# OPTIMUM MULTIVARIATE DESIGNS 

R. H. FARRELL, ${ }^{1}$ J. KIEFER, ${ }^{1}$ and A. WALBRAN<br>Cornell University

## 1. Introduction

1.1. Notation and preliminaries. This paper is concerned with the computation of optimum designs in certain multivariate polynomial regression settings.

Let $f=\left(f_{1}, \cdots, f_{k}\right)$ be a vector of $k$ real-valued continuous linearly independent functions on a compact set $X$. We shall work in the realm of the approximate theory discussed in many of the references, wherein a design is a probability measure $\xi$ (which can be taken to be discrete) on $X$. The information matrix $M(\xi)$ of the design $\xi$ for problems where the regression function is $\sum_{1}^{k} \theta_{i} f_{i}(x)$ (with $\theta=\left(\theta_{1}, \cdots, \theta_{k}\right)$ unknown and with uncorrelated homoscedastic observations and quadratic loss considerations of best linear unbiased estimators) has elements $m_{i j}(\xi)=\int f_{i} f_{j} d \xi$. Thus, $\operatorname{det} M^{-1}(\xi)$ is proportional to the generalized variance of the best linear estimators of all $\theta_{i}$. We denote by $\Gamma$ the space of all $M(\xi)$. We shall have occasion to consider the set of all distinct functions of the form $f_{i} f_{j}, i \geq j$, and shall write them as $\left\{\phi_{t}, 1 \leq t \leq p\right\}$. We then write $\mu_{t}(\xi)=$ $\int \phi_{t} d \xi$. Whether or not some $\phi_{t}$ is a nonzero constant (as it is in our polynomial examples), we define $\phi_{0}(x) \equiv 1$ and $\mu_{0}=1$.

The main results of this paper characterize, for certain $X$ and $f$, some designs $\xi^{*}$ which are $D$-optimum; that is, for which

$$
\begin{equation*}
\operatorname{det} M\left(\xi^{*}\right)=\max _{\xi} \operatorname{det} M(\xi) \tag{1.1}
\end{equation*}
$$

Define, for $M(\xi)$ nonsingular,

$$
\begin{align*}
d(x, \xi) & =f(x) M^{-1}(\xi) f(x)^{\prime} \\
\bar{d}(\xi) & =\max _{x \in X} d(x, \xi) . \tag{1.2}
\end{align*}
$$

The quantity $d(x, \xi)$ is proportional to the variance of the best linear estimator of the regression $f(x) \theta^{\prime}$ at $x$. A result of Kiefer and Wolfowitz [8] is that $\xi^{*}$ satisfies (1.1) if and only if it satisfies the $G$-(global-) optimality criterion

$$
\begin{equation*}
\bar{d}\left(\xi^{*}\right)=\min _{\xi} \bar{d}(\xi), \tag{1.3}
\end{equation*}
$$

and that (1.1) and (1.3) are satisfied if and only if

$$
\begin{equation*}
\bar{d}\left(\xi^{*}\right)=k . \tag{1.4}
\end{equation*}
$$

If the support of an optimum design is exactly $k$ points, then $\xi$ is uniform on those points. Our main way of finding $D$ - and $G$-optimum (hereafter simply

[^0]
[^0]:    ${ }^{1}$ Research supported by ONR Contract Nonr-401(03).

