# On Infinite-Dimensional Convex Programs 

E. J. Bel.trami<br>Department of Applied Analysis, State of New York, Stony Brook, Long Island, New York

Received November 27, 1967


#### Abstract

One way to approach infinite-dimensional nonlinear programs is to append increasingly large cost or penalty terms to the objective function in such a way that the minima of the augmented but unconstrained functions converge to the constrained minimum in the limit. In this paper we establish the convergence of the penalty argument on reflexive B-spaces, and then apply it to obtain the Kuhn-Tucker necessary conditions for convex programs in Hilbert space. The proof is constructive and suggests a computationally feasible algorithm for solving such programs.


In this note we look at an iterative method for solving nonlinear programming problems based on the penalty function concept of Courant [1]. The idea is to append increasingly large cost or penalty terms to the objective function in such a way that the resulting minima of the augmented, but otherwise unconstrained, functions converge to the constrained solution in the limit. In this way a constrained minimization problem is reduced to solving a sequence of unconstrained ones. A similar technique was made the basis of a computational algorithm for convex programs on $E^{n}$ by Fiacco-McCormick but under different hypothesis [2]. The method has the virtuc that necessary conditions in mathematical programming can be obtained in a constructive (i.e., computationally feasible) manner by passing to the limit with the necessary conditions for each unconstrained problem as the penalty term increases. Several specific examples on $E^{n}$ have been computed by this approach and the algorithm appears to be quite effective [3].

In this first section we establish existence and necessary conditions for convex programs on a Hilbert space by appealing to the behavior of convex functionals on closed convex sets in reflexive $B$-spaces. However, there is no pretense that our argument leads to the best statement of the necessary conditions (the paper by HalkinNeustadt [4] gives a more general treatment, for example). Instead we simply wish to indicate a concrete approach to the problem of necessacy conditions within the larger framework of actually constructing optimal programs. In the last section, in fact, we show how the penalty argument, together with the classical Ritz method, allows us to reduce an infinite-dimensional program to one of solving a sequence of unconstrained finite-dimensional programs. Thus the penalty idea is at once an iterative method for
proving existence, a constructuve device for establishing necessary conditions, and a specific technique for computing solutions.

## A Multiplier Rule

The mathematical program to be discussed is that of minimizing a convex functional $f$ subject to the $m$ constraints $g_{j}=0, j \leqslant r$, and $g_{j} \leqslant 0, r<j \leqslant m$, where $0 \leqslant r \leqslant m$ and $f, g_{j}$ are mappings of a Hilbert space $\mathscr{H}$ to $E^{1}$.

As a matter of convenience all constraints will be written as equality constraints. To do this in the case $0 \leqslant r<j \leqslant m$ we define $H_{j} \in \mathscr{L}\left(\mathscr{H}, E^{1}\right)$ by $H_{j}=1$ whenever $g_{j}(x)>0$ and by $H_{j}=0$ otherwise, and then note that $H_{j} g_{j}=0$ if and only if $g_{j} \leqslant 0$; when $j \leqslant r$ let $H_{j} \equiv 1$. Thus we have $m$ constraints $H_{j} g_{j}=0$ or, equivalently, $\left(H_{j} g_{j}\right)^{2}=0$. Now let $K$ an $m \times m$ diagonal matrix with positive entries $k_{j}$. Then $K_{n} \rightarrow \infty$ means that all entries $k_{n, j}$ in the sequence $K_{n}$ increase without bound as $n \rightarrow \infty$. The quadratic form $\sum_{j \leqslant m} k_{n, j}\left(H_{j} g_{j}\right)^{2}$ will be denoted by ( $\mathrm{Hg}, K_{n} \mathrm{Hg}$ ) with $H g$ a mapping of $\mathscr{H}$ to $E^{m}$. In Theorem 1 below we assume that the $g_{j}{ }^{2}$ are lower semicontinuous (l.s.c.) and convex. This implies the l.s.c. and convexity of $\left(H_{j} g_{j}\right)^{2}$ and hence of ( $\mathrm{Hg}, \mathrm{K}_{n} \mathrm{Hg}$ ) as well.

We begin by quoting without proof two lemmas that will be needed in the sequel. For a proof see, for example, [5], pp. 125-6. Then two additional lemmas are proven by combining known results in functional analysis. They are followed by the first theorem, strengthening a result of Butler-Martin [6] which, in turn, is based on the argument given in the Courant notes [7]. This theorem establishes the validity of the penalty argument. In the proofs we deal with a reflexive Banach space $B$ and by weak convengence to zero of $\left\{x_{n}\right\}$ in $B$ is meant that $f\left(x_{n}\right) \rightarrow 0$ for all $f$ in the dual $B^{\prime}$.

## Lemma 1. Every bounded sequence in $B$ has a weakly convengent subsequence.

Lemma 2. A closed convex set in $B$ is zeakly closed.
Lemma 3. If $f$ is a convex and l.s.c. functional on $B$ then $f$ is weakly l.s.c.
Proof. Let $S(\alpha)=\{x \mid f(x) \leqslant \alpha\}$. It is not hard to see that $f$ is l.s.c. if and only if $S$ is closed for all $\alpha$ (see, for example, [15], p. 40). Since $f$ is convex, l.s.c. then $S$ is convex, closed for all $\alpha$ and so, by Lemma 2 , weakly closed. Hence $f$ is weakly l.s.c.

Lemma 4. Let $f$ be convex and l.s.c. on a closed convex subset $\Omega$ of $B$. If $f \rightarrow+\infty$ as $\|x\| \rightarrow \infty$, then it attains a minimum on $\Omega$.

Proof. Let $d=\inf _{x \in \Omega} f$ and let $\left\{x_{n}\right\}$ be a minimizing sequence in $\Omega$. Since $f \rightarrow+\infty$ as $\|x\| \rightarrow \infty$ the set $\left\{x_{n}\right\}$ is bounded. Hence, by Lemma 1, there exists a subsequence
$\left\{x_{n_{k}}\right\}$ which tends weakly to some $x_{0} \in B$. By Lemma 2, $x_{0} \in \Omega$ and finally, by Lemma 3, $f$ is weakly l.s.c., so that $d \approx \underline{\lim } f\left(x_{n_{k}}\right) \geqslant f\left(x_{0}\right) \geqslant d$, which shows that $f\left(x_{0}\right)=d$.

Theorem 1. Let $f, g_{j}{ }^{2}, j=1, \ldots, m$, be convex and l.s.c. on a closed convex set $\Omega_{0}$ in $B$ and suppose $f \rightarrow-\infty$ as $\boldsymbol{x} ; \rightarrow \infty$. Also let us suppose that $\Omega_{1}=\left\{x \mid H_{j} g_{j}=0\right\}$ has a nonempty intersection with $\Omega_{0}$.

Then for every sequence of matrices $K_{n} \rightarrow \infty$ as $n \rightarrow \infty$ there exists a corresponding sequence $x_{n} \in \Omega_{0}$ with the property that

$$
\min _{x \in \Omega_{0}}\left[f \vdash \frac{1}{2}\left(H g, K_{n} H g\right)\right]
$$

is attained by $x_{n}$ and such that, for some subsequence $x_{n_{k}}, x_{n_{k}}$ tends weakly to $x_{0} \in \Omega_{0} \cap \Omega_{1}$, where $f\left(x_{0}\right)=-\inf _{x \in \Omega_{0}} f$ (i.e., $x_{0}$ is a minimum for $f$ subject to the constraints).

Proof. First note that $f_{n} \rightarrow+\infty$ as ${ }^{1} \boldsymbol{x} \| \rightarrow \infty$ so that from Lemma 4 we have that $f_{n}$ takes on a minimum $d_{n}$ at some $x_{n} \in \Omega_{0}$. Since $f_{n} \rightarrow+\infty$ it also follows that $\left\{x_{n}\right\}$ is a bounded set in $\Omega_{0}$ and so for some subsequence, also denoted by $x_{n}$, we have that $x_{n} \rightarrow x_{0} \in \Omega_{0}$ weakly as $n \rightarrow \infty$ (Lemma 1). It remains to show that $f\left(x_{0}\right)=d$. Now $f=f_{n} \geqslant d_{n}$ for all $x \Omega_{0} \cap \Omega_{1}$ and so $d_{n} \leqslant d$. Thus $d \geqslant \lim f\left(x_{n}\right) \geqslant f\left(x_{0}\right)$ and, in fact, $f\left(x_{n}\right) \geqslant f\left(x_{0}\right)-1$ for all $n$ greater than some $N$ since, by Lemma $3, f$ is weakly l.s.c. Hence
$f\left(x_{0}\right)-1 \therefore \frac{1}{2}\left(H g\left(x_{n}\right), K_{n} H g\left(x_{n}\right)\right) \leqslant d \quad$ or $\quad \frac{1}{2}\left(H g\left(x_{n}\right), K_{n} H g\left(x_{n}\right)\right) \leqslant$ constant
for all $n \geqslant N$. Since $K_{n} \rightarrow \infty$ as $n \rightarrow \infty$ it follows that $\left(H_{j} g_{j}\left(x_{n}\right)\right)^{2} \rightarrow 0$ for each $j$. But then

$$
0=\underline{\lim }\left(H_{j} g_{j}\left(x_{n}\right)\right)^{2} \geqslant\left(H_{j} g_{j}\left(x_{0}\right)\right)^{2} \geqslant 0
$$

and so $x_{0} \in \Omega_{0} \cap \Omega_{1} \subset \Omega_{0}$. Together with the fact that $f\left(x_{0}\right) \leqslant d$ it now follows that $f\left(x_{0}\right)==d$, which proves the theorem.

The content of the above Theorem is that the minima of the unconstrained functions $f_{n}$ tend weakly to the minimum of the constrained $f$ as $n \rightarrow \infty$ since ( $\mathrm{Hg}, \mathrm{K}_{n} \mathrm{Hg}$ ) necessarily tends to zero as the cost of violating the constraints increases without bound. For this reason $K$ is called a matrix of penalty constants. Note that the theorem also establishes the existence of a minimum for the constrained function since, as we saw, $f\left(x_{0}\right)=\inf f$ on $\Omega_{0} \cap \Omega_{1}$. In the proof we assumed $\Omega_{0}$ is closed, convex. Actually, $\Omega_{0} \cap \Omega_{1}$ is also closed, convex as we now show; this allows us to infer the existence of a minimum of $f$ on $\Omega_{0} \cap \Omega_{1}$ directly from Lemma 4. Let

$$
\Omega_{j}=\left\{x \mid\left(H_{j} g_{j}\right)^{2}=0\right\}=\left\{x \mid\left(H_{j} g_{j}\right)^{2} \leqslant 0\right\} ;
$$

for $r<j \leqslant m \Omega_{j}=\left\{x!g_{j} \leqslant 0\right\}$. Since $\left(H_{j} g_{j}\right)^{2}$ is convex it follows that the sets $\Omega_{j}$ are also convex for all $j=1, \ldots, m$. But then so is $\Omega_{1}=\cap \Omega_{j}$. Also if $z_{k} \in \Omega_{j}$ and if $z_{k} \rightarrow z$ then

$$
0=\underline{\lim }_{\mathrm{inf}}{\left.I H_{j}{ }^{2} g_{j}^{2}\left(z_{k}\right) \geqslant{H_{j}{ }^{2} g_{j}{ }^{2}(z) \geqslant 0}^{2}\right)=0}
$$

since $\left(H_{j} g_{j}\right)^{2}$ is l.s.c. and so $z \in \Omega_{j}$. Hence $\Omega_{1}$ is closed which shows that $\Omega_{0} \cap \Omega_{1}$ is closed, convex. Finally, note that if $\Omega_{0}$ is bounded one does not need the hypothesis that $f \rightarrow+\infty$ as $\| x \rightarrow \infty$.

The next theorem establishes a necessary condition for optimality in terms of a multiplier rule. To simplify notation and reduce wordiness in the proof we restrict ourselves to inequality constraints below (i.e., with $r=0$ ), but essentially the same reasoning yields a theorem even when $r>0$ except that the resulting multipliers will be unrestricted in sign for $j \leqslant r$. Also $B$ is now specialized to a Hilbert space $\mathscr{H}$.

We recall that a continuous functional $f$ is differentiable on an open set $\Omega^{\prime}$ of $\mathscr{H}$ if for every $x \in \Omega^{\prime}$ there exists a continuous linear mapping $f^{\prime}(x) \in \mathscr{H} *$, the conjugate space of $\mathscr{H}$, called the Frechet derivative of $f$ such that

$$
\underline{f(x \therefore h)-\frac{f(x)}{h}-\left(f^{\prime}(x), h\right)} \rightarrow 0 \quad \text { as } \quad . \mid h \rightarrow 0, \quad h \in \mathscr{H}
$$

(sce Dieudonne [8], p. 143). Thus $f^{\prime}(x)$ or simply $f^{\prime}$ is a mapping of $\Omega^{\prime}$ into $\mathscr{H}{ }^{*}$ and if $f^{\prime}$ is weakly continuous on $\Omega^{\prime}$ we say that $f$ has a weakly continuous derivative on $\Omega^{\prime}$. It follows immediately that the existence of such a derivative for $g_{j}$ implies that $g_{j}{ }^{2}$ is l.s.c.

Theorem 2. Let $x_{0}$ be given as a local minimum of $f$ on $\Omega^{\prime} \cap \Omega_{1} \neq \emptyset$ where $\Omega^{\prime}$ is some open subset of $\mathscr{H}$ and suppose $f, g_{i}$ have weakly continuous derivatives on $\Omega^{\prime}$. Assume also that $f$ is strictly convex and the $g_{j}{ }^{2}$ convex on $\Omega^{\prime}$. Moreover, suppose that $\left(g_{j}^{\prime}\left(x_{0}\right), h\right)<0$ for some $h \in \mathscr{H}, j \in J=\left\{j \mid g_{j}\left(x_{0}\right)=0\right\}$. Then there exists $\lambda_{j} \geqslant 0$ such that

$$
\begin{equation*}
f^{\prime}=-\sum_{j=1}^{m} \lambda_{j} g_{j}^{\prime} \tag{1}
\end{equation*}
$$

at $x_{0}$ and such that $\lambda_{j}=0$ whenever $j \notin J$.
Proof. Let $\Omega_{0} \subset \Omega^{\prime}$ be a closed ball about $x_{0}$. Then $\Omega_{0}$ is closed, convex and bounded and we identify $\Omega_{0}, \Omega_{1}$ with the corresponding sets in Theorem 1. Moreover $x_{0}$ is a unique global minimum on $\Omega_{0} \cap \Omega_{1}$ since $f$ is strictly convex.

Let $f_{n}=f+\frac{1}{2}\left(H g, K_{n} H g\right)$ and note that if $f_{n}$ attains its minimum at $x_{n} \in \Omega_{0}$ then, by Theorem 1 , there exists a subsequence, also denoted by $\left\{x_{n}\right\}$, such that $x_{n}$ tends weakly to some $x$ in $\Omega_{0} \cap \Omega_{1}$ for which $f(x)=d$. Since the minimum of $f$ is
unique, $x=x_{0}$. For $n$ large enough, $x_{n}$ is in the interior of $\Omega_{0}$ and since $f_{n}$ is unconstrained we have

$$
\begin{equation*}
f_{n}^{\prime}=f^{\prime} \quad-\sum_{j \leqslant m} k_{n, j} H_{j} g_{j} g_{j}^{\prime}-0 \tag{2}
\end{equation*}
$$

at $x_{n}$ (see [8], p . 145). Also, $x_{n}$ does not belong to the interior of $\Omega_{J}= \begin{cases}x & \left.g_{j} \leqslant 0, j \in J\right\}\end{cases}$ for all sufficiently large $n$. To see this, note that $x_{0}$ is on the boundary of $\Omega_{J}$ and since $f_{n}=f$ on $\Omega_{J}$ this implies $x_{n}-x_{0}$ whenever $x_{n} \in \Omega_{J}$. By the same reasoning, $x_{n}$ belongs to the interior of $\Omega_{1}-\Omega_{J}=\left\{x \mid g_{j} \leqslant 0, j \notin J\right\}$. Thus, for some $N$, we have $0 \leqslant k_{n, j} g_{j}\left(x_{n}\right)$ for all $n \geqslant N$ and $j \in J$ and $k_{n, j} H_{j} g_{j}\left(x_{n}\right) \cdot 0$ for $n \geqslant N$ and $j \notin J$. Since $\left(g_{j}^{\prime}\left(x_{0}\right), h\right)<0$ for $j \in J$ and $h$ some fixed element of $\mathscr{H}$, then $\left(g_{j}^{\prime}\left(x_{n}\right), h\right)<-\delta$ when $n$ is sufficiently large and $\delta$ is sufficiently small since $g_{j}^{\prime}$ is weakly continuous and $x_{n} \rightarrow x_{0}$ weakly. Moreover, using Lemma 1 one can show that $\left(f^{\prime}(x), h\right)$ is bounded on $\Omega_{0}$ for each $h$ since $f^{\prime}$ is also weakly continuous. Hence from Eq. (2) we obtain

$$
M \geqslant\left(f^{\prime}\left(x_{n}\right), h\right)--\sum_{j \in J} k_{n, j} g_{j}\left(x_{n}\right)\left(g_{j}^{\prime}\left(x_{n}\right), h\right) \leqslant \delta \sum k_{n, j} g_{j}\left(x_{n}\right) \geqslant \delta k_{n, j} g_{j}\left(x_{n}\right)
$$

for all sufficiently large $n$. But then $k_{n, j} g_{j}\left(x_{n}\right) \leqslant$ constant, $n \geqslant N$. Thus one can choose a suitable subsequence $\left\{x_{n_{\nu}}\right\}$ so that $k_{n_{v} . j} g_{j}\left(x_{n_{v}}\right) \cdots \lambda_{j} \geqslant 0$ as $\nu \rightarrow \infty$. Since $f^{\prime}$, $g_{j}^{\prime}$ are weakly continuous we obtain

$$
f^{\prime}=-\sum_{j \leqslant m} \lambda_{j} g_{j}=-\sum_{j \in J} \lambda_{j} g_{j}^{\prime}
$$

at $x_{0}$ by passing to the limit in (2) as $x_{n_{\nu}} \rightarrow s_{0}$. This establishes (1).
Theorem 2 establishes the validity of a multiplier rule for convex programs on a Hilbert space. The conditions can and have been weakened by others. However, as was already stated, our purpose here is not generality but simply to indicate how an algorithm for computing optimum programs can also be used in a constructive way to obtain necessary conditions for a minimum. Such an approach has an obvious conceptual advantage. The essential point of the proof is in showing that at least one representation of the form (1) holds with multipliers $\lambda_{j} \geqslant 0$.

In the case where the Hilbert space is $E^{n}$ the theorem specializes to the usual Kuhn-Tucker necessary conditions [9] except that $f^{\prime}, g_{j}^{\prime}$ become the gradients $\nabla f, \nabla g_{j}$.

Remark. Suppose that $l$, the number of elements in $J$, satisfies $l \leqslant n$ for $\mathscr{H}=E^{n}$ and that rank $\nabla G==l$ at $x_{0}$. Here $\nabla G$ is the $l \times n$ Jacobian matrix with columns $\nabla g_{j}, j \in J ; \nabla G_{f}$ will denote the $(l+1) \times n$ matrix with $l+1$ columns $\nabla f, \nabla g_{j}$. Under these conditions and if $r=l \cdots m$ (the classical constrained Lagrange problem) then $\nabla f=-\sum k_{n, j} g_{j}\left(x_{n}\right) \nabla g_{j}$ implies rank $\nabla G_{f} \leqslant m$ at $x_{n}$. Thus $\operatorname{det} G_{f}==0$ and it remains zero as $n \rightarrow \infty$ since $f, g_{i} \in C^{1}$. But then rank $G_{f}=\operatorname{rank} G=m$ at $x_{0}$ and
so there exists a unique set of multipliers $\lambda_{j}$ so that $\nabla f=-\sum_{j \leqslant m} \lambda_{j} \nabla g_{j}$. Our proof of Theorem 2 follows a similar argument given in the notes [7] for the case $n=2$ and $r=m=1$, in which case the existence of a multiplier is equivalent to asserting that the $2 \times 2$ Jacobian $G_{f}$ has rank $<2$.

Note that for $\mathscr{H}=E^{n}$ the closed ball $\Omega_{0}$ used in the proof of Theorem 2 is compact and so it is not necessary to require that $f, g_{j}$ be convex in this case, only that they be 1.s.c. But then even if $\Omega_{0}$ is chosen so that $x_{0}$ is a global minimum on $\Omega_{0} \cap \Omega_{1}$ it need not be unique. To overcome this difficulty we replace $f$ by the objective function $u=f+\left\|x-x_{0}\right\|^{2}$ which does have a unique minimum at $x_{0}$. The multiplier rule holds for $u$ but since $\nabla u=\nabla f$ at $x_{0}$ it holds for $f$ also.

Finally one observes from Theorem 2 that the multipliers $\lambda_{j}$ are obtained as the limits of $k_{n, j} g_{j}$ as the $x_{n}$ tend weakly to $x_{0}$. This is actually seen in specific examples, as indicated un [3]. Indeed, that the theoretical arguments are vindicated in practice has already been established by computing on a number of examples on $E^{n}$.

## A Feasible Algorithm

We now indicate on how to proceed to compute an optimal conver program on $L_{2}$. Actually the same procedure will be applicable to programs on other spaces in a formal way. First one replaces the constrained minimization problem by an unconstrained one determined by $f_{n}=f+\frac{1}{2}\left(H g, K_{n} H g\right)$ as prescribed by Theorem 1. Then $f_{n} \in \mathscr{H} \rightarrow E^{1}$ is replaced by a problem in the setting $f_{n}: E^{n} \rightarrow E^{1}$. This is done as follows, using an idea of $W$. Ritz [10]. Let $W$ denote the collection of finite linear combinations of constant functions with compact support (step functions). Then $W$ is dense in $L_{2}$ and so for every $\epsilon>0$ there exists $w \in W$ such that $f_{n}(w)-f_{n}(x) \leqslant \epsilon$ for any $x \in L_{2}$ ( $f_{n}$ is assumed continuous). Thus, if $\left\{x_{i}\right\}$ is a minimizing sequence for $f_{n}$ (recall that $f_{n}$ is bounded below) then $f_{n}\left(x_{i}\right)-d_{n} \leqslant \epsilon$ for $i$ is large enough. Now let $d_{n, k}=\min f_{n}(w)=f_{n}\left(w_{k}\right)$ over all $w \in W$ consisting of exactly $k$ steps (the minimum clearly exists since $f_{n}$ is now restricted to $E^{k}$ ) and note that $d_{n, k}$ is monotone-decreasing to some $d_{n}$ as $k \rightarrow \infty$. Thus for some $k$ there exists a $w$ in $E^{k}$ for which

$$
d_{n, k}=f_{n}\left(w_{k}\right) \leqslant f_{n}(w) \leqslant f_{n}\left(x_{i}\right)+\epsilon \leqslant d_{n}+2 \epsilon
$$

and so $\left\{w_{k}\right\}$ is a minimizing sequence. At this point all that is needed is a procedure for finding $\min f_{n}: E^{k} \rightarrow E^{1}$ for such $k$. What follows is a brief outline of one such procedure. Let $H$ be any positive definite $k$ by $k$ matrix; then $H$ defines a metric on $E^{k}$ via the norm $\|x\|_{H}$. For any starting vector $x \in E^{k}$ we move down the negative gradient of $f_{n}$ in this metric, i.e., in the direction - $\alpha H \nabla f_{n}$ (if $\nabla f_{n}$ is not explicitly known then a suitable procedure approximation to it will do). We stop when the onedimensional minimum of $f_{n}$ versus $\alpha$ is attained. At the new $x$ we evaluate $\nabla f_{n}$ and then update $H$ according to the formula given by Fletcher-Powell in [11], which
modifies an algorithm of Davidon [12]. It is proven in [II] that the updated $H$ remains positive-definite and therefore the procedure is stable (i.e., strictly downhill).

In summary, then, the method is this. Replace the problem of minimizing $f$ on $\Omega_{0} \cap \Omega_{1}$ by the unconstrained problem of minimizing $f_{n}$ on $\Omega_{0}$. Then parametrize $\Omega_{0} \subset L_{2}$ by some approximating set $\Omega_{k} \subset E^{k}$ and minimize $f_{n}$ on $\Omega_{k}$. Repeat the last step by updating $k$ until no further improvement is obtained for that $n$. Now update $n$ itself and repeat until the desired accuracy is achieved. A stopping rule in each case is, for example, to terminate when successive iterates agree by a prescribed amount. Further details on the method for nonlinear programs on $E^{n}$ is given in [3]. Initial computer trials in this setting indicate that the proposed technique is quite effective and a program for computing on problems in infinite dimensional space is now in preparation.

We note here that the penalty idea has already been used successfully in conjunction with the maximum principle of Pontriagin in several nonlinear control problems with inequality constraints by McGill [13] and Beltrami-McGill [14]. Such control problems can, of course, be considered as infinite dimensional programs. The method used in [13] and [14] was indirect, however, in contrast to the one proposed above, and did not utilize a parametrization procedure.

It is worth mentioning, finally, that the essential ingredients for the computational approach outlined above were already available in a classic paper of Courant in 1943 [ 1 ], in which he discussed the combined use of the Ritz method, the penalty argument, as well as gradient techniques in function space to solve variational problems.

## References

1. R. Courant. Bull. Am. Math. Soc. 49, 1-23 (1943).
2. A. V. Fiacco and G. P. McCormick. SIAM J. 15, 505-515 (1967).
3. E. J. Beltranif. A new iterative method for non-linear programs (to be published).
4. H. Halkin and L. W. Neustadt. Proc. Natl. Acad. Sci. U.S. 56, 1066-1071 (1966).
5. K. Yosida. "Functional Analysis." Springer-Verlag, New York, 1965.
6. T. Büler and A. V. Martin. J. Math. Phys. (Cambridge) 41, 291-299 (1962).
7. R. Courant. Calculus of Variations and Supplementary Notes and Exercices, New York University Lecture Notes, (1956-7).
8. J. Dieudonne. "Foundations of Modern Analysis." Academic Press, New York, 1960.
9. H. W. Klhn and A. W. Tlcker. Nonlinear programming, in Proceedings of the Second Berkeley Symposium in Mathematical Statistics," pp. 481-492. University of California Press, 1961.
10. W. Ritz. Cber eine neue methode zur losung gewisser variations problem der mathematischen physik. J. Reine Angew. Math. 135 (1908).
11. R. Fletcher and M. J. D. Powell. Computer J. 6, 163-168 (1963).
12. W. C. Davidon. Variable Metric Method for Minimization. Argonne Natl. Labs Report ANL-5990 Rev., November, 1959.
13. R. McGill. SIAM J. Control 3, 291-298 (1965).
14. E. J. Beltramil and R. McGill. Operations Res. 14, 267-278 (1966).
15. A. A. Goldstein. "Constructive Real Analysis." Harper \& Row, New York, 1967.
