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MULTI-OBJECTIVE GENETIC ALGORITHM FOR SUSTAINABLE OPTIMALIZATION

Sándor BALOGH, Béla CSUKÁS
Kaposvár University, Faculty of Economic Science, Hungary
balogh.sandor@ke.hu

ABSTRACT

The long term, large scale, hybrid, multidisciplinary models of Computational Sustainability requires new optimization methodologies. In achieving optimal process design and control we have to choose the "best" from various structures and parameters. The usual objectives are minimal cost or maximal profit. One of the accepted approaches is to find the exact optimal solution for a simplified model formulated by sophisticated mathematical constructs like MINLP. Another approach is based on the qualitative knowledge of engineers and described by heuristic rules and rule-based decision algorithms. Optimization for sustainable development cannot often controlled by a single, aggregated objective. We have to consider multiple objectives according to short, middle, or long time horizons. Besides the economic goal function, we have to consider the environmental impacts (e.g. the necessary recycling, etc.). This needs detailed model-based multi-objective process development. Accordingly, in our work we use an engineering approach that focuses on the search for "good enough" solutions, based on the most detailed models. In the solution of practical problems, priority ranking of the constraints and evaluations combined with a new grid method helps to focus on the very part of the Pareto-front where the good solutions are found. The elaborated, multi-objective genetic algorithm supports effective coding and the multi-criteria evaluation of sustainable processes.
Keywords: meta-heuristic, multi-criteria, development, modeling, optimization

INTRODUCTION

In the conventional optimization methodologies the model of the investigated problem used to be simplified to the formalism of a mathematical construct that makes possible the determination of the exact optimum.

Considering the importance of the details in the engineering problem solving, in the past decades increasing effort has been made for the possibly most detailed model based optimization. The dynamic simulation tools for the various processes developed rapidly, while the optimization of more and more complex hybrid (continuous/discrete) models became intractable in the development of in-parallel optimization methods. Another actual challenge is the optimal solution of the large scale, long term processes of changing structure with increasing complexity (*Csukás and Balogh*, 1998).

Having recognized these difficulties, the inexact, heuristic and/or evolutionary methods of the Artificial and Computational Intelligence became more and more important (*Siarry*, 2008). In the case of an inexact approach there is no guarantee for the determination of the absolute optimum. This disadvantage is compensated by the fact, that good enough solutions can be determined on the basis of the necessarily most detailed models. One of the heuristic optimization methods of the Computational Intelligence is the Genetic Algorithm (*Holland*, 1975). This work is characterized and motivated by the demand on optimization detailed and/or large scale hybrid problems, coming from various field of application, which could not be solved with the available tools (*Balogh*, 2010). Moreover, in addition to the economic objective, we have to optimize according to a number of natural criteria, or we have to combine the economic and natural objectives. The in-parallel developing generic simulation method more and more tolerates the arbitrary discrete and continuous changes. In addition, we considered also the general tendency of continuously increasing computational demand for the simulation of the possible solutions.

MATERIALS AND METHODS

In the present research and development work many open source code software development tools, as well as the collaborating generic simulator, developed by our research team were applied. For the realization of the macro granularly parallel evolutionary development, a computer cluster was built and configured. Accordingly, the methods applied for the development and testing of the elaborated genetic algorithm were the followings:

- software tools, applied for the development of the genetic algorithm;
- the generic simulator, collaborating with the genetic algorithm;
- hardware and software tools, applied for the realization of the macro granularly parallel operation.

The most important open source software tools, used for the development of the genetic algorithm were the followings:

- fox toolkit (*www.fox-toolkit.org*);
- plplot (*www.plplot.org*);
- tclap (*http://tclap.sourceforge.net*);
- c++ compilers: g++ (*http://gcc.gnu.org*), mingw (*www.mingw.org*).

For the macro granularly parallel execution of the evolutionary simulations, a PC cluster, containing 16 units was built. The operation of the cluster was solved by the adaptation of the OpenSSI (*www.openssi.org*) software.

Regarding the demonstrated example applications:

- the programs of the benchmark test tasks has been written by myself (*Balogh*, 2010);
- the simulation of the detailed example applications has been solved by the generic simulator based on the Direct Computer Mapping (*Csukás*, 1998) of processes, developed in the research school of process informatics, using the version running under Windows® with Excel® interface.

RESULTS AND DISCUSSION

The methods, applied for the economic optimization of complex systems in practical problem solving, have to satisfy many criteria. One of the two most important demands is supporting of the multi-criteria evaluation in decision making. The other is, the capability for the representation of the complex possibility spaces, characterizing the economic and/or technological processes.

In the development of the genetic algorithm, prepared for the multi-criteria economic optimization, was motivated by the above criteria.

Supporting of the multi-criteria decisions has a keynote role in the elaboration of the new algorithm. In the solution we made possible fitting the preferences of the decision maker by each of the 'a priori', interactive and 'a posteriori' methods. In the declaration of the evaluating criteria, we can define the optional properties. These properties are the priority, as well as the apparent lower bounds of the given objective. By means of these properties the decision maker can guide the optimization process to the preferred regions of the Pareto-front.

The flexible possibility for the unified consideration of constraints, priorities and objectives, makes possible the application of a ranked fitness calculation, according to a modified Pareto-dominance in the multi-criteria genetic algorithm. The ranking can be used both for a single objective and in the multi-criteria evaluation with the possibility of the treatment of conditions. There are various strategies for the fitness calculation, and the majority of the published methods can be applied. For example we can use the number of the dominated variants or the number of the variants, dominating a given variant, as well as the depth of the Pareto-front. In the calculation of the dominance, first the conditions are evaluated one after the other. Optionally, a priority ranking can be defined for the conditions. This makes possible the combined use of the condition violations (i.e. how many conditions are violated by the given variant), followed by the consideration of the summarized or maximal measure of constrain violations (i.e. how long is the distance from the awaited range).

The evaluating criteria have a priority ranking, too. In a given priority group, first the fulfillment of the objectives are compared (i.e. the variants that fulfill the objectives are better). Next, the variants that fulfill the objectives are compared according to the value of the criteria. The procedure of the calculation is illustrated in *Figure 1*.

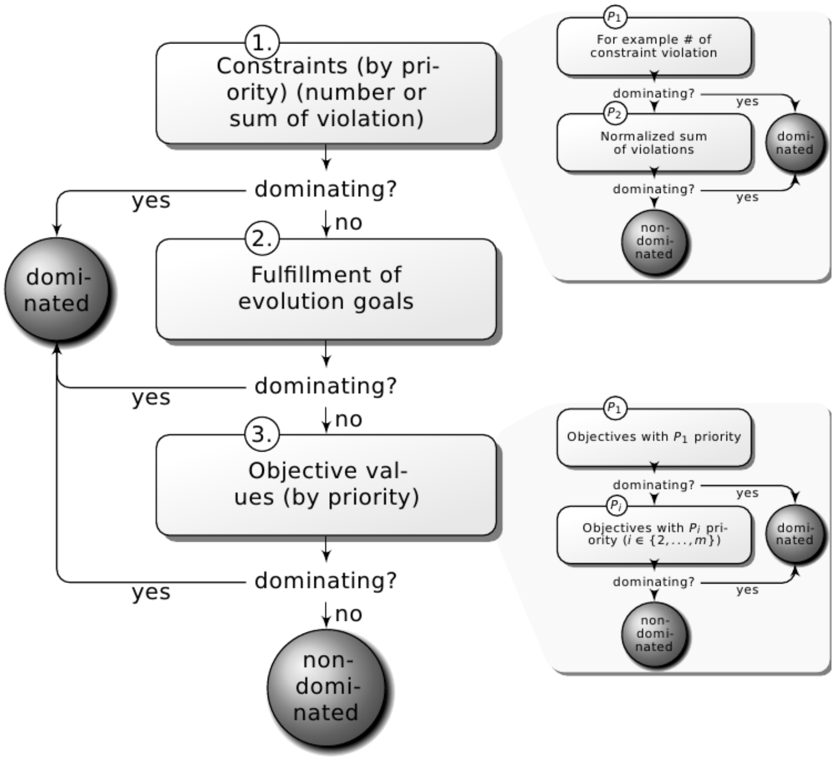
The necessary conditions for the good estimation of the Pareto-front are those proposed solutions, which have a uniform distribution along the front. Therefore, in addition to the fitness values, the variants are characterized by a crowding parameter.

In the applied selection algorithm, this crowding parameter was used for the selection and replacement of the comparison of the parents for the variants, having the identical fitness values. This helps the uniform distributed identification of the Pareto-front.

Because of the small population size, the number of the non-dominated solutions in the last population is also small. Consequently, it is advantageous to save all of the known Pareto-optimal solutions in outer archive storage. The size of the archives can be configured freely. Having reached the maximal size of the archives, the saved Pareto-optimal variants are deleted, according to their crowding parameters.

Figure 1

The calculation of modified Pareto-dominance



As an example for the use of multiple natural and economic criteria see the so-called Single Switch Server problem (*Perkins and Kumar*, 1989; *Agarwal et. al.*, 2002; *Bánkuti and Csukás*, 2003) in *Figure 2*.

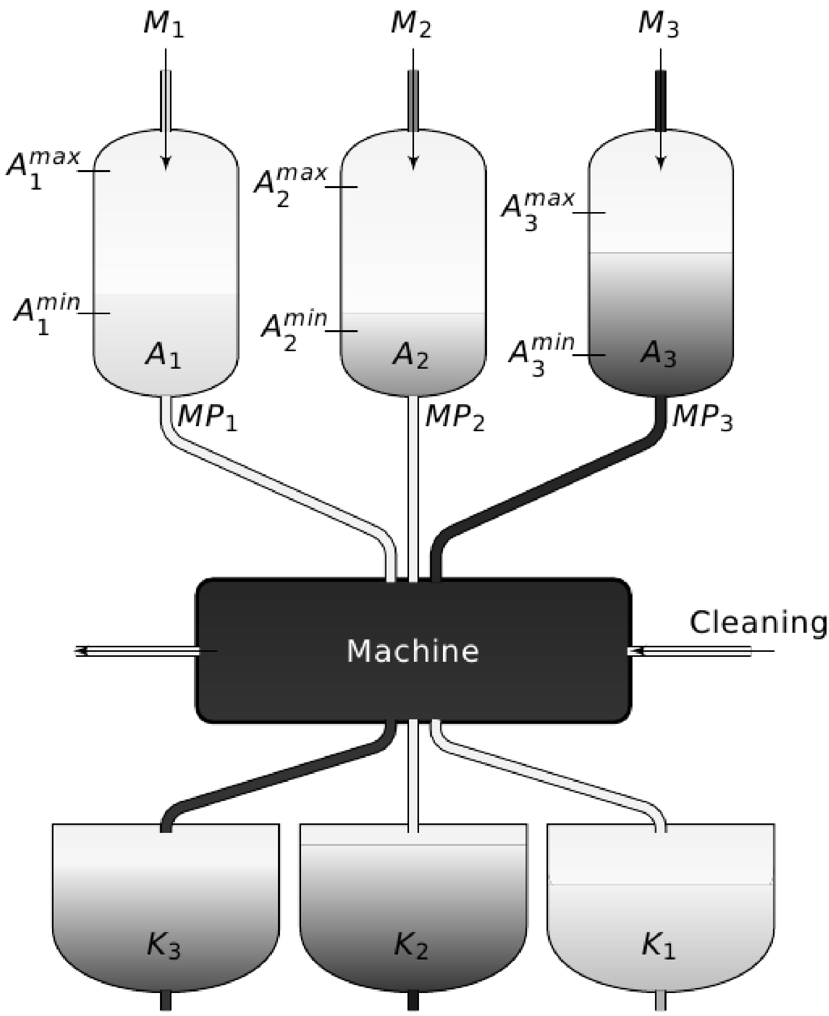
This is one of the simplest discrete / continuous, switched, hybrid dynamic system. The suppliers send materials in the buffer tanks A_1, A_2 and A_3 at constant flow rates of M_1, M_2 and M_3, respectively. Machine can process any one material at a time at rate MP_1, MP_2 and MP_3. The level of materials changes in the buffers, however there are determined minimal and maximal levels. A material specific setup time is incurred each time machine switches to different material. The goal is to design a switching strategy, which satisfies various single or multiple objectives, e.g. maximal production, minimal setup and waiting time, minimal buffer levels, etc. There is an obvious interaction between the continuous and discrete (logic) components, i.e. it is a simple prototype of the hybrid dynamic systems.

The estimated three dimensional "full" Pareto front of three natural evaluation criteria can be seen in *Figure 3* Evaluation criteria were the following:

- f_1: sum of production (maximize)
- f_2: sum of buffer levels (minimize)
- f_3: sum of setup, waiting and cleaning times (minimize)

Figure 2

Single Switch Server problem



Usually the decision maker does not want to see the "full" Pareto front, but only a region of it. The result of excluding the excessively low production (less than 50000) visualized in *Figure 4* and *Figure 5*.

In this studied example we performed a single objective economic evaluation with estimated cost coefficients. The location of that solution with maximal profit (the larger black point on the Pareto front) illustrated in *Figure 3* and *Figure 4*.

Example of constraints handling of the elaborated genetic algorithm can be seen in *Figure 3* and *Figure 5*. The larger gray point represents a solution with constrained production structure.

Figure 3

The "full" Pareto front

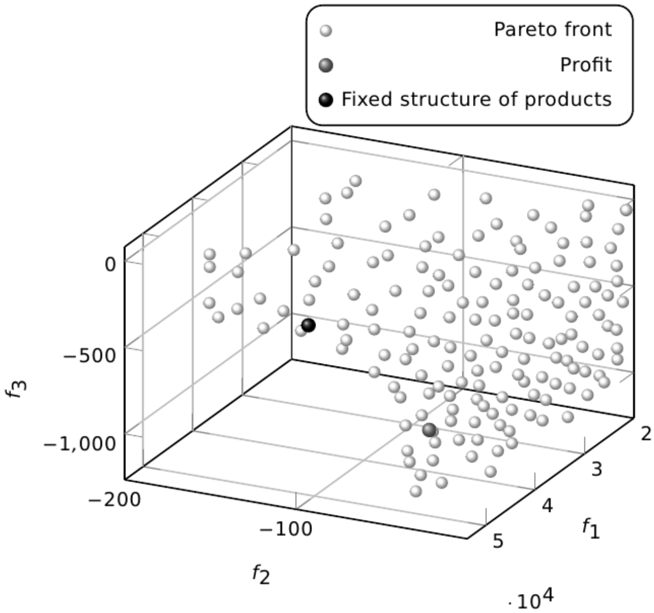


Figure 4

Maximal profit solution on narrowed Pareto front

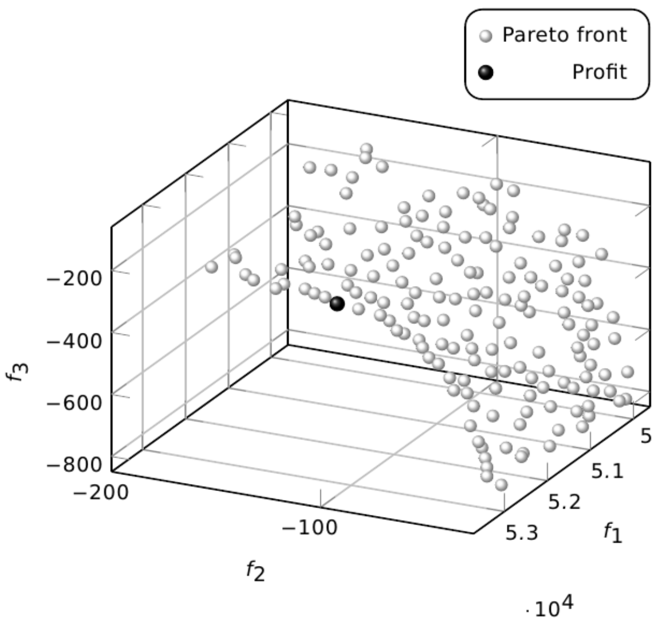
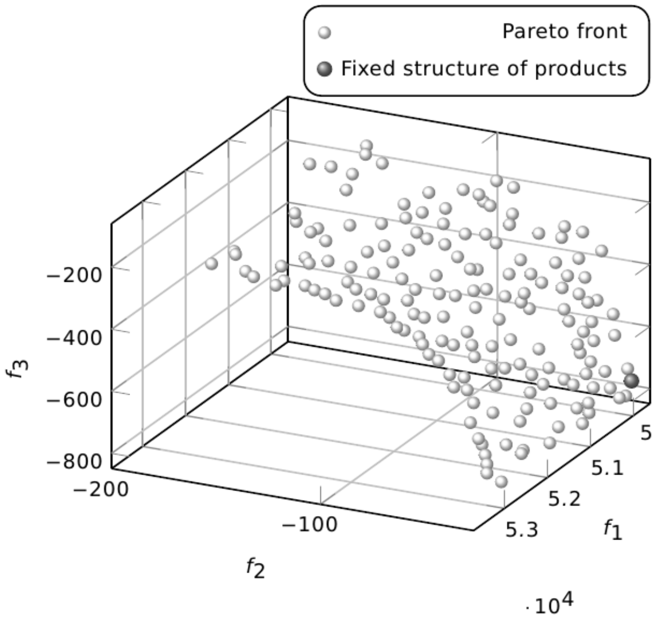


Figure 5

Constrained solution on narrowed Pareto front



CONCLUSIONS

Considering the above described research results, as well as the experiences, obtained from the application of the continuously developing genetic algorithm, the most important conclusions are the followings:

One of the lessons, coming from the, practical optimization and identification problems was that it is not possible or it does not worth to aggregate the evaluation into a single objective function. In optimization, almost everybody wants to make an economic evaluation (i.e. minimizing the cost or maximizing the profit), however the data for the calculation of the economic goal function are not known. It is a typical case, when we have to optimize one, by-itself also complex, part of a large technological process, consisting of many steps. The economic parameters of the input and output materials are often not known. Consequently, the study ought to be extended to a greater system, consisting of this part. On the other hand, the field experts can declare very good natural objective functions. Nevertheless, the ongoing methodological development tends to bridge the existing gap between the technological and economical processes, and this makes possible the more and more correct economic evaluation. In accordance with the results, obtained from the logistical example in the present work, the combined application of the economic and natural evaluations seems to be a feasible method.

The experiences, obtained with the continuously developing and presently further developed, integrated genetic algorithm, proved that the applied coding and operators, as well as the archived storage of the investigated variants support the optimization process with small population and generation number.

The optimization of the practical tasks with great computational demand for the evaluation can be solved by the macro-granularly parallel simulation and evaluation of the variants. The method, implemented in a PC cluster, can accelerate the genetically controlled evolutionary process almost proportionally with the number of CPUs in the cluster.

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