

CLEARINGHOUSE FOR FEDERAL SCIENTIFIC AND TECHNICAL INFORMATION, CFSTI  
DOCUMENT MANAGEMENT BRANCH 410.11

LIMITATIONS IN REPRODUCTION QUALITY

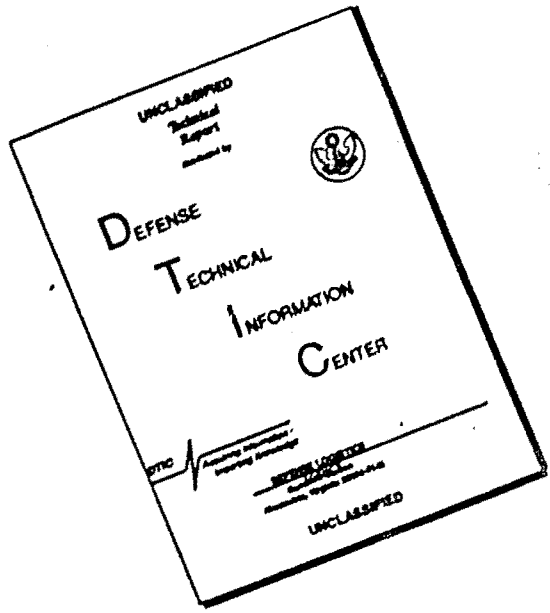
Accession # 604646

- 1. We regret that legibility of this document is in part unsatisfactory. Reproduction has been made from best available copy.
- 2. A portion of the original document contains fine detail which may make reading of photocopy difficult.
- 3. The original document contains color, but distribution copies are available in black-and-white reproduction only.
- 4. The initial distribution copies contain color which will be shown in black-and-white when it is necessary to reprint.
- 5. Limited supply on hand; when exhausted, document will be available in Microfiche only.
- 6. Limited supply on hand; when exhausted document will not be available.
- 7. Document is available in Microfiche only.
- 8. Document available on loan from CFSTI (TT documents only).
- 9.

Processor:

Pm

# DISCLAIMER NOTICE



THIS DOCUMENT IS BEST QUALITY AVAILABLE. THE COPY FURNISHED TO DTIC CONTAINED A SIGNIFICANT NUMBER OF PAGES WHICH DO NOT REPRODUCE LEGIBLY.

604646

AD-604646

*Jan* (1)

**THE FIXED CHARGE PROBLEM**

by  
**Warren M. Hirsch**  
**George B. Dantzig**

R-648

1 December 1954

Approved for OTS release

*22p*

COPY	<i>22</i>	OF	<i>22</i>
HARD COPY	\$	<i>1.00</i>	<i>f</i>
MICROFICHE	\$	<i>0.50</i>	

**DDC**  
**REGISTERED**  
**AUG 27 1964**  
**DDC-100 R**

The **RAND** Corporation  
 1700 MAIN ST. • SANTA MONICA • CALIFORNIA

### SUMMARY

A fundamental unsolved problem in the programming area is one in which various activities have fixed charges (e.g., set-up time charges) if operating at a positive level. Properties of a general solution to this type problem are discussed in this paper. Under special circumstances it is shown that a fixed charge problem can be reduced to an ordinary linear programming problem.

*i*

THE FIXED CHARGE PROBLEM

by

Warren M. Hirsch  
George B. DantzigSTATEMENT OF PROBLEM

Many problems of economics and logistics involve the planning of a large number of interdependent activities in as economical a way as is possible. Mathematically, such problems often can be reduced to the following form: Let  $Q, P_1, \dots, P_n$  be vectors in  $m$ -dimensional Euclidean space, and let  $X$  denote the set of all vectors  $x = (x_1, x_2, \dots, x_n)$  in  $n$ -dimensional Euclidean space which satisfy the relations

$$(1) \quad \sum_{j=1}^n x_j P_j = Q \quad m < n$$

$$(2) \quad x_j \geq 0 \quad j=1, 2, \dots, n.$$

Suppose  $\phi = \phi(x)$  is a real-valued function. Find a vector  $\hat{x} \in X$  such that

$$\phi(\hat{x}) \leq \phi(x)$$

for all  $x \in X$ . In problems of linear programming,  $\phi$  is of the form

$$(3) \quad \phi(x) = \sum_{i=1}^n \phi_i(x_i) \quad ,$$

where  $\phi_i$  is a linear function, and techniques for its solution are available. [Ref. 1, 2, 3, and 4] (It may be assumed without loss of generality that each of the functions  $\phi_i$  vanish at the origin, for it is clear that the problem of minimizing  $\sum_{i=1}^n a_i x_i$  is equivalent to that of minimizing  $\sum_{i=1}^n a_i x_i + \dots$ .)

There are, however, numerous applications in which the functions  $\phi_i$  appearing in (3) are linear only for positive values of the argument and have a jump discontinuity of magnitude  $\beta_i$  at the origin. In this case, putting

$$\delta(u) = \begin{cases} 1 & , \quad u > 0 \\ 0 & , \quad u = 0 \end{cases} \quad ,$$

we can write  $\phi$  in the form

$$(4) \quad \phi = \sum_{i=1}^n a_i x_i + \beta_i \delta(x_i) \quad ,$$

where  $a_1, \dots, a_n, \beta_1, \dots, \beta_n$  are constants. The fact that  $\phi$  is piecewise linear (and a fortiori non-linear) makes it difficult to apply directly the methods of linear programming. We shall refer to the problem of minimizing (4) under the constraints (1) and (2)

as the fixed charge problem, and to the constant  $\beta_1$  as the fixed charge associated with the  $1^{\text{th}}$  activity.

A practical situation in which this problem may arise is the following: Consider a factory in which  $n$  distinct operations are performed by each of  $m$  machines. Let  $h_{1j}$  and  $c_{1j}$ ,  $i=1,2,\dots,m$ ,  $j=1,2,\dots,n$  denote, respectively, the time consumed and cost incurred by the  $j^{\text{th}}$  machine in performing the  $i^{\text{th}}$  operation on a unit amount of goods. Suppose that there is incurred a fixed cost, say  $\beta_{1j}$ , in setting up the  $j^{\text{th}}$  machine to perform the  $i^{\text{th}}$  operation. (We ignore the time involved in this activity.) Let  $x_{1j}$  denote the quantity of goods on which the  $i^{\text{th}}$  operation is performed by the  $j^{\text{th}}$  machine, and  $b_1$  the total quantity of goods on which it is required to perform the  $i^{\text{th}}$  operation. Evidently the quantities  $x_{1j}$  must satisfy the conditions

$$(5) \quad \sum_{j=1}^n x_{1j} = b_1, \quad i=1,2,\dots,m$$

and

$$(6) \quad x_{1j} \geq 0 \quad \begin{array}{l} i=1,2,\dots,m \\ j=1,2,\dots,n \end{array}$$

Moreover, if  $c_j$  denotes the total machine hours available for the  $j^{\text{th}}$  machine, we have the additional constraints

$$(7) \quad \sum_{i=1}^m r_{ij} x_{ij} = c_j, \quad j=1, 2, \dots, n.$$

The total cost of operation is given by the function

$$(8) \quad \sum_{i=1}^m \sum_{j=1}^n [c_{ij} x_{ij} + \beta_{ij} \delta(x_{ij})],$$

which has the form (4). Thus the problem of minimizing the operating cost (8) under the restrictions (5), (6), and (7) is just the fixed charge problem.

#### SOLUTION IN SPECIAL CASE

Under special circumstances it is possible to reduce the fixed charge problem to that of linear programming. In particular, if the fixed charges are all equal and non-negative, we have the following theorem:

Theorem 1: Let  $\phi = \sum_{i=1}^n a_i x_i + \beta \sum_{i=1}^n \delta(x_i)$ ,  $\beta \geq 0$ , and

$\phi_1 = \sum_{i=1}^n a_i x_i$ . Suppose that the vector  $Q$  appearing in (1) does not lie in any sub-space of Euclidean  $n$ -space spanned by fewer than  $m$  of the vectors  $P_1, \dots, P_m$  (non-degeneracy assumption). Then there exists an extreme point  $\hat{x} \in X$ , having exactly  $m$  positive components, at which both  $\phi_1$  and  $\phi$  are minimized. Moreover, any point  $\hat{x}$  with



$m$  positive components which minimizes  $\phi_1$  also minimizes  $\phi$ .

Proof: Under the non-degeneracy assumption, it is clear that any vector  $x \in X$  satisfying (1) must have at least  $m$  non-zero components. Since the sum,  $\sum_{i=1}^n \delta(x_i)$ , is equal to the number of non-zero components of  $x = (x_1, \dots, x_n)$ , we have

$$(9) \quad \min_{x \in X} \phi(x) \geq \min_{x \in X} \phi_1(x) + \beta \min_{x \in X} \sum_{i=1}^n \delta(x_i) \geq \min_{x \in X} \phi_1(x) + m\beta .$$

It is well known from the theory of linear programming that, under the assumption of non-degeneracy, there is an extreme point  $\hat{x} \in X$  having exactly  $m$  positive components at which  $\phi_1$  is a minimum. Let  $\hat{x}$  be any such point. At this point the function  $\phi$  assumes the value

$$\phi(\hat{x}) = \phi_1(\hat{x}) + m\beta .$$

Hence, from (9),

$$\phi(\hat{x}) = \phi_1(\hat{x}) + m\beta \geq \min_{x \in X} \phi(x) \geq \min_{x \in X} \phi_1(x) + m\beta = \phi_1(\hat{x}) + m\beta = \phi(\hat{x}) .$$

Thus it is clear that

---

\* Since the simplex method leads to a point  $\hat{x}$  with  $m$  positive components at which  $\phi_1$  is a minimum, this method can also be used to solve the fixed charge problem with a constant positive fixed charge.

$$s(x) = \min_{x \in X} g(x)$$

### EXISTENCE THEOREM

In the general case when the fixed charges  $\beta_i$  vary with  $i$ , although we have no expedient computational algorithm, we shall prove that the form (4) is minimized at an extreme point of the convex  $X$ . More precisely, we have the following theorem:

**Theorem 1.** Suppose that  $\beta_i \geq 0$ ,  $i = 1, \dots, n$ , and  $\beta_i = 0$  for  $i = 1, \dots, k$ . Then

if  $\beta_{k+1} > 0$ , there exists an extreme point  $x^* \in X$  such that

$$\sum_{i=1}^n \beta_i x_i^* = \beta_{k+1} \quad \text{with no assumption of non-negativity in } x_i^*.$$

**Proof.** (1) The existence of such a point is as follows. Let  $x^*$  be a point in the convex set  $X$ . Since the hyperplane defined by the equations (1), (2) is the intersection of a hyperplane in  $n$ -space with the positive orthant, through the point  $x^*$ , there exists a line segment  $L$  which lies entirely in the convex set and intersects a bounding plane  $P$  of the positive orthant in one direction, although it may extend to infinity in the other direction. Let

(1) It is a pleasure to acknowledge the helpful suggestions of R. S. Lehman in formulating this proof.

$$f_1(x) = \sum_{j=1}^n a_j x_j$$

and

$$f_2(x) = \sum_{j=1}^n \beta_j \theta_j(x_j)$$

Then

$$f = f_1 + f_2$$

As we proceed along  $L$  from  $x$  to  $W$  the number of non-zero components of points on  $L$  (and hence the function  $f_2$ ) remains constant. Accordingly, the restriction of  $f$  to these points is linear, and in one direction  $f$  increases (more precisely, does not decrease), while in the other direction it decreases. If the line is finite in extent, we take  $W$  to be the plane in the direction of which  $f$  is decreasing. If the line extends to infinity in one direction,  $f$  must decrease on  $L$  in the other direction (i.e., toward  $W$ ) for otherwise  $f \rightarrow \infty$  as  $x \rightarrow \infty$  on  $L$ , contrary to assumption. Now at the point  $x'$  of intersection of  $L$  and  $W$  an additional zero component is added to the argument of  $f_2$ , and since the coefficients  $\beta_j$  are non-negative, this implies that

$$f_2(x') < f_2(x).$$



By this we see that

$$f(x') < f(x).$$

An iteration of the argument starting with  $x'$  leads in a finite number of steps to an extreme point at which  $f$  is minimized.

We now fill in the gaps in the preceding discussion by supplying an analytic proof which, of course, is nothing but a translation of the geometric argument.

A point  $x \in X$  is an extreme point of  $X$  if and only if the vectors  $F$ , associated with its non-zero components in (1) are linearly independent. Hence the set  $Z$  of extreme points of  $X$  is finite. We shall prove Theorem 2 by showing that to each point  $x \in X$  there corresponds an extreme point  $x' \in Z$  such that

$$(10) \quad f(x') \leq f(x),$$

and, accordingly, that

$$(11) \quad \inf_{x \in X} f(x) = \min_{x \in Z} f(x).$$

Let  $x$  be an arbitrary point, not an extreme point, of  $X$ . There exist distinct points  $\xi \in X$ ,  $\eta \in X$  such that

$$(12) \quad x = \lambda_0 \xi + (1 - \lambda_0) \eta \quad 0 < \lambda_0 < 1, \quad \xi \neq \eta$$

We put

$$(13) \quad x(\lambda) = \eta + \lambda(\xi - \eta)$$

and observe that

$$(14) \quad x(\lambda_0) = x$$

Denoting the  $i^{\text{th}}$  component of  $x(\lambda)$  by  $x_i(\lambda)$ , we have

$$\sum_{j=1}^n x_j(\lambda) P_j = \sum_{j=1}^n [\eta_j P_j + \lambda (\sum_{j=1}^n \xi_j P_j - \sum_{j=1}^n \eta_j P_j)] = \eta + \lambda(\xi - \eta) = x$$

Hence  $x(\lambda) \in X$  for all  $\lambda$  such that  $x_i(\lambda) \geq 0$ ,  $i=1, 2, \dots, n$ .

Accordingly, it follows that  $x(\lambda) \in X$  for all  $\lambda > 0$ , if and only

if, for all indices  $i$ ,  $\xi_i \geq \eta_i$ . Similarly  $x(\lambda) \in X$  for all  $\lambda < 0$

if and only if  $\xi_i \leq \eta_i$  for all  $i$ . Thus, the set  $\Lambda$  of all  $\lambda$ 's for

which  $x(\lambda) \in X$  is bounded either above or below. We assume without

loss of generality that

$$-\infty < \inf_{\lambda \in \Lambda} \lambda$$

Let

$$\underline{\lambda} = \inf_{\lambda \in \Lambda} \lambda \leq 0$$

Let  $\lambda_0$  be a root of (15). Then, we have

$$x_1(\lambda_0) = 0 \quad \lambda_0 < \bar{\lambda}$$

We shall show that for  $\lambda_0 < \lambda < \bar{\lambda}$ ,  $x_1(\lambda)$  is zero or positive according as  $x_1(\lambda_0)$  is zero or positive. We begin with the case that  $x_1(\lambda_0) = 0$ , that is,

$$(16) \quad \lambda_0 \xi_1 + (1 - \lambda_0) \eta_1 = 0$$

Since  $0 < \lambda_0 < 1$ ,  $\xi_1 \geq 0$ ,  $\eta_1 \geq 0$ , equation (16) holds only if  $\xi_1 = 0$  and  $\eta_1 = 0$ . Hence

$$x_1(\lambda) = \eta_1 + \lambda(\xi_1 - \eta_1) = 0 \quad \lambda_0 < \lambda < \bar{\lambda}$$

Suppose now that  $x_1(\lambda_0) > 0$ . Then, if  $\xi_1 \neq \eta_1$ , we see from (13) that  $x_1(\lambda)$  is a strictly monotonic function of  $\lambda$ . Consequently, since  $\lambda_0 < \lambda < \bar{\lambda}$ , (15) can hold only if  $x_1(\lambda) > 0$  for  $\lambda_0 < \lambda < \bar{\lambda}$ . On the other hand, if  $\xi_1 = \eta_1$ , we see from (13) that

$$x_1(\lambda) = \eta_1(1 - \lambda) > 0$$



From the linearity of the functions  $x_1(\lambda)$  and the fact that  $x(\lambda) \in X$  for  $\lambda < \underline{\lambda}$ , it follows that there is an integer  $i_0$  such that  $x_{i_0}(\lambda_0) > 0$  and  $x_{i_0}(\lambda) < 0$  for  $\lambda < \underline{\lambda}$ . The continuity of the function  $x_{i_0}(\lambda)$ , together with (15), then assures that

$$x_{i_0}(\underline{\lambda}) = 0.$$

Summarizing the results of the preceding paragraphs, we have seen that any zero component of  $x(\lambda_0)$  is a zero component of  $x(\underline{\lambda})$ , while  $x(\underline{\lambda})$  has at least one zero component for which the corresponding component in  $x(\lambda_0)$  is positive. Evidently,  $x(\underline{\lambda}) \in X$ .

If  $\bar{\lambda} < \infty$ , similar considerations show that the vector  $x(\bar{\lambda})$  has at least one more zero component than  $x(\lambda_0)$ , and  $x(\bar{\lambda}) \in X$ .

Recalling that  $\phi_1(x) = \sum_{j=1}^n a_j x_j$  and  $\phi_2(x) = \sum_{j=1}^n \beta_j \delta(x_j)$ ,

it is now clear that

$$(18) \quad \phi_2(x(\underline{\lambda})) < \phi_2(x(\lambda_0)) = \phi_2(x)$$

and, if  $\bar{\lambda} < \infty$ ,

$$(19) \quad \phi_2(x(\bar{\lambda})) < \phi_2(x(\lambda_0)) = \phi_2(x).$$

At  $\bar{\lambda} = \infty$ ,

$$(20) \quad \phi_2(x(\lambda)) = \phi_2(x(\lambda_0)) = \phi_2(x)$$

for all  $\lambda \geq \lambda_0$ , since, for  $\underline{\lambda} < \lambda < \bar{\lambda}$ ,  $x_1(\lambda)$  is zero or positive according as  $x_1(\lambda_0)$  is zero or positive.

Observing now that  $\phi_1(x(\lambda))$  is a linear function of  $\lambda$ , it follows that if  $\bar{\lambda}$  is finite, either

$$(21) \quad \phi_1(x(\underline{\lambda})) \leq \phi_1(x(\lambda_0)) = \phi_1(x)$$

or

$$(22) \quad \phi_1(x(\bar{\lambda})) \leq \phi_1(x(\lambda_0)) = \phi_1(x).$$

If  $\bar{\lambda} = \infty$ , then (21) must hold; for, in this case, the relation  $\phi_1(x(\underline{\lambda})) > \phi_1(x(\lambda_0))$  implies that  $\phi_1(x(\lambda)) \rightarrow -\infty$  as  $\lambda \rightarrow \infty$ , since  $\phi_1$  is linear. This contradicts the assumption  $\inf_{x \in X} \phi(x) > -\infty$ .

From (18) - (22) we see that there is a point  $x' \in X$  for which

$$\phi(x') = \phi_1(x') + \phi_2(x') \leq \phi_1(x) + \phi_2(x) = \phi(x),$$

where  $x'$  has at least one more zero component than  $x$ . (If  $\bar{\lambda} = \infty$ , then  $x' = x(\underline{\lambda})$ ; if  $\bar{\lambda} < \infty$ , then  $x'$  is one of the two vectors  $x(\underline{\lambda}), x(\bar{\lambda})$ .) If  $x'$  is an extreme point, (10) is proved. Otherwise, an iteration of the argument replacing  $x$  by  $x'$  yields a new point  $x''$  such that



$$g(x'') \leq g(x'),$$

where  $x''$  has at least one more zero component than  $x'$ . It is clear that after at most  $n$  such constructions there is produced an extreme point  $x^*$  satisfying (10).

### A MORE GENERAL FIXED CHARGE PROBLEM

In certain logistical problems, in particular in connection with the question of transshipment, one is led to consider a generalization of the fixed charge problem. Suppose that  $k$  is a divisor of  $n$ , say,

$$n = k \cdot p,$$

and put

$$(23) \quad V(x) = \sum_{j=1}^n a_j x_j + \sum_{r=1}^p \beta_r \delta \left( \sum_{j=(r-1)k+1}^{rk} x_j \right).$$

Clearly,  $V$  reduces to the function  $g$  defined in (4) when  $k=1$  and  $p=n$ .

We refer to the problem of minimizing  $V$  under the side conditions

(1) and (2) as the generalized fixed charge problem. For this prob-

lem there is no easy analogue of theorem 1. However, the statement

and proof of theorem 2 carry over without change; so that if

$\inf_{x \in X} V(x) > -\infty$  there is an extreme point  $\hat{x} \in X$  such that  $V(\hat{x}) \leq V(x)$ .

for all  $x \in X$ .

We have encountered this generalization of the fixed charge problem in connection with the following transportation question: Consider a hypothetical network of cities between each pair of which specified quantities of homogeneous cargo are to be delivered. Let  $b_{ij}$  denote the cargo to be delivered from city  $i$  to city  $j$ . Suppose that the cost of shipping  $u$  units of cargo from  $i$  to  $j$  is given by a function of the form

$$g_{ij}(u) = \alpha_{ij}u + \beta_{ij}\delta(u) .$$

The problem is to route shipments so that the total cost of shipments is minimized. Let  $x_{ijk}$ ,  $i=1,2,\dots,n$ ,  $j=1,2,\dots,n$ ,  $k=1,2,\dots,n$ ,  $i \neq k$ ,  $i \neq j$ , denote the quantity of material to be shipped from  $i$  to  $j$  for ultimate transshipment to  $k$ . Observe that  $\sum_{\substack{j=1 \\ j \neq i}}^n x_{ijk}$  represents the

total goods shipped from  $i$  for the final destination  $k$ . Since

$\sum_{\substack{j=1 \\ j \neq i \\ m \neq i \\ m \neq k}}^n x_{mjk}$  represents cargo received by  $i$  for ultimate transshipment

to  $k$ , the variables  $x_{ijk}$  must satisfy the constraints

$$(24) \quad \sum_{\substack{j=1 \\ j \neq i}}^n x_{ijk} - \sum_{\substack{m=1 \\ m \neq i \\ m \neq k}}^n x_{mjk} = b_{ik} , \quad \begin{matrix} i=1,2,\dots,n \\ k=1,2,\dots,n \\ i \neq k \end{matrix}$$

The total quantity of goods shipped from  $i$  to  $j$  ( $i \neq j$ ) is given by  $\sum_{k=1}^n x_{ijk}$ . Hence the cost of shipment from  $i$  to  $j$  is

$$a_{ij} \sum_{k=1}^n x_{ijk} + \beta_{ij} \delta \left( \sum_{k=1}^n x_{ijk} \right),$$

and the total cost of all shipments is

$$(25) \quad \sum_{\substack{i,j=1 \\ i \neq j}}^n \left[ a_{ij} \sum_{k=1}^n x_{ijk} + \beta_{ij} \delta \left( \sum_{k=1}^n x_{ijk} \right) \right].$$

The problem of minimizing (25) under the side conditions (24) and

$$(26) \quad x_{ijk} \geq 0,$$

is evidently of the generalized fixed charge type.

RELATION TO QUADRATIC PROBLEMS

It is of some interest to note that we may replace the problem of minimizing the non-linear function  $\Psi$  defined in (23) under linear side conditions by one of minimizing a linear function under linear side conditions plus an additional quadratic constraint. Specifically let  $(x, y) = (x_1, \dots, x_n, y_1, \dots, y_p)$  represent a point in  $n+p$

dimensional Euclidean space. Suppose that  $(\hat{x}, \hat{y}) = (\hat{x}_1, \dots, \hat{x}_n, \hat{y}_1, \dots, \hat{y}_p)$  minimizes the function

$$(27) \quad \Psi(x, y) = \sum_{i=1}^n a_i x_i + \sum_{r=1}^p \beta_r y_r$$

under the constraints (1), (2), and

$$(28) \quad 0 \leq y_r \leq 1, \quad r=1, 2, \dots, p$$

$$(29) \quad \sum_{r=1}^p (1 - y_r) \cdot \sum_{i=(r-1)k+1}^{rk} x_i = 0.$$

The constants  $\beta_r, r=1, 2, \dots, p$  are assumed to be non-negative. We shall prove that  $\hat{x} = (\hat{x}_1, \dots, \hat{x}_n)$  minimizes the function  $\Psi$  in (27) under the side conditions (1) and (2). In the first place,

$$(30) \quad \inf \tilde{\Psi}(x, y) \leq \inf \Psi(x)$$

(where the infimum is taken over the appropriate side conditions), since to each point  $x$  satisfying (1) and (2) there corresponds a point  $y$  such that  $(x, y)$  satisfies (1), (2), (28), and (29), and

$$\tilde{\Psi}(x, y) = \Psi(x).$$

Indeed, we need only define

$$y_r = 0 \left( \sum_{i=(r-1)k+1}^r x_i \right)$$

Observe next that if  $\sum_{i=(r-1)k+1}^r x_i > 0$ , then in order to satisfy

(29) we must have  $\hat{y}_r = 0$ . If  $\sum_{i=(r-1)k+1}^r x_i = 0$ , we must have  $\hat{y}_r = 0$ ,

for otherwise we could achieve a lower value for (29) by setting  $\hat{y}_r = 0$ . It is thus clear that

$$\hat{y}_r = 0 \left( \sum_{i=(r-1)k+1}^r x_i \right)$$

and, accordingly, that

$$(31) \quad \inf \psi(x) \geq \inf \tilde{\psi}(x, y) = \tilde{\psi}(\hat{x}, \hat{y}) = \psi(\hat{x}) \geq \inf \psi(x),$$

where again the infimum is taken over the appropriate set of constraints. We see from (31) that

$$\inf \psi(x) = \inf \tilde{\psi}(x, y),$$

which completes the proof.

Another form of the problem can be obtained by putting  $z_r = 1 - x_r$ .

The function  $\tilde{\psi}(x, y)$  to be minimized can then be replaced by

$$(32) \quad V^*(x, z) = \sum_{j=1}^n a_j x_j - \sum_{r=1}^p \beta_r z_r,$$

omitting the constant,  $\sum_{r=1}^p \beta_r$ , which is inessential. The constraints then become

$$(33) \quad 0 \leq z_r \leq 1$$

and

$$(34) \quad \sum_{r=1}^p z_r \sum_{i=(r-1)k+1}^{rk} x_i = 0.$$

This form suggests a possible connection between the generalized fixed charge problem and other programming problems involving the optimization of a linear form where, in addition to being non-negative, the variables are constrained by a condition of the form

$$(35) \quad x_i = 0 \text{ or } 1, \quad i=1, 2, \dots, n$$

or of the form

$$(36) \quad x_i = 0 \text{ or } x_i \geq a_i.$$

Both (35) and (36) can be recast as quadratic constraints formally similar to (34). For example, (35) becomes

$$(37) \quad \sum_{i=1}^n x_i(1-x_i) = 0$$

Feasible computational methods for solving problems involving (35) have been developed for special cases, for example, in the case of the traveling-salesman problem. Whether or not these methods can be carried over to the fixed charge problem is still an open question.



REFERENCES

1. A. Charnes and C. S. Lemke, Minimization of Non-Linear Separable Convex Functionals, O.N.R. Research Memorandum, No. 16, (1954), Graduate School of Industrial Administration, Carnegie Institute of Technology.
2. G. B. Dantzig, Maximization of a Linear Function of Variables Subject to Linear Inequalities, Activity Analysis of Production and Allocation, Edited by T. C. Koopmans, John Wiley and Sons, New York, 1951.
3. G. B. Dantzig, A. Orden, and P. Wolfe, The Generalized Simplex Method for Minimizing a Linear Form under Linear Inequality Restraints, The RAND Corporation, Research Memorandum RM-1204, April 2, 1954.
4. H. W. Kuhn and A. W. Tucker, Non-linear Programming, Proceedings of the Second Berkeley Symposium on Mathematical Statistics and Probability, University of California Press, 1951.
5. T. Dorn, Application of Linear Programming to the Theory of the Firm, Berkeley; University of California Press, 1951.
6. J. von Neumann, A Numerical Method to Determine Optimum Strategy, Naval Research Logistics Quarterly, Office of Naval Research, Vol. 1, No. 2, June, 1954.