Design Optimization of Microsystems

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ABSTRACT

At systems level, however, the extreme complexity of FEM models (many network nodes, long computer times) requires the use of models determined analytically. As the complexity of the search space of such analytical models becomes very high already if only a few sizes of a microsystem are treated, manually controlled simulations for only a few design variants, as a rule, will not result in optimum systems designs. Part-automated design optimization can be achieved by replacing human operators by a tool which studies the parameter space of the systems parameters. Human activities, in this case, are reduced to predefining an evaluation (a description of the quality goals and priorities). The tool then directs the search into that part of the parameter space in which optimum design variants can be found. Part-automated design optimization does not depend on a type of model, as only values of formal parameters are exchanged between the simulator and the optimization tool. The convergence reliability of a traditional numerical method is compared with a heuristic search technique in an example of design optimization.

Keywords: Analytical Model, Design Variants, Design Optimization, Heuristic Search Technique.

INTRODUCTION

In engineering and physics, complex objects are first modeled, and a system of regularities, e.g. in the format of mathematical equations, is then set up with these models. A model is considered correct if the conclusions resulting from this step (e.g. simulation results) are in agreement with the phenomena observed in nature (e.g. measured results).

This approach must be used in the development of microsensors and microactuators because these microsystems are very complex as a consequence of the required high functionality on a minimum of space (chip size), and also because of the sophisticated manufacturing techniques. Consequently, the manufacturing step should be preceded by simulation models, the simulation results of which may constitute a basis for making a laboratory specimen.

Measurements conducted on laboratory specimens, in turn, furnish data for comparison, thus allowing the model and the laboratory specimen to be validated.

Systems design on the physical level by means of FEM simulation models normally is feasible only for systems components, because of the rapidly growing complexity of the model and the resultant long simulation times. A higher degree of model abstraction linking components can be described by analytical models, which lead to much shorter computation times with a circuit simulator. These analytical models can both be adapted to FEM component models and combined into systems models, and then improved by preset optimization goals, by means of a suitable search technique improving their quality [1].

Our search technique can be used also on other design problems, for instance, in the field of optics. One example of such an application will be given in the next chapter.

The techniques listed above are supported by the open tool environment developed at the Institute for Applied Computer Science of the Karlsruhe Research Center, **SIMOT** (**Simula**tion and **O**ptimization **T**ool Environment) [2] (Fig. 1).

OPTIMIZATION OF A MICRO-OPTICAL COLLIMATION SYSTEM

Many micro-optical applications require modifications in the emission characteristics of sources (in general, lasers or optical fibers), i.e. their collimation or focusing [3]. This is done by micro-optical lenses or combinations of various lenses.

The system described here uses two ball lenses to collimate the emission from a single-mode fiber (SMF) and image the collimated waist of the beam onto a photodiode (Fig. 2).

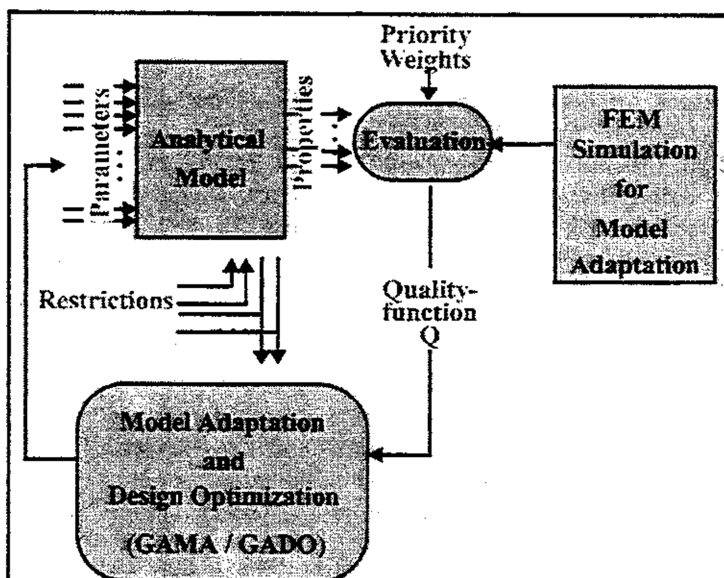
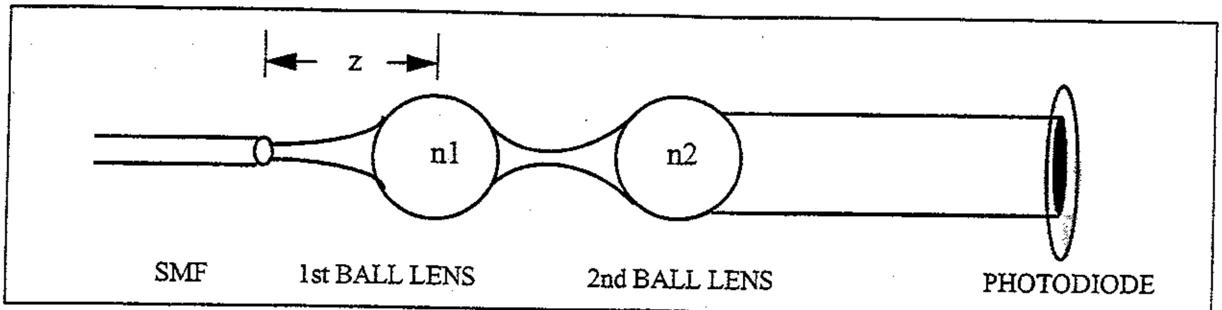


Fig. 1: Flowsheet of the automated design optimization using the SIMOT tools GAMA and GADO



Lens Distance:		[80...1400μm]
Illumination:	$\frac{\text{beam width at the location of the photodiode}}{\text{photodiode diameter}}$	[80...100%]
Stability:	$\frac{\text{minimum beam width at the photodiode}}{\text{maximum beam width at the photodiode}}$	[>90%]
Waist Position:	position of the collimated beam waist	[4000...4600μm]

Fig. 2: Basic diagram of the collimation system made up of a single-mode fiber (SMF), two ball lenses, and a photodiode. The upper part of the figure shows the optimization parameters, n1, n2, and z, while the bottom part shows the evaluation criteria, lens distance, illumination, stability, and waist position.

In the ideal case of geometric optics, under certain conditions, another lens can be found for each ball lens of a specific focal length; in this way, any emission can be generated. Unlike this ideal case, also tolerance effects are to be considered which arise from the incorporation of optical elements into prefabricated LIGA structures [4] (Fig. 3). These incorporation tolerances affect the beam width at the location of the photodiode and also affect the location of the waist of the beam. A collimation system is to be determined now which is as insensitive as possible to the expected inaccuracies, due to incorporation of the individual elements.

The systems parameters which can be varied in the optimization calculations are the indices of refraction of the two ball lenses (n1 and n2), and the distance between the fiber feeding light into the system and the first ball lens (z). The optimization parameters defined are illumination, stability, position of the beam waist, and distance between the lenses.

Description of the optimization parameters:

- Illumination: Illumination is defined as the quotient of the maximum beam width at the position of the photodiode and the diameter of the photosensitive region of the photodiode. The goal of optimization with respect to illumination is a value of 0.9 to prevent blanketing of the photodiode in case of lateral beam displacement.
- Stability: Stability is defined as the quotient of the minimum and the maximum beam widths as a function of tolerance effects. The goal of optimization with respect to stability is a level close to 1 so that fluctuations in the illumination of the photodiode as a function of tolerance effects are minimized.
- Beam waist position: The optimum value of this parameter is 4300 esponds to the distance between the second ball lens and the photodiode. This optimization criterion ensures that the collimated beam waist is imaged onto the photodiode.
- Lens distance: The distance between lenses was introduced as a criterion in order to define a size limit of the whole system. The values aimed at should be in the range between 80

THE OPTIMIZATION CONCEPTS

The techniques used for automatic optimization can be subdivided into two categories:

- Traditional numerical methods.
- Heuristic search methods.

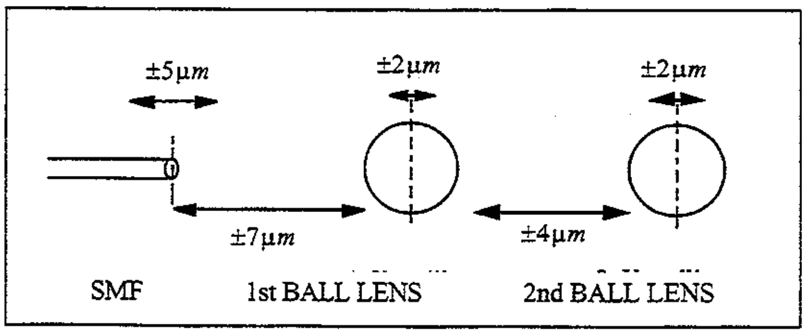


Fig. 3: Illustration of the incorporation tolerances (2D case)

These methods or, more correctly, optimization algorithms in general can be assessed in the light of these criteria:

- Convergence reliability
  (a measure of the probability of a satisfactory solution being found).
- Convergence rate
  (indicating the time required to solve an optimization problem).
- Boundary conditions
  (conditions imposed upon the optimization problem by the technique).

The two types of possible optimization functions described in Fig. 4 as a function of a characteristic value can be used, for instance, to indicate the different convergence reliabilities of traditional and heuristic optimization techniques.

These two types of functions can occur especially also in the optimization of microsystems. As a rule, optimization functions have one optimum and a large number of suboptima (multimodal function as in Fig. 4, left diagram). Restrictions in the search space and characteristics of the system may give rise to discontinuities in the solution space (Fig. 4, right diagram).

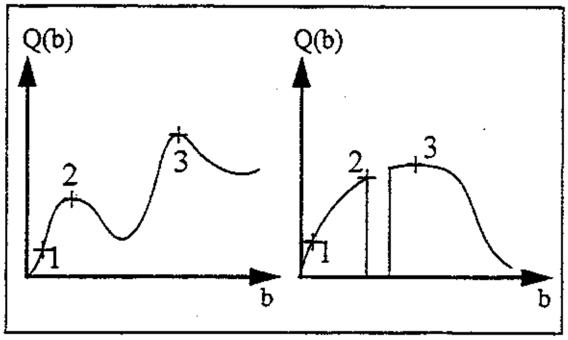


Fig. 4: Two types of possible optimization functions

Traditional approaches, such as the gradient method, will find only local optima (see diagrams, point 2) when starting, for instance, from solution 1 (see diagrams, point 1). On the other hand, the use of appropriate heuristic search methods promises that the global optimum will be found with very high probability (see diagrams, point 3). So, convergence reliability is higher in our heuristic technique than in the traditional numerical processes especially in the two typical examples shown here, which will corroborated by a comparison in Chapter 4.

Traditional Numerical Techniques:

One traditional numerical technique is the iterative gradient method. In optimizing given problems, gradient methods use the local gradient of a function in order to find the optimum of that function. In principle, these search methods are deterministic methods successively generating results each of which is based only on the preceding one. These methods are subject to a number of restrictions:

- The problem to be optimized must be a steady-state problem, which means that derivations of the function representing the search space must exist.
- Gradient methods find only the local optimum in the vicinity of the instantaneous point. The global picture of the search space remains obscure.

Combining the approach of random searching with the gradient method offers the possibility to scan the search space with different, randomly chosen initial conditions. Also this approach offers no guarantee that the global optimum will really be found; however, at least it provides information about the existence or absence of suboptima.

Heuristic Search Methods:

The GAMA and GADO tools used in SIMOT [5] are based on heuristic methods and have been under development at the Karlsruhe Research Center since 1988. The tools are components of the GLEAM/AE application and experimental environments and are based on the **GLEAM** (Genetic Learning Algorithm and Method) evolutionary algorithm [6].This algorithm is based on both the genetic algorithms established by J. Holland through his studies of adaptive systems [7], and on the evolution strategies established by I. Rechenberg [8] and H.P. Schwefel [9].

The phylogenetic development of living beings from lower to higher forms is an example of an *evolutionary process*. This development process is based on *genetic* and *evolutionary* mechanisms changing the characteristics of living beings. In the formal description of these development processes, living beings are referred to as *individuals*. The total population of individuals of one species in a specific geographic space is called a *population*. Genetic processes, such as *mutation* and *recombination*, contribute to modifications in individuals. Mutations cause spontaneous changes in the hereditary material. Recombination is the new combination of hereditary factors, i.e., the exchange of hereditary factors of two individuals. This gives rise to new progeny. This progeny is subject to a *selection process* in which progeny of higher quality has a better chance, in turn, to generate progeny and in this way pass on its hereditary characteristics to the next generation. *Evolutionary algorithms* are an abstraction of these fundamental evolutionary principles.

In *genetic algorithms*, an individual corresponds to a design variant, i.e., all relevant characteristics of a system (system parameters) are described in this individual by a specific data structure. In a mutation, a characteristic is changed, for instance, by a random number generator. In a recombination, some characteristics (data) of two individuals are exchanged. Selection allows individuals with good characteristics to pass these on to their progeny with a higher degree of probability. In this way, the quality of individuals may rise from generation to generation.

Also *evolutionary strategies* begin with a population of individuals. However, an individual contains not only design characteristics, but also additional information about the so-called mutation step lengths which act as strategic parameters. The mutation step lengths specify the standard deviation of a normally distributed random variable with the expected value of zero, thus raising the probability of minor variations occurring. A recombination of two parent parts can be achieved either in the design characteristics by a random mix of several parent parts or in the mutation step length, i.e., by averaging the two parent parts. In the subsequent selection step the best individuals are selected either from the parent/progeny generation or only from the progeny generation.

Evolutionary algorithms are general methods of planning and optimization, and their use is advantageous whenever very many parameters must be processed and local optima, perhaps also additional restrictions and discontinuities, exist. Especially in a non-linear, multimodal, and discontinuous optimization function, traditional methods may well cease to be effective (see above). The use of evolutionary algorithms makes sense especially in those cases in which nothing is known about the specific problem at hand (evaluation space). However, existing previous knowledge may be introduced to reduce the optimization time. On the other hand, evolutionary algorithms do not impose any conditions upon the evaluation space (optimization function, quality criterion), such as continuity or differentiability. These properties of evolutionary algorithms may turn out to be advantages over traditional optimization techniques, because traditional techniques, such as the gradient method, presuppose mathematical knowledge about the optimization problem.

Unlike traditional methods, evolutionary algorithms do not start from one solution only, but from an entire population containing several individuals (solutions). As in biological development, several subpopulations may exist at the same time. In this case, the search departs from various points located within the search space. The result of the search in that case will not be only one solution, but will be made up of several solutions whose number may be preset. These solutions may exist at roughly the same locations in the search space, provided there is a global optimum whose quality differs greatly from those of any local optima that may exist. However, if there are several local optima of similar quality, the solutions may be spread about these optima in the search space.

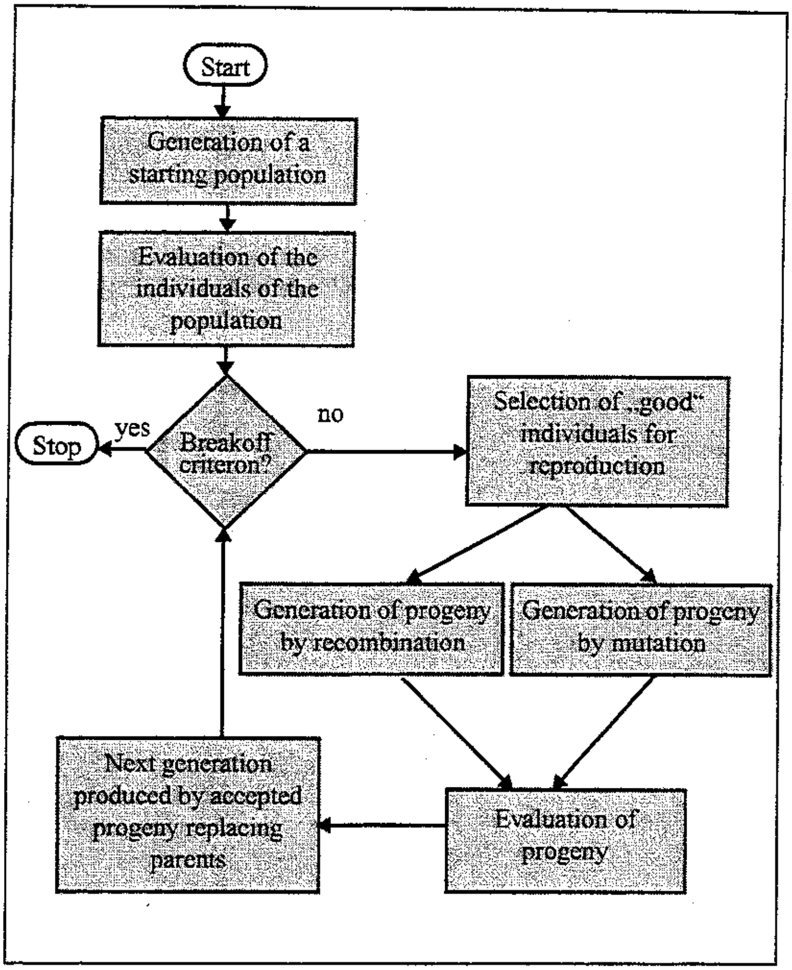


Fig. 5: Flowsheet of the GLEAM evolutionary method

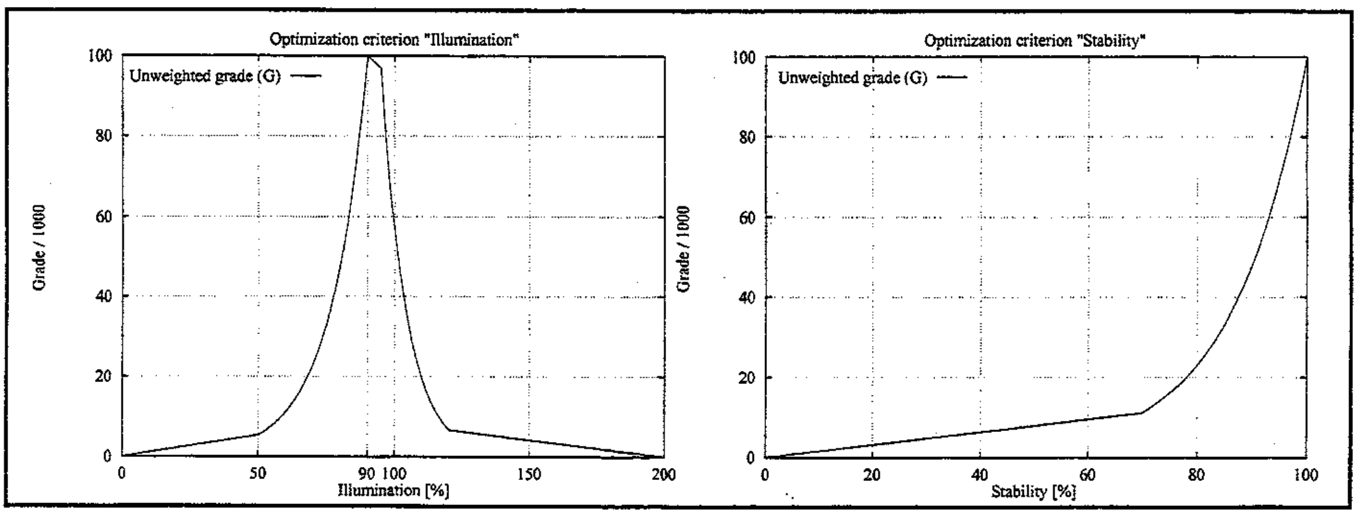


Fig. 6: Evaluation function of two criteria

Index	Criterion	Class	Max grade	Required grade	Required value
1	Lens distance	1	10000	8000	80-1400 µm
2	Illumination	2	25000	14216	80-100 %
3	Waist Position	2	25000	8333	4000-4600 µm
4	Stability	3	40000	19229	90 %

Fig. 7: Multi criteria evaluation function

The approach used in GLEAM can be broken down into two steps (see also Fig. 5):

- Initialization and evaluation of the starting population.
- Generation of new follow-on generations by means of evolutionary mechanisms (mutation, selection, recombination...).

The second step is executed until a break-off criterion defined by the user has been reached.

The large number of simulations necessary in this heuristic search technique has caused less attention to be devoted to this process than to other optimization methods because of the low convergence rate. However, the optimization time can be reduced drastically by parallelization, i.e., the use of several computers in a computer network. Also the progress made in computer power reduces optimization times, thus furthering the use of some of these techniques.

The high convergence reliability inherent in these techniques, as they are based on not only one, but several solutions, would favor the use of these methods especially in problems where traditional methods are no longer effective. More precise studies of this aspect were conducted with the example of the "asymmetric traveling salesman problem" [10].

The Qualityfunction of the Collimation System

As input for the optimization tool GLEAM the designer has to describe the evalution criteria in form of a multi criteria evaluation function. In Fig. 6 two criteria are given.

Fig. 7 shows the combination of all criteria, which have different priorities and different weights (given by the designer).

Fig. 8 describe the evaluation of the best individual estimated by the heuristic search.

RESULTS

Fig. 9 and Tab. 1 shows the result of the evolutionary GADO method used as compared to the results of the iterative gradient method. While an optimum result was found with GADO, the optimum values determined by the gradient method clearly differ from each other. The result of GADO (with high probability) represents the global optimum of the optimization function. The iterative gradient method, however, arrived at various local optima because of the multimodal nature of the optimization function as a function of the initial values.

As there are a random number of configurations achieving the desired collimation in an ideal case, as described in Section 2 above, there are also a random number of suboptima or, to illustrate the point more graphically, a random number of islands in the sea of the search space. A method of optimization, such as the iterative gradient method, which takes into account in its calculations only the immediate vicinity of the point under consideration, can furnish only local optima in such a multimodal optimization function.

Design Parameter:		Simulation results:	
Refraction lens 1:		Lens distance:	948.408 µm
n1	: 1.82	Illumination:	89.90 %
Refraction lens 2:		Waist position :	4300.7 µm
n2	: 1.53	Stability :	91.1 %
Distance SMF to lens 1:			
z	: 569.3 µm		

Evaluation:

Index	Criterion	Class	Weight [%]	unw. grade	min grade	weighted grade
1:	Lens distance:	1	10	100000	8000	10000
2:	Illumination:	2	25	100000	14216	25000
3:	Waist position:	2	25	100000	8333	25000
4:	Stability:	3	40	52577	19229	20725
Total grade						80725

Fig. 8: Evaluation of the best individual estimated by the heuristic search

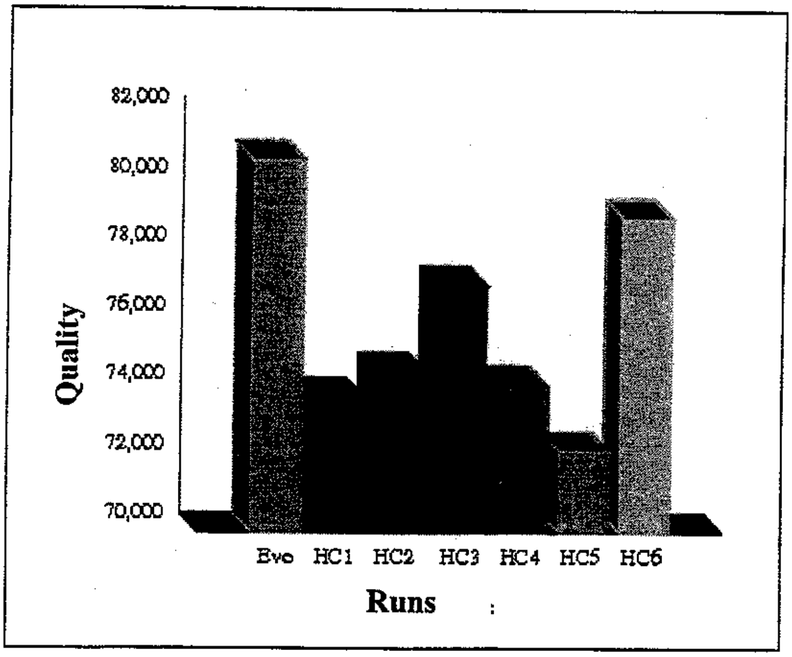


Fig. 9: Optimization results of GADO compared with those of the iterative gradient method.

Run	**n1**	**n2**	**z [µm]**	**Illum. [%]**	**Stab. [%]**	**Waist Pos. [µm]**	**Quality**
Evo	1.82	1.53	569.3	89.9	91.1	4300.7	80725
HC1	1.42	1.93	1437.8	94.9	86.2	4300.1	73851
HC2	1.43	1.87	1369.3	94.2	87.0	4297.2	74598
HC3	1.79	1.71	703.5	92.5	88.7	4298.7	77095
HC4	1.42	1.90	1414.9	94.5	86.6	4297.5	74225
HC5	1.64	1.95	991.7	95.3	85.7	4297.2	72340
HC6	2.00	1.58	495.0	90.7	90.3	4294.3	79068

Table 1: Comparison of two optimization methods

In order for the global optimum to be found, methods must be employed which are able to deal with multimodal search spaces, such as evolutionary algorithms.

OUTLOOK

The comparatively large number of simulations (several 10,000) still required for evolutionary algorithms limit the possibilities to use this otherwise rather promising method. For this reason, modifications are currently being prepared and tested which are intended to reduce the number of simulations while preserving convergence reliability. In addition, SIMOT is continuously added further simulators in accordance with applications.

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