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A novel approach for optimization of correlated multiple responses based on desirability function and fuzzy logics

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ABSTRACT

Many real world applications consist of finding optimal inputs (design variables) to the system that yields in desirable values for stochastic outputs (Responses). Several studies in the literature have suggested approaches addressing these problems but most of them assume that the responses are independent and their variances are constant over the experimental space. Furthermore, in many situations the relationship between the response variables and design variables is too complex to be efficiently estimated using traditional surface fitting approaches. In this paper, a method is presented for optimizing the problem of correlated multiple responses where relationship among response and design variables is highly nonlinear by means of Neuro-Fuzzy and principal component analysis derived desirability function. As another advantage over existing works, we have relaxed the assumption that variance of each response is invariant over the feasible region. Finally, effectiveness of the proposed method is illustrated through a numerical example.

1. Introduction

In many real world applications problems are faced in which design variables to the system that yield in desirable values for stochastic responses are to be determined. Simultaneous optimizing these responses is called Multiple response optimization (MRO). This filed consists of three main stages:

1. Data gathering
2. Model building
3. Optimization

A usual practice for Data Gathering is called Design-Of-Experiments (DOE) which enables us to find the most valuable information about the features of the system to be optimized.

In Model building we intend to investigate the relation among design variables and responses. In most practices Response Surface Methodology (RSM) is used as a common tool. In this method the relationship is developed using mathematical tools and there is the assumption that this relationship is linear or quadratic and predetermined. But in most practical problems this relationship is complicated and nonlinear. In such cases usually Artificial Intelligence (AI) tools such as Neural Networks or Fuzzy Inference Systems (FIS) are used.

For the Optimization module a common approach consists of methods that combine the multiple responses into a single aggregated function and solve it as a single objective optimization problem. These approaches can be categorized into two major types:

1. Approaches that assume independence of responses
2. Approaches that consider correlation among responses

Most of the existing methods in MRO are categorized into the first type. Typical examples are Harington [1], Deringer and Suich [2], Plante [3] and Kim and Lin [4] to name a few.

Solution approaches in the second category consist of: loss function-based methods (Pignatiello [6], Ames et al. [5], Vinning [7] and Ko et al. [8]) and Principal component analysis-based (PCA-based) methods (Antony [9], Liao [10] and Su and Tong [11]). But each of these methods has deficiencies in certain areas:

1. Loss function-based methods do not guarantee the optimal response values to occur within specification limits. Also, in most of them the distance metric used is applied to responses with specific target values, and hence their usefulness for responses to be minimized (maximized) is under question.
2. PCA-based methods use Principal Components (PCs), which are linear combinations of original response variables, to resolve the issue of dependency among original responses. But this way they also may lose the optimization directions of each individual response, i.e., regardless of minimization or

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maximization of each response, PCA-based methods maximize PCs. Moreover almost all PCA-based papers consider only discrete design variables.

All of the above approaches result in a single objective problem which is optimized using different tools from exact to meta-heuristics.

Main contributions of this paper could be summarized as follows:

1. A novel method for optimization of correlated multiple response problems is developed. This new method relaxes limitations of traditional approaches.
2. The approach used to model building phase is Adaptive Neuro-Fuzzy Inference System (ANFIS), to resolve shortcomings of abovementioned RSM, to capture nonlinearity in relationship.

The rest of this paper is organized as bellow:

In Section 2 the literature of multi response optimization is reviewed. Then the proposed method is detailed in Section 3 and the progress of the method is illustrated through a flowchart. Finally a numerical example is conducted to show the effectiveness of the proposed method over existing approaches.

2. Literature review

As this paper introduces a new method based on AI and PCA for the correlated multi-response problem, thus, in Sections 2.1 and 2.2 the literature on MRO studies which contain AI and PCA characteristics in their structure is reviewed.

2.1. AI-based studies in MRO

An important point in the optimization process of the responses is to estimate the relationship between each response and design variables. In many situations, regression methods do not have the ability to estimate properly this relationship and there can be seen large amounts of Mean Square Error (MSE) for regression models. It shows poor quality of these relationships (Kim et al. [12]). In most cases this problem occurs for two reasons: (i) requirement for a priori assumption about the relationship (linear, quadratic…), (ii) existence of a complex relationship between response and design variables. In these cases, intelligent approaches (approaches based on neural networks or fuzzy logics) are an appropriate alternative to achieve a good estimation. In this regard, Su and Hsieh [13] proposed an approach based on neural networks to solve the quality optimization problem in Taguchi's dynamic experiment. However, this method is applicable only when there is a single response variable.

Liao [14] proposed a neural network and data envelopment analysis (DEA) approach (Charnes et al. [15]) to efficiently optimize the multiple response problems using Taguchi method. To estimate the signal to noise (SN) ratios of responses, the experimental data for each design variable combination, which is also named decision making unit (DMU), the neural network, is used. Then DEA is employed to find each DMU's relative efficiency so that the optimal design variable setting can be found by the highest relative efficiency. A three step approach presented by Gutierrez and Lozano [16] which consists of: (1) using neural networks to estimate mean square deviation (MSD) of responses for all possible combinations of design variables, (2) using DEA to compute the relative efficiency for all combinations and selecting the most efficient ones, and (3) using DEA again to select among the efficient combinations the one which leads to the most robust quality loss penalization. A four step procedure to resolve the parameter design problem involving multiple responses is proposed by Antony et al. [17]. In this method, multiple SN ratios are mapped into a single performance index called multiple-response-statistic (MRS) through Neuro-Fuzzy based model to identify the optimal levels of each design variable. Finally analysis of variance is conducted to identify design variables significant to the process. The above literature, discuss only design variables used in experimental trials, which have discrete values. Hence, they cannot find the global optimal design variable settings within the corresponding bounds, that is, they do not afford continuous search.

Hsieh and Tong [18] presented an approach for solving problems with multi-responses using neural networks. In this approach two neural networks are used, one for discovering optimal design vector and the other for estimating responses. Although optimal settings can be obtained, the effect of design variables on responses still cannot be achieved. A similar method based on artificial neural networks (ANN) is presented by Hsieh [19], in which, the effect of the design variables on multiple responses can be also obtained. At the same time this method can be employed, no matter whether the design variables are discrete or continuous. Noorossana et al. [20] proposed to use an artificial neural network to estimate the quantitative and qualitative response functions. In the optimization phase, a genetic algorithm (GA) in conjunction with a desirability function (DF) is used to determine the optimal design variables. Chang [21] presented a data mining approach to dynamic multiple response problem consisting of four stages which apply the methodologies of ANN, exponential desirability function (EDF) and simulated annealing (SA). First, an ANN is employed to construct the response model of a dynamic multiple response system by applying neural network to the experimental data. The trained model then is employed to predict the corresponding quality responses by inputting specific design variables. Second, each of the responses is evaluated using EDF. Third, EDFs are integrated into an overall performance index (OPI) for evaluating a specific design variable combination. Finally, SA is performed to obtain the optimal design. Another dynamic multi-response approach was presented by Chang and Chen [22]. In this method, similar to Chang's [21] work, optimization phase is performed by GA. Chiang and Su [23] focused on an optimization problem that involves multiple qualitative and quantitative responses in the thin quad flat pack (TQFP) modeling process. First a fuzzy quality loss function is performed on qualitative responses. Then neural network is applied to estimate a nonlinear relationship between response and design variables. A GA together with EDF is incorporated to determine the optimal setting. Lu and Antony [24] presented the use of fuzzy-rule base reasoning and SN ratios for the optimization of multiple responses. The idea is to combine multiple SN ratios into a single performance index called multiple performance statistic (MPS) output, in which the optimum level setting of design variables could be found by maximizing MPS. A similar approach to Lu and Antony [24] for optimizing the electrical discharge machining process with multiple performance characteristics has been reported by Lin et al. [25]. In this research, several fuzzy rules are derived based on the performance requirement of the process. Next, the inference engine performs a fuzzy reasoning on fuzzy rules to generate a fuzzy value. Eventually, the defuzzifier converts the fuzzy value into a single performance index and the optimal setting of the machining parameters can be specified based on maximizing performance index. Cheng et al. [26] formulated MRO problem as a multi-objective decision making problem, and follow the basic idea of Zimmermann [27]. This approach first models the responses through multiple adaptive neuro-fuzzy inference system (MANFIS), then according to the max-min approach the overall satisfaction is achieved by comprising via the use of membership functions among all responses. Finally, GA is used to search the optimal setting on the response surfaces modeled by MANFIS.

With respect to the aforementioned approaches, it can be concluded that the major focus of these methods is on the location effect only, ignoring the dispersion effect of the responses. In other