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MULTIDISCIPLINARY OPTIMIZATION IN URBAN SERVICES MANAGEMENT

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Abstract

Optimization methods may be applied to the services operations management. A comprehensive objective function (a cost-function to be minimized) leads to a multidisciplinary optimization, considering all aspects of a services business unit. However, this introduces a very large number of variables (examples with tens of thousands of variables are presented), making classical optimization methods inadequate. The paper introduces the use of genetic algorithms and illustrates it in one example: leisure services. Multidisciplinary optimizations may play a crucial role in the success of any services business, and genetic algorithms are the most adequate computation resource in this type of optimizations.

Keywords: optimization, urban services management, total cost, risk, leisure services

1. Introduction

Optimization methods may be applied to the services operations management. A comprehensive objective function (a cost-function to be minimized) leads to a multidisciplinary optimization, considering all aspects of a services business unit. However, this introduces a very large number of variables (examples with tens of thousands of variables are presented), making classical optimization methods inadequate (Bertbente, Pleter and Berbente, 2000). The paper introduces the use of genetic algorithms and illustrates it in one example: leisure services. Multidisciplinary optimizations may play a crucial role in the success of any services business, and genetic algorithms are the most adequate computation resource in this type of optimizations.

2. Methodological ground

The multidisciplinary optimization of a subsystem *k* will pursue the minimization of the following function:

$$TCR_k = \sum_i C_{i,k} + \sum_j p_j \times R_{j,k} = \min$$

Where:

TCR_k represents the value of the total costs and risks function for the subsystem *k*

$C_{i,k}$ are the costs generated by the subsystem *k* in the solution

$R_{j,k}$ are the damages estimated for the subsystem *k*

p_j are the probabilities of the damages to occur, as a function of the solution

The most interesting feature of the TCR function is its additivity, which facilitates its applications to complex systems. Thus, for a system made up by N subsystems, the multidisciplinary optimization will be the result of the minimization of the following aggregate objective function (Schim and Siegel, 1999; Sprague, 1994):

$$TCR = \min(\sum_{k=1}^{N} TCR_k = \sum_{k=1}^{N}\left(\sum_i C_{i,k} + \sum_j p_j \times R_{j,k}\right))$$

We have successfully applied this formalization in several problems, one of which is illustrated in this paper: the operations management in leisure business, where a service area represents a subsystem of a “leisure mall' system (Moldoveanu, 2007).

3. Choosing genetic algorithms as an optimization method

The numerical optimization methods research is 60 years old. Today, many optimization methods are in use. We will present a classification framework and we will reveal the method of our choice for (non-linear) multidisciplinary optimization problems.

The first classification is based on the global minimum search strategy:

- complete or exhaustive search methods
- stochastic search methods

The former are remarkable resource consuming. The computation effort increases with the factorial of the number of variables, making them inapplicable for multidisciplinary problems, which may reach to tens of thousands of variables. The later methods are economical, but they suffer from convergence problems and with finding an arbitrary stop criterion. The stochastic methods do not guarantee finding an *optimum*, but a *quasi-optimum*, which is still very useful in practice.

On the highest degree of the derivatives of the objective function which have to be calculated in the optimization process, the classification brings three types:

- methods without derivatives

- methods with first order derivatives
- methods with second order derivatives

The best known methods for non-linear optimization are the *gradient methods*, which use partial derivatives of the objective function with respect of each variable:

$$\nabla F(x) = \left(\frac{\partial F(x)}{\partial x_1}, \frac{\partial F(x)}{\partial x_2}, \ldots, \frac{\partial F(x)}{\partial x_N} \right)$$

The *best* known *gradient* methods are:

- Steepest Descent / Gradient Method = Gradient Search
- Conjugate Gradient Method
- Non-linear Conjugate Gradient Method
- Advanced Nonlinear Gradient Methods = Stochastic Gradient Descent
- Quasi-Newton Methods
- Davidon-Fletcher-Powell Method
- Broyden-Fletcher-Goldfarb-Shanno Method
- Levenberg-Marquardt Method

There are also a few *non-gradient* methods, which do not require the partial derivatives of the objective function:

- Multi-Dimensional Search
- Random Search (Monte Carlo)
- Genetic Algorithms = Evolutionary Search / Strategy

As we have already mentioned, the gradient and the exhaustive search methods are not applicable to multidisciplinary optimizations with many dimensions or variables. The Random Search and Genetic Algorithms type methods remain the only applicable in such circumstances, of which the *genetic algorithms* proved to offer the best results as revealed after a couple of years of research.

The genetic algorithms, known also under the acronym *EMO* (*Evolutionary Multi-Criterion Optimizations*), are inspired by the methods used by the species of animals and plants to adapt to the environment (Pleter, Ştefănescu and Constantinescu, 2006). These represent the optimization of each species as an adaptation process in order to survive. The human genome contains some 40,000 relevant genes, thus the human species optimization problem has the same number of independent variables or degrees of freedom. Exhaustive optimization would lead to an overwhelming computational effort, to the order of 40.000! = 2.09×10^{166713}. Therefore, stochastic optimization remains the sole applicable to the living world.

Holland John Henry (1975) extended the applications of genetic algorithms to artificial systems, opening the way to large dimensional multidisciplinary optimizations.

The genetic algorithms are iterative procedures operating on a 'population' of 'individuals', each 'individual' being represented by a finite string of symbols also known as a genome, coding a possible solution in the given space of o problem. This search space consists of all possible solutions to the given problem. This is recommended when the search space is too large to allow an exhaustive search (like the gradient methods).

Selection itself does not open new routes in the search space, and we resort to genetics for specific operators: *crossover* and *mutation*. Unlike other search methods, which operate a single solution at a time, genetic algorithms operate with an entire population of solutions at any given moment.

To implement a genetic algorithm, we need to find a representation of the solution: this is known as a *chromosome*. Through crossovers and mutations, new individual solutions are created out of the existing ones. There are some methods to select candidates for breeding, all relying on an objective function measuring the *fitness* of each individual, or how close is the individual to the desired characteristics. A good choice of chromosome representation and objective function guarantee the success of the genetic algorithm no matter which version of selection method we choose, but certain variations in convergence speed could make the difference.

The two chromosome operators "borrowed" from nature are illustrated in Figure 1.

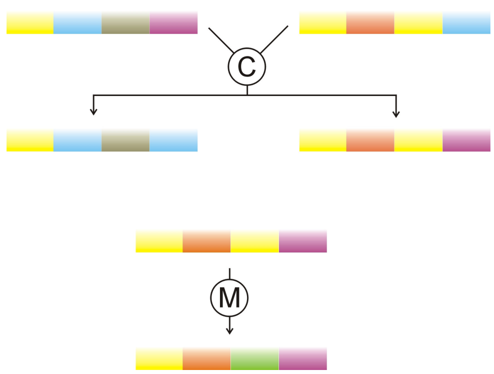

FIGURE 1 - THE CHROMOSOME OPERATORS: *CROSSOVER* AND *MUTATION*

The *crossover operator* generates two or more "children" chromosomes as combinations of two "parent" chromosomes. The main purpose of the crossover is to ensure that future generations include the good genetic heritage of the current one. The probability to inherit from one of the parents is known as the *crossover rate*. This mechanism is widely used in nature, moving the whole process to more promising areas of the search space with every new generation.

The *mutation operator* introduces a random evolution in the population, and this is essential to keep the optimization process safe from the local minima traps, allowing it to progress towards the *minimum minimorum*. The generation may stay segregated (*direct inheritance*) or may merge (*generation overlap*).

To get results, the objective function needs to be converted into a fitness function, which besides minimization, ensures the genome diversity. The process is known as *scaling*, and it may be done in various ways:

- *Linear* - is a simple rescaling of the objective function
- *Sigma* - those individuals who fall outside the standard distribution are eliminated
- *Sharing* - introduces a notion of chromosome distance, and an individual is penalized proportionally with the number of similar individuals

Based on the nature of the hyper surface of the objective function, a combination of the following *elimination methods* is usually employed:

- Replacing the individuals with the lowest fitness index (least adapted)
- Replacing the most similar or closely related individuals
- The "revolution" - keeping just the least similar individuals

These methods may be changed during the process, as the generation index moves forward. Usually we are after a high variety of the genome at the beginning of the optimization process, whereas further on we need to accelerate convergence speed.

The drawbacks of the genetic algorithms are the following:

- There is no theoretical demonstration of their convergence
- Their convergence is not granted
- There is no intrinsic stop criteria, the computation may continue to infinity (in other words they are quasi-optimum methods)
- They are big memory consumers (entire populations need to be stored at each generation)
- Computing time consumption is also an issue
- In case of insufficient genetic diversity (which could exist from the start, or even occur spontaneously, at least in theory) the genetic algorithm may fail (diverging or entering an infinite cycle)

These drawbacks are outnumbered by the advantages important to a number of applications:

- There is a statistic proof of their convergence in many types of problems (including all examples from the biology)

- They are adequate for N-dimensional problems where N is big
- They are also adequate for problems with a variable N
- They function even if the objective function depends on qualitative variables, provided there is a quantitative representation of those (this facility is particularly useful in business applications)
- They function with Boolean variables (discreet optimization) and with any mixture of variables
- They do not fall in the "saddle" trap
- They can handle singularity points or areas in the hyper surface
- They escape easily from the local minima traps, being suitable for rough or hilly hyper surfaces
- Genetic algorithms are the fastest convergent non-gradient method (definitely faster than Monte-Carlo and Multi-Dimensional Search)

4. Leisure mall service management case study

We tried to address the problem to optimize a space aimed at leisure and commerce services for a relatively high number of visitors (between 3,000 and 20,000 simultaneous visitors) who arrive by car (a parking place for each 1.6 visitors is needed). The optimization variables are the shape of construction, the shape and location of the parking lots, the number of levels, the shape and the size of the shops and service outlets (Downs and Flitan, 2005; Pleter, 2005).

The *TCR* objective function in this case aimed at optimizing the following costs:

- the penalizing cost for the duration of walking from the car to the points of interest and return; the distance walked in the open was additionally penalized due to the risk of rain, blizzard, heat or frost
- the opportunity cost with the unrealized commercial goodwill (this depends on the intensity of visitor traffic, being maximum on the corner shops; likewise, it depends on the distance in meters and in levels from the entrance; also, it depends on the size of the opening to the gallery hall, intensity of light, and the area of traffic from where the outlet is visible)
- the energy cost to ensure illumination, heating, cooling and ventilation of the volume (depends on the area of outer walls, the glass walls adding to the thermal transfer and the use of the natural light; the orientation of the building with respect to the North is also influential for the isolation)
- a penalty cost of walking to the toilet from any point
- a conventional cost regarding the car access to the outlet through the existing roads and boulevards, which influences the outlet location

Also the following risks were considered in the *TCR* function:

- the risk from the rapid evacuation, including the case of blocking any of the entrances
- the spontaneous crowding risk of any passing corridors
- the risk of equipment failure (HVAC central, artificial light)

This research is developing and we may only provide some provisional interesting conclusions:

- the optimum shape for a leisure mall is cylindrical, with four median atriums (Figure 2) ground level + 2 floors
- 4 main entrances at the ground level and 4 entrances from the roof
- surrounding parking on ground and also parking on the roof
- location with access to at least three boulevards with minimum two lanes each way, out of which two boulevards linking the outlet to high demographic concentration areas
- automated HVAC systems with increased reliability

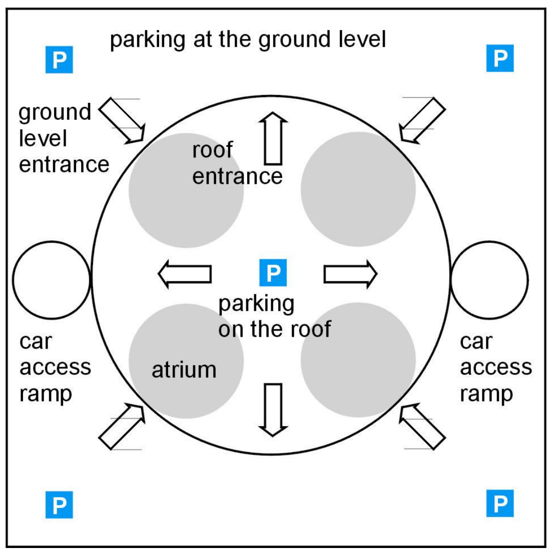

FIGURE 2 - THE SHAPE OF A *LEISURE MALL* OPTIMIZED USING GENETIC ALGORITHMS

5. Conclusions

The non-linear multidisciplinary optimization using genetic algorithms is rich in applications in management, showing a high degree of accuracy in representing the details of the economic phenomenon under all or most aspects.

The use of the total costs and risks function (*TCR*) is an instrumental alternative to the use of more or less arbitrary constraints in the optimization process. The function is expressed directly in currency units (for instance €), ensuring additive and allowing aggregation in the optimization of complex, multi-hierarchy systems.

The genetic algorithms are the only usable method in many practical situations, due to the large number of variables and to the inadequacy of the linear models. The computing time may be reduced by distributed computing in a LAN, using the distributed processing feature of the genetic algorithms.

The results in this line of research in the latest years have been encouraging, and for this reason we expect to use the method further in business applications, and also to publish more case studies for the benefit of the international scientific community.

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