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Testing of Genetic Algorithms Using a Modular System for Solving Optimization Problems

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Abstract: *The paper introduces a modular system for testing with Genetic Algorithms (GAs) to solve optimization problems. The system consists of several modules that include blocks with different purpose which are interconnected in various ways. The GA is realized via different methods of GA set-ups, search processes and evolutionary models, thus allowing the estimation of the practical efficiency of the algorithm.*

Keywords: *Genetic algorithms, optimization, selection, crossover, mutation.*

I. Introduction

Genetic Algorithms (GAs) are a method for search, based on the selection of the best species in the population in analogy to the theory of evolution of Charles Darwin.

Their origin is based on the model of biological evolution and the methods of random search. From the bibliographical sources [1, 2], 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 GAs is twofold:

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

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

Following [3, 4, 5], GAs differ from other optimization search procedures with respect to the items following below:

- they operate with a coded set of parameters, not with the problem parameters;
- they realize the search not by improving a single solution but by simultaneous usage of several alternatives for the given solution set;
- they use the Fitness Function (FF), not its different increases to estimate the quality of the taken decision;
- they apply probabilistic rules for the optimization problem, not deterministic ones.

During the last years a new paradigm is applied to solve optimization problems – GA-based and modifications of GA. EA realize searching the balance between efficiency and quality of solutions at the expense of selecting the strongest alternative solution [1, 2].

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 the domain of GA.

In order to give a general fancy for the type of applications, they could be classified in four main directions [1]:

- science – to increase the level of various scientific research [1, 2, 6-11];
- engineering – to solve specific engineering problems [5, 13-15];
- industry – to increase the quality and the amount of production for some industrial processes [4, 5, 14, 16-19];
- various other directions (miscellaneous applications) [1, 6, 20-25].

The present paper introduces a way to improve the qualities of the applied algorithms for solving various classes of optimization problems. This is done by a modular program system that is GA-based for testing. It allows the application of elaborated various methods for set-ups of genetic operators at the execution time with respect to the search process, the different evolutionary models included.

II. The approaches proposed

The new program modular system to test using genetic algorithms for solving optimization problems is realized as a set of program devices consisting of various program modules, each one including different blocks (Fig. 1).

block 1 – Block for Input; block 2 – Optimization Problems Editor used for editing different optimization tasks; block 3 – Set-Up Block including three set-up sub-blocks:

block 3.1 – Set Up Genetic Operators block;
block 3.2 – Set Up Search Methods block;
block 3.3 – Set Up Evolutionary Models block.

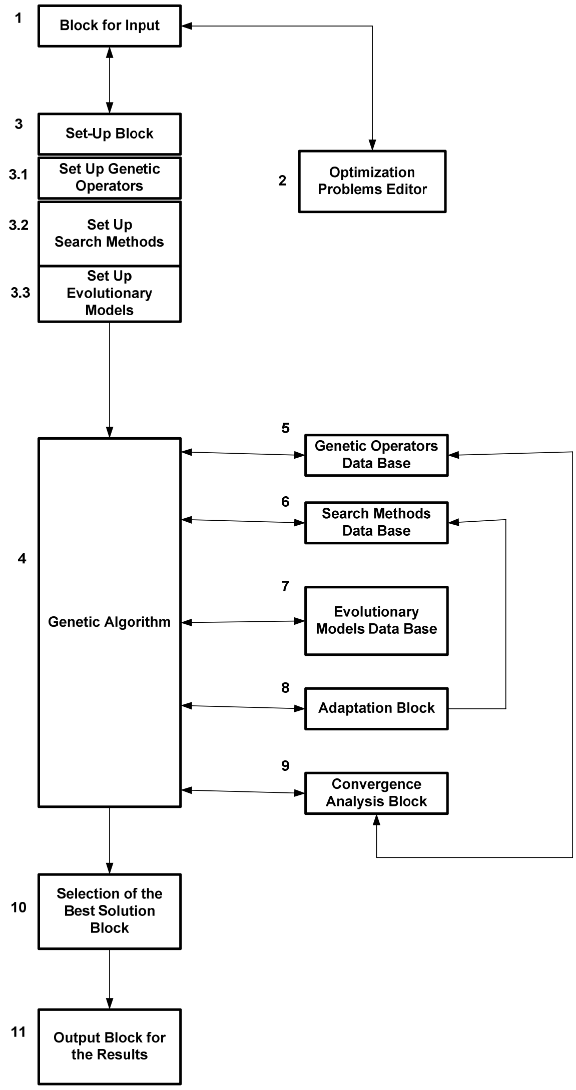

Fig. 1

block 4 – Genetic Algorithm block for the already fulfilled set-ups of algorithms with genetic operators, search methods and evolutionary methods; block 5 – Genetic Operators Data Base; block 6 – Search Methods Data Base; block 7 – Evolutionary Models Data Base; block 8 – Adaptation Block; block 9 – Convergence Analysis Block; block 10 – Selection of the Best Solution Block; block 11 – Output Block for the Results.

Based on the already presented blocks, a synthesis was performed of several program modules that are combinations of the introduced blocks.

MODULE 1 is used to explore various modifications of genetic operators: a recombination operator, a crossover operator, a mutation operator, an inversion operator, a segregation operator, a translocation operator, of their modifications and also of their joint operation.

The introduced module based on GAs is realized and it is used to compare original properties of one and the same GA for different genetic operators. The result of this comparison includes the operation time of the algorithm, the best solution from the execution, the algorithm convergence estimate. The general structural graph of the program module includes blocks with numbers 1, 2, 3.1, 4, 5, 10 (Fig. 2).

The input of the set-up data for the algorithm is done in block 3.1 (population size, types of applied operators, probability for their usage, etc.) and the Data Base (DB) for various types of genetic operators is realized in block 5.

Different set-ups of GA are performed in block 4 and the results are obtained in block 10.

MODULE 2 is applied to explore the enabled heuristic search methods. It is realized analogously to MODULE 1 and it consists of blocks with numbers 1, 2, 3.2, 4, 5, 6, 10 (Fig. 3).

Blocks with numbers 1 and 2 operate in the already known way, with the introduced functions.

Block 1 is the block for input of data about the problem (input of variables and parameters of the investigated block, combination matrices, various criteria, etc.);

Block 3.2 inputs the set-up parameters for the algorithm (the search automation functions included), so that various methods improving the search process can be enabled or disabled.

Block 4 is oriented to GA with its set-up about the search optimization to produce information of the current value of the best FF and also the graph of the solution modifications along all generations of the algorithm.

Block 6 is related to the data base with different search methods.

During the process of operation block 10 produces an output file with the code of all chromosomes, all iterations of the current generation and the result about the global extremum.

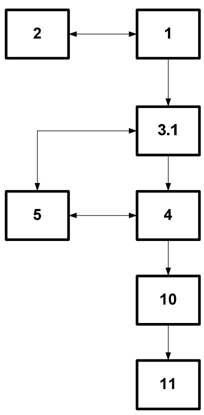

Fig. 2

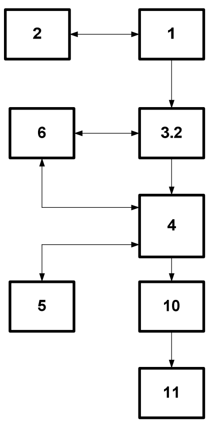

Fig. 3

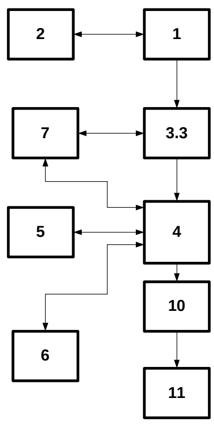

Fig. 4

MODULE 3 concerns the research of the evolutionary models applied in the algorithm. It includes blocks with numbers 1, 2, 3.3, 4, 5, 6, 7, 10 (Fig. 4).

The blocks listed below are more specific:

Block 3.3 – to input the set-up parameters for the algorithm (they enable the search optimization functions). The block enables or disables various methods to improve the search process and also various evolutionary models.

Block 4 is oriented to GA with its set-up about the search optimization to produce information for the current value of the best fitness function (FF) and also the graph of the solution modifications along all generations of the algorithm.

Block 7 is the Evolutionary Models Data Base block.

Block 10 is the Output Block for the Results. The output data are the same as the features of MODULE 2.

MODULE 4 is used during the research process of the search methods applied in the algorithm, of the evolutionary models, the iterative and statistical improvement, the adaptation and the analysis of convergence. The realization of this scheme is analogous to the rest of the MODULEs and it contains blocks with numbers from 1 to 10:

- input of the task data and of the algorithm set-up parameters (the search optimization included) – block 1;
- optimization task editing – block 2;
- set-up of genetic operators, search methods and evolutionary methods – block 3 (3.1, 3.2, 3.3 included);
- GA with all set-ups – block 4;
- three types of DBs (genetic operators DB, search methods DB and evolutionary models DB) are realized as blocks with numbers 5, 6, 7;
- the feedbacks and the balance between the procedures are achieved in block 8 for adaptation;
- the analysis and the convergence are realized in block 9;
- the obtained results are recorded in block 10.

The execution of a given program MODULE of some subsystem begins with the input of information about the performed task(s). Then a set-up is performed of the global and the private parameters of the algorithm, namely:

- the initial distribution of the coefficients and the criteria;
- the initial population size;
- the upper limit of the iteration number for the algorithm (the number of steps);
- the upper limit of the number of generations (the number of algorithm (re)starts);
- the limits (upper and lower) for the FF values (the global optimum, if neither is given);
- the probability for applying the genetic operators.

Private parameters for MODULE 1 are various types of operators:

- for crossover – single dot, two dots, cyclic, universal, etc.;
- for mutation – single dot, two dots;
- for translocations;
- for segregation;
- for selection – randomly, according to a given criterion, elite, tournament, etc.

The execution of all established genetic operators is followed by a check of the FF. The research process restarts iff the FF value is unsatisfactory.

The search parameters about the DB methods (MODULE 2, block 6) are enable flags to use heuristics based on:

- optimization statistical methods;
- gradient methods;
- dichotomy methods;
- Fibonacci methods;
- golden-section methods;
- fractal sets, etc.

GA is executed after the performance of all established search methods. If the stop criterion is reached then the algorithm finishes (the execution), else the research process restarts.

The MODULE 3 Evolutionary Models Data Base program block 7 parameters are as listed below:

- Darwin-evolution model;
- *Lamarckism* – Lamarck-evolution model;
- *saltationism* – de Vries model of evolution;
- K. Popper's model of evolution;
- synthetic theory of evolution.

The GA is realized via the best operator set that is determined during the test. The elaborated methods cited above are applied during the execution time of the algorithm. The main idea is representation of the general improvement embedded by the heuristics during the search which includes their behavior for various types of problems.

This is followed by execution of GA according to the result about the operator set from the execution of all heuristic procedures and all evolutionary models included. The operative set-up influences the Adaptation Block No 8 that realizes the balance between the procedures and the Convergence Analysis Block No 9 to overcome the algorithm convergence. This is the way to achieve the best features at execution time and also raising the algorithm robustness.

III. Conclusions

The basic idea of the performed testing was to receive better features at run time for the set of algorithms, and an increase in their stability. The determination of the improvement parameters includes approaches, algorithms, software modules, DBs, etc. They are performed by three basic series: testing genetic operators and the GAs, testing methods for searching and testing of the evolutionary models.

The conception of the presented system covers testing of the cited below aspects:

- Algorithms for a specific problematic case by successive enabling of all elaborated heuristics from a standard problem and the determination of the values of the improved parameters. In this way it is possible to estimate the efficiency of the methods applied in the algorithm to optimize the search.

• Algorithms of some standard tests followed by comparing the obtained results with the already existing ones for a given benchmark that are calculated by another algorithm(s). So it is possible to estimate the efficiency of the algorithm and of the program modules.

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Тестирование генетических алгоритмов при помощи модульной системы для решения задач оптимизации

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(Р е з ю м е)

В статье представлены модульные системы для тестирования генетических алгоритмов (ГА) для решения задач оптимизации. Система состоит из нескольких модулей, которые включают в себе блоки различного назначения, которые связаны между собой различными способами. ГА осуществляются при помощи разных методов: ГА установок, процессов поиска, также как и эволюционных моделей таким образом, что позволяют оценить практическую эффективность алгоритма.