Design optimization of microsystems based on adaptive search techniques

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Abstract

The concept of a partial automated design optimization and its first application on the improvement of a micropump is described. Starting with an analog simulation model, described in the HDL-A language, parameters of this model are modified using evolutionary algorithms until an improved behaviour of the system is reached. As the quality of the optimization depends highly on the quality of the simulation model, we describe a concept for improving the analog simulation model by using FEM-simulation results and evolutionary algorithms. The described method is applicable to optimize the design of various (micro)systems. Our first application was the optimization of a thermo-pneumatic-driven micropump.

1 Introduction

One property of an intelligent microsystem is the existence of various physical domains such as microelectronics, micromechanics, microfluidics, microcalorics and microoptics. Several simulators exist to investigate the behaviour of the microsystem but in most cases it is only possible to consider one physical domain of the system with a particular simulator. For most microsystems it is not sufficient to investigate and to simulate each domain separately because the different phenomena depend strongly on each other. Thus for the investigation of the behaviour of a total microsystem it is necessary either to couple different simulators or to build a model containing the description of all phenomena in a common description language so that the overall system can be simulated with a single simulator. We focus on the latter alternative.

An often applied method is the description of the physical effects in analogy to the electronics. This type of model is a network model and can be simulated with
a circuit simulator. Analytical studies are necessary to build the model and often it is unavoidable to make simplifications as for example to neglect the friction or to make the assumption that the fluid do not possess a temperature gradient. Depending on the complexity of the system component and its mathematical description the devices of the network can be formulated preferably as usual electronic devices like resistors, capacitors, or sources or can be HDL-A\(^1\)-models. With the hardware description language HDL-A both simple devices and more complex components can be described. For the description of components with known nonlinear behaviour the HDL-A-language is very comfortable. This language permits to build a model with differential equations or implicit equations in a simple way. The advantage of such models is that simulation is relatively fast but the disadvantage is that the accuracy of the simulation results often leaves to be desired. Another simulation method is based on the Finite Element Method (FEM). The FEM-model is more exactly due to the discretization of the space, but the simulations are very time consuming and in many cases the system possess such a complexity that it is not practicable to build a FEM-model of the entire system. To overcome these limitations only system components are investigated with the latter method.

2 The General Concept

We developed a concept for the partially automated design optimization of microsystems by using the advantages of both simulation methods. Our SIMulation and Optimization Tool Environment SIMOT consists of four tools: GAMA (Genetic Algorithm for Model Adaptation), GADO (Genetic Algorithm for Design Optimization), ANSYS\(^2\) (FEM simulator) and ELDO\(^3\) (analog network simulator). SIMOT will on one hand support the designer in development and optimization of macromodels and on the other hand at the optimization of complex (micro-)systems or components. The simulation tools ANSYS and ELDO are commercial tools, the optimization tools GAMA and GADO are both based on adaptive search techniques and are developments of our institute.

The designer has to formulate macromodels for the various functional components of the microsystem. If this is not possible or too complex in a purely analytical way with the required precision, than the designer can make an FEM-model. Using the results of the FEM-simulation the designer can optimize the analytical macromodel with GAMA. Macromodels being made in this way may be coupled to an entire model (Fig. 1). This model is able to describe the behavior of the microsystem adequately exactly and fulfills still the performance requirements concerning computing time consumption.

This improved entire model is the basis for the design optimization process. It is a model with high accuracy, it is parameterizable and the duration of one simu-

1. HDL-A is a trademark of ANACAD EES Ltd.
2. ANSYS is a registered trademark of SAS IP
3. ELDO is a trademark of ANACAD EES Ltd.
Fig. 1: SIMOT (Simulation and Design Optimization Tool Environment)

A simulation run is small enough for the optimization process. During an optimization many simulations with various parameter settings have to be done. The engineer is faced with an extremely large search space of possible designs and so it is not possible for the engineer to investigate the search space systematically. The personal knowledge, previous experiments with similar microsystems and luck are the foundations for this search (Fig. 2a).

The idea of our concept is to substitute the human being by an automated explorer (Fig. 2b). 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. The explorer is based on the evolutionary algorithm GLEAM (Genetic Learning Algorithms and Methods) [1], which integrates aspects of traditional adaptive search techniques like Genetic Algorithms [2] and Evolution Strategies [3] with a spatially structured population approach. More details are given in section 5.

3 First Application of SIMOT: A micropump

At the IMT (Institute for Microstructure Technology), another institute of our research centre, a thermo-pneumatic-driven micropump was developed [4]. Figure 3 shows a single micropump in comparison with an ant.
These micropumps have two working states. One is the heating phase: The heating coil which is located on the membrane warms up the gas in the closed actor chamber. The expansion of this gas is the reason for the elastic deformation of the pump membrane. The gas in the channel will then be pressed through the outlet valve.

A schematic view of the micropump is shown in Figure 4.

We have chosen the micropump as a first application of SIMOT, because the design of the micropump is complex enough, a model description is available, and we do have real data of micropumps already build. In addition, the results of our simulations will be part of future design cycles.

### 4 The Model of the Micropump

The first macromodel was written for the circuit simulator PSPICE: It includes the description of the thermal and of the pneumatic behaviour in analogy to the electronics. Therefore the thermal resistance and the fluidic resistance will be compared with an electric resistance and the temperature flow and the volume flow are comparable with the current. The main devices of this first macromodel are resistors, capacitors and sources. The voltage at the network nodes represents the temperature in the thermal domain and the pressure in the fluidic domain and the current through the network devices represents the heat flow rate respectively the volume flow rate. The behaviour of the passive valves, the gas in the actor chamber (air) and the gas in the pump chamber (at present air) and the behaviour of the membranes are nonlinear and as mentioned above their description in

**Typical properties of a micropump:**
- flow rate (air) 200 \( \mu l/min \)
- frequency 20 Hz
- max. outlet pressure 100 hPa
- geometry 9x10x1 mm³

Fig. 3: A micropump in comparison with an ant

![Schematic view of the micropump](image.png)

Fig. 4: Schematic view of the micropump

PSPICE is long winded. This model contains controlled sources with tables to describe the nonlinear behaviour. Such network models are rough models.

**The FEM-Model of the passive microvalve**

For our purposes this first micropump model was not accurate enough because it used some components for which we had to make assumptions to build a model. So it was necessary to build improved models of these components.

One component of the micropump with a nonlinear behaviour is the passive valve. Physical effects of different domains like fluidics, mechanics and calorics influence each other and the geometry of the valve is too complex to be described with exact mathematical equations.

The valve is built up axis symmetrically. It consists of a valve seat and a thin elastic valve membrane with a hole. A difference pressure at the valve causes a deflection of the membrane. Depending on the sign of the difference pressure the valve is either opened or closed (Fig. 5). A very narrow coupling exists between the mechanical behaviour of the membrane and the fluidic behaviour of the medium. This plays a central role when considering the behaviour of the valve and was also taken into account in the development of the FEM-model (Fig. 6a).

The valve like a high-pass behaves at the time constants which appear due to the electric control in the micropump. The simplified circuit of the valve is shown in Fig. 6c. It contains a nonlinear resistance and a nonlinear capacity. This nonlinear resistance corresponds to the fluidic resistance. The nonlinear capacity corresponds to the fluidic capacity which is formed by the membrane of the valve. The behaviour of the fluidics and the mechanical behaviour of the membrane can be considered as being quasistationary.

The FEM-model is completely parameterizable so that various variants of the valve design can be simulated with little expenditure. Firstly, the FEM-model was used to investigate on the influence of the various geometrical parameters as there are the valve radius, the valve gap radius, the hole radius of the membrane...
and other properties of the valve. Using these results the parameter space of the valve which need to be searched by the design optimization can be reduced. In the following we varied the valve radius and the valve gap radius only. For a series of selected values of these parameters the fluid flow rate was calculated with the FEM-simulation (Fig. 6b).

**The Modeladaptation**

The macromodel of the valve which already was contained in the complete model of the pump is then fitted with GAMA to the FEM-results. Before doing this different correction parameters need to be inserted in the macromodel of the valve. These are then permanently varied by GAMA during the process of fitting. The macromodel is simulated with ELDO with the correction values being delivered by GAMA. The comparison of this result of simulation with the result of the FEM-simulation is the goodness of fit being returned to GAMA. Using the same genetic machine as in GADO the search space of the correction parameters is searched for the best sets of parameters by GAMA (Fig. 7). The macromodel of the valve could be improved clearly with GAMA.

![Model Adaptation with GAMA](image)

**5 The Evolutionary Algorithm**

The search space our automated explorer is faced with will be in general multi-modal, highly non-linear, more or less high dimensional, restricted and discontinuous. Thus it is a suitable application area for an adaptive search technique. The GLEAM [1] concept combines the traditional approaches of Genetic Algorithms [2] and Evolution Strategies [3] with modern computer science and data modeling. It has approved its performance in such different areas of application as machine learning [5], robot path planning [7], resource planning and job shop scheduling.

GLEAM uses a list-like hierarchical data structure. The elements of the data structure depend on the actual application. The hierarchy may be used to treat parts of the data structure as a unit and thus prevent them from being separated by the crossover operators or to hide them completely thus prevent them from being modified by the genetic operators.

The mutation operator is inspired from its counterpart in evolution strategies in the sense that small variations of genetic values are more likely than larger vari-
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ations. GLEAM allows the usage of any arbitrary alphabet for the internal representation being mostly naturally induced by the application considered. Assuming that the elements of the underlying alphabet (i.e. the values a certain gene can take) are sorted by some criteria, we create before any mutation a division of the range of values into classes. By mutation a change of the current gene value to a random value within the nearby classes is very likely and this probability shortens with the distance of a class as defined by a prespecified step function.

There are various crossover operators implementing traditional n-point crossover, uniform crossover, and crossover operators respecting the relative positioning, the absolute positioning, or the order of the elements in the parents. Each crossover operator may be activated on a percentage basis. Each time a crossover operator is chosen, a new offspring is generated. Thus if several crossover operators have a percentage of choice greater than zero, there will be a chance that more than one offspring will be generated. The resulting set of offsprings will be evaluated and only the best will be considered to be included into the population. The population is distributed geographically. A linear ring structure has been chosen and the selection process is limited to nearby individuals. The size of the neighborhood of any individual is chosen to be 9. Each individual and its partner being chosen by local linear ranking produce offsprings by means of mutation and crossover. These are evaluated and the best of them is compared with the individual and replaces it immediately, but only if the offspring is better than the weakest in the neighborhood and with the exception of those individuals being the local best, then the offspring must be better than the individual itself (local elitism) [5, 6]. This process is continued until a termination criterion like elapsed time or the already achieved quality is reached.

The high amount of computing time consumed by each simulation, varying between 3 and 4 minutes, limits the practical possible size of the population. The experiments reported in this paper use a population size of 60. The linear population structure and the small neighborhood size limit the speed of the information flow by the diffusion process. This together with a strong survival rule of offsprings permit the observation of the effects of the isolation-by-distance, despite of the relatively small population size. So, we observe as the result of an optimization run a set of in most cases different solutions of more or less high quality. The resulting quality depends on the details of the evaluation formulas, the degrees of freedom for the search process itself and on the time or amount of generations spend in the search process.

The usage of a geographical population structure and local-only selection and replacement makes GLEAM explicit parallel. This allows a "natural" parallelization with an observed linear speed-up.

6 Design Optimization of the Micropump

The goals of the optimization of the micropump design are a high flow rate and efficiency coupled with a low temperature of the micropump by parameter vari-
ation of geometry, production process (e.g. membrane tension), and power supply.

Our first optimization task was the variation of the form of the heating impulses. 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. 8). After the completion of an ELDO 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 temperature of the heating coil, the electrical power, and the efficiency.

The genetic search process is very sensitive to the interpretation of the simulation results. In most cases of multicriteria optimization we do have several conflicting fitness functions. In our specific case, a high pressure of a pump will decrease the flow rate and vice versa. By adjusting the weights of the various criteria under consideration the direction of compromise for guiding the search process can be expressed.

Restrictions, like the pump temperature, can in general be incorporated into the search process in two ways. Firstly, as soon as a restriction is met the simulation is stopped and the proposed solution is rejected. Secondly, we can continue the simulation and modify the resulting fitness value by some sort of penalty. This mechanism guides the search from unwanted 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.

Originally the micropump was actuated with a short heating impulse with high magnitude (Fig. 9a). The result of our optimization run gave an improved form of the heating impulse as follows: medium magnitude, long rise time and long fall time, but a short width of the pulse itself. Fig. 9b shows the result of first optimization runs. With this power supply the air flow rate is significantly improved and the pump will get not too hot.

Although these first optimizations consider only five control parameters of the power supply the search space has already a size of about $10^{22}$. As first experiments show it is multimodal and due to its restrictions discontinuous. If the above mentioned geometrical and production parameters are taken into account too, the complexity grows very rapidly.

Next we investigate the parameter space of 7 evolutionary solutions found in the same run and compare these to the measurement data. Fig. 10 shows how the solutions are placed in the parameter space if we consider the values of pulse width...
vs. frequency found. We observe three niches of different characteristics being established in the population. Medium frequency is either combined with very low or high pulse width or a high frequency with medium pulse width is found. Of course the magnitude is different to prevent a burn through of the micropump, i.e. a small pulse width is combined with a high magnitude of 1200 mA and a high pulse width is combined with only 275 mA. Comparing the optimization values with the measurement values (the nine values within the ellipse in the lower left corner) we realize that the latter have been taken in a small subspace only.

Fig. 10: The parameter space

Fig. 11: Variation of the power supply

Fig. 11 visualizes the behavior of the micropump in terms of the air flow rate and maximal heater temperature of both, the behavior of the standard pump (stnd) and the seven solutions found with improved behavior (1-7). The optimization results are sorted by the maximal temperature of the heater.

These results demonstrate that the efficiency of the micropump model may easily be quadrupled. We realized that the way of human thinking is often too restrictive compared to the space of promising solutions. But, it shows too that our simulation model needs verification for a much larger parameter space.

7 Further Application: Heterodyne Receiver

Another application of SIMOT will be the optimization of a heterodyne receiver, which is a microoptical communication module. The basic idea behind the heterodyne receiver is to mix the received signal coherently with another optical wave before it is incident on the photodetector. The optical wave is generated locally at the receiver by using a narrow-linewidth laser (the so called local oscillator). In the case of heterodyne detection the local oscillator frequency is chosen to differ from the signal-carrier frequency such that the intermediate frequency is in the microwave region.

Beside the optical effects like e.g. diffraction and misalignment of the passive or active optical components there are environmental effects that influence the performance of the receiver. These effects are mainly induced by local temperature variations caused by thermal radiation of the surrounding electronics or by variation of the ambient temperature. Therefore not only an optical simulation is
needed to describe this system but also a simulation of these environmental effects.

References