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Solving a multiresponse simulation-optimization problem with discrete variables using a multiple-attribute decision-making method

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Abstract

The simulation model is a proven tool in solving nonlinear and stochastic problems and allows examination of the likely behavior of a proposed manufacturing system under selected conditions. However, it does not provide a method for optimization. A practical problem often embodies many characteristics of a multiresponse optimization problem. The present paper proposes to solve the multiresponse simulation-optimization problem by a multiple-attribute decision-making method—a technique for order preference by similarity to ideal solution (TOPSIS). The method assumes that the control factors have discrete values and that each control factor has exactly three control levels. Taguchi quality-loss functions are adapted to model the factor mean and variance effects. TOPSIS is then used to find the surrogate objective function for the multiple responses. The present paper predicts the system performances for any combination of levels of the control factors by using the main effects of the control factors according to the principles of a robust design method. The optimal design can then be obtained. A practical case study from an integrated-circuit packaging company illustrates the efficiency and effectiveness of the proposed method. Finally, constraints of the proposed method are addressed.

Keywords: Multiple-attribute decision-making; Simulation optimization; TOPSIS; Integrated circuit packaging; Taguchi method

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1. Introduction

The simulation model is a proven tool in solving nonlinear and stochastic problems, and allows examination of the likely behavior of a proposed manufacturing system under selected conditions [1]. However, simulation is essentially a trial-and-error approach, and is therefore, time-consuming. It does not provide a method for optimization. There is a significant body of literature devoted to the problem of simulation optimization [2]. To solve a simulation-optimization problem, there are two general approaches—the response surface method (RSM) and the metaheuristic method.

The RSM simulation-optimization approach uses a simulation metamodel to suggest a functional relationship between selected decision variables and system responses. It provides a statistical summary of simulation results, allows some extrapolation from the simulated range of system conditions, and therefore, has the potential to offer assistance in optimization [3,4]. There are, however, two well-known problems associated with RSM: (i) the steepest descent is scale-dependent and (ii) the step size along the steepest descent path is selected intuitively [5].

Metaheuristics (such as simulated annealing, genetic algorithms, Tabu search, or scatter search) can be used as an embedded search algorithm associated with simulation software for a simulation-optimization problem. The search strategies proposed by metaheuristic methodologies result in iterative-procedures that have the ability to escape local optimal points.

Although there is a significant body of literature that addresses single-response optimization problems, practical problems often embody many characteristics of a multiresponse optimization problem. For example, one such practical problem is the maintenance of a satisfactory system throughput while simultaneously maximizing machine utilizations and minimizing the amount of work-in-process [6]. A survey by Khuri [7] showed that most of the existing multiresponse optimization approaches combine multiple responses into a single response by appropriate transformation. The type of transformation differs according to the particular method—and is an arbitrary choice. This arbitrary choice is recognized as being a drawback.

Angün et al. [8] proposed to solve the multiresponse problem by choosing one of the responses as objective and treating the remaining responses as constraints. They generalized the estimated steepest-descent search direction to multiple responses. The search direction is the scaled and projected estimated steepest-descent direction—also called the estimated affine scaling search direction. Yang and Tseng [9] used a hybrid RSM and a lexicographical goal-programming approach to solve a multiresponse problem. Their approach satisfied the simulation response in prioritized sequence, rather than solving a complete goal-programming model at each point determined by the RSM procedure. In fact, no goal-programming problem was actually solved in their method. Although there are other variations in modeling the multiresponse simulation-optimization problem, most of them use the descent-search method to find a solution.

Myers and Carter [10] introduced the dual-response approach to model the problem with two responses. Their objective was to find the optimal operating settings that optimize a *primary* response—subject to the condition that a *secondary* response takes on a desirable value. Del Castillo and Montgomery [11] extended this concept to more than two responses. Their methodology treated all responses, other than the primary response, as constraints. The resulting formulation can be solved by a nonlinear programming solution method.

Fan and Del Castillo [12] proposed to solve a dual-response system based on Monte Carlo simulation of the system under study. Their method explicitly considered the sampling variance of the fitted