

# 國立中山大學應用數學研究所

## 碩士論文

混合實驗在Scheffé模型之正合D-最適設計

## **Exact** *D***-optimal designs for mixture experiments**

## in Scheffé's quadratic models

研究生:吴憲忠 撰

指導教授:羅夢娜教授

中華民國 九十五 年 七月



## 致謝

我要感謝我的指導教授羅夢娜教授。能夠完成這篇論文,她給了我很多 的幫助,不論是在內容的指導還是寫作期間所遭遇到的種種問題,她都能夠 很有耐心的幫我解答並作適當的建議。而她也與我分享了許多人生的經驗並 且讓我得到了很多的鼓勵,讓我對於未來能夠有更多的信心。

我也要感謝所有應用數學所統計組的教授們,感謝你們在課業上給予我的 許多指導讓我能夠學習到更多有關統計的專業知識,這讓我有足夠的基礎能 夠完成這篇論文。非常謝謝你們的教導。

感謝全濱學長與湘伶學姐,和你們的討論讓我對於相關的基楚知識有相當 的認識並且獲益良多。也要感謝所有統計組的同學們,在課業上你們也給了 我非常多的幫助。

感謝所有同研究室的同學們,感謝你們給我的許多幫助,而和你們在學校 的這段期間都是我最美好的時光。

最後感謝我的父母們,感謝你們讓我在生活上沒有後顧之憂並能快樂安心 的讀書,謝謝你們。

## 摘要

關於多項式迴歸模型下之最適設計問題己經在很多文獻中被討論到。對 於定義在[a,b]之多項式迴歸型,其正合D-最適設計的最小樣本數 Huang (1987)和 Gaffke (1987)都給出了相似的充分條件。在本文中我們則是對一 混合實驗模型作探討。一混合實驗為一包含q個非負成分 $\{x_1,...,x_q\}$ ,且  $\sum_{i=1}^{q} x_i = 1$ 的q = 1維之機率空間 $S^{q-1}$ 上的實驗設計。Kiefer (1961)證明了在 Scheffé 的二次混合實驗模型下之D-最適設計,而基於此一結果我們證明 2 維與 3 維在 Scheffé 的二次混合實驗模型下之正合D-最適設計,並對於 4 維 至 9 維的模型給出一些數值的結果。

**關鍵字:**Scheffé二次模型、*D*-最適設計、正合*D*-最適設計、訊息矩陣、正 交多項式。

# Exact *D*-optimal designs for mixture experiments

in Scheffé's quadratic models

by

Shian-Chung Wu

Advisor

Mong-Na Lo Huang

Department of Applied Mathematics National Sun Yat-sen University Kaohsiung, Taiwan, 804, R.O.C.

June, 2006

### Abstract

The exact *D*-optimal design problems for regression models has been investigated in many literatures. Huang (1987) and Gaffke (1987) provided a sufficient condition for the minimum sample size for an certain set of candidate designs to be exact *D*-optimal for polynomial regression models on a compact interval. In this work we consider a mixture experiment with q nonnegative components, where the proportions of components are subject to the simplex restriction  $\sum_{i=1}^{q} x_i = 1, x_i \ge 0$ . The exact *D*-optimal designs for mixture experiments for Scheffé's quadratic models are investigated. Based on results in Kiefer (1961) results about the exact *D*-optimal designs for mixture models with two or three ingredients are provided and numerical verifications for models with ingredients between four and nine are presented.

**Keywords :** Scheffé's quadratic models, *D*-optimal design, exact *D*-optimal design, information matrix, orthonormal polynomial

## Contents

Abstract	i
Lists of Figures and Tables	iii
1 Introduction	1
2 Preliminaries	3
3 Two and three ingredients	7
3.1 Two ingredients	7
3.2 Three ingredients	8
4 Four or more ingredients	15
5 Conclusion	16
References	17

# List of Figures

Figure 1.	(2,2)-lattice	12
Figure 2.	Subregion of $A_1$ and $A_{12}$	13

# List of Tables

Table 1.	Maximum $p$ for	ingredients from 4 to 9	0
----------	-----------------	-------------------------	---

### 1 Introduction

Consider a mixture experiment with q nonnegative components, where the proportions of components are subject to the simplex restriction  $\sum_{i=1}^{q} x_i = 1, x_i \ge 0$ . The qproportions can be expressed as a column vector  $\mathbf{x} = (x_1, \ldots, x_q)'$  in  $S^{q-1}$  where

$$S^{q-1} = \{ (x_1, \dots, x_q)' \in [0, 1]^q : x_1 + \dots + x_q = 1, \quad x_i \ge 0 \quad i = 1, \dots, q \}$$

An observation  $y(\mathbf{x})$  is obtained at  $\mathbf{x} \in S^{q-1}$  with  $E(y(\mathbf{x})) = \beta' f(\mathbf{x})$  and variance  $\sigma^2$ independent of  $\mathbf{x}$ , where  $f(\mathbf{x})$  is a known function and  $\beta$  is an unknown parameter vector. In Scheffé's quadratic model the expectation is expressed as

$$E(y(\mathbf{x})) = \beta_1 x_1 + \dots + \beta_q x_q + \beta_{12} x_1 x_2 + \dots + \beta_{(q-1)q} x_{q-1} x_q \tag{1}$$

with regression function  $f(\mathbf{x}) = (x_1, \ldots, x_q, x_{12}, \ldots, x_{(q-1)q})'$ . An exact design with sample size N is a probability measure on a design space which puts weight  $p_i > 0$  at n distinct support points,  $n \leq N$  such that  $\sum_{i=1}^{n} p_i = 1$  and  $Np_i$ ,  $i = 1, \ldots, n$  are integers. An approximate design removes the integer restrictions on  $Np_i$ ,  $i = 1, \ldots, n$ . Denote a probability measure  $\xi$  for a mixture experiment as follows

$$\xi = \begin{pmatrix} \mathbf{x}_1 & \cdots & \mathbf{x}_n \\ p_1 & \cdots & p_n \end{pmatrix} = \begin{pmatrix} \begin{pmatrix} x_{1,1} \\ \vdots \\ x_{1,q} \end{pmatrix} & \cdots & \begin{pmatrix} x_{n,1} \\ \vdots \\ x_{n,q} \end{pmatrix} \\ p_1 & \cdots & p_n \end{pmatrix},$$

where  $\mathbf{x}_1, \ldots, \mathbf{x}_n$  denote the finite supports with the corresponding weights  $p_1, \ldots, p_n$ . The information matrix is therefore defined by

$$M(\xi) = \sum_{i=1}^{n} \xi(\mathbf{x}_i) f(\mathbf{x}_i) f'(\mathbf{x}_i),$$

and the corresponding dispersion function is given by

$$d(\mathbf{x},\xi) = f'(\mathbf{x})M^{-1}(\xi)f(\mathbf{x})$$

According to the Equivalence Theorem (Kiefer and Wolfowitz 1960) a design  $\xi^*$  is called an approximate *D*-optimal designs if  $\xi^*$  maximizes det $(M(\xi))$  over all feasible designs on the design space. Kiefer (1961) showed that an approximate design for the Scheffé's quadratic model which assigns measure 2/q(q+1) to each point of the (q-1,2)-lattice. If an exact design  $\xi^*_N$  maximizes det $(M(\xi_N))$  over all feasible exact designs on the design space, then it is called an exact *N*-points *D*-optimal design.

For a polynomial model on a closed interval [a, b], Salaevskii (1966) conjectured that an exact design which distributes the weights as even as possible on the support points of the approximate designs. The conjecture of Salaevskii had been studied by Constantine and Studden (1981), Gaffke and Krafft (1982), Gaffke (1987), Huang (1987) and had verified the Salaevskii conjecture holds for most of the cases. Chang and Chen (2004) discussed the exact *D*-optimal design problem for multivariate linear polynomial models on a simplex, parallelgram and quadratic polynomial models with or without intercept on the *q*-ball for some cases, and provided some numerical results.

In this work, we investigate the exact D-optimal design for mixture experiments in Scheffé's quadratic models based on results in Kiefer (1961) and provide some results for models with two and three ingredients and numerical verifications for models with ingredients between four and nine.

### 2 Preliminaries

Kiefer (1961) proved that an approximate *D*-optimal design  $\xi^*$  on a simplex is supported equally with weights p = 2/q(q+1) on the (q-1,2)-lattice with q(q+1)/2 points, where  $\mathbf{x}_i^*$ ,  $i = 1, \ldots, q$  are the vertexes and  $\mathbf{x}_{ij}^*$ ,  $1 \le i < j \le q$  are the certres of the sides, i.e.

$$\xi^* = \left( \begin{array}{cccc} 1 \\ 0 \\ \vdots \\ 0 \end{array} \right) \begin{array}{c} 0 \\ 1 \\ \vdots \\ 0 \end{array} \right) \begin{array}{c} 0 \\ 1 \\ \vdots \\ 0 \end{array} \right) \begin{array}{c} 0 \\ 0 \\ \vdots \\ 1 \end{array} \right) \begin{array}{c} 1/2 \\ 1/2 \\ \vdots \\ 0 \end{array} \right) \begin{array}{c} 1/2 \\ 0 \\ 1/2 \\ \vdots \end{array} \right) \begin{array}{c} 1/2 \\ 0 \\ 1/2 \\ \vdots \end{array} \right) \begin{array}{c} 0 \\ \vdots \\ 1/2 \\ 1/2 \\ 1/2 \end{array} \right) \\ p \end{array} \right).$$

For the (q-1, 2)-lattice, Kiefer (1961) provided a q(q+1)/2 system of quadratic orthonormal polynomials with respect to the q(q+1)/2 support points in  $\xi^*$  such that each of which vanishes at all other support points expect at one point of the lattice. More explicitly the system consists of the functions  $[2q(q+1)]^{\frac{1}{2}}x_i(x_i - \frac{1}{2}), 1 \leq i \leq q$ , and  $[8q(q+1)]^{\frac{1}{2}}x_ix_j,$  $1 \leq i < j \leq q$ , these functions are very useful in expressing the corresponding dispersion function for design supports on the lattice points.

Now let  $g(\mathbf{x})$  denote the vertor of the orthonormal polynomials mentioned above where

$$g(\mathbf{x}) = \begin{pmatrix} g_1(\mathbf{x}) \\ g_2(\mathbf{x}) \\ \vdots \\ g_q(\mathbf{x}) \\ g_{12}(\mathbf{x}) \\ \vdots \\ g_{(q-1)q}(\mathbf{x}) \end{pmatrix} = \begin{pmatrix} 2x_1(x_1 - \frac{1}{2}) \\ 2x_2(x_2 - \frac{1}{2}) \\ \vdots \\ 2x_q(x_q - \frac{1}{2}) \\ 4x_1x_2 \\ \vdots \\ 4x_{q-1}x_q \end{pmatrix}$$

For designs supported on  $S^* = {\mathbf{x}_1^*, \dots, \mathbf{x}_q^*, \mathbf{x}_{12}^*, \dots, \mathbf{x}_{(q-1)q}^*}$ , we may transform the regression function  $f(\mathbf{x})$  in the Scheffé's quadratic model into  $g(\mathbf{x})$ . More explicitly  $g(\mathbf{x})$  may be expressed as

$$g(\mathbf{x}) = \mathbf{F}^{-1} f(\mathbf{x}), \quad \mathbf{x} \in S^{q-1}$$

where  $\mathbf{F} = (f(\mathbf{x}_1^*), \dots, f(\mathbf{x}_k^*), f(\mathbf{x}_{12}^*), \dots, f(\mathbf{x}_{(q-1)q}^*).$ 

Furthermore by the celebrated Kiefer-Wolfowitz Equivalence Theorem it can be shown

$$\sum_{i=1}^{q} g_i^2(\mathbf{x}) + \sum_{i \leq j} g_{ij}^2(\mathbf{x}) \leq 1, \ \forall \mathbf{x} \in S^{q-1}.$$

Similarly as in the Salaevskii conjecture, if the total number of trials is N = kp + t where k = q(q+1)/2,  $p, t \in \mathbb{N}$ , t < k, there are  $\binom{k}{t}$  different chadidate exact designs  $\xi_{N,T}^*$  with  $|T| = t, T \subset \mathbb{T}$ , originated from  $\xi^*$  and  $\mathbb{T} = \{1, \ldots, k, 12, \ldots, (q-1)q\}$  is the index set. That is

$$\xi_{N,T}^{*} = \left\{ \begin{array}{cccc} \mathbf{x}_{1}^{*} & \dots & \mathbf{x}_{q}^{*} & \mathbf{x}_{12}^{*} & \dots & \mathbf{x}_{(q-1)q}^{*} \\ n_{1}/N & \dots & n_{q}/N & n_{q+1}/N & \dots & n_{k}/N \end{array} \right\}$$
(2)

where  $n_{\ell} = p + 1$  if  $\ell \in T$  or  $n_{\ell} = p$  if  $\ell \notin T$ . Then the information matrix of  $\xi_{N,T}^*$  can be expressed as

$$M(\xi_{N,T}^*) = \sum_{i \in \mathbb{T}} p_i f(x_i) f'(x_i) = \sum_{i \in \mathbb{T}} p_i Fg(x_i) g'(x_i) F'$$
$$= F\begin{pmatrix} p_1 & \cdots & 0\\ \vdots & \ddots & \vdots\\ 0 & \cdots & p_{(q-1)q} \end{pmatrix} F'$$

and the inverse matrix of  $M(\xi_{N,T}^*)$  is

$$M^{-1}(\xi_{N,T}^*) = (F^{-1})' \begin{pmatrix} p_1^{-1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & p_{(q-1)q}^{-1} \end{pmatrix} F^{-1}.$$

Hence, the dispersion function of  $\xi_{N,T}^*$  is rewritten as

$$\begin{aligned} d(x,\xi_{N,T}^{*}) &= f'(x)M^{-1}(\xi_{N,T}^{*})f(x) \\ &= g'(x)F'(F^{-1})' \begin{pmatrix} p_{1}^{-1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & p_{(q-1)q}^{-1} \end{pmatrix} F^{-1}Fg(x) \\ &= \sum_{\ell \in \mathbb{T}} \frac{g_{\ell}^{2}(x)}{p_{\ell}}, \end{aligned}$$

where  $p_{\ell} = (p+1)/N$  if  $\ell \in T$  and  $p_{\ell} = p/N$ ,  $\ell \notin T$ .

Gaffke and Krafft (1982) proved the exact D-optimality of the above candidate designs for quadratic regression on [a, b], based on the geometric-arithmetic means inequality of the information matrix i.e.

$$\frac{\det(M(\xi_1))}{\det(M(\xi_2))} \le \left[\frac{1}{k} \operatorname{Tr}(M^{-1}(\xi_2)M(\xi_1))\right]^k,\tag{3}$$

where  $\xi_1$  and  $\xi_2$  are two arbitrary designs defined on [a, b]. Note that

$$\operatorname{Tr}(M^{-1}(\xi_2)M(\xi_1)) = \frac{1}{N} \sum_{i=1}^N f'(\mathbf{x_i})M^{-1}(\xi_2)f(\mathbf{x_i}) = \frac{1}{N} \sum_{i=1}^N d(\mathbf{x_i}, \xi_2),$$

where  $\mathbf{x}_i$ , i = 1, ..., N are the corresponding design points of  $\xi_1$ .

Gaffke (1987) and Huang (1987) independently verified Salaevskii's conjecture for the most of the cases of polynomial regression. In the following we provide some lemmas analogous to that in Huang (1987) which will be useful to prove the main results.

**Lemma 1.** There exists  $p_0 \in \mathbb{N}$  such that for all  $p \ge p_0$ 

$$\sum_{\ell \in \mathbb{T}} g_{\ell}^2(\mathbf{x}) \le \frac{p_0}{p_0 + 1} + \frac{R^2(\mathbf{x})}{p_0 + 1} \le \frac{p}{p + 1} + \frac{R^2(\mathbf{x})}{p + 1},\tag{4}$$

where

$$R^{2}(\mathbf{x}) = \max\{g_{\ell}^{2}(\mathbf{x}), \ell \in \mathbb{T}\}, \quad \forall \mathbf{x} \in S^{q-1}.$$
(5)

Note that (4) can be rewritten in another form as

$$\frac{1 - R^2(\mathbf{x})}{1 - \sum_{\ell \in \mathbb{T}}^k g_\ell^2(\mathbf{x})} \le p_0 + 1.$$
(6)

The proofs of Lemma 1 for q = 2 and 3 are deferred to Section 3.

Let

$$A_{\ell} = \{ \mathbf{x} | R^2(\mathbf{x}) = g_{\ell}^2(\mathbf{x}), \ \mathbf{x} \in S^{q-1} \}, \quad \ell \in \mathbb{T},$$
(7)

then we define the region  $A_T$  used in Lemma 2 where

$$A_T = \bigcup_{\ell \in T} A_\ell, \quad T \subset \mathbb{T}.$$

**Lemma 2.** For all  $p \ge p_0$ ,  $p \in \mathbb{N}$ , let  $\xi_{N,T}^*$  be as defined in (2) with  $T \subset \mathbb{T}$ , N = kp + t, then

$$\frac{1}{N}d(\mathbf{x},\xi_{N,T}^*) \leq \frac{1}{p+1}, \ \forall \mathbf{x} \in A_T, \frac{1}{N}d(\mathbf{x},\xi_{N,T}^*) \leq \frac{1}{p}, \quad \forall \mathbf{x} \notin A_T.$$

**Conjecture 1.** For  $N = kp + t \ge kp_0$ , where  $1 \le t \le k - 1$ , and  $p_0$  is defined as in (4), each of the  $\xi_{N,T}^*$  designs is exact *D*-optimal.

The key steps of proving Conjecture 1 is based on the fact that if conditions in Lemmas 1 and 2 hold, then for any exact design with N trials supported on  $\{\mathbf{x_1}, \ldots, \mathbf{x_N}\}$ , there is  $T \subset \mathbb{T}$  such that  $n_1 \ge t(p+1)$  where  $n_1$  is the amount of trials in  $A_T$ ,  $1 \le n_1 \le N$ , and for design  $\xi_{N,T}^*$ ,

$$\begin{aligned} \frac{1}{N} \sum_{i=1}^{N} d(\mathbf{x}_{i}, \xi_{N,T}^{*}) &\leq \frac{n_{1}}{p+1} + \frac{N-n_{1}}{p} = \frac{N(p+1)-n_{1}}{p(p+1)} \\ &\leq \frac{N(p+1)-t(p+1)}{p(p+1)} = k. \end{aligned}$$

This implies that  $\det(M(\xi)) \leq \det(M(\xi_{N,T}^*))$  by (3).

Hence, Lemma 2 and Conjecture 1 will hold for Scheffé's quadratic models if  $p_0$  defined in Lemma 1 can be found.

In the following we find the exact *D*-optimal designs for Scheffé's quadratic models with two or three ingredients. We will show in two steps. First we will identify the maximum functions  $R(\mathbf{x})$  in the design region and use it to partition  $S^{q-1}$  into several regions according to which  $g_{\ell}(\mathbf{x})$  is the maximum function. Then we can find  $p_0$  defined in Lemma 1 such that inequality (1) holds. Later, we find exact *D*-optimal designs for some sample sizes.

### 3 Two and three ingredients

In this section we would like to find the minimum sample size such that Conjecture 1 holds for two and three ingredients. Lemma 1 is the main tool to derive the results.

#### 3.1 Two ingredients

We start from experiments with two ingredients that q = 2. Then the model is

$$E[y(\mathbf{x})] = \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2, \quad \mathbf{x} \in S^1.$$

For this model, the approximate *D*-optimal design  $\xi^*$  is given by

$$\xi^* = \left( \begin{array}{cc} \begin{pmatrix} 1 \\ 0 \end{pmatrix} & \begin{pmatrix} 0 \\ 1 \end{pmatrix} & \begin{pmatrix} 1/2 \\ 1/2 \end{pmatrix} \\ 1/3 & 1/3 & 1/3 \end{array} \right)$$

and the quadratic orthonormal polynomials with respect to  $\xi^*$  are  $g_1^2(\mathbf{x})$ ,  $g_2^2(\mathbf{x})$  and  $g_{12}^2(\mathbf{x})$ as defined in Section 2.

For q = 2, we find  $R^2(\mathbf{x})$  as defined in (5) and the regions  $A_\ell$  as defined in (7) with respect to  $g_1^2(\mathbf{x})$ ,  $g_2^2(\mathbf{x})$  and  $g_{12}^2(\mathbf{x})$ . Then Theorem 1 holds for the special case with q = 2as below.

**Theorem 1.** The design  $\xi_{N,T}^*$  as defined in (2) is an exact D-optimal design in Scheffé's quadratic models with two ingredients where  $T \subset \mathbb{T} = \{1, 2, 12\}$  if  $N \geq 3$ .

**Proof.** Firstly, we identify the sets  $A_{\ell}$ ,  $\ell \in \mathbb{T}$  as defined in Section 2. Let  $g_1^2(\mathbf{x}) \ge g_2^2(\mathbf{x})$ and  $g_1^2(\mathbf{x}) \ge g_{12}^2(\mathbf{x})$  then we have  $A_1 = \{\mathbf{x} | \frac{5}{6} \le x_1 \le 1, \mathbf{x} \in S^1\}$ . Similarly, it can be found that  $A_2 = \{\mathbf{x} | 0 \le x_1 \le \frac{1}{6}, \mathbf{x} \in S^1\}$  and  $A_{12} = \{\mathbf{x} | \frac{1}{6} \le x_1 \le \frac{5}{6}, \mathbf{x} \in S^1\}$ . Let

 $L(\mathbf{x}) = (1 - R^2(\mathbf{x}))/(1 - \sum_{\ell \in \mathbb{T}} g_\ell^2(\mathbf{x}))$  and  $L'(\mathbf{x})$  and  $L''(\mathbf{x})$  denote the first and second order derivative of  $L(\mathbf{x})$ . Note that in  $A_1$ ,  $L(\mathbf{x}) = (1 - g_1^2(\mathbf{x}))/(1 - \sum_{\ell \in \mathbb{T}} g_\ell^2(\mathbf{x}))$ . Since  $x_2 = 1 - x_1$ , then for  $\mathbf{x} \in A_1$  we have

$$L(\mathbf{x}) = \frac{1 + x_1 + 4x_1^3}{6(1 - 2x_1)^2 x_1},$$

and

$$L'(\mathbf{x}) = \frac{1 - 6x_1 - 4x_1^2 - 8x_1^3}{6x_1^2(-1 + 2x_1)^3}.$$

It is easy to see that  $L'(\mathbf{x}) < 0$  by  $\mathbf{x} \in A_1$ , then  $L(\mathbf{x})$  is monotone decreasing in  $A_1$ and the maximum of  $L(\mathbf{x})$  is  $28/15 \approx 1.8667$  on  $x_1 = 5/6$ . Since  $L(\mathbf{x})$  is symmetric with  $x_1 = x_2$ , the maximum of  $L(\mathbf{x})$  in  $A_2$  is also 28/15. Similarly for all  $\mathbf{x} \in A_{12}$ ,  $L(\mathbf{x}) = (1 - g_{12}^2(\mathbf{x}))/(1 - \sum_{\ell \in \mathbb{T}}^k g_\ell^2(\mathbf{x}))$ , then

$$L(\mathbf{x}) = \frac{1 + x_1 - 4x_1^2}{6x_1 - 6x_1^2},$$

and

$$L''(\mathbf{x}) = \frac{-1 + 3x_1 - 3x_1^2}{3(-1 + x_1)^3 x_1^3}$$

Also we find that  $L''(\mathbf{x}) > 0$ ,  $\forall \mathbf{x} \in A_{12}$ , then  $L(\mathbf{x})$  is convex in  $A_{12}$  and the maximum of  $L(\mathbf{x})$  is 28/15 on  $x_1 = 1/6$  and  $x_1 = 5/6$ . From (6) we have  $p_0 = 1$  and by Lemma 2, Conjecture 1 holds for Scheffé's quadratic models with two ingredients if the total trials  $N \ge kp_0 = 3$ .  $\Box$ 

#### 3.2 Three ingredients

Now we discuss the case with ingredients q = 3, the Scheffé's model turns to

$$E[y(\mathbf{x})] = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3, \quad \mathbf{x} \in S^2$$

Then the approximate D-optimal design is given by

$$\xi^* = \left( \begin{array}{ccc} \begin{pmatrix} 1\\0\\0\\1/6 \\ 1/6 \\ 1/6 \end{array} \right) \left( \begin{array}{c}0\\0\\1\\1/6 \\ 1/6 \\ 1/6 \end{array} \right) \left( \begin{array}{c}1\\\frac{1}{2}\\0\\1\\1/6 \\ 1/6 \\ 1/6 \end{array} \right) \left( \begin{array}{c}1\\\frac{1}{2}\\0\\\frac{1}{2}\\1\\2 \\ 1/6 \\ 1/6 \end{array} \right) \left( \begin{array}{c}0\\\frac{1}{2}\\\frac{1}{2}\\\frac{1}{2}\\1\\2 \\ 1/6 \end{array} \right) \right),$$

and the corresponding orthonormal polynomials are  $\{g_{\ell}(\mathbf{x}), \ell \in \mathbb{T}\}$  where  $g_{\ell}(\mathbf{x}), \ell \in \mathbb{T}$ are defined as in Section 2 and  $\mathbb{T} = \{1, 2, 3, 12, 13, 23\}$ . Similarly, we must identify the regions of  $A_{\ell}$  for every  $g_{\ell}^2(\mathbf{x}), \ell \in \mathbb{T}$ . In order to find each  $A_{\ell}, \ell \in \mathbb{T}$ , we first define the following sets  $A_i^*$  and  $A_{ij}^*$ ; for  $i = 1, \ldots, k$ ,

$$A_i^* = \left\{ \mathbf{x} | \mathbf{x} \in S^{q-1}, \ g_i^2(\mathbf{x}) \ge g_j^2(\mathbf{x}), 1 \le j \le q, j \ne i \right\}$$

where  $g_i(\mathbf{x})$  is the corresponding orthonormal polynomial with  $g_i(\mathbf{x_i}^*) = 1$ , and for  $1 \le i < j \le k$ ,

$$\begin{aligned} A_{ij}^* &= \{ \mathbf{x} | \mathbf{x} \in S^{q-1}, \ g_{ij}^2(\mathbf{x}) \ge g_{kl}^2(\mathbf{x}), \ g_{ij}^2(\mathbf{x}) \ge g_i^2(\mathbf{x}), \\ g_{ij}^2(\mathbf{x}) \ge g_j^2(\mathbf{x}), \ 1 \le k < l \le q, \ kl \ne ij \} \end{aligned}$$

where  $g_{ij}(\mathbf{x})$  is the corresponding orthonormal polynomial with  $g_{ij}(\mathbf{x}_{ij}^*) = 1$ .

For example, we have  $A_1^*$  and  $A_{12}^*$  being the sets that

$$\begin{aligned} A_1^* &= \{ \mathbf{x} | \mathbf{x} \in S^2, \ g_1^2(\mathbf{x}) \ge g_{12}^2(\mathbf{x}), \ g_1^2(\mathbf{x}) \ge g_{13}^2(\mathbf{x}) \}, \\ A_{12}^* &= \{ \mathbf{x} | \mathbf{x} \in S^2, \ g_{12}^2(\mathbf{x}) \ge g_1^2(\mathbf{x}), \ g_{12}^2(\mathbf{x}) \ge g_2^2(\mathbf{x}), \\ g_{12}^2(\mathbf{x}) \ge g_{13}^2(\mathbf{x}), \ g_{12}^2(\mathbf{x}) \ge g_{23}^2(\mathbf{x}) \}. \end{aligned}$$

It is obvious that

$$\bigcup_{\ell \in \mathbb{T}} A_{\ell}^* = S^{q-1}.$$

For q = 3, by comparing the functions  $g_i^2(\mathbf{x})$  w.r.p  $g_j^2(\mathbf{x})$  as well as with  $g_{ij}^2(\mathbf{x})$ , we have

$$A_i^* = \{ \mathbf{x} | \mathbf{x} \in S^2, \ x_i \ge \frac{1}{2} + 2x_j, \ j \ne i, \}, \quad i = 1, 2, 3,$$

as well as for  $1 \le i < j \le 3$ ,

$$A_{ij}^* = \{ \mathbf{x} | \mathbf{x} \in S^2, \ x_i \le \frac{1}{2} + 2x_j, \ x_j \le \frac{1}{2} + 2x_i, \\ x_i \ge x_k, \ x_j \ge x_k, \ k \ne i, j, \ k = 1, 2, 3 \}.$$

In the following Lemma 3, it shows that  $A_i = A_i^*$  and  $A_{ij} = A_{ij}^*$ .

**Lemma 3.** For all  $\mathbf{x} \in A_{\ell}^*$ ,  $g_{\ell}^2(\mathbf{x})$  is the maximum among all  $g_i^2(\mathbf{x})$  where  $\ell, i \in \mathbb{T}$ . That is  $A_{\ell} = A_{\ell}^*$ .

**Proof.** Because in  $S^2$ ,  $g_2^2(\mathbf{x})$  and  $g_3^2(\mathbf{x})$  are symmetric with  $g_1^2(\mathbf{x})$  for  $x_1 = x_2$  and  $x_1 = x_3$ ,  $g_{13}^2(\mathbf{x})$  and  $g_{23}^2(\mathbf{x})$  are symmetric with  $g_{12}^2(\mathbf{x})$  for  $x_2 = x_3$  and  $x_1 = x_3$ , we only need to verify that  $g_1(\mathbf{x})$  is the maximum in  $A_1$  and  $g_{12}(\mathbf{x})$  is the maximum in  $A_{12}$ . Firstly, form the definition of  $A_1^*$ , we have for all  $\mathbf{x} \in A_1^*$ ,  $g_1(\mathbf{x}) \ge g_{12}(\mathbf{x})$  and  $g_1(\mathbf{x}) \ge g_{13}(\mathbf{x})$ . Now we verify that  $g_{12}^2(\mathbf{x}) \ge g_{23}^2(\mathbf{x})$ ,  $\forall \mathbf{x} \in A_1^*$  which in turns implies  $g_1(\mathbf{x}) \ge g_{23}(\mathbf{x})$ . Note that  $g_{12}^2(\mathbf{x})$  can be expressed as

$$g_{12}^{2}(\mathbf{x}) = 16x_{1}^{2}x_{2}^{2} = 16(1 - x_{2} - x_{3})^{2}x_{2}^{2}$$
  
=  $16x_{2}^{2}x_{3}^{2} + 16(1 + x_{2}^{2} + x_{3}^{2} - 2(x_{2} + x_{3}) + 2x_{2}x_{3})x_{2}^{2}$ 

Since  $x_2 + x_3 \leq \frac{1}{2}$ , for all  $\mathbf{x} \in A_1^*$ , we have

$$g_{12}^2(\mathbf{x}) \ge 16x_2^2x_3^2 = g_{23}^2(\mathbf{x}).$$

Similarly, it can be shown that

$$g_{12}^{2}(\mathbf{x}) = 16x_{1}^{2}x_{2}^{2}$$

$$\geq 16x_{2}^{2}(\frac{1}{2}(1+4x_{2}))^{2} = 4x_{2}^{2}(1+4x_{2})^{2}$$

$$\geq 4x_{2}^{2}(x_{2}-\frac{1}{2})^{2} = g_{2}^{2}(\mathbf{x})$$

then  $g_1^2(\mathbf{x}) \ge g_{23}^2(\mathbf{x})$  and  $g_1^2(\mathbf{x}) \ge g_2^2(\mathbf{x})$ . Again, as  $g_1^2(\mathbf{x}) \ge g_{13}^2(\mathbf{x})$ ,  $\forall \mathbf{x} \in A_1^*$ , it implies  $g_1^2(\mathbf{x}) \ge g_{23}^2(\mathbf{x})$  and  $g_1^2(\mathbf{x}) \ge g_3^2(\mathbf{x})$ . Therefore  $g_1^2(\mathbf{x})$  is the maximum function on  $A_1^*$  and  $A_1^* \subset A_1$ . Secondly, from definition of  $A_{12}^*$  is given above where

$$A_{12}^* = \{ \mathbf{x} | \mathbf{x} \in S^2, x_1 \le \frac{1}{2} + 2x_2, x_2 \le \frac{1}{2} + 2x_1, x_1 \ge x_3, x_2 \ge x_3 \}.$$

We now check  $g_{12}^2(\mathbf{x}) \ge g_3^2(\mathbf{x})$  on  $A_{12}^*$  by expressing in the follow

$$g_{12}^2(\mathbf{x}) - g_3^2(\mathbf{x}) = (4x_1x_2 + 2x_3(x_3 - 1/2))(4x_1x_2 - 2x_3(x_3 - 1/2)).$$

Because for all  $\mathbf{x} \in A_{12}^*$ ,  $x_3 \leq 1/3$ , then  $(4x_1x_2 - 2x_3(x_3 - 1/2)) \geq 0$ . In fact as  $x_3 = 1 - x_1 - x_2$ , the other part  $4x_1x_2 + 2x_3(x_3 - 1/2)$  can be rewritten as  $h(x_1, x_2)$  where

$$h(x_1, x_2) = 1 + 2x_1^2 - 3x_2 + 2x_2^2 + x_1(8x_2 - 3).$$

In order to find the extrme value of  $h(x_1, x_2)$  in  $A_{12}^*$  we try to find the critical points. The critical points of  $h(x_1, x_2)$  is  $(\frac{1}{4}, \frac{1}{4}, \frac{1}{2})$  and is not in  $A_{12}^*$ . Hence the location of the minimum of  $h(x_1, x_2)$  is on the boundary of  $A_{12}^*$  and the minimum value is  $\frac{9}{32}$  at  $(\frac{1}{8}, \frac{3}{4}, \frac{1}{8})$  or  $(\frac{3}{4}, \frac{1}{8}, \frac{1}{8})$ . Then  $g_{12}^2(\mathbf{x}) - g_3^2(\mathbf{x}) \ge 0$ ,  $\mathbf{x} \in A_{12}^*$  and  $R(\mathbf{x}) = g_{12}^2(\mathbf{x})$  in  $A_{12}^*$ . Then we have  $A_{12}^* \subset A_{12}$ .

From the above discussions we have  $A_{\ell}^* \subset A_{\ell}, \ \ell \in \mathbb{T}$ . It is follows that  $A_{\ell}^* = A_{\ell}, \ \ell \in \mathbb{T}$ since  $\bigcup_{\ell \in \mathbb{T}} A_{\ell}^* = S^{q-1}$ .  $\Box$ 

From Lemma 3 there is a partition on the design region as in Figure 1 and this partition is  $P = \{A_1, A_2, A_3, A_{12}, A_{13}, A_{23}\}$ . In the following we prove that Lemma 1 is ture for  $p_0 = 2$ .

**Lemma 4.** When  $p \ge 2$  the inequality in (4) holds for  $\mathbf{x} \in S^2$ .

**Proof.** Let

$$Q(\mathbf{x}) = \sum_{i=1}^{k} g_i^2(\mathbf{x}) - \frac{R^2(\mathbf{x})}{p_0 + 1},$$

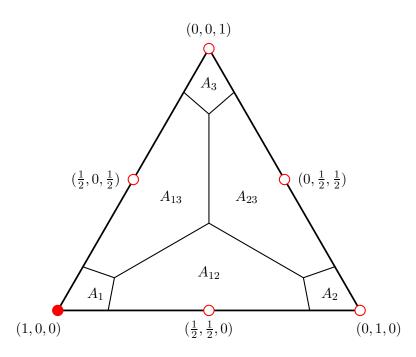


Figure 1: (2,2)-lattice

and we want to prove  $Q(\mathbf{x}) \leq 2/3$ . It is obvious that  $Q(\mathbf{x})$  is symmetric with  $x_1 = x_2$ ,  $x_2 = x_3$ , and  $x_1 = x_3$ . To find the maximums of  $Q(\mathbf{x})$  for every  $\mathbf{x} \in A_i$ , is sufficient to find the maximum of  $Q(\mathbf{x})$  in  $A_1$  and  $A_{12}$ . Then we only need to consider the regions in  $A_1$  and  $A_{12}$ . Note that  $\forall \mathbf{x} \in A_{12}$ ,

$$Q(\mathbf{x}) = \sum_{i=1}^{k} g_i^2(\mathbf{x}) - \frac{g_{12}^2(\mathbf{x})}{p_0 + 1}.$$

Let the parametric representation of  $\mathbf{x}$  in  $A_{12}$  be (t - s, t + s, 1 - 2t) where  $1/3 \le t \le 1/2$ and  $-a_t \le s \le a_t, a_t \in \mathbb{R}^+$ . All parametric vectors for a fixed t are parallel to the vector from (1, 0, 0) to (0, 1, 0). Then  $Q(\mathbf{x})$  can be expressed with a new function  $q_{12}(s, t)$  as

$$q_{12}(s,t) = \frac{1}{3}(3 + 56s^4 - 36t + 258t^2 - 696t^3 + 632t^4 + 2s^2(51 - 228t + 232t^2)).$$

Because  $q_{12}(s,t)$  is a 4<sup>th</sup> degree polynomial with the highest coefficient to be positive for

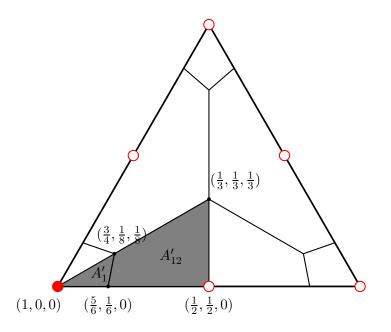


Figure 2: Subregion of  $A_1$  and  $A_{12}$ 

s and is symmetric with s = 0, then for a fixed t and  $a_t$  the maximum of  $q_{12}(s, t)$  will be attained at s = 0,  $s = a_t$  or  $s = -a_t$ . Hence, if we want to find the maximum of  $Q(\mathbf{x})$ on  $A_{12}$ , it is just to find the maximum of  $Q(\mathbf{x})$  on the boundary of  $A'_{12}$ , the half region of  $A_{12}$ , see Figure 2. It is obvious that the boundary of  $A'_{12}$  is composed of four segments and the boundary of  $A'_1$  is composed of three segments. In the following we would like to find the maximum of  $Q(\mathbf{x})$  on the boundary of  $A'_{12}$  and the segments are specified in the following. To this end let p(s,t) or p(t) denote the parametric vector of  $\mathbf{x}$  on each segment.

(i) For segment from (5/6, 1/6, 0) to (1/6, 5/6, 0)

It is apparent that the maximum of  $Q(\mathbf{x})$  on this segment will occur at (5/6, 1/6, 0), (1/6, 5/6, 0) or (1/2, 1/2, 0). Since  $Q(\mathbf{x}) = 2/3$  at (1/2, 1/2, 0) and  $Q(\mathbf{x}) = 4/9$  at

- (5/6, 1/6, 0) and (1/6, 5/6, 0), the maximum is 2/3 in the segment.
- (ii) For segment from (1/3, 1/3, 1/3) to (1/2, 1/2, 0)

Let s = 0,

$$q_{12}(0,t) = 1 - 12t + 86t^2 - 232t^3 + \frac{632t^4}{3}, \quad \frac{1}{3} \le t \le \frac{1}{2},$$

then

$$q_{12}'(0,t) = \frac{4}{3}(-9 + 129t - 522t^2 + 632t^3).$$

By Bolzano Theorem, we are assured the interval where three roots of t for  $q'_{12}(0,t) = 0$ locate, because  $q'_{12}(1/2) = 16/3$  and  $q'_{12}(1/3) = -64/81$ ,  $q'_{12}(1/4) = 2/3$  and  $q'_{12}(1/10) = -334/375$ . Hence  $q'_{12}(0,t)$  is positive in  $1/3 \le t \le 1/2$  and the maximum will be attained at t = 1/3 or 1/2. Moreover  $q'_{12}(0,1/3) = 137/243$  and  $q'_{12}(0,1/2) = 2/3$  then the maximum of  $Q(\mathbf{x})$  in this segment is 2/3.

(iii) For segment from (1/3, 1/3, 1/3), to (3/4, 1/8, 1/8)

Let the parametric vector of  $\mathbf{x}$  be (1 - t, t, t) where  $1/8 \le t \le 1/3$ , and let  $p(t) = Q(\mathbf{x})$ then

$$p(t) = \frac{1}{3}(1 - 36t + 242t^2 - 632t^3 + 584t^4)$$

and

$$p'(t) = \frac{4}{3}(-9 + 121t - 474t^2 + 584t^3).$$

That is, there is only one real root 0.129911 for p'(t) = 0. Hence maximum can be found on t = 1/8, t = 1/3, or t = 0.129911. The maximum of  $Q(\mathbf{x})$  is 127/243 at t = 1/3. (iv) For segment from (3/4, 1/8, 1/8) to (5/6, 1/6, 0)

Let the parametric vector of x be (5/6 - t/12, 1/6 - t/24, t/8) where  $0 \le t \le 1$ , and let  $p(t) = Q(\mathbf{x})$  then

$$p(t) = \frac{1}{124416} (65536 - 45184t + 35376t^2 - 6832t^3 + 433t^4).$$

and

$$p''(t) = \frac{1}{10368}(5896 - 3416t + 433t^2).$$

Because p''(t) is positive for  $0 \le t \le 1$ , p(t) is convex and the maximum can be obtained with t = 0 or t = 1 and the maximum value is 128/243 with t = 0, then the maximum of  $Q(\mathbf{x})$  is 2/3.

From the above (i)-(iv), we see that the maximum of  $Q(\mathbf{x})$  on the boundary of  $A'_{12}$  is less than or equal to 2/3, then the maximum of  $Q(\mathbf{x})$  on  $A_{12}$  is 2/3.

In  $A_1$ , we can obtain the maximum of  $Q(\mathbf{x})$  with the same procedure. It can be found that  $Q(\mathbf{x})$  is convex on each segment of the boundary of  $A_1$  and the maximum is 2/3 at (1,0,0). Then  $Q(\mathbf{x})$  is also less than or equal to 2/3 in  $S^2$  and the proof is complete.

From Lemma 4 and Theorem 1, exact *D*-optimal design in Scheffé's quadratic models for q = 3 and  $N \ge 12$  is stated explicitly in Theorem 2.

**Theorem 2.**  $\xi_n^*$  in (2) is an exact *D*-optimal design in Scheffé's quadratic models with three ingredients for sample size  $N \ge 12$ .

### 4 Four or more ingredients

In Section 3, we have discussed cases with two and three ingredients. For four or more ingredients the same method as in Section 3 can be used, but it is more complicated to calculate the maximum on the subregion with respect to those orthonormal polynomials. In (4), we can see that the right side of the inequality is an increasing function of p for fixed  $R^2(\mathbf{x})$ . If a real solution  $p \in \mathbf{R}$  can be found for the equality in (4) holds for each  $\mathbf{x} \in S^{q-1}$  as expressed in (8), the minimum integer upper bound for these p, called  $p_0$  Conclusion

can be obtained, then Conjecture 1 will hold in  $S^{q-1}$ . Here  $p_0$  is the same as defined in Lemma 1.

$$\sum_{\ell \in \mathbb{T}} g_{\ell}^2(\mathbf{x}) = \frac{p}{p+1} + \frac{R^2(\mathbf{x})}{p+1} = 1 - \frac{1 - R^2(\mathbf{x})}{p+1}, \qquad \mathbf{x} \in S^{q-1}.$$
(8)

We try to compute the  $p_0$  numerically by generating 100000 points uniformly on the design regions  $S^{q-1}$  and solve for p in (7) with each generated  $\mathbf{x}$  in  $S^{q-1}$ , then find the corresponding  $p_0$  through the maximum p resulted from the 100000 points. Table 1 lists the maximum p values for ingredients from 4 to 9.

Table 1: Maximum p for ingredients from 4 to 9

ingredients	3	4	5	6	7	8	9
p	1.16143	1.14157	1.10068	1.10919	1.12676	1.13648	1.10333

It is obvious that in this table p is always less than 7/6, where 7/6 is also the p value for (7) to hold when  $\mathbf{x}$  is on the centroids of depth 3. Hence the integer supremum of pseems to be 2 for every ingredient. For this result we propose a conjecture below.

**Conjecture 2.** For any finite sample size  $N \ge kp_0$ ,  $p_0 = 2$ , k = q(q+1)/2, and q is the ingredient, there is at least one design as defined in (2) for mixture experiments in Scheffé's quadratic models to be exact D-optimal.

### 5 Conclusion

In Section 3 we prove the exact *D*-optimality of candidate designs for mixture experiments with ingredients q = 2 and q = 3 for most of the sample size *N*. For experiments with the number of ingredients range from 4 to 9, we obtain the numerically computed  $p_0$ , or the smallest sample size N for the candidate designs to be exact D-optimal. The proofs for the general cases will be investigated in the future.

## References

- Atkinson, A. C. and Donev, A. N. (1992). Optimum Experimental Designs. Clarendon Press, Oxford, New York.
- [2] Chang, F. C. and Chen, Y. H. (2004). D-Optimal Designs for Multivariate Linear and Quadratic Polynomial Regression. *Journal of the Chinese Statistical Association*, 42, 479-497.
- [3] Fedorov, V. V. (1972). Theory of Optimal Experiments. Translated and edited by W. J. Studden and E. M. Klimko. Academic press, New York.
- [4] Gaffke, N. (1987). On D-optimality of exact linear regression designs with minimum support. Journal of Statistical Planning and Inference, 15, 189-204.
- [5] Gaffke, N. and Krafft, O. (1982). Exact D-Optimum Designs for Quadratic Regression. Journal of the Royal Statistical Society. Series B (Methodological), 44, 394-397.
- [6] Huang M.-N. L. (1987). Exact D-optimal designs for polynomial regression. Bulletin of the Institute of Mathematics, Academia Sinica, 15, 59-71.
- [7] Kiefer, J. (1961). Optimal designs in regression problems, II. Annals of mathematical Statistics, 32, 298-325.
- [8] Pukelsheim F. (1993). Optimal Design of Experiments. Wiley, New York.

- [9] Salaevskii, O, V (1966). The problem of the distribution of observations in polynomial regression. Proceedings of the Steklov Institute of Mathematics, 79, 146-166.
- [10] Scheffé, H. (1958). Experiments with mixtures, Journal of the Royal Statistical Society. Series B (Methodological), 20, 344-360.
- [11] Scheffé, H. (1963). The simplex-centroid design for experiments with mixtures. Journal of the Royal Statistical Society, Series B (Methodological), 25, 235-263.