{eb} is the surface of the original block. The maximal meaning of K_u

is K_u =1 but it is very hard to achieve this value in reality. If we know the obtained value of K_u and if we compare it with K_u =1 then we make conclusion(s) about the quality of the performed cutting. The solution of such class of problems in our case is based on imitative modeling and a genetic algorithm for optimization.

The imitative model describes the operation of the system realizing rational positioning (arrangement of the orders). The original information about the model is the portfolio of the received orders which consists of a definite set of orders with given dimensions (length and width) and also the number in the portfolio. As a result of the operation the model must position the orders along the surface of the original block and after the end of the operation it must issue the rational value for K_u, which must be near to the optimal one and equal to it. The GA is used to solve the problem for K_u optimization. The basis of the imitative model is the algorithm realizing positioning of the orders. It describes the operation of the system, i.e., it checks the possibility to position the successive order and it performs the operation. Its original data include the values of the order numbers that are issued by the algorithm of optimization, i.e., GA [17]. Each order has its identification number which describes it precisely. The process of positioning the orders along the surface of the original block requires that the order number must be determined; it is taken from the portfolio of the orders and the sequence to position them along the surface of the original block must be found. Every order in the portfolio of the orders has a serial number related to it, which varies between zero and the number of the orders in the order portfolio.

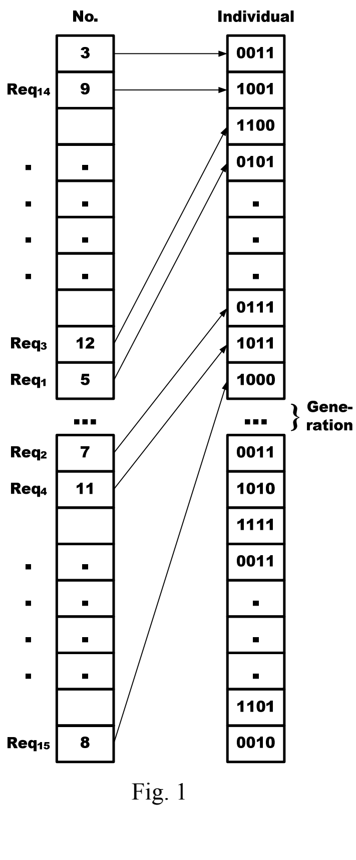

Fig. 1

After any initialization the system automatically determines the length and the string of the chromosome. The number of genes in every individual is equal to the number of orders in the table of back orders. The binary encoding of the order numbers, necessary for GA operation, is shown on Fig. 1. Let the number of the obtained orders be 15. Therefore the individual is a binary string-chromosome with a length of 60 bits. The genes in this string are 4 bits long each. These genes by themselves are the encoded values of the sequential order numbers. Every gene has a length of 4 bits which follows from the condition for encoding the maximal order number. In this case 4 bits allow binary encoding of 15. The number of genes equals to the number of orders, i.e., it is equal to 15. So we obtain a solution for every individual where every single gene determines the successive number for the respective order.

III. Using a genetic algorithm

The solution of the problem above stated is based on a genetic algorithm. The solution of the already postulated problem is via a new GA which is created on the basis of a combination of elements from algorithms of Gen and Cheng [14], Falkenauer [7] and Goldberg [22] as a probabilistic approach to quasi-optimal solutions, using certain parts of the algorithms, above mentioned and we have also added some supplementary elements, that allow larger choice of the criteria and better selection after the population accomplished, which leads to decrease in the number of the necessary computations.

The optimizable GA quantity is the goal function that is intended for the individuals. Hence, the goal function must increase with the growth of the criterion value; the role of the latter performed by C_u. The function is chosen based on the experiments done with the model to ensure correct development of the population.

The main GA parameters are selected after preliminary experiments with the model; the cited below values are accepted:

- number of individuals in the population – 35;
- crossover probability – 0.65.
- mutation probability – 0.35.

The operation of the imitative model follows the algorithm for disposing the requests along the surface of the original block. The input data for its operation is the set of sequential block numbers determined by the GA.

The generalized block scheme including also the GA is given in Fig. 2.

Briefly, the idea of operation is formulated below:

Step 1. During the startup initialization the portfolios are loaded with the possible requests which can be principally realized and which can be continuously updated.

Step 2. Dimensions of the original blocks of standard glasses are determined. They can be of various sizes, thickness and quality.

Step 3. Input of the current order requests.

Step 4. Decoding of bits. The string-chromosome is decoded, i.e., the serial numbers are determined.

Step 5. Choice of the serial number. Sequential numbers are counted and the serial number is determined.

Step 6. Validity test is performed for a request with such number. If there is no such number, then go to Step 5. In the opposite case the algorithm chooses the request with this number.

Step 7. The request is disposed if possible.

Step 8. Go to Step 5 if the request is not final.

Step 9. If the request is final, then a validity test is performed for the number of the individual.

Step 10. The next consecutive steps concern the choice of the fitness function and the respective genetic procedures, such as sorting, crossover and mutation.

Step 11. The Fitness Function (FF) is calculated.

Step 12. Finally the best solution from all generations is passed to the cutting machine which realizes the cutting-out of the original standard block.

The end condition is determined from the inequality:

(2) $$\frac{FF_{max} - FF_{mid}}{FF_{max}} > 0.80,$$

where FF_{max} and FF_{mid} are respectively the maximal and middle values in the current population.

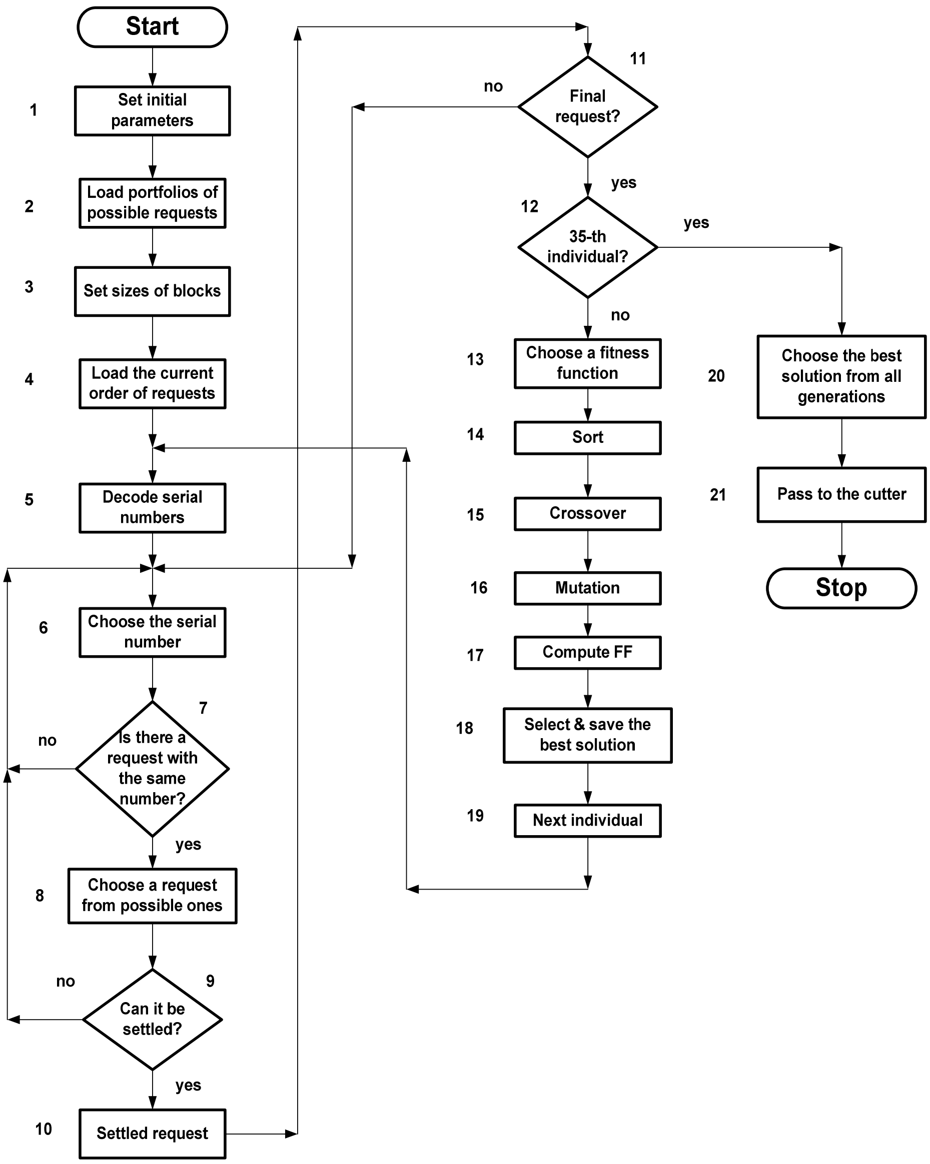

Fig. 2. A generalized blockscheme

It is a statistical requirement that the individual with the biggest FF value must be fixed; if it is the best one for all preceding generations then it is fixed as an intermediate result from the solution of the optimization problem. After the end of the GA the role of an individual is performed by the best individual from all generations.

IV. Conclusions

The estimation criterion for the obtained results is K_u. The operation of GA is based on apriori selected portfolios with requests giving high values for K_u. With so selected parameters the GA finds solutions in 80-90% of the cases when the average waste is between 10 and 15% depending on the size of the original block.

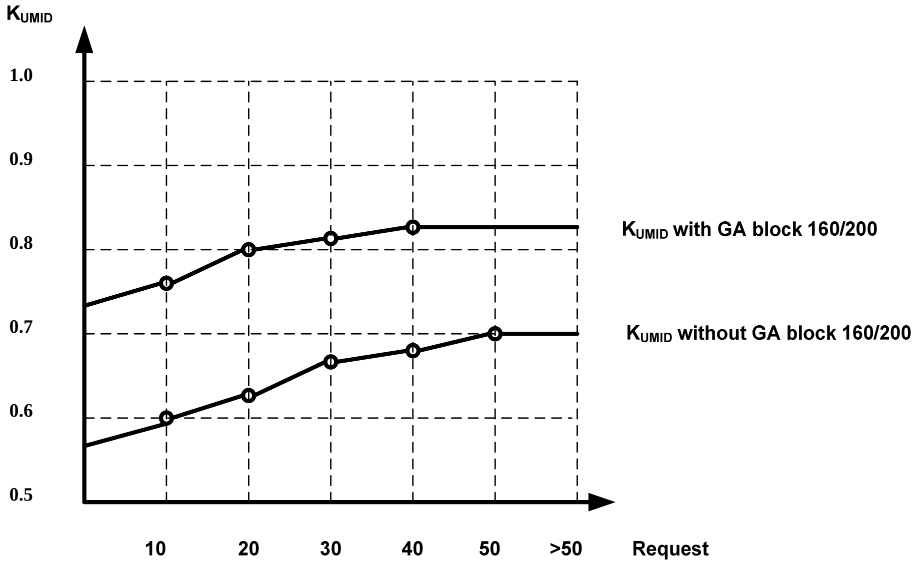

Fig. 3. Graphics of the coefficient K_u

In our case we used a GA for an Italian cutting machine in a company for production of plastic panels. This machine had an optimized program for just a single standard plastic panel – 160/200.

The implementation of the new system for cutting applying GA led to increased possibilities for cutting new original blocks and K_u was considerably improved; the plastic panels waste, which varied between 25 and 35% , dropped down to 10-15%.

Fig. 3 and Fig. 4 present the graphics of the middle values of K_u before and after application of the GA.

The research in this area may continue in search for practical solutions for the case when the requests are divided in urgent and usual ones. Then the fitness function will be a function of three parameters – P_1 for urgent requests, P_2 – for priority and P_3 – determining the coefficient of usage.

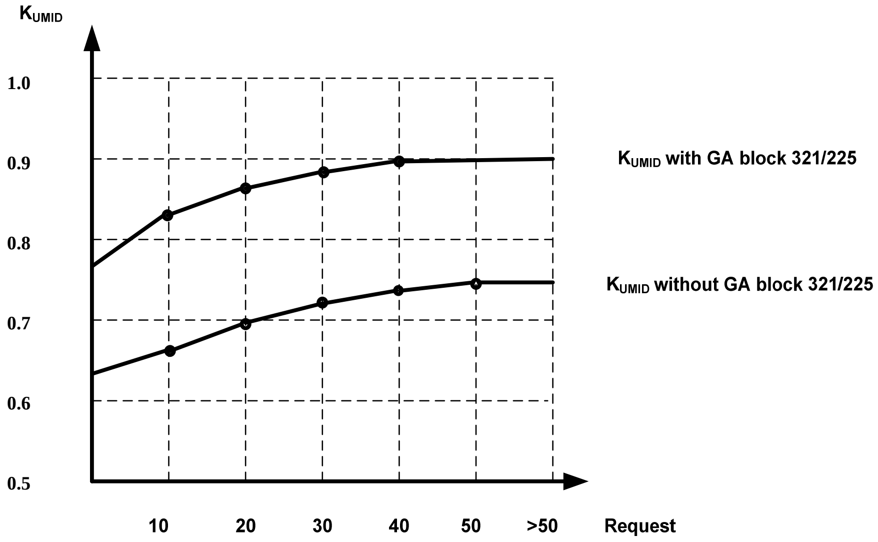

Fig. 4. Graphics of the coefficient K_u

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Оптимизация при помощи генетических алгоритмов для решения практических задач

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(Р е з ю м е)

В работе обсуждается применение генетических алгоритмов для решения практических задач оптимизации – например срез стандартных пластмассовых панелей разнородного применения.