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Optimal Cutting of the Glass and the Profiles for Joinery Work with Application of Genetic Algorithms

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Abstract: *The application of genetic algorithms for optimal cutting panes of glass and the profiles for joinery work is introduced. A combined GA is used as a probabilistic approach in the search of quasi-optimal solutions. The performed research show that the usage of these algorithms significantly reduces the unutilized material, the cutting time is decreased and also that there is a significant economic effect. The usage of described system will contribute for decreasing of the price, materials and time for design of joinery work.*
Keywords: *genetic algorithms, optimization, random search, selection, crossover, mutation, profiles, glass, joinery work*

I. Introduction

Genetic algorithms (GA) are a method for search based on the selection of the best species in the population in analogy to the theory of evolution of Ch. Darwin.
Their origin is based on the model of biological evolution and the methods of random search. From the bibliographical sources [1-4] it is evident that the random search appeared as a realization of the simplest evolutionary model when the random mutations are modelled during random phases of searching the optimal solution and the selection is modelled 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;
- Modelling natural evolutionary processes for efficient solution of determined class of optimization and other problems.

During the last years a new paradigm is applied to solve optimization problems GA-based and modifications of GA. GA realize searching 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 the practical implementations during the last years is a stable proof of the growing expansion of the scientific and application research in the domain of GA. In order to give a general fancy for the type of applications, they could be classified in four main directions [7]: science, engineering, industry and various other directions (miscellaneous applications).
We propose in the rest of the paper the usage of the GA for effective cutting for joinery work.

II. Formulation the problem

Cutting stock problems can be encountered at the production stage of profiles and glass for joinery work. Cutting stock problems consist in cutting large pieces (objects), available in stock, into a set of smaller pieces (items) in order to fulfil their requirements, optimizing a certain objective function, for instance, minimizing the total number of objects cut, minimizing waste, minimizing the cost of the objects cut, etc. These problems are relevant in the production planning of many industries such as the paper, glass, furniture, metallurgy, plastics and textile industries. In the last four decades cutting stock problems have been studied by an increasing number of researchers [8 -15], [19, 20]. The interest in these problems can be explained by their practical application and the challenge they offer to academia. For despite their apparent simplicity, they are, in general, computationally difficult to solve. The continuous growth of the prices of the materials and of the energy requires minimization of the production expenses for every element. The coefficient of usage K_u [16] is used as a criterion of efficiency. In order to solve similar problems, a set of mathematical methods are proposed. The cutting stock problem is an optimization problem, or more precisely an integer linear programming problem that minimizes the total waste while satisfying the given demand [17].

(1) $$\min \rightarrow \sum_{j=1}^{n}\sum_{i=1}^{p} c_{ji}x_{ji}$$

(2) $$\sum_{j=1}^{n}\sum_{i=1}^{p} a_{jik} x_{ji} = b_k,\ k = 1,\dots,q$$

(3) $$x_{ji} \geq 0,\ j = 1,\dots,n;\ \ I = 1,\dots,p$$

Where (1) is the objective function, (2) are constraints determining the number of pieces needed to complete the order and (3) are conditions of non-negativity of the variables.

One the cutting stock problems is cutting out glass surfaces and profiles in the production of glass packets for windows, shop windows, doors, roofs and other for joinery work. The dimensions of the glass are different depending on the case considered. Depending on the type of the orders/requests, rod sheets which differ in size, width and brands, are used for cutting out. That is why the portfolio of the orders is divided into groups, depending on the characteristics of the initial parameters [1, 16]. The cutting problem can be formulated in the following way: a number of items (glass for doors, windows, etc.) must be selected from the requests portfolio and depending on the size and type of the primary material, optimal cutting out must be done, with minimal loss of the material used. Since these losses have to be minimal, it is necessary to maximize K_u according to the formula [1, 16]:

(4) $$K_u = \frac{\sum_{r=1}^{n} S_r}{S_{eb}}$$

Where the numerator is the sum of the areas in the requests portfolio and S_{eb} is the area or length of the source material. The maximal value of $K_u = 1$, but in real life it is hardly reached. Knowing the value obtained for K_u and comparing it with $K_u = 1$, we could make a conclusion about the optimality of the cutting. The scientific area, connected with the present study, is operational research. It includes a scientific approach for making an optimal decision under conditions of technical, economic and other constraints, connected with the definition of adequate mathematical models and the formulation and solution of the corresponding optimization problems.

As an illustrative example for solving such class of problems, we will show the use of an imitation model and a genetic algorithm (GA) for optimization [13, 16]. The imitation model describes the system operation, realizing the rational ordering of the requests. The input information of the model is the portfolio of the requests, which consists of a certain set of requests, containing the dimensions and a number in the portfolio. As a result of the operation the model must realize the positioning of the requests on the surface of the output building, and after completion of the work it must give the rational value of K_u, that must be close or equal to the optimal one. In order to solve the optimization problem of K_u, GA is used [1, 16]. The basis of the imitation model is the algorithm realizing the requests allocation. It describes the system performance, i.e., it checks the possibility to place the consequent order and to realize it. The output data for it are the values of the requests numbers, issued by the optimization algorithm GA. Each request has its identification number that defines it in the requests portfolio. In order to analyze the process of requests positioning on the surface of the output building, the requests number must be defined, taken from the requests portfolio and then the sequence of their locating in the building is defined. Each request in the orders portfolio has a respective number which accepts values from zero up to the number of orders in the requests portfolio. With the successive numbers in the optimization algorithm, in which a set of successive numbers is a separate solution, that is realized by the imitation model and for which K_u is determined.

III. Using a genetic algorithm to solve the problem

The solution of the above stated problem is based on a genetic algorithm (GA). 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 [18], Falkenauer [3] and Goldberg [2] 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 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 is performed by C_u. The function is chosen based on the experiments done with the model to ensure the correct development of the population.

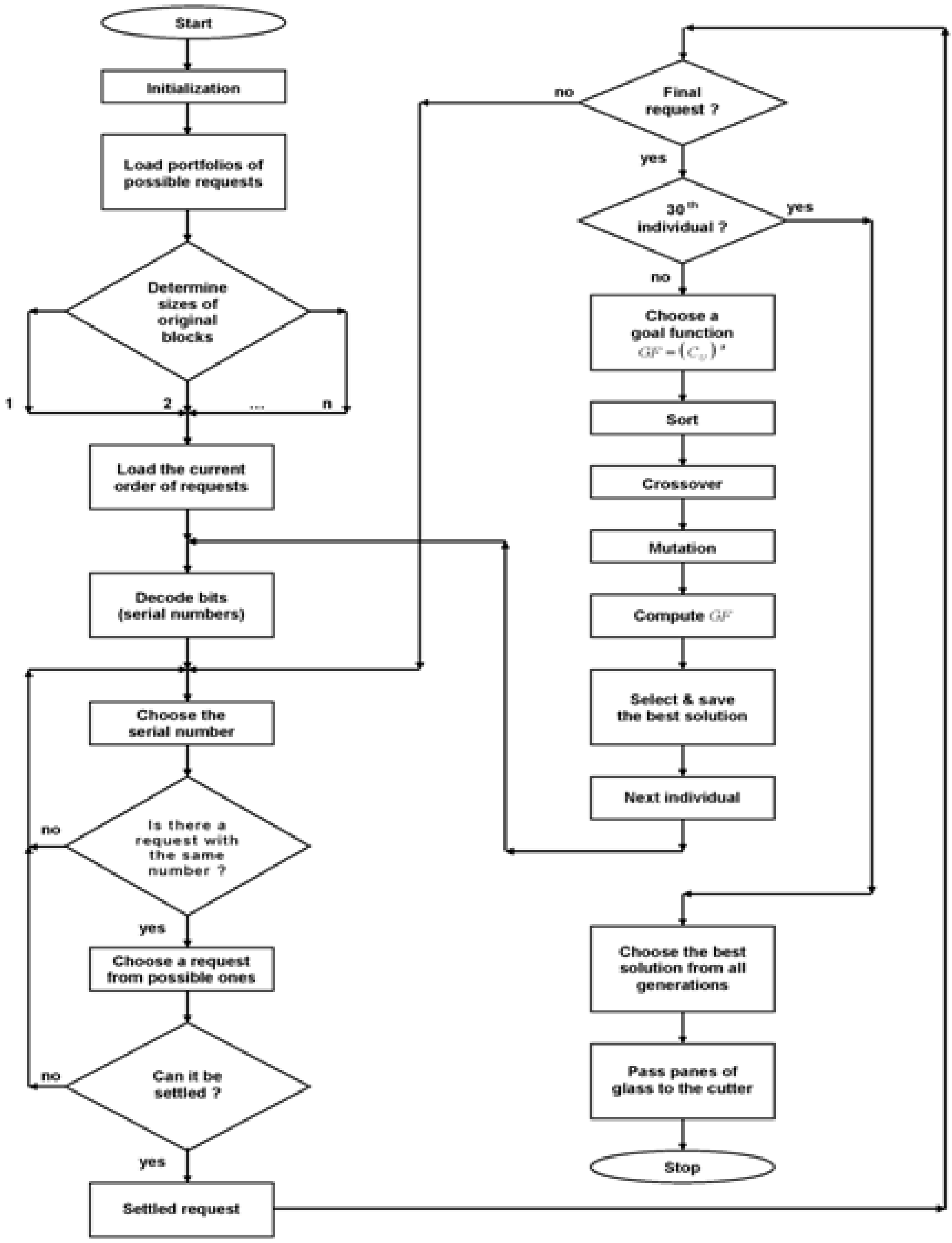

Fig. 1 Generalized block scheme

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

- number of individuals in the population – 30;
- 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. 1.

Briefly the idea of operation is formulated below:

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

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 the GA operation is shown at Fig. 2 Let the number of the obtained orders is 15.

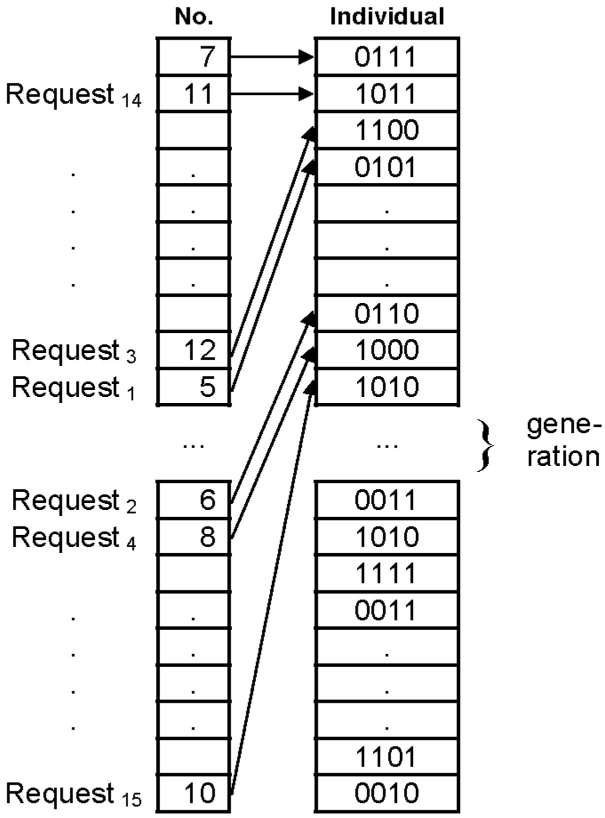

Fig. 2 Order positioning encoded

Therefore the individual is a binary string-chromosome with a length of 60 bits. The genes in this string are 4 bits long each of them. 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 the 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.

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

1. Input of the current order requests.
2. Decoding of bits. The string-chromosome is decoded, i.e. the serial numbers are determined.
3. Choice of the serial number. Sequential numbers are counted and the serial number is determined.
4. 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.
5. The request is disposed if possible.
6. Go to step 5 if the request is not final.
7. If the request is final then a validity test is performed for the number of the individual.
8. The next consecutive steps concern the choice of the goal function and the respective genetic procedures such as sorting, crossover and mutation.
9. The goal function (GF) is calculated.
10. 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:

$$\frac{GF_{max} - GF_{mid}}{GF_{max}} > 0{,}85 \qquad (5)$$

where GF_{max} and GF_{mid} are respectively the maximal and middle meanings in the current population.

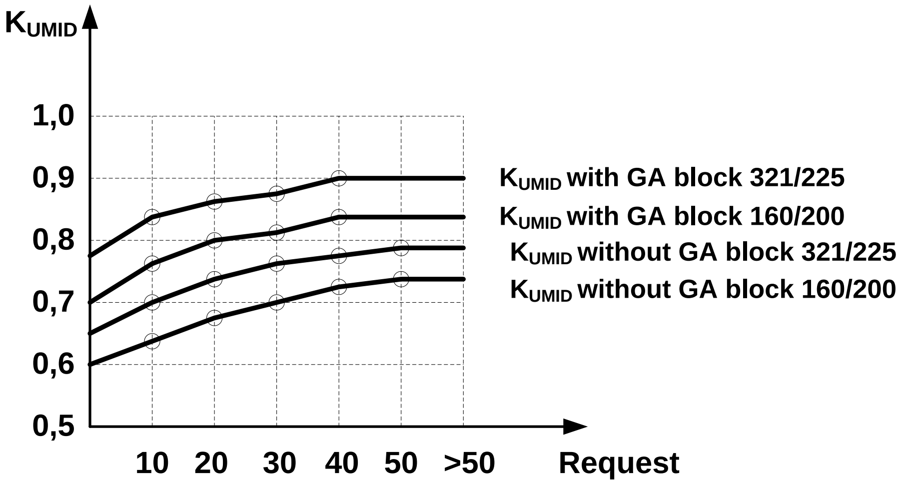

Fig.3 Graphics of the coefficient K_u

It is a statistical requirement that the individual with the biggest GF 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 a priori 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.

In our case we used a GA for an Italian cutting machine in a company for production of glass panes for windows, doors, window-glasses, roofs. This machine had an optimized program for just a single standard block of glasses – 160/200. The implementation of the new system for cutting applying the GA led to increased possibilities for cutting new original blocks and K_u was considerably improved; the glass waste which varied between 25 and 35% dropped down to 10-15%.

Fig. 3 presents the graphics of the middle values of K_u before and after the application of the GA The research in this area may continue in pursuit of practical solutions for the case when the requests are divided in urgent and usual ones. Then the goal 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.

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