Multi-Objective Evolutionary Design of Mold Temperature Control using DACE for Parameter Optimization

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Abstract. The design of mold temperature control strategies (MTCS) is a challenging multi-objective optimization task which demands for advanced optimization methods. Evolutionary algorithms (EA) are powerful stochastically driven search techniques. In this paper an EA is applied to a multi-objective problem using aggregation. The performance of the evolutionary search can be improved using systematic parameter adaptation. The DACE technique (design and analysis of computer experiments) is used to find good MOEA (multi-objective evolutionary algorithm) parameter settings to get improved solutions of the MTCS problem. SPO (sequential parameter optimization), i.e., an automatic and integrated approach, which extends DACE, is applied to find the statistically significant and most promising EA parameters.

Keywords: Multi-Objective Evolutionary Algorithms (MOEA), Design and Analysis of Computer Experiments (DACE), Mold Temperature Control Systems (MTCS), Sequential Parameter Optimization (SPO)

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1. Introduction

An optimal temperature control of die and injection casting tools is an important factor for the increasing of production efficiency. Injection casting and die casting is used in mass production. A critical point is the cycle time of the tool, which is mainly dominated by the cooling time. The geometric structure of the cooling bore cycles is decisive for the quality and efficiency of the cooling. Finding a proper cooling is a multi-objective problem of global and local cooling and manufacturing cost and can be controlled by the proper positioning of the bores. In the following a new automatic software tool for finding tradeoff solutions is described. This evolutionary optimization tool for mold temperature control design has been developed at the ISF.

The efficiency of evolutionary algorithms generally strongly depends on the quality of the algorithm's parameters itself. Sequential parameter optimization (SPO) is an efficient mean to find adequate parameter settings with very few experiments and a low amount of process knowledge. Therefore, SPO combines classical and modern statistical techniques to a heuristic acting in sequential steps. The software package called SPOT (sequential parameter optimization toolbox), which has been developed at the Chair of Systems Analysis in Dortmund, is an automatic tool that supports experimental design and visualization of response surfaces using DACE.

The publication is divided into a part about the encoding, evaluation and evolutionary optimization of mold temperature control systems (MTCS), a description of the SPO technique and a part about the practical application of this technique to the MTCS.

2. Mold temperature control: encoding, evaluation and evolutionary optimization

Today CAD designs of injection and die casting molds are constructed manually by experts. The verification of the design with FEM is seldom. Often only application tells the designer about the quality of the layout. An improved cooling of injection tools can reduce the cycle time up to 50 percent [1]. A wrong cooling strategy can lead to insufficient workpiece quality and even to tool breakage. The cost of modern die casting tools can be several hundred thousand Euros. Therefore, an exact, comprehensive and intuitive measure of the effect of cooling bores is decisive for a profitable tool. An automatic optimization depends on a fast and correct estimation of the cooling effects and costs of the layout.

The analysis tool introduced here consists of a geometry kernel, a quality evaluation kernel and an evolutionary optimizer. The internal CAD kernel utilizes a triangulation of the tool surfaces. Triangulation is the most common and flexible standard CAD format. Cooling circuits are represented by polylines which can be characterized by the position of the 3D-vertices. Additionally the directions of the real bores are considered in the encoding. One complete cooling circuit consisting of m bores (m is fix) is described by a vector with $n=3(m+1)+(m-2)$ elements. A model with four bores and a half-spherical die surface is shown in Fig. 1.

Often the cooling effect of a bore layout is estimated via finite element analysis. FEM is a precise but also quite time consuming technique. Therefore, a fast estimation method has been developed at the ISF. The so called radiation approach interprets each line of a polyline as a long and thin source of light. So we see each bore hole as a “neon lamp”. The “illumination intensity” of the die surface correlates with the real cooling intensity of a bore [2, 3]. The evaluation time of the half sphere example using FEM takes about 10 minutes while the radiation approach needs less than 1ms. For many cases the quality of the radiation model is very similar to the FEM solutions.

Multi-objective problems can be solved by a priori or a posteriori techniques [5, 6]. Due to the fact that the Pareto-front is known to be convex and the preferences of each objective can be given in advance, an aggregation technique was applied [2]. The radiation approach determines the cooling efficiency f_t via the strength of the illumination of a triangle of the die surface. The cost f of the manufacturing of a circuit is mainly dominated by the number and the length of the bores f_l. Geometric and technical restrictions f_{pen} as well as limitations of the drilling machine or special machining preferences are also considered. The parameter $d_l \in [0,1]$ in formula (1) is a weighting factor.

$$f = f_t \cdot (1.0 + f_{pen}) \cdot (1.0 + d_l \cdot f_l) \qquad (1)$$

The aggregation method has several advantages. An important benefit is that standard and well tested single-objective optimizers can be used. Analysis using more complex multi-objective techniques such as the application of the NSGA-II and *m-to-1* mappings such as the MMBBH or the S-metric are described in [2,3,4]. The MO-evolutionary algorithm with aggregation used here is a variation of an evolution strategy. The specific change is to limit the step size by an exponential decreasing lower limit. This limiting is important to avoid stagnation in pre-Pareto-fronts. The factor for the exponential function depends on the maximum number of generations and has been chosen in a way that all experiments can be compared with each other.

3. DACE and SPO

An appropriate design is a key element of any experiment. Sequential parameter optimization is an approach that uses advanced statistical methods such as DACE for analyzing and optimization of the design of a non deterministic computer experiment.

An algorithm design D_A is a specification of the ranges of the values of d so called design variables used for the experiments. A design point $x \in D_A$ is a vector with specific settings for the design variables to be optimized. Here, a subset of the MOEA's parameters is considered as design variables. The problem design D_P provides data related to the optimization problem, such as the fixed parameters or termination criteria. In this contribution the problem is to optimize the layout of bores cooling a half-spherical die surface using not more than 40.000 evaluations to suggest a solution. The experimental design D consists of the problem design D_P and the algorithm design D_A.

Experiments with EA cause stochastic results. Hence, the outcome of each experiment is a realization of a stochastic variable $Y(x)$ with $x \in D_A$. Although the original concept of DACE [8] is deterministic, SPO encapsulates the stochastic nature of the search heuristic under optimization to improve the performance of non-deterministic algorithms. Therefore it includes methods to handle stochastic variables and each design point is evaluated several times. As described in [8,9], to predict the results of further, non initial design points, the response is modeled as a realization of a regression model and a random process. A Gaussian correlation function and a regression model with polynomial order 2 is typically used.

$$Y(x) = \sum_{j=1}^{q} \beta_j f_j(x) + Z(x), \qquad (2)$$

where $Z(\cdot)$ is a random process with mean zero and covariance $V(u,v) = \sigma^2 \mathcal{R}(\theta,w,x)$ with process variance σ^2 and the correlation model $\mathcal{R}(\theta,w,x)$. The value of q in formula (2) depends on the type of the regression model and the number of design variables d. The Gaussian correlation function is

$$\mathcal{R}(\theta,\mathrm{w},\mathrm{x}) = \prod_{j=1}^{d} exp\ (-\theta_j\ (w_j\text{-}x_j)^2). \tag{3}$$

As in [8,10] we restrict attention to the Gauss correlation function. The initial design points are determined by Latin Hypercube Sampling (LHS). Latin hypercube sampling is a strategy that ensures that all portions of the vector space are represented. Due to the space filling characteristic of the LHS, a special strategy is used that tries to maximize the minimal distance between each design point. LHS usually generates real values by definition. Therefore parameters are rounded to integers where necessary. The ranges of the LHS are not normalized. To build a quadratic model (2) from the initial design points the minimum number k of required points equals $d\ (d\text{-}1)/2\ +\ 3d\ +1$, where d is the number of factors to analyze.

After performing one complete design, i.e. r experiments for each design point are made, the r outcomes are summarized to a single value representing the performance of the design point. The model is build, additional new design points are created and selected by computing the generalized expected improvement criterion following [7,11]. This criterion estimates the probability of a candidate point to be better than the known best so far by taking the modeling error into account. The best estimates are chosen for new design points. The cycle of evaluating, regression and choosing new design points is repeated until a termination criterion holds, e.g. a maximum time is exceeded.

4. Experimental Setup

In earlier analyses [2] using a similar evolutionary algorithm, but without exponential step size limitation, classical factorial design analyses showed, that there are *d=4* parameters, so called factors, that have a statistical relevant influence on the EAs performance. Therefore, we need to evaluate *k=19* initial design points. Parameters under optimization are: number of parents $\mu \in \mathbb{N}$, $\mu \in [5, 25]$, offspring-parent ratio $\nu \in \mathbb{R}$, $\nu \in [2, 7]$ (also called selection pressure), initial standard deviation $\sigma_0^0 \in \mathbb{R}$, $\sigma_0^0 \in [0.1, 0.3]$ (also called initial step size; the zero indices indicate initial conditions) and the variation multiplier $\tau_0^m \in \mathbb{R}$, $\tau_0^m \in [0.2, 2.0]$, which is used as an additional scalar for the classical step size adaptation as described in [12]. The number of offspring $\lambda \in \mathbb{N}$ can be calculated from the offspring-parent-ration, i.e. $\lambda = \lfloor \mu\nu \rfloor$. To simplify the analysis, the EA uses only one step size in the experiments. The maximum number of generations was chosen according to the design point's number of offspring, to ensure that all design points consume a comparable amount of computational power, measured by the number of evaluations (40.000). Following the results in [2], we choose a $(\mu+\lambda)$-strategy. The EAs task is to optimize m=4 bores to cool a half-spherical die surface, i.e. the dimension *n* of the problem is 17 (n = 5 × 3D-vertices + bore directions for the 2 internal bores). All experiments were performed on standard PCs. The analyses were done using Matlab (SPO) and the open source statistics toolbox R [13].

5. Analysis

In the initial step of the SPO each design point has been evaluated 25 times. In sequential steps the number of evaluations was doubled. As DACE expects deterministic experiments, we have to merge the set of results for each design point into a single value. This value has to reflect our intention to discover an EA parameter setting, able to produce good results with a low number of optimization runs. As EA are non-deterministic algorithms, bad settings can lead to good results and good settings to bad ones. So the design point's value has to reflect the distribution of the experimental results, it should be able to tell the user, what to expect if the algorithm was run repeatedly. An approach similar to the bootstrap was chosen in order to estimate the best result we could expect from a particular setting performing three runs. To do so, three results of a design point were drawn and put back 1000 times and each time the best result out of these three values was recorded. The mean value of the 1000 records estimates the expectation about a design point.

The experiments of the first SPO step show that large μ and ν values lead to better results. This means that large initial populations should be preferred to small ones. One has to keep in mind that the maximum number of fitness evaluations and therefore the computational afford is fixed for all settings. This result is problem specific. Standard parameter settings would give suboptimal results. The first experiments also show that small τ_0^m values and medium σ_0^0 values should be preferred. The influence of the σ_0^0 values is nearly neutral.

Figure 2 shows parameter effects and interactions, extracted from the Kriging model on the average experiment response. The effect plots (diagonal) show the changes of the average model response, so called main response. Here the considered parameters are fixed to a specific value. To get the main response, a large space filling design M containing 2000 design points was used and the average model response at these points were calculated.

To get the effect of fixing a parameter $p \in \{\mu,\ \nu,\ \sigma_0^0,\ \tau_0^m\}$ to a certain x in the design space we change the setting of p in all design points in M to x and compute the difference between the new design's average and the main response. Negative values show that an improvement can be expected, positive values indicate a deterioration of performance on the average. For example, the effect plots of μ and ν in Figure 2 confirm that high values are a good choice for most settings and not just for the specific setting found during optimization. One can also see that any further improvement by setting sigma below 0.2 cannot be expected.

The interaction plots (upper right triangle) show the effect of fixing two parameters. To get these effects, two parameters in every design point in *M* are fixed to specific values and the new average model response is computed. Instead of just subtracting the main response, we also subtract the effects of setting just one of our two parameters to a new value. The remainder is the effect resulting from the interaction of the two parameters. For example, the interaction between σ_0^0 and ν might explain that a small sigma can be chosen without showing an improvement on its own. High ν and small σ_0^0 are a good choice on the average.

The global structure of the response surface is roughly quadratic in the area under consideration. A third SPO step increased estimation of the best fitness values from 0.2038 (first step) over 0.18581 (second step) to 0.17601 (third step), i.e. a relevant improvement of 13 percent. The best parameters found are $\mu=18$, $\nu=6.79$, $\sigma_0^0=0.1348$, $\tau_0^m=1.108$.

5. Summary and Conclusions

Proper parameter settings of an aggregating MOEA solving the complex mold temperature control problem have been found using the SPO technique. This helps to further improve the quality and productivity of the cost intensive injection tools. The responses of the experiments show that unexpected high initial population sizes seem to be beneficial for the problem solution. DACE and an efficient bore design evaluation model keep the computational effort in acceptable limits. The Kriging approach is superior to the conventional quadratic approximation because the real shape of the response surface can be modeled. The SPO approach proved to be very efficient, easy to use, flexible and statistically as well as intuitively expressive for the analyses of stochastic computer experiments. The experimental results have been improved significantly.

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Figure captions

Fig. 1 Model of a triangulated die surface and two mold temperature control circuits.

Fig. 2 Parameter effects and interactions.

Figures

Figure 1

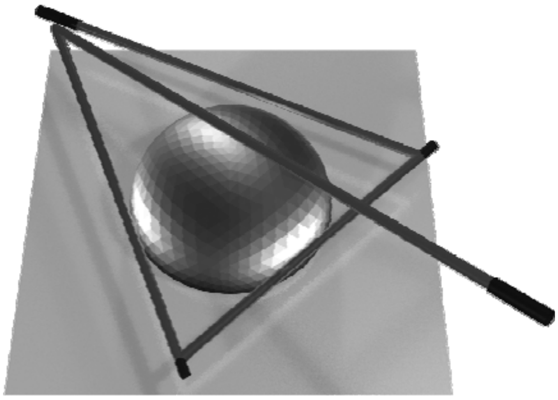

Figure 2