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PARTIAL AUTOMATED DESIGN OPTIMIZATION BASED ON ADAPTIVE SEARCH TECHNQUES

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ABSTRACT

The concept of a partial automated design optimization and its first application on the improvement of a micro-pump design is desrcribed. Starting with an analog simulation model an evolutionary algorithm is used to modify the parameters of this model until an optimal behaviour of the system is obtained. The quality of the optimization depends highly on the quality of the simulation model thus we give an outlook on a concept for improving the analog simulation model by using FEM results.

INTRODUCTION

Industrial applications of microsystems require short development times as well as reliable designs comparable to the state of the art in micro electronics. To achieve this goal CAD based design techniques and simulation is necessary but not sufficient as outlined below. During the design process the engineer is faced with an extremely large search space of possible design solutions and parameterizations. Although a great percentage of the search space can be dismissed due to available knowledge and the experience gained from previous designs in most cases the remaining search space will be still far too large for a systematical investigation. Thus a trial-and-error process is started, which can be described as *poking in the fog* rather than a systematic search. It is mainly based on three properties: the experience and knowledge of the engineer, his attitude and on luck. To overcome this unsatisfactory situation a more systematic exploration of the search space would be necessary.

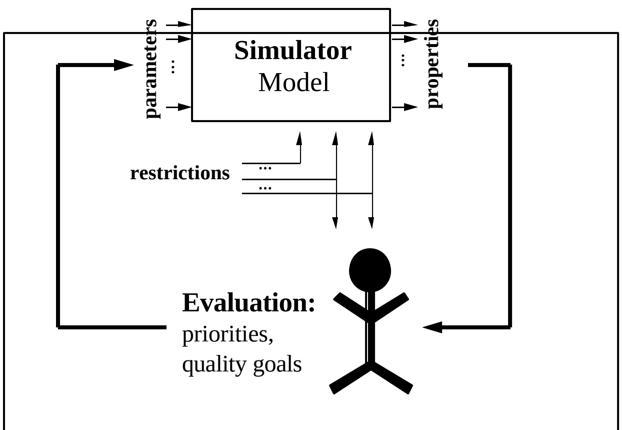

Fig. 1: Conventional Design Process

The overall idea of the concept presented in this paper is to substitute the human in Fig.1 by an automated explorer and to involve the engineer in high level decision making only. The task of the explorer is to implement an "intelligent" search focusing on promising areas of the search space, avoiding suboptima and adapting itself to the search landscape on hand. The proposed explorer will utilize an adaptive search technique called GLEAM. The GLEAM (Genetic Learning Algorithms and Methods) concept [1] utilizes hierarchical list-like data structures of genes and representation specific genetic operators. It incorporates aspects of Genetic Algorithms [2] and the Evolution Strategy [3].

Chapter 2 introduces the overall concept, the involved simulator and the idea of Evolutionary Algorithms. Chapter 3 describes our first design example, the micropump, its model and the first optimization results. Chapter 4 motivates the need for both improved simulation modelling and models and gives an outlook to further work on the adaptive search method itself.

CONCEPT

The evaluation of a given design will in many cases be done by simulation. The result of a simulation run is the computation of values for the system properties of interest. Using these values the design engineer constructs a quality measure to assess the design either intuitively or more explicitly by calculating some reference numbers which can be weighted and summed up in order to form a single quality value. Thus a multicriteria evaluation can be done which is the base for a multicriteria optimization by ranking the designs suggested so far. The quality value is used to direct the search process by the automated explorer. The task of the engineer is now focused on the definition of appropriate global designs, both the constraints and the parameters, and the associated evaluation functions and weights. The latter means to define the design goals and the lines of compromise. Based on the results of some optimization runs these global terms and figures have to be readjusted in order to achieve a satisfactory solution. This scenario still reflects an iterative design process but the work of the human concentrates on much higher levels of abstraction and the evolutionary algorithm now investigates the space of possible solutions which is done much more thoroughly as the strategy is not limited by the human way of thinking. The achieved results are in general of higher quality and provided that enough computer power is available also be achieved in a reasonable time.

Analog Simulation with ELDO

The ELDO®-system is a tool for analog and mixed signal simulation. Analog models are usually derived analytically and their simulation can be done in short time. For circuit simulators like SPICE it is necessary to build the model with electrical devices as resistors and capacities. This can be done because the behaviour of a system can be described with a mathematical equation which can often be alternately described by an electrical network where only the parameters are different. For those components, which can not be described in analogy to an electrical network, it is necessary to prepare tables or to use controlled sources. In contrast to that the analog hardware description language (HDL-A) of the ELDO-system allows to use mathematical equations explicitly [4]. Thus various physical domains for example electrical, mechanical, thermal or fluidic can be described with one common language. This is important in those cases where heterogeneous systems have to be simulated.

Evolutionary Algorithms

The search space our automated explorer is faced with will be in general multimodal, highly non-linear, more or less high dimensional, restricted and discontinuous. In those (few) cases of unimodal and continuous spaces simpler techniques like hill climbing [5,6] are absolutely sufficient. But in the general case a more powerful adaptive search technique like GLEAM is necessary. The concept of combining the traditional approach of Genetic Algorithms and Evolution Strategies with modern computer science and data modelling has approved its performance in such different areas of application as machine learning [7], robot path planning [7,8], resource planning [9] and job shop scheduling [9,10]. An important advantage of GLEAM compared to other adaptive search techniques like Simulated Annealing [11] or Threshold Acceptance [12] is its explicit parallelism which allows a "natural" parallelization with linear speed up [10,13].

Due to the lack of space we can give only a very brief description of the GLEAM concept here. It is based on the principles of evolution, i.e. a set of possible design solutions forms a "population", which is changed (mutation) and which produces offsprings by mixing their information (crossover). The resulting offsprings are evaluated and in order to their fitness they will be either accepted or rejected (survival of the fittest). By this means better solutions evolve from generation to generation. It is more a breeding process rather than a calculation of a solution, like engineers are used to do. The process is continued until a termination criterion like elapsed time or a specified quality is reached. The result of such a run is not a single but a set of in most cases different solutions of a more or less high quality. The resulting quality depends on the details of the evaluation formulas, the degrees of freedom and on the time or amount of generations spend in the search process.

Design Optimization Environment

Our simulation and optimization tool environment (SIMOT) consists at the present stage of implementation of two parts, a genetic engine based on GLEAM and tailored for the needs of multicriteria parameter optimization and a powerful simulation tool, here ELDO as shown in Fig. 2. Both software components are linked via pipes in order to achieve a fast communication. Restrictions are as far as possible already taken into account by the Genetic Engine, see also the last chapter.

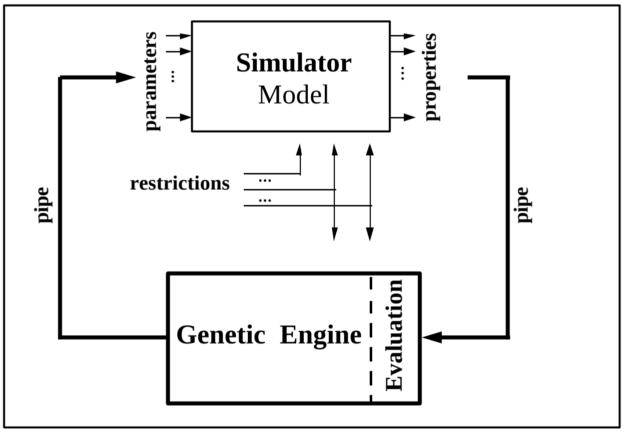

Fig. 2: Part of SIMOT (Simulation and Optimization Tool Environment

As the evaluation is very sensitive to the overall search process, we will take a closer look to it. In most cases some criteria will contradict each other; e.g. a high pressure of a pump will decrease the flow rate and vice versa. By adjusting the weights the direction of compromise for guiding the search process can be expressed. Restrictions can in general be incorporated in the search process in two ways. Either the simulation is stopped when the restriction is met and the proposed solution is rejected or the simulation is continued but the resulting fitness value is modified by a penalty function. The idea of the latter approach is to guide the search from prohibited areas of the search space to legal ones rather than leaving it with no information how to overcome the rejection. As designs are usually highly restricted this is an important technique to meet these restrictions.

Fig. 3 demonstrates this using the example of the heater temperature of our pump. If the heater gets to hot it will burn through. So this is a restriction which has to be met under all circumstances. Nevertheless we allow the exceeding of the given limit (here 850 degrees Kelvin) dur-

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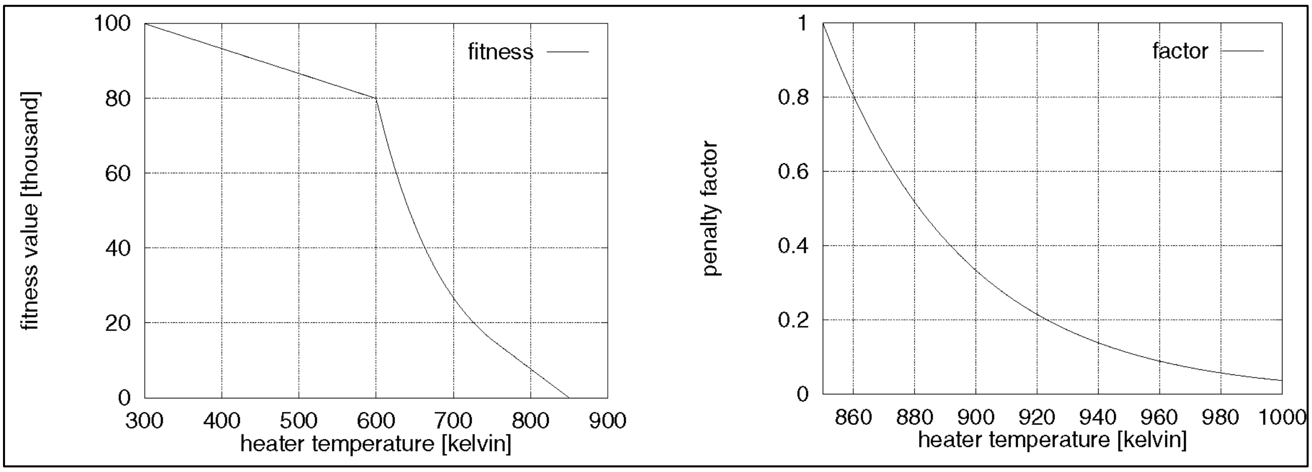


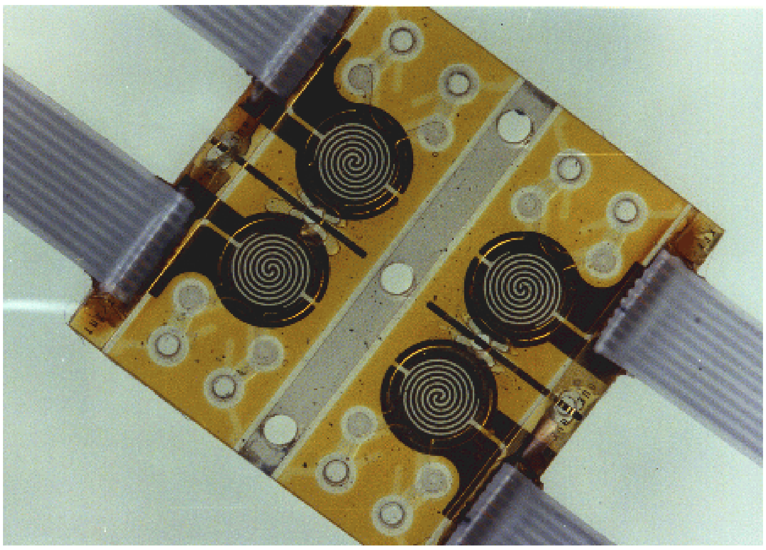
Fig. 3: Fitness Calculation: Fitness Function (left part) and Penalty Factor (right part)

ing the simulation but apply the penalty function. It delivers a factor of 1.0, if the restriction is just fulfilled, as shown in the right part of Fig 3. In those cases where the temperature is higher, the overall fitness is multiplied by the computed factor according to the shown exponential function. As with increased temperature the penalty factor and with it the resulting fitness drastically drop the search process is quasi *pushed* to the legal parts of the search space. The left part of the figure shows the original fitness function for the temperature and how a wanted low temperature of about 600 degrees Kelvin can be incorporated into it. The increase of the fitness is significantly lowered when the desired value is reached. On the other hand further improvements on the temperature are still honored.

APPLICATION EXAMPLE: MICROPUMP

The method described above is applicable to optimize the design of various (micro-)systems. Our first application is the optimization of a thermo-pneumatic-driven micropump which was developed at the IMT (Institute of Microstructural Engineering), another institute of our research centre [15]. Fig 4 shows a block of four of these micropumps. Each pump consists of a heating coil, which can be easily identified, two passive valves and one inlet and one outlet. The pumps are already assembled with a cable for the power supply.

A schematic overview of the pump together with the analog model is shown in Fig. 5. During the heating phase the heating coil, which is mounted on the membrane warms up the gas in the closed actor chamber. The resulting expansion of the gas causes an elastic deformation of the membrane, which presses the gas in the channel of the pump through the outlet valve. This phase is shown in Fig. 5. This phase ends, when the current is switched of and the cooling phase starts. During the cooling process the pressure in the actor chamber drops and the membrane moves back. Thus the passive outlet valve closes, the inlet valves opens and new gas streams into the pump channel. This pump cycle is repeated with a frequency of about 30 Hertz.



Flow Rate	0.22 ml/min
Frequency	30 Hz
max Outlet Pressure	130 hPa
Geometry [mm]	7 x 10 x 1

Fig. 4: Block of four micropumps with assembled connectors

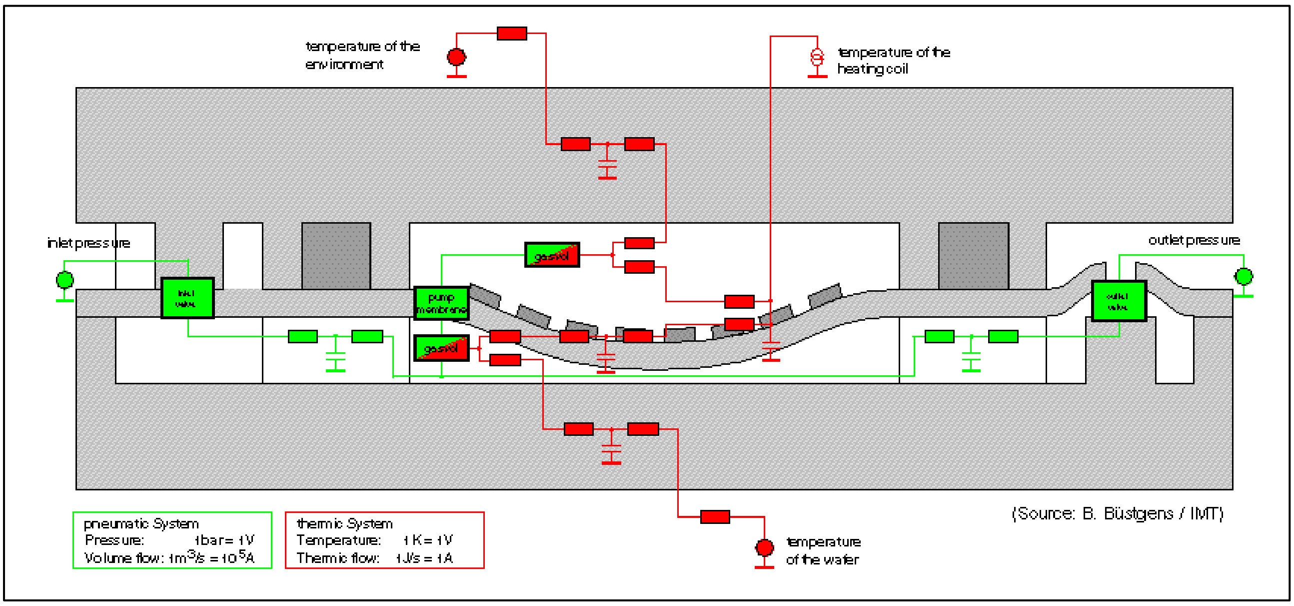


Fig. 5: Electrical Analog Model of the Micropump

Model of the Micropump

The first model of the micropump was an analogous model, see Fig. 5. Resistors, capacities and sources (lump elements) are the devices with which the heat flow and the volume flow are described. The electrical, the thermal and the pneumatic domain are included in this model. In the thermal system the voltage represents the temperature and the current the heat flow rate. In the pneumatic system the pressure is the analogy to the voltage and the volume flow rate is the analogy to the current. The behaviour of the valves, of the gas and also of the membrane is nonlinear and so tables or controlled sources are needed to include their behaviour into the model.

For analytical models with a certain complexity usually some simplifications have to be done. On the other hand that type of model satisfies the requirements for an optimization: the models are parameterizable and the simulation is considerable fast. We used this rough model for our first runs.

First Optimization

Our first optimization application of SIMOT was to optimize the form of the heating impulses. This aspect reflects more the system design rather than the design of the pump itself. We choose this task because evaluations of the simulation model could be done much more easily if only one pump is required and the control parameters of the heating device are varied.
The heating impulse depends on five parameters: the magnitude, the rise time, the fall time, the width of the pulse, and the period (see Fig. 6). After the completion of a simulation the results are prepared so that the following six values are derived from the obtained waves: the rate of fluid flow, the pressure over both valves, the maximum of the temperature of the heating coil, the electrical power and the efficiency.

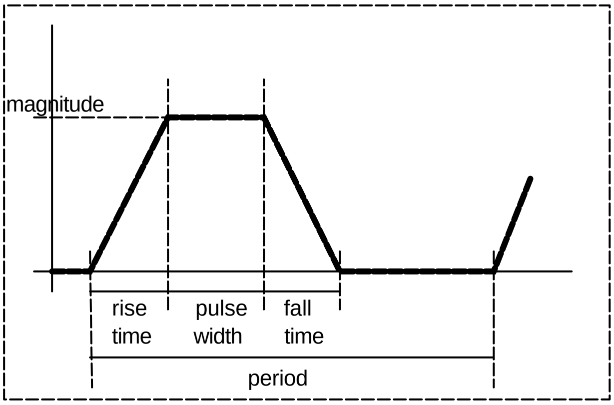


Fig. 6: Pulse modulated power supply

Fig. 7 shows the result of first optimization runs. Originally the micropump was actuated with a short heating impulse with high magnitude (see Fig. 7a). Our optimization had shown that an improved form of the heating impulse is like the following: medium magnitude, long rise time and long fall time, but a short width of the pulse itself (Fig. 7b). With this power supply the flow rate is significantly greater and the pump will get less hot.

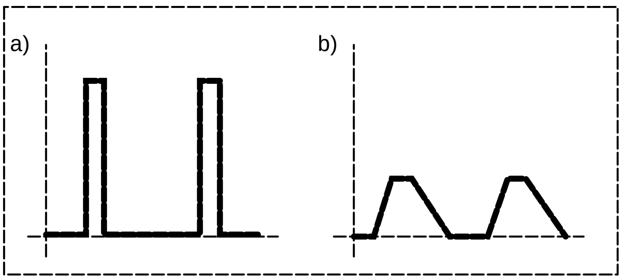


Fig. 7: Original heating puls (a) and improved (b)

The optimization of the entire design of the micropump is a very complex problem, so that it is not sufficient to find the solution with trial and error. Although our first optimization considers only five control parameters of the power supply the search space has already a magnitude of about 10^{22}, it is multimodal and due to its restrictions discontinuous. Furthermore other parameters are also of great interest for the optimization, so the geometric parameters and also some properties of the materials. If these parameters are taken into account additionally the complexity grows very rapidly. This recommends the utilization of GLEAM rather than of the already mentioned simpler techniques.

Our first model was a rough model. Building this model required simplifications and so it is not accurate enough. With an improved model the optimizations should help to generate an improved design of the micropump resulting in high efficiency and stability. We want to achieve the improvement of the model by fitting the values of the lump elements with the help of FEM-simulations as described in the next section.

OUTLOOK

Further work will concentrate on three main topics: Improvement of the simulation models together with the modelling process itself and improvement of the performance by parallelization and by extentions to the evolutionary algorithm.

Adaptive Model Building

To improve the quality of an analog simulation model, we work on an evolutionary model adaptation method, similar to an off-line parameter estimation [16], which is usually used for the calculation of unknown model parameter values. The standard off-line parameter estimation method is based on the variation of unknown parameter values of an analog simulation model until the desired coincidence of the model behaviour with a behaviour reference, for example a measuring series of a real system, is obtained.

Using this procedure we want to improve analog simulation models with support of Finite Element Method (FEM) analysis [17]. Especially in system components with a complex geometry like a micro valve in which the fluid resistance can not be determined analytically with the necessary precision, the FEM can be used successfully for the determination of such items in an analog simulation model. This advantage of our approach is that we can obtain now parameterizable analog simulation models. This means that also functional dependencies of design parameters like geometry or material constants can be taken into account, which is an important assumption for their application in the area of design optimization. The creation of behaviour references with FEM, which reflects the behaviour of the system about the complete design parameter range, requires a lot of additional computing power. But this has to be done only once and the resulting analog simulation model or parts of it can be reused later.

Speed-up by Parallelization

For practical applications short turn around times (e.g. one night run) are necessary. One way to achieve this is to utilize the parallel nature of the evolutionary search process itself. Earlier investigations [10, 13] using a transputer cluster have shown that with structured populations a linear speed up can be achieved. As transputers are no longer the hardware platform of first choice and as they are less available in industry we now reimplement our approach on a network of sun workstations under Unix. As our parallel algorithm does not need any central control and work asynchronously we can utilize an inhomogenous network. This means that we can use up all the idle times of a net during the day and the complete net in the night or on week end. Because of the absence of central control the communication overhead does not increase with the number of processors involved. So we can spread our software over hundreds of machines if available and necessary.

Speed-up by Improvements to the Method

Additional to the parallelization of the procedure we want to reduce the amount of computational load for one optimization run in general. We want to achieve this without lowering the performance or stability of the evolutionary search itself. As a simulation run takes more than 99% of the computing power of one optimization, another field of future work will be efforts to reduce the amount of fitness evaluations. Three improvements are under consideration and test.

The first one is simple: We calculate the hamming distance between the two parents and if this distance is to small no recombination will be performed. The second is also based on the already calculated hamming distance. We can identify spots of (nearly) identical individuals within the population. These spots can be regarded as stagnating subpopulations which waste computing power. So we will introduce a reinitialisation operator which keeps some of the individuals of the spot. A variant of this operator identifies the best of the spot and adds it to the group of survivors. The disadvantage of these two approaches is that they start to work in a more or less late phase of an optimization run when the population or subpopulations are in the process of convergence.

The third improvements reflects the fact that a human would restrict the search by eliminating parts of the parameter space which can safely be ignored. In our example this can be done for heating impulses with to much power because they will surely burn the heater. As we do not know a priori, whether the impulse should be like a needle or like a brick, we have to allow high magnitudes as well as long durations although we know that both, a high *and* long impulse will destroy the pump. So we can build a filter which simply calculates the energy of the impulse and rejects to high values. But what means „to high“? As we do not know this a priori too, one can only estimate it and we need an adaptive adjustment. This approach works during the complete run and a simple version gave us already promising results. A more sophisticated variant is now under implementation.

The first two approaches are of general nature while the third one incorporates some domain specific knowledge. As it significantly improves the performance especially in the early phase of a run, we use it despite of the fact that it has to be readjusted or even reimplemented for different applications. We are working on a generalized version which shall cover a wider range of applications.

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