

APPLICATION OF LINEAR PROGRAMMING  
TECHNIQUES TO MINIMAX APPROXIMATION

by

Mary Elizabeth Evans

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Approved by

DR. McCausler

Director

Examining Committee

John P. Forney  
E.E. Posey

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## CHAPTER I

### A. Interpolation and Approximation

The problem with which we are concerned is that of finding some function  $P(x)$  which "most closely" approximates a given function  $F(x)$ . There are two main ways of doing this--interpolation and approximation. Here we will consider in detail only the latter--actually only Chebychev approximation. However it will be useful to first ask ourselves when we approximate and especially when we choose to use Chebychev approximation.

The interpolation method consists of finding a polynomial which passes exactly through each one of a given set of points. We can get this result by using an interpolating polynomial of degree  $n-1$ , where  $n$  is the number of given points. This method can be quite accurate and easy to use with a relatively "small" number of points. However, if we try to interpolate 1000 points, we would have to use a  $999^{\text{th}}$  degree polynomial, which would be extremely "wiggly." This property is due to the error term in interpolation,

which is

$$E(x) = \frac{\prod_{i=1}^{n+1} (x-x_i) F^{(n+1)}(\xi)}{(n+1)!}$$

where  $\xi \in [x_1, x_{n+1}]$ . Note that if the  $(n+1)^{\text{st}}$  derivative of  $F(x)$  gets large relative to  $(n+1)!$ , this error term can become extremely large when we have a large number of points.

Therefore, when using many points we can be sure only that the polynomial passes through the given points. We have no idea about its behavior between these points. For example, suppose we wanted to interpolate at many points on the curve



Our large-degree interpolating polynomial might look like



which certainly is not an accurate approximation between points.

Another disadvantage of interpolation is that we need to know the points exactly in order to interpolate accurately. A small error in one point can change significantly the coefficients and hence the interpolating polynomial at that point.

The disadvantages above do not apply to approximation. Therefore when we have a large number of points and/or data which may be in error it is safer to approximate.

In the approximation problem we may have either the discrete case (given a set of points) or the continuous case (given a function over an entire interval). In either case we seek to minimize the "distance" between the approximating function and the given function.

The two most common methods of approximation are "least

squares" and "Chebychev" (or "minimax"). In least squares approximation we measure distance just as we do in the plane; i.e., the distance between the two functions is the square root of the sum of the squares of the distances between the given points and their approximating points. In Chebychev approximation, on the other hand, the distance between the functions is defined as the maximum distance between any of the given points and its approximating point.

We can say in general that Chebychev approximation is "better" in the sense of being more uniform. For example, suppose we use least squares approximation at four points. We could get a "best" approximation either with the set of errors (5,5,5,5) or with the set (9,3,3,1), since

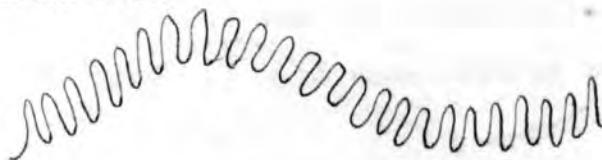
$$\sqrt{5^2+5^2+5^2+5^2} = \sqrt{100}$$

and

$$\sqrt{9^2+3^2+3^2+1^2} = \sqrt{100}$$

Thus it is possible using least squares to obtain the least possible overall error while still having relatively large error at certain points. Since Chebychev approximation seeks to minimize the maximum distance, the errors are as a rule more nearly equal.

An important use of approximation is that of "smoothing" functions. Suppose that experimental data give a function which looks like



Chebychev or least squares approximation using a low-

degree polynomial will "smooth the ripples" and give the form of the curve by eliminating high frequency noise factors.

### B. The Approximation Problem

We will consider here only the approximation of real continuous functions of a single variable, denoted by  $F(x)$  or simply by  $F$ . The approximation problem may be stated as follows:

Given a real-valued continuous function  $F$  defined on a set  $X$ , find the real-valued approximating function  $P$  on  $X$  such that the distance between  $P$  and  $F$  is a minimum.

Such a function  $P$  is called a "best approximation."

To elaborate on this statement we now need to define the method of measuring the distance between  $F$  and  $P$ , which we want to minimize. The "distance functions" are norms and metrics, denoted by  $\| \cdot \|$  and  $\rho(\cdot)$  respectively. A norm on a vector space of functions has the following properties:

1.  $\|F(x)\| \geq 0$  and  $\|F(x)\|=0$  if and only if  $F(x)=0$ .
2.  $\|cF(x)\|=|c| \|F(x)\|$  for all real numbers  $c$ .
3.  $\|F(x)+G(x)\| \leq \|F(x)\| + \|G(x)\|$ .

Geometrically, a norm is the "length" of a vector in a given vector space.

A metric measures the distance between two points in a vector space (in this case between two functions) and is defined as follows:

1.  $\rho(F(x), F(x))=0$  and  $\rho(F(x), G(x))>0$ .

$$2. \ell(F(x), G(x)) = \ell(G(x), F(x)).$$

$$3. \ell(F(x), G(x)) \leq \ell(F(x), H(x)) + \ell(H(x), G(x)).$$

Note that there is a metric associated with every norm:

$$\ell(x, y) = \|x - y\|.$$

An important class of norms is that of the " $L_p$ " norms, defined for functions by

$$\|F(x)\| = \left\{ \sum_{i=1}^n |F(x_i)|^p \right\}^{1/p}$$

for the discrete case, and

$$\|F(x)\| = \left\{ \int_a^b |F(x)|^p dx \right\}^{1/p}$$

for the continuous case. In each case  $p$  is defined to be  $\geq 1$ , since the triangle inequality for the corresponding metric does not hold if  $p < 1$ . We mention briefly the three main  $L_p$  norms.

The  $L_1$  norm is defined as

$$\|F(x)\|_1 = \sum_{i=1}^n |F(x_i)| \quad \text{or} \quad = \int_a^b |F(x)| dx.$$

The  $L_2$  norm is the familiar "Euclidean norm":

$$\|F(x)\|_2 = \left\{ \sum_{i=1}^n |F(x_i)|^2 \right\}^{\frac{1}{2}} \quad \text{or} \quad = \left\{ \int_a^b |F(x)|^2 dx \right\}^{\frac{1}{2}}.$$

Finally the " $L_\infty$ " norm, or Chebychev norm, with which we are mainly concerned, is defined as

$$\|F(x)\|_\infty = \max_{[a,b]} |F(x)|.$$

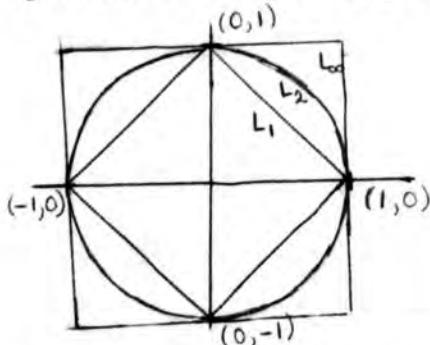
The associated Chebychev metric is  $\ell(F(x), G(x)) = \max_{[a,b]} |F(x) - G(x)|$ .

This norm is called " $L_\infty$ " since it behaves much the same as the  $L_p$  norms for very large values of  $p$ .

In all  $L_p$  approximations we seek the function  $P(x)$  which

minimizes the appropriate norm  $\|F(x) - P(x)\|$ .

This brings us to the important consideration of the uniqueness of the "best" approximation  $P(x)$ . The problem is best illustrated by looking at the unit spheres of the  $L_p$  norms. A unit sphere is defined as the set of all  $X$  such that the distance from  $X$  to the origin is one; i.e.,  $\ell(X, 0) = 1$  or  $\|X\| = 1$ . The following diagram illustrates the unit spheres for the  $L_1$ ,  $L_2$ , and  $L_\infty$  norms in two-dimensional space. The unit spheres for  $2 < p < \infty$  lie between the  $L_2$  and  $L_\infty$  spheres.



It is easy to see how these are constructed. Note that for  $L_1$ ,  $x+y=1$  for all  $(x,y)$ ; for  $L_2$ ,  $(x^2 + y^2)^{\frac{1}{2}}=1 \Rightarrow x^2 + y^2=1$ , which is the familiar equation of a circle; for  $L_\infty$ ,  $\max(x,y)=1$  for all  $(x,y)$  on the unit sphere.

Also observe that all unit spheres except  $L_1$  and  $L_\infty$  will have "curved" sides. At this point we need a brief definition of a "convex" set. A set  $K$  is called convex if for every  $X, Y$  in  $K$ , the line segment connecting  $X$  and  $Y$  is also in  $K$ . Furthermore,  $K$  is said to be strictly convex if every line segment connecting two points in  $K$  lies completely in the interior of  $K$ . Hence, all unit spheres except  $L_1$  and  $L_\infty$  are strictly convex sets, while  $L_1$  and  $L_\infty$  are merely convex sets.

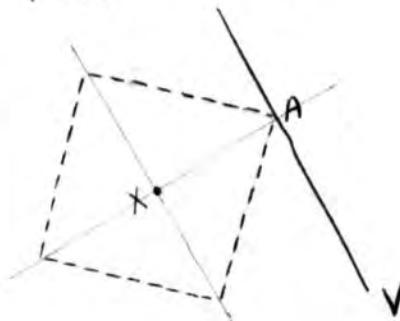
Given a vector space  $V$  of functions, the function  $P(x)$

in  $V$  which is the best approximation to  $F(x)$  depends on the norm being used. The approximation problem can be viewed intuitively as a process of expanding the unit sphere of the norm in question. The best approximation to  $F(x)$  at a point  $x$  is found by placing a unit sphere at  $x$  and expanding this sphere uniformly until it "touches"  $V$ . The point at which it "first" touches  $V$  is the best approximation to  $F(x)$ .

To illustrate this, we must use a very simple example. Suppose  $V$  is a line and we want to find the best approximation to a point  $x$  not on the line.

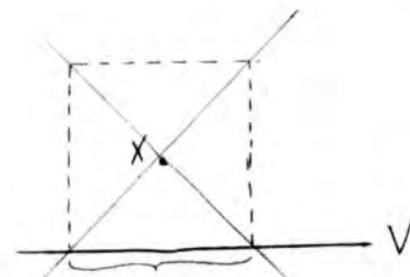
#### Case 1: $L_1$ approximation

(a)



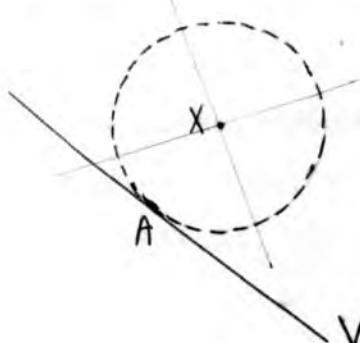
Here we get a unique best approximation at point A.

(b)

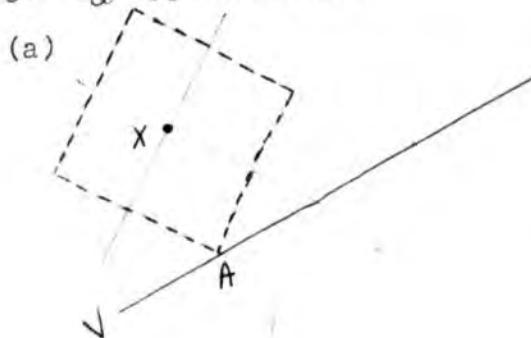


Here there is no unique best approximation. There are infinitely many points which touch  $V$  at the same time.

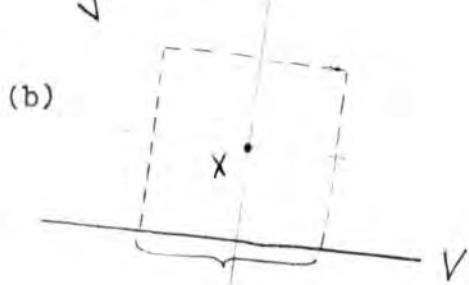
#### Case 2: $L_2$ approximation



In every case we will get a unique best approximation A.

Case 3:  $L_\infty$  approximation

Here we get a unique best approximation  $A$ .



But here, as in the  $L_1$  case, there are infinitely many "best" approximations.

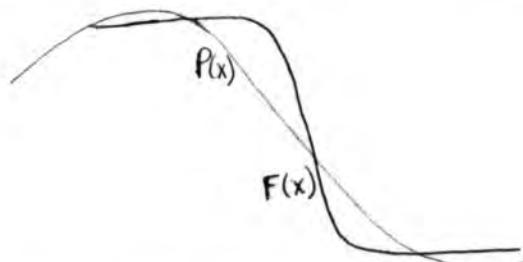
The above drawings illustrate the fact that with strictly convex unit spheres, i.e., "curved sides," we are always guaranteed a unique best approximation, but with the  $L_1$  and  $L_\infty$  norms there may not be a unique one.

## C. Choosing an Approximating Function

Basically, the choice of an appropriate approximating function depends on intuition and on an understanding of the properties of the function being approximated. However there are a few guidelines available.

The main objective is to find an approximating function which has generally the "same behavior" as the given function. In practice there are only a few types of functions from which to choose. These include polynomials, rational functions, trigonometric sums, logarithmic and exponential functions, Bessel functions, and piecewise polynomials.

The most common and easiest to apply are those with a limited range of behavior, i.e., the polynomials and trigonometric sums. These are accurate for functions with fairly "smooth" variations, but cannot approximate sharp bends followed by "flat" behavior as shown.



Note that the polynomial tends to "curve" more gently and to have a smaller slope. It is sometimes possible by increasing the degree of a polynomial to more closely approximate functions with such behavior, but this can make the approximating function quite complicated and often difficult to evaluate.

More flexibility can be gained by using rational functions of the form

$$R(x) = \frac{P(x)}{Q(x)}$$

where  $P$  and  $Q$  are polynomials. Low degree rational functions can take on forms impossible to approximate except by high degree polynomials. For instance, rational functions have singularities at points where the denominator vanishes, and therefore they are useful for approximating functions with singularities. Also rational functions can take on infinite values for finite  $x$  values, whereas polynomials cannot, and thus can approximate over an infinite range. (A simple

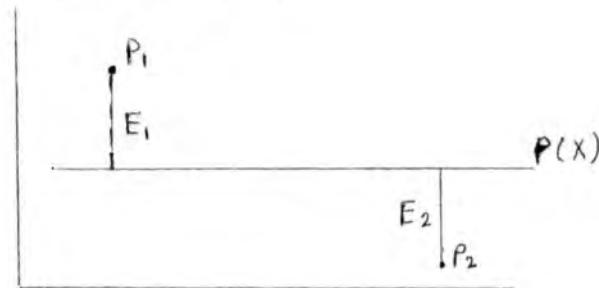
example is  $1/x$ .) Computation of rational approximations is much more difficult than that of polynomials, but this disadvantage becomes less important with the development of new techniques and high-speed computers.

There are other classes of approximating functions which are in some cases more desirable than either polynomials or rationals. For instance a function using exponentials should be used if  $F$  increases or decreases exponentially. Another class is that of "piecewise" polynomials, which divide the given interval into several smaller intervals by a set of points called "joints." Between these joints the approximating function is a polynomial of specified degree. An important subclass of this group is that of "spline functions", which are  $n^{\text{th}}$  degree piecewise polynomials joined so that they have  $n-1$  continuous derivatives; i.e., there can be a discontinuity at the joints only in the  $n^{\text{th}}$  derivative.

## CHAPTER II

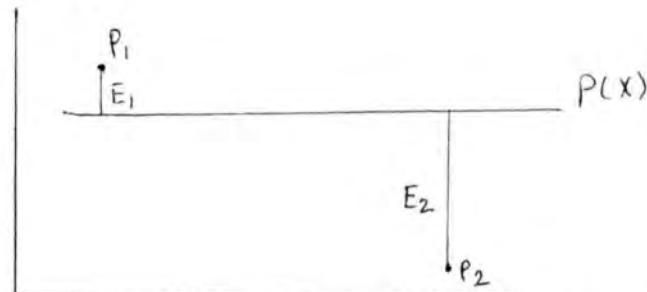
## A. An Intuitive Approach to Chebychev Approximation

1. Suppose we are given two points and wish to find the "best" approximating constant function,  $P(x)=c$ , to these using Chebychev approximation.



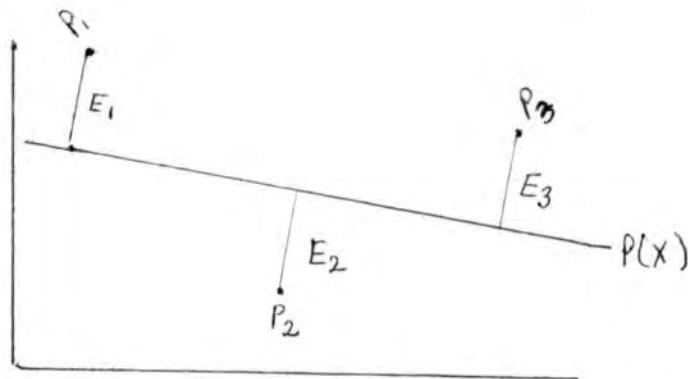
Note that here the two errors  $E_1$  and  $E_2$  are equal and alternating.

2. Now if we shift  $P(x)$  up, note that  $E_2$  becomes larger. Thus the maximum error becomes larger; but since we want to minimize the maximum error, moving  $P(x)$  gives a worse Chebychev approximation.

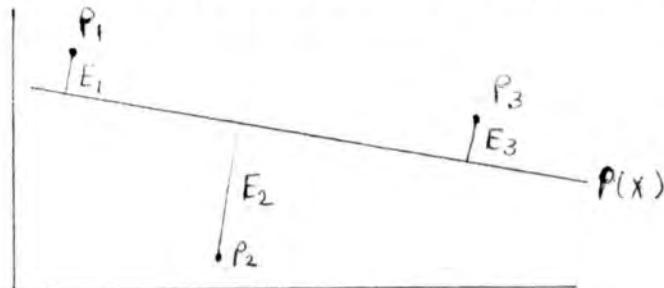


Therefore the best approximating function in this case is that in which the errors are equal and alternating.

3. Now look at a similar case using the points  $P_1$ ,  $P_2$ , and  $P_3$  which we want to approximate by a line  $P(x)=Ax+B$ . Again the errors are equal and alternating.

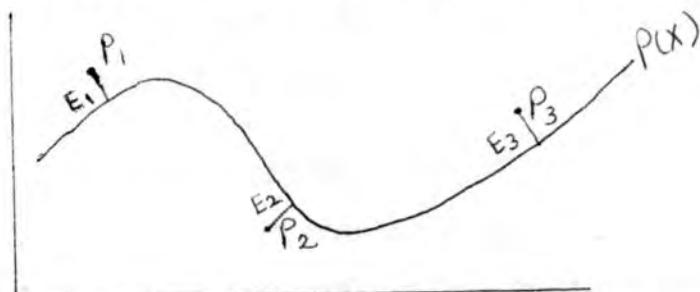


4. Moving the function again, we can make  $E_1$  and  $E_3$  smaller, but at the same time we make  $E_2$  larger, and thus go contrary to our purpose in Chebychev approximation.



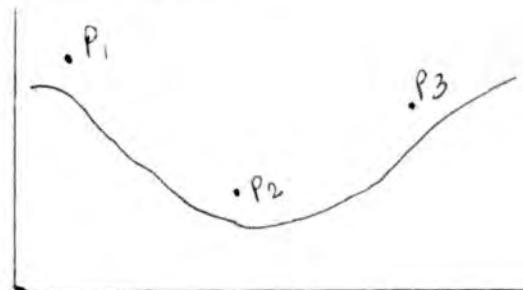
Therefore our best approximation is again the one in which the errors are equal and alternating. This can be extended to cases involving more points.

5. We have been using straight line approximating functions as illustrations. Note also that the same properties are true when the approximating polynomial is of degree  $\geq 2$ .



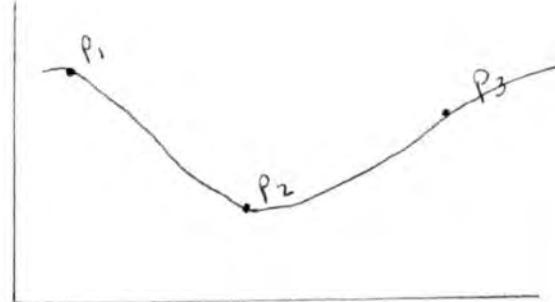
6. A good question is: Why must the errors alternate? Why can they not all fall on the "same side" of the

approximating function?



In this drawing, the errors are all "above" the function. However, note that we can "shift" the function as shown.

7.



Now there are no errors at the points, and therefore the function in drawing 6 was not the best approximation at all.

As a rule, when all the errors are on the same side of the approximating function, a better approximation can be found. There are some exceptions to this rule, but we will not consider these here. Approximation problems which obey the rule are called "normal."

#### B. Minimax Polynomial Approximation

Let us now consider the problem of approximating a function  $F$  in the closed interval  $[a, b]$ , using a polynomial  $P_n$  of degree  $\leq n$  where  $n$  is some non-negative integer. For our purpose, the criterion for a best approximation is

either:

1. The polynomial  $P_n$  such that  $\max_{[a,b]} |P_n - F|$  is a minimum (absolute error criterion), or
2. The polynomial  $P_n$  such that  $\max_{[a,b]} \left| \frac{P_n - F}{F} \right|$  is a minimum (relative error criterion).

Since Chebychev approximation minimizes the maximum error over the interval, it is often called minimax approximation. We will be concerned only with the absolute error criterion, since it is used in our computer applications.

P.L. Chebychev developed the basic minimax polynomial approximation theorem. Fike [4] states it as follows:

Let  $u(x)$  denote a function continuous in a closed, finite interval  $[a,b]$ , and let  $v(x)$  denote a function continuous and nonzero in  $[a,b]$ . Let  $V_n$  denote the set of polynomials of degree  $\leq n$ . There exists a unique polynomial  $P_n^*(x)$  in  $V_n$  such that

$$\max_{[a,b]} \left| \frac{P_n^*(x) - u(x)}{v(x)} \right| = \min_{P_n \in V_n} \max_{[a,b]} \left| \frac{P_n(x) - u(x)}{v(x)} \right|$$

Let  $P_n(x)$  denote a polynomial in  $V_n$ . Then  $P_n(x)$  is  $P_n^*(x)$  if and only if there exists  $N \geq n+2$  points in  $[a,b]$ ,

$$x_1^* < x_2^* < x_3^* < \dots < x_N^*,$$

such that

$$\frac{P_n(x_k^*) - u(x_k^*)}{v(x_k^*)} = (-1)^k \mu^* \text{ for } k=1, 2, 3, \dots, N$$

$$\text{where } |\mu^*| = \max_{[a,b]} \left| \frac{P_n(x) - u(x)}{v(x)} \right|.$$

We can make the following important observation concerning this theorem:

When  $v(x)=1$  and  $u(x)=F$ , the quantity

$\left| \frac{P_n(x) - u(x)}{v(x)} \right|$  becomes the absolute error function

$|P_n(x) - F(x)|$ . In this case the theorem states that there is a unique polynomial  $P_n^*$  of degree  $\leq n$  which approximates  $F$  with minimax absolute error in  $[a, b]$ . Further we see that  $P_n^*(x)$  is uniquely characterized by the fact that the absolute error function has at least  $n+2$  extreme points in  $[a, b]$  at which it is alternately positive and negative and at which  $P_n$  and  $F$  are equally far apart.

The points  $x_1^*, x_2^*, \dots, x_N^*$  at which the error function has maximum magnitude are called "critical points" and the oscillation of the function between these points is called "equal ripple."

It is important to note that this theorem assures us that there does indeed exist a unique solution to the minimax polynomial approximation problem.

### C. Minimax Rational Approximation

Having dealt with the fundamentals of minimax polynomial approximation, let us now turn to the rational case. The theory is quite similar to that for polynomials.

Whereas before we were interested in approximating in the set of polynomials of degree  $\leq n$ , now we are doing so in a set of rational functions denoted by  $V_{m,n}[a, b]$ . A function in this set can be expressed as an irreducible fraction  $P_m(x)/Q_n(x)$  where  $P$  and  $Q$  are polynomials of degrees  $\leq m$  and  $\leq n$  respectively, and  $Q_n(x) \neq 0$  in  $[a, b]$ .

Chebychev's theorem on rational approximation is a generalization of the polynomial theorem, and states [4]:

Let  $u(x)$  denote a function continuous in a finite interval  $[a, b]$ , and let  $v(x)$  denote a function continuous and nonzero in  $[a, b]$ . Let  $V_{m,n}[a, b]$  denote the family of rational functions defined above. There exists a unique rational function  $R_{m,n}^*(x)$  in  $V_{m,n}[a, b]$  such that

$$\max_{[a,b]} \left| \frac{R_{m,n}(x) - u(x)}{v(x)} \right| = \min_{R_{m,n} \in V_{m,n}} \max_{[a,b]} \left| \frac{R_{m,n}(x) - u(x)}{v(x)} \right|$$

A rational function  $R_{m,n}(x)$  is  $R_{m,n}^*(x)$  if and only if there exist  $N \geq m+n+2$  points in  $[a, b]$ ,

$$x_1^* < x_2^* < x_3^* < \dots < x_N^*$$

such that

$$\frac{R_{m,n}(x_k^*) - u(x_k^*)}{v(x_k^*)} = (-1)^k \mu^* \text{ for } k=1, 2, 3, \dots, N$$

$$\text{where } |\mu^*| = \max_{[a,b]} \left| \frac{R_{m,n}(x) - u(x)}{v(x)} \right|$$

If  $P(x)$  is identically zero, then in the above statement we need only  $N \geq m+2$ .

We can observe the absolute error case:

If  $v(x)=1$  and  $u(x)=F$ , then

$$\left| \frac{R_{m,n}(x) - u(x)}{v(x)} \right| = \left| R_{m,n}(x) - F(x) \right|$$

is an absolute error function, and the theorem states the existence of a unique rational function in  $V_{m,n}[a, b]$  which approximates  $F$  with minimax absolute error in  $[a, b]$ .

The phenomenon of equal ripple is observed here also, with  $m+n+2$  critical points.

It is of interest to note that, while  $m$  and  $n$  may theoretically be any non-negative integers, practical experience shows that the best choices for rational approximations are those in which  $m$  and  $n$  are equal or nearly so, since more accuracy is obtained in such approximations. This phenomenon becomes more important when  $m$  and  $n$  are large.

An important question is that of whether to use polynomial or rational approximation when faced with a given problem. It is usually true that rational approximation gives better results than polynomial approximation having the same number of coefficients. This advantage increases with the number of coefficients in the approximation.

Note that here we are considering only linear approximation. Given a basis for our vector space of approximating functions, we generate this vector space by forming linear combinations of the basis elements. For example, the usual basis for the space of polynomials is the set  $(1, x, x^2, \dots, x^n)$ . Our vector space is made up of combinations of the form

$$A_0 + A_1x + A_2x^2 + \dots + A_nx^n.$$

We do not include non-linear combinations such as

$$\frac{x^2(x^5 - 1)}{x^3}.$$

## CHAPTER III

## A. Introduction

Before considering the applications of linear programming to minimax approximations, we must discuss briefly the general linear programming problem. It will be necessary here to assume a basic knowledge of linear algebra. A good mathematical background is presented in [5].

The problem may be stated as follows:

Find the vector  $X = (x_1, x_2, \dots, x_n)$  which minimizes the objective function

$$cX = c_1x_1 + c_2x_2 + \dots + c_nx_n$$

subject to the constraints  $x_j \geq 0$  for  $j=1, 2, \dots, n$ .

and  $a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n \leq b_1$

$$a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n \leq b_2$$

$$\begin{matrix} \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \end{matrix}$$

$$a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n \leq b_m$$

where the latter set of equations is written simply as

$AX \leq b$ . We assume that this last set of equations has been multiplied by -1 where necessary to make all inequalities  $\leq$  for  $i=1, 2, \dots, m$ .

We define a linear functional,  $f(x)$ , to be a real-valued function on an  $n$ -dimensional vector space such that for  $X = \alpha Y + \beta Z$ ,

$$f(X) = f(\alpha Y + \beta Z) = \alpha f(Y) + \beta f(Z)$$

for  $X, Y, Z$   $n$ -dimensional vectors and  $\alpha, \beta$  scalars. The following theorem will be useful later.

Theorem 3.1:  $cX$  is a linear functional for the  $x_i$  satisfying the constraints above.

Proof: Let  $\mathbf{X}$ ,  $\mathbf{Y}$ ,  $\mathbf{Z}$  be vectors satisfying the given constraints, and let  $\alpha, \beta$  be scalars. Suppose  $\mathbf{X} = \mathbf{Y} + \mathbf{Z}$ .

Now  $\mathbf{Y} = (y_1, y_2, \dots, y_n)$  and  $\mathbf{Z} = (z_1, z_2, \dots, z_n)$ ; therefore,

$\alpha\mathbf{Y} = (\alpha y_1, \alpha y_2, \dots, \alpha y_n)$  and  $\beta\mathbf{Z} = (\beta z_1, \beta z_2, \dots, \beta z_n)$ .

$$\begin{aligned}\text{Thus we know } \mathbf{X} &= (\alpha y_1, \alpha y_2, \dots, \alpha y_n) + (\beta z_1, \beta z_2, \dots, \beta z_n) \\ &= (\alpha y_1 + \beta z_1, \alpha y_2 + \beta z_2, \dots, \alpha y_n + \beta z_n)\end{aligned}$$

And by definition

$$\begin{aligned}c\mathbf{X} &= c_1(\alpha y_1 + \beta z_1) + c_2(\alpha y_2 + \beta z_2) + \dots + c_n(\alpha y_n + \beta z_n) \\ &= c_1\alpha y_1 + c_1\beta z_1 + c_2\alpha y_2 + c_2\beta z_2 + \dots + c_n\alpha y_n + c_n\beta z_n \\ &= \alpha(c_1 y_1 + c_2 y_2 + \dots + c_n y_n) + \beta(c_1 z_1 + c_2 z_2 + \dots + c_n z_n) \\ c\mathbf{X} &= \alpha c\mathbf{Y} + \beta c\mathbf{Z}. \quad \text{QED}\end{aligned}$$

We can transform the constraints into a set of linear equalities by introducing  $m$  non-negative slack variables, one in each equation, giving us the linear system:

$$\begin{array}{lll} a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n + x_{n+1} & & = b_1 \\ a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n & + x_{n+2} & = b_2 \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n & + x_{n+m} & = b_m \end{array}$$

We added  $m$  slack variables, and note that the coefficient matrix for these variables is  $E_m$ , the  $m \times m$  identity matrix. Thus we may write the system as  $(A, E_m)X = b$  [12]. This system can now be solved.

Some basic definitions must be stated before the discussion can proceed. These are:

1. A set of  $m$  linearly independent columns of  $(A, E_m)$  is called a basis. The numbers of the columns which form the basis are called basic indices. Variables with basic indices are called basic variables; other variables are called

non-basic variables

2. A feasible solution to the problem is a vector  $x = (x_1, x_2, \dots, x_n)$  which satisfies the constraints mentioned above. If no feasible solution exists, the linear program is called infeasible.

3. A minimum feasible solution is a feasible solution which also minimizes the objective function  $cX$ .

4. A convex combination of points  $P_i$ ,  $i=1,2,\dots,n$ , is some point  $P = \alpha_1 P_1 + \alpha_2 P_2 + \dots + \alpha_n P_n$  where the  $\alpha_i$  are non-negative scalars such that

$$\sum_{i=1}^n \alpha_i = 1. [5].$$

The set of all convex combinations of two points is the line segment connecting these points.

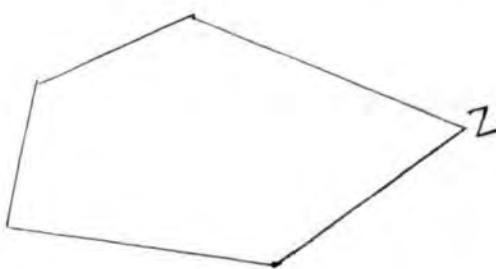
5. A convex set  $K$  is a set of points such that for any two points  $A$  and  $B$  in  $K$ , the convex combination  $P = \alpha_1 A + \alpha_2 B$  is also in  $K$ .

6. A closed convex set is one which contains its boundary points.

7. An extreme point  $Z$  of a convex set  $K$  is a point which cannot be expressed as a convex combination of any two distinct points in  $K$ .

8. The convex hull of a set of points  $S$  is the smallest convex set containing  $S$ .

Geometrically, a convex set  $K$  can be pictured as



The extreme point Z can be viewed as one of the "corners" of K.

Theorem 3.2: The set K of all feasible solutions to the linear programming problem is convex.

Proof: We must prove that every convex combination of two feasible solutions is itself a feasible solution. If there is only one feasible solution, the theorem is obviously true. Suppose then that there are at least two solutions  $x_1$  and  $x_2$ . Then  $Ax_1 = b$  and  $Ax_2 = b$ , and  $x_1, x_2 \geq 0$  by definition. We can write a convex combination of  $x_1$  and  $x_2$  as

$$X = \alpha x_1 + (1-\alpha)x_2 \quad \text{for } 0 \leq \alpha \leq 1.$$

Note that X is non-negative since all the factors involved are non-negative. Now

$$\begin{aligned} AX &= A(\alpha x_1 + (1-\alpha)x_2) \\ &= \alpha Ax_1 + (1-\alpha)Ax_2 \\ &= \alpha b + (1-\alpha)b \\ &= b \end{aligned}$$

Therefore X is in K and K is a convex set. QED

Note that K is formed by the intersection of the finite constraint sets mentioned in the definition of the problem, and therefore has a boundary consisting of parts of the hyperplanes formed by the constraints. (A hyperplane is

an "object" formed by one linear condition in  $E_n$ ; in  $E_2$  a linear condition defines a line, in  $E_3$  a plane, etc.)

The constraints state that the linear combinations of  $x_i$  are always less than or equal to  $b_i$ ; therefore  $K$  includes these boundaries and is a closed convex set.  $K$  may be either void, a convex polygon, or an unbounded convex region.

If  $K$  is void, the linear programming problem has no solution. If it is unbounded, a solution exists, but the minimum may be unbounded. However, if  $K$  is a convex polygon, we can be sure that there is a minimum finite solution to the problem. Therefore we assume that all sets  $K$  discussed here are convex polygons.

Theorem 3.3: A minimum feasible solution  $X$  occurs at an extreme point of  $K$ .

Proof: We have assumed that  $K$  is a convex polygon; therefore  $K$  has a finite number of extreme points. Let us denote the objective function by  $cX$  and the extreme points by  $x_1, x_2, \dots, x_n$ . Call the minimum feasible solution  $x_0$ . Then we know that  $cx_0 \leq cx_i$  for  $i=1, 2, \dots, n$ . If  $x_0$  is an extreme point, then the theorem is automatically true.

But suppose  $x_0$  is not an extreme point. Then  $x_0$  can be written as a convex combination of the extreme points of  $K$ .

$$(x_0 = \sum_{i=1}^n \alpha_i x_i \text{ where } \alpha_i \geq 0 \text{ and } \sum_{i=1}^n \alpha_i = 1.)$$

Thus since we have already shown that  $cX$  is a linear functional, we know that

$$cx_0 = c(\sum_{i=1}^n \alpha_i x_i) = \alpha_1 cx_1 + \alpha_2 cx_2 + \dots + \alpha_n cx_n = m$$

where  $m$  is the minimum of  $cX$  for all  $X$  in  $K$ .

Now we know that all  $\alpha_i \geq 0$ , and therefore we can substitute

for each  $cx_i$  the minimum value of  $cx_i$ . Let  $cx_m$  be this minimum value. Then

$$\begin{aligned} cx_0 &\geq \alpha_1 cx_m + \alpha_2 cx_m + \dots + \alpha_n cx_m \\ &= (\alpha_1 + \alpha_2 + \dots + \alpha_n) cx_m = cx_m \end{aligned}$$

We also assume that  $cx_0 \leq cx$  for all  $x$  in  $K$ ; therefore since  $cx_m \leq cx_0 \leq cx_m$ , then  $cx_0 = cx_m = m$ . Therefore a minimum feasible solution occurs at an extreme point of  $K$ . QED

Proofs of theorems 3.2 and 3.3 came largely from [5].

#### B. The Simplex Method

Theorem 3.3 assures us that to find the desired minimum feasible solution to a given linear programming problem, it is necessary only to look at the extreme points of  $K$ . The Simplex Method is a procedure which finds an extreme point and then determines if it is a minimum feasible solution. If this point is not the desired minimum, the method proceeds to find the next extreme point which makes the value of the objective function less than or equal to the preceding value. (Again referring to the figure above, we can think of the Simplex Method as "going around the boundary of  $K$  and examining the corners.") A minimum feasible solution can thus be found in a finite number of steps.

Using this method we can determine whether the problem has a feasible solution and a finite minimum solution, and if so what the desired minimum feasible solution is.

#### C. Application to Minimax Polynomial Approximation

Now we turn again to the polynomial minimax problem. That is, we wish to minimize the maximum value of

$$|P(x_k) - F(x_k)| \text{ for } k=1, 2, \dots, n.$$

We can introduce  $\epsilon > 0$  and formulate the following linear programming problem:

Minimize  $\epsilon$  subject to the constraints

$$\begin{aligned} P(x_k) - F(x_k) &\leq \epsilon && \text{for } k=1, 2, \dots, n \\ \text{and } P(x_k) - F(x_k) &\geq -\epsilon \end{aligned}$$

(Note that these constraints follow from the one constraint  $|P(x_k) - F(x_k)| \leq \epsilon$ , which leads to  $-\epsilon \leq P(x_k) - F(x_k) \leq \epsilon$ ).

We can express the polynomial  $P(x)$  as

$$P(x_k) = c_{k0} + \sum_{i=1}^m c_{ki} x_i \quad \text{where the } c_i \text{ are constants,}$$

and express  $F(x_k)$  as  $y_k$ .

Then we have:

Minimize  $\epsilon$  subject to

$$\begin{aligned} c_{k0} + \sum_{i=1}^m c_{ki} x_i - y_k &\leq \epsilon \\ \text{and } c_{k0} + \sum_{i=1}^m c_{ki} x_i - y_k &\geq -\epsilon \end{aligned}$$

which is equivalent to:

$$\begin{aligned} c_{k0} + \sum_{i=1}^m c_{ki} x_i - \epsilon &\leq y_k && \text{for } k=1, 2, \dots, n \\ \text{and } -c_{k0} - \sum_{i=1}^m c_{ki} x_i - \epsilon &\leq -y_k \end{aligned}$$

We now have a linear programming problem with  $2n$  constraints, and the Simplex Method can be applied to solve it.

One slight modification is necessary, however, before this method is effective. Remember that the linear programming problem assumes that the variables  $x$  for which it is solving are non-negative. In the approximation problem

we are solving for the coefficients of the approximating polynomial, which may be negative in the best approximation.

Therefore we must express each coefficient  $c_i$  as

$c_i = a_i - b$  where both  $a_i$  and  $b$  are non-negative and where  $b$  is the same for every  $a_i$ ,  $i=1,2,\dots,n$ . Intuitively this "shifts" the convex set of feasible solutions entirely into the first quadrant.

Thus the problem becomes finally:

Minimize  $\epsilon$  subject to

$$(a_{k0} - b) + \sum_{i=1}^m (a_{ki} - b)x_i - \epsilon \leq y_k \quad k=1,2,\dots,n$$

$$\text{and } -(a_{k0} - b) - \sum_{i=1}^m (a_{ki} - b)x_i - \epsilon \leq -y_k$$

#### D. Application to Minimax Rational Approximation

Remember that in this case we want to find

$R(x) = P(x)/Q(x)$  such that the maximum value of  $|F(x_k) - R(x_k)|$   $= |F(x_k) - P(x_k)/Q(x_k)|$  is minimized. Suppose we pick  $\epsilon > 0$  just as in the polynomial case. Then the problem is:

Minimize  $\epsilon$  subject to the constraints

$$F(x_k) - P(x_k)/Q(x_k) \leq \epsilon \quad k=1,2,\dots,n$$

$$\text{and } -F(x_k) + P(x_k)/Q(x_k) \leq \epsilon$$

We assume that  $P(x)$  and  $Q(x)$  have no common factor. Furthermore, to prevent division by zero, we assume that  $Q(x)$  is bounded away from zero; i.e.,  $Q(x) \geq c > 0$  for some constant  $c$ .

The constraints thus become:

$$\begin{aligned}
 F(x_k)Q(x_k) - P(x_k) &\leq \epsilon Q(x_k) \\
 -F(x_k)Q(x_k) + P(x_k) &\leq \epsilon Q(x_k) \\
 -Q(x_k) &\leq -c \\
 \text{for } k=1,2,\dots,n
 \end{aligned}$$

Introducing the notation  $p_{ki} = P_i(x_k)$  and  $q_{kj} = Q_j(x_k)$ , and  $y_k = F(x_k)$ , and adding another unknown  $L$ , which will be explained below, the problem finally becomes:

Minimize subject to the constraints:

$$\begin{aligned}
 \sum_{j=0}^n y_k q_{kj} B_j - \sum_{i=0}^m p_{ki} A_i - \sum_{j=0}^n q_{kj} B_j \epsilon - L &\leq 0 \\
 -\sum_{j=0}^n y_k q_{kj} B_j + \sum_{i=0}^m p_{ki} A_i - \sum_{j=0}^n q_{kj} B_j \epsilon - L &\leq 0 \\
 -\sum_{j=0}^n q_{kj} B_j &\leq -c
 \end{aligned}$$

which resembles a linear programming problem. However the constraints as stated are not linear in  $A_i$  and  $B_j$  since  $\epsilon$  is unknown; therefore we do not yet have a true linear programming problem. We can form such a problem by assigning to  $\epsilon$  a positive value  $\epsilon_0$ . The problem can then be solved using an iterative technique described by Loeb [9] as the "linear inequality method."

By letting  $\epsilon = \epsilon_0 > 0$ , we make the constraints linear with unknowns  $A_i$  and  $B_j$ . We then ask the question "are there rational approximations to  $F(x)$  with the maximum deviation

$$\max_{1 \leq k \leq n} |F(x_k) - R(x_k)| \leq \epsilon_0 ?$$

This question can be answered by linear programming methods, using the variable  $L$  as an objective function. If  $L$  is found to be non-positive, the linear program has a

feasible solution for the given value of  $\epsilon$ .

To obtain our answer, we apply the technique iteratively. If a solution is found for the original  $\epsilon_0$ , we try to find a solution for  $\epsilon = \epsilon_1 < \epsilon_0$ . If no solution can be found for  $\epsilon_0$ , we try  $\epsilon = \epsilon_1 > \epsilon_0$ . Thus we finally arrive at the smallest  $\epsilon$  (within bounds on error and number of iterations) for which a solution exists, and this  $\epsilon$  is the answer to our linear programming problem. The method used is that of "halving the interval," and can be described as follows:

1. Let  $\epsilon_0 = \frac{1}{2} \max_{1 \leq k \leq n} |F(x_k)|$  and  $\Delta\epsilon = \epsilon_0/2$ .

(We know that a solution exists for  $\epsilon = \max_{1 \leq k \leq n} |F(x_k)|$  since

$\max_{1 \leq k \leq n} |F(x_k) - R(x_k)| \leq \max_{1 \leq k \leq n} |F(x_k)|$  when  $R(x_k) = 0$ . Therefore

we can actually set  $\epsilon_0$  at the value stated.) Let  $\Delta\epsilon = \epsilon_0/2$ .

2. For the  $i^{\text{th}}$  iteration do one of the following:

- a. If both  $\epsilon_i$  and  $\epsilon_{i-1}$  give feasible solutions, let  $\epsilon_{i+1} = \epsilon_i - \Delta\epsilon$ .
- b. If  $\epsilon_i$  gives a feasible solution and  $\epsilon_{i-1}$  does not, let  $\Delta\epsilon = \Delta\epsilon/2$  and  $\epsilon_{i+1} = \epsilon_i - \Delta\epsilon$ .
- c. If  $\epsilon_{i-1}$  gives feasible solution and  $\epsilon_i$  does not, let  $\Delta\epsilon = \Delta\epsilon/2$  and  $\epsilon_{i+1} = \epsilon_i + \Delta\epsilon$ .
- d. If neither  $\epsilon_i$  nor  $\epsilon_{i-1}$  gives a feasible solution, let  $\epsilon_{i+1} = \epsilon_i + \Delta\epsilon$ .

Note that  $\lim_{i \rightarrow \infty} \Delta\epsilon = 0$ . Thus we can get the minimum feasible  $\epsilon$  with arbitrary accuracy.

In essence, the above process amounts to the following:  
Choose  $\epsilon_0$  first to halve the range of approximation. Then

if a feasible solution can be found with  $\epsilon_0$ , halve the lower half of the interval; if no such solution can be found, halve the upper half. Repeat this process until desired accuracy is obtained.

## CHAPTER IV

It is useful to know some approximation methods which are not minimax methods, since in many cases these are for practical purposes as accurate, and much easier to calculate than are minimax approximations.

An excellent approximation to a function  $F(x)$  is the Maclaurin series

$$F(x) = \sum_{k=0}^{\infty} c_k x^k$$

If we truncate this series after the term  $c_n x^n$ , we obtain a polynomial of degree  $\leq n$  which approximates  $F(x)$  for  $x$  near zero. Power series expansions are known for many functions, and are easy to manipulate algebraically. Also, if we are working with a power series expansion of  $F(x)$ , we do not need to be able to evaluate  $F(x)$  directly.

The main disadvantage of the power series method is that it usually does not give as good an approximation as do other methods.

There is no general method for determining exactly the coefficients of minimax polynomial approximations, and numerical methods are usually used to compute approximate values for these coefficients. An important iterative method of this type is known as Remez' method.

Suppose we want to determine the best approximation  $P_n^*(x)$  to  $F(x)$ , and assume that the error function  $P_n^*(x) - F(x)$  is standard. Then we know from Chebychev's theorem that  $P_n^*(x) - F(x)$  has exactly  $n+2$  critical points in  $[a, b]$ , including the end points. These may be written as

$$a = x_1^* < x_2^* < x_3^* < \dots < x_{n+2}^* = b$$

and we know that

$$a_0^* + a_1^* x_k^* + \dots + a_n^* (x_k^*)^n - F(x_k^*) = (-1)^k \mu^*$$

for  $k=1, 2, \dots, n+2$ , where

$$|\mu^*| = \max_{[a, b]} |P_n^*(x) - F(x)|.$$

Since we do not know the critical points, we cannot solve the system of linear equations above. The purpose of Remez' method is to compute iteratively the values of the  $x_k^*$ ,  $\mu^*$ , and the coefficients of  $P_n^*(x)$ .

The method is:

1. Select  $n+2$  numbers  $x_k$ ,  $k=1, 2, \dots, n+2$ , such that

$$a = x_1 < x_2 < x_3 < \dots < x_{n+2} = b.$$

2. Compute the coefficients of some polynomial  $P_n(x) = a_0 + a_1 x_k + \dots + a_n x_k^n$  and some number  $\mu$  by solving the linear system

$$a_0 + a_1 x_k + \dots + a_n x_k^n - (-1)^k \mu = F(x_k)$$

for  $k=1, 2, \dots, n+2$ .

for the  $n+2$  unknowns  $a_0, a_1, \dots, a_n$ , and  $\mu$ .

3. Locate the extreme points in  $[a, b]$  of the error function  $P_n(x) - F(x)$ . Assume here that there are exactly  $n+2$  of these, including the endpoints. Call them  $y_k$  as follows:

$$a = y_1 < y_2 < y_3 < \dots < y_{n+2} = b$$

4. Replace  $x_k$  by  $y_k$  for  $k=1, 2, \dots, n+2$ , and repeat beginning with step 2.

We want  $x_k$  to converge to  $x_k^*$ ,  $a_k$  to  $a_k^*$ , and  $\mu$  to  $\mu^*$ . It can be proved that this does occur for any starting values for which the value of  $\mu$  is computed to be nonzero.

Remez' method can be extended to the rational case by a similar procedure using  $m+n+2$  extreme points. For a detailed explanation, see [4].

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APPLICATION OF LINEAR PROGRAMMING  
TECHNIQUES TO MINIMAX APPROXIMATION

Volume II

Computer Results

by

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341511

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2. TWOAPP
3. THRAPP
4. LINAPP
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## DSIMPL

The simplex subroutine DSIMPL can be used to solve a linear programming problem of the form:

$$\text{Minimize } \sum_{j=1}^n C_j x_j$$

subject to the constraints

$$\sum_{j=1}^n a_{ij} x_j = b_i \quad i=1, 2, \dots, m$$

and  $x_j \geq 0$ ;  $j=1, 2, \dots, n$ , where  $C_j$ ,  $a_{ij}$ ,  $b_i$  are fixed numbers.

The calling sequence is

```
CALL DSIMPL(II,M,N,A,B,C,KO,X,P,JH,XX,Y,PE,DSOLN)
```

where II = 0

M = number of rows

N = number of variables

A, B, C are as above

KO = a subscripted variable of dimension 6

X = a subscripted variable of dimension N or more

P, JH, XX, Y, and PE = subscripted variables of dimension M or more

E = a subscripted variable of dimension  $M^2$  or more

Upon exiting from the subroutine,

DSOLN(i),  $i=1, 2, \dots, n$  contains the solution  $x(i)$ ,  $i=1, 2, \dots, n$

P(i),  $i=1, 2, \dots, m$  contains the shadow prices

KO(1) contains a 0 if problem was feasible, 1 if problem was infeasible, 2 if problem had infinite solution, and 4 or 5 if algorithm did not terminate.

KO(2) is the number of iterations taken

KO(3) is number of pivots performed since last inversion

KO(4) is number of inversions performed

KO(5) is number of pivot steps performed

KO(6) contains number of the variable that was infinite, if problem had infinite solution

```

C AUTOMATIC DOUBLE PRECISION SIMPLEX      REDUNDANT EQUATIONS CAUSE INFEASIBILITY
0001      SUBROUTINE DSIMPL(INFLAG,MX,NN,A,B,C,KO,KB,P,JH,X,Y,PE,E,DSOLN)
0002      DOUBLE PRECISION B(2),C(2),P(2),X(2),Y(2),PE(2),E(2),DSOLN(2)
C THE FOLLOWING DIMENSION SHOULD BE THE SAME HERE AS IT IS IN CALLER
0003      DOUBLE PRECISION A(40,45)
0004      DOUBLE PRECISION AA,ALJT,BB,COST,DT,RCOST,TEXP,TPIV,TY,XOLD,XY,XY,
*          XT,YMAX
0005      INTEGER INFLAG,MX,NN,KO(6),KB(1),JH(1)
0006      INTEGER I,IA,INVc,ITER,J,JI,K,KBJ,L,LL,M,M2,MM,N
0007      INTEGER NCUT,NPTV,NUMVR,NVER,FEAS,VER,NEG,TRIG,KO,ABSC

C
C      SET INITIAL VALUES, SET CONSTANT VALUES
0008      ITER=0
0009      NUMVR=0
0010      NUMPV=0
0011      M=MX
0012      N=NN
0013      TEXP=.5**16
0014      NCUT=4*M + 10
0015      NVER=M/2 + 5
0016      M2=M**2
0017      FEAS=0
0018      IF (INFLAG) 1400,1,1400
C* 'NEW' START PHASE ONE WITH SINGLETON BASIS
0019      1 DO 1402 J=1,N
0020          KB(J)=0
0021          KO=0
0022          DO 1403 T=1,M
0023              IF (A(I,J)) 2,1403,2
0024              2 IF (KO) 3,3,1402
0025              3 IF (A(T,J)) 1402,4,4
0026              4 KO=1
0027      1403 CONTINUE
0028      KB(J)=1
0029      1402 CONTINUE
0030      1400 DO 1401 I=1,M
0031          JH(I)=-1
0032      1401 CONTINUE
C* 'VER' CREATE INVERSE FROM 'KB' AND 'JH' (STEP 7)
0033      1320 VER=1
0034          TNVC=0
0035          NUMVR=NUMVR+1
0036          TRIG=0
0037          DO 1101 T=1,M2
0038              E(T)=0.0
0039      1101 CONTINUE
0040          MM=1
0041          DO 1113 T=1,M
0042              E(MM)=1.0
0043              PE(I)=0.0
0044              X(I)=B(I)
0045              IF (JH(I)) 5,6,5
0046              5 JH(I)=-1
0047              6 MM=MM+M+1

```

```

0048      1113 CONTINUE
C          FORM INVERSE
0049      DO 1102 JT=1,N
0050      IF (KB(JT)) 600,1102,600
C 600    CALL JMY
C          CHOOSE PIVOT
0051      1114 TY=0.0
0052      KO=0
0053      DO 1104 I=1,M
0054      IF (JH(I)+1) 1104,7,1104
0055      7  IF (DABS(Y(I))-TPIV) 1104,1104,8
0056      8  IF (KO) 9,9,1116
0057      9  IF (X(I)) 10,1115,10
0058      10  IF (DABS(Y(I)/X(I))-TY) 1104,1104,11
0059      11  TY=DABS(Y(I)/X(I))
0060      GO TO 1118
0061      1115 KO=1
0062      GO TO 1117
0063      1116 IF (X(I)) 1104,12,1104
0064      12  IF (DABS(Y(I))-TY) 1104,1104,1117
0065      1117 TY=DABS(Y(I))
0066      1118 IR=I
0067      1104 CONTINUE
0068      KB(JT)=0
C          TEST PIVOT
0069      IF (TY) 1102,1102,900
C          PIVOT
C 900    CALL PIV
0070      1102 CONTINUE
C          RESET ARTIFICIALS
0071      DO 1109 I=1,M
0072      IF (JH(I)+1) 14,13,14
0073      13  JH(I)=0
0074      14  IF (JH(I)) 1109,15,1109
0075      15  FEAS=0
0076      1109 CONTINUE
0077      1200 VER=0
C          *** PERFORM ONE ITERATION ***
C* 'XCK' DETERMINE FEASIBILITY (STEP 1)
0078      NEG=0
0079      IF (FEAS) 16,16,500
0080      16 FEAS=1
0081      DO 1201 T=1,M
0082      IF (X(T)) 1250,17,17
0083      17  IF (JH(T)) 1201,18,1201
0084      18  FEAS=0
0085      1201 CONTINUE
C* 'GET' GET APPLICABLE PRICES (STEP 2)
0086      IF (FEAS) 500,501,500
0087      500 DO 503 I=1,M
0088      P(I)=PE(I)
0089      IF (X(I)) 19,503,503
0090      19  X(I)=0.
0091      503 CONTINUE

```

```

0092      ABSC=0
0093      GO TO 599
0094      1250 FEAS=0
0095      NEG=1
0096      501 DO 504 J=1,M
0097      P(J)=0.
0098      504 CONTINUE
0099      ABSC=1
0100      DO 505 T=1,M
0101      MM=T
0102      IF (X(T)) 20,507,507
0103      20 ABSC=0
0104      DO 508 J=1,M
0105      P(J)=P(J)+E(MM)
0106      MM=MM+M
0107      508 CONTINUE
0108      GO TO 505
0109      507 IF (JH(T)) 505,21,505
0110      21 IF (X(T)) 22,23,22
0111      22 ABSC=0
0112      23 DO 510 J=1,M
0113      P(J)=P(J)-E(MM)
0114      MM=MM+M
0115      510 CONTINUE
0116      505 CONTINUE
C* 'MTN' FIND MINIMUM REDUCED COST (STEP 3)
0117      599 JT=0
0118      BB=0.0
0119      DO 701 J=1,N
0120      IF (KB(J)) 701,24,701
0121      24 DT=0.0
0122      DO 303 T=1,M
0123      DT=DT+P(T)*A(T,J)
0124      303 CONTINUE
0125      IF (FEAS) 26,26,25
0126      25 DT=DT+C(J)
0127      26 IF (ABSC) 29,28,27
0128      27 DT=-DABS(DT)
0129      28 IF (DT-BB) 29,701,701
0130      29 BB=DT
0131      JT=J
0132      701 CONTINUE
C TEST FOR NO PIVOT COLUMN
0133      IF (JT) 203,203,30
C TEST FOR ITERATION LIMIT EXCEEDED
0134      30 IF (ITER-NCUT) 31,160,160
0135      31 ITER=ITER+1
C* 'JMY' MULTIPLY INVERSE TIMES A(..JT) (STEP 4)
0136      600 DO 610 I=1,M
0137      Y(I)=0.0
0138      610 CONTINUE
0139      LL=0
0140      COST=C(JT)
0141      DO 605 T=1,M

```

```

0142      AIJT=A(I,JT)
0143      IF (AIJT) 32,602,32
0144      32 COST=COST+AIJT*PE(I)
0145      DO 606 J=1,M
0146      LL=LL+1
0147      Y(J)=Y(J)+AIJT*E(LL)
0148      606 CONTINUE
0149      GO TO 605
0150      602 LL=LL+M
0151      605 CONTINUE
C      COMPUTE PIVOT TOLERANCE
0152      YMAY=0.0
0153      DO 620 T=1,M
0154      YMAY=DMAX1(DABS(Y(T)),YMAY)
0155      620 CONTINUE
0156      TPYV=YMAY*TEXP
C      RETURN TO INVERSION ROUTINE, IF INVERTING
0157      IF (VER) 33,33,1114
C      COST TOLERANCE CONTROL
0158      33 RCOST=YMAY/BB
0159      IF (TRIG) 35,35,34
0160      34 IF (BB+TPYV) 35,203,203
0161      35 TRIG=0
0162      IF (BB+TPYV) 37,36,36
0163      36 TRIG=1
C* 'ROW' SELECT PIVOT ROW          (STEP 5)
C AMONG EQUATIONS WITH X=0, FIND MAXIMUM Y AMONG ARTIFICIALS, OR IF NONE,
C GET MAX POSITIVE Y(I) AMONG REALS.
0164      37 TR=0
0165      AA=0.0
0166      KO=0
0167      DO 1050 I=1,M
0168      IF (X(I)) 1050,38,1050
0169      38 IF (Y(I)-TPYV) 1050,1050,39
0170      39 IF (JH(I)) 40,1044,40
0171      40 IF (KO) 1045,1045,1050
0172      1045 IF (Y(I)-AA) 1050,1050,1047
0173      1044 IF (KO) 41,41,1045
0174      41 KO=1
0175      1047 AA=Y(I)
0176      TR=T
0177      1050 CONTINUE
0178      IF (TR) 1099,42,1099
0179      42 AA=1.0E+20
C      FIND MIN. PIVOT AMONG POSITIVE EQUATIONS
0180      DO 1010 I=1,M
0181      IF (Y(I)-TPYV) 1010,1010,43
0182      43 IF (X(I)) 1010,1010,44
0183      44 IF (Y(I)*AA-X(I)) 1010,1010,45
0184      45 AA=X(I)/Y(I)
0185      TR=T
0186      1010 CONTINUE
0187      IF (NEG) 46,1099,46
C FIND PIVOT AMONG NEGATIVE EQUATIONS, IN WHICH X/Y IS LESS THAN THE

```

C MINIMUM X/Y IN POSITIVE EQUATIONS, THAT HAS THE LARGEST ABSF(Y)

```

0188    46 BB=-TPYV
0189    DO 1030 I=1,M
0190      IF (X(I)) 47,1030,1030
0191    47 IF (Y(I)-BB) 48,1030,1030
0192    48 IF (Y(I)*AA-X(I)) 49,49,1030
0193    49 BB=Y(I)
0194      IR=I
0195    1030 CONTINUE
C TEST FOR NO PIVOT ROW
0196    1099 IF (IR) 207,207,50
C* 'PIV' PIVOT ON (IR, JT)          (STEP 6)
0197      50 TA=JH(IR)
0198      IF (TA) 900,900,51
0199      51 KB(TA)=0
0200    900 NUMPV=NUMPV+1
0201      JH(IR)=JT
0202      KB(JT)=IR
0203      YT=-Y(IR)
0204      Y(IR)=-1.0
0205      LL=0
C TRANSFORM INVERSE
0206    DO 904 J=1,M
0207      L=LL+IR
0208      IF (E(L)) 905,52,905
0209      52 LL=LL+M
0210      GO TO 904
0211    905 XY=E(L)/YT
0212      PE(J)=PE(J)+COST*XY
0213      E(L)=0.0
0214      DO 906 I=1,M
0215      LL=LL+1
0216      E(LL)=E(LL)+XY*Y(I)
0217    906 CONTINUE
0218    904 CONTINUE
C TRANSFORM X
0219      XY=X(IR)/YT
0220    DO 908 I=1,M
0221      XOLD=X(I)
0222      X(I)=XOLD+XY*Y(I)
0223      IF (VER) 908,53,908
0224      53 IF (X(I)) 54,908,908
0225      54 IF (XOLD) 908,55,55
0226      55 X(I)=0.
0227    908 CONTINUE
0228      Y(IR)=-YT
0229      Y(IR)=-XY
0230      IF (VER) 56,56,1102
0231      56 IF (NUMPV-M) 1200,1200,57
C TEST FOR INVERSION ON THIS ITERATION
0232      57 INV=INV+1
0233      IF (INV-NVER) 1200,1320,1200
C* END OF ALGORITHM, SET EXIT VALUES ***
```

0234 207 IF (FEAS) 58,203,58

```
0235      58 IF (RCOST+1000.) 203,203,59
          C INFINITE SOLUTION
0236      59 K=2
0237      GO TO 250
          C PROBLEM IS CYCLING
0238      160 K=4
0239      GO TO 250
          C FEASIBLE OR INFEASIBLE SOLUTION
0240      203 K=0
0241      250 TF (FEAS) 61,60,61
0242      60 K=K+1
0243      61 DO 1399 J=1,N
0244      XX=0.0
0245      KBJ=KB(J)
0246      TF (KBJ) 62,63,62
0247      62 XX=X(KBJ)
0248      63 DSOLN (J)=XX
0249      1399 CONTINUE
0250      KO(1)=K
0251      KO(2)=ITTER
0252      KO(3)=TNVC
0253      KO(4)=NUMVR
0254      KO(5)=NUMPV
0255      KO(6)=JT
0256      RETURN
0257      END
```

FORTRAN IV G LEVEL 1, MOD 2

DSTIMPL

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15/57/40

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SCALAR MAP									
SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION
TEXP	438	TY	440	TPIV	448	BB	450	DT	458
COST	460	AIJT	468	YMAX	470	RCOST	478	AA	480
XY	488	XOLD	490	XX	498	ITER	4A0	NUMVR	4A4
NUMPY	4A8	M	4AC	MX	4B0	N	4B4	NN	4B8
NCUT	4BC	NVER	4C0	M2	4C4	FEAS	4C8	INFLAG	4CC
J	4D0	KO	4E4	I	4D8	VER	4DC	INVVC	4E0
TRIG	4E4	MM	4E8	JT	4EC	TR	4F0	NEG	4F4
ABSC	4F8	LL	4FC	IA	500	YT	504	L	508
K	50C	KBJ	510						

ARRAY MAP									
SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION
B	514	C	518	P	51C	X	520	Y	524
PE	528	E	52C	DSOLN	530	A	534	KO	538
KB	53C	JH	540						

SUBPROGRAMS CALLED									
SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION
FRYPIT#	544	DMAX1	548						

TOTAL MEMORY REQUIREMENTS 001590 BYTES

TWOAPP  
(Approximation of two points by a line)

Note that this case of approximation is essentially the same as interpolation, since we are using a polynomial of degree  $n-1$  to approximate  $n$  points. Therefore we would expect the error to be zero. The problem is a simple one, and was especially set up so that answers could easily be checked.

The original equation is  $Ox + 92 = y$   
and the given points are  $x_1 = 67$  and  $x_2 = 324$

We wish to approximate using  $P(x) = Ax + B$ , and hope to obtain  $A = 0$  and  $B = 92$ .

The problem is set up for linear programming as follows:

$$-\epsilon \leq Ax + B - y \leq \epsilon$$

or 
$$\begin{aligned} -Ax - B + y &\leq \epsilon \\ Ax + B - y &\leq \epsilon \end{aligned}$$
 for  $x_1, x_2$

and expressing each coefficient as the difference of two positive numbers, we obtain

$$\begin{aligned} -(A-C)x - (B-C) + y &\leq \epsilon \\ (A-C)x + (B-C) - y &\leq \epsilon \end{aligned}$$

or 
$$\begin{aligned} -Ax + Cx - B + C + y &\leq \epsilon \\ Ax - Cx + B - C - y &\leq \epsilon \end{aligned}$$

which finally becomes

$$\begin{aligned} -Ax - B + C(x+1) - \epsilon &\leq -y & \text{for } x_1, x_2 \\ Ax + B - C(x+1) - \epsilon &\leq y \end{aligned}$$

Thus our linear programming matrix of constraints is

$$\left[ \begin{array}{cccc} -67 & -1 & 68 & -1 \\ -324 & -1 & 325 & -1 \\ 67 & 1 & -68 & -1 \\ 324 & 1 & -325 & -1 \end{array} \right] \begin{pmatrix} A \\ B \\ C \\ \epsilon \end{pmatrix} \leq \begin{pmatrix} -92 \\ -92 \\ 92 \\ 92 \end{pmatrix}$$



C APPROXIMATION OF TWO POINTS BY A LINE

```

0001      DOUBLE PRECISION A(4,8),B(4),C(8),P(4),XX(4),Y(4),PE(4),X(8),
0002      *E(16),DSOLN(8),JH(4),T(8),MINOBJ
0003      DIMENSION KO(6)
0004      WRITE(3,6)
0005      READ(1,1) II,M,N,NR
0006      DO 2 I=1,M
0007      2 READ(1,4) (A(I,J),J=1,N) } Read in A and B matrices
0008      READ(1,4) (B(I),I=1,M)
0009      DO 5 I=1,N
0010      5 C(I)=0.0 } insert objective function
          C(NR)=1.0

```

C PRINT OUT A,B, AND C VALUES

```

0011      WRITE(3,102)
0012      DO 20 I=1,M
0013      20 WRITE(3,100) (A(I,J),J=1,N)
0014      WRITE(3,101) (B(I),I=1,M)
0015      WRITE(3,90) (C(I),I=1,N)
0016      CALL DSIMPL(II,M,N,A,B,C,KO,X,P,JH,XX,Y,PE,E,DSOLN)
0017      NR1=NR-1
0018      NR2=NR-2
0019      DO 7 I=1,NR2
0020      7 T(I)=DSOLN(I)-DSOLN(NR1) } Here we subtract the two positive components of the coefficient
0021      WRITE(3,97) (T(I),I=1,NR2) to get its true value
0022      MINOBJ=0.0
0023      DO 13 I=1,N
0024      13 MINOBJ=MINOBJ+C(I)*DSOLN(I) ) Find minimum value of objective function
0025      WRITE(3,24) MINOBJ
0026      6 FORMAT(' SIMPLE POLYNOMIAL APPROXIMATION')
0027      1 FORMAT(4I10)
0028      4 FORMAT(8D7.1)
0029      102 FORMAT(' MATRIX OF CONSTRAINTS, BY ROWS')
0030      100 FORMAT(4D28.16)
0031      101 FORMAT(' RIGHT HAND SIDE VECTOR'/(4D28.16))
0032      90 FORMAT(' OBJECTIVE FUNCTION'/(1',4D28.16))
0033      97 FORMAT(' SOLUTION'/(2D28.16))
0034      24 FORMAT(' MINIMUM VALUE OF OBJECTIVE FUNCTION IS ',D28.16)
0035      RETURN
0036      END

```

N COVS

M ROWS

$$C_1 A + C_2 B + C_3 C + C_4 E = \xi$$

FORTRAN IV G LEVEL 1, MOD 2

MAIN

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SCALAR MAP									
SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION
MINOBJ	C0	TI	C8	M	CC	N	DO	NR	D4
I	D8	J	DC	NR1	E0	NR2	E4		

ARRAY MAP									
SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION
A	E8	B	1E8	C	208	P	248	XX	268
Y	288	PE	2A8	X	2C8	E	308	DSOLN	388
JH	3C8	T	3E8	KO	428				

SUBPROGRAMS CALLED									
SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION
IBCOM#	440	DSTMPL	444						

FORMAT STATEMENT MAP									
SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION
6	484	1	4A8	4	4AE	102	4B5	100	4D8
101	4DF	90	504	97	528	24	53F		

TOTAL MEMORY REQUIREMENTS 00090A BYTES

```

IEF285I SYS69126.T122805.RP007.TWOAP631.LOADSET PASSED
IEF285I VOL SER NOS= HYPERD.
IEF285I SYS1.FORTLIB KEPT
IEF285I VOL SER NOS= HYPERD.
IEF285I SYS1.SUBLIB KEPT
IEF285I VOL SER NOS= HYPERD.
IEF285I SYS69126.T122805.RP007.TWOAP631.UT1 DELETED
IEF285I VOL SER NOS= HYPERD.
IEF285I SYSOUT
IEF285I VOL SER NOS=
IEF285I SYS69126.T122805.RP007.TWOAP631.LOADSET PASSED
IEF285I VOL SER NOS= HYPERD.
IEF285I SYS69126.T122805.RP007.TWCAP631.OBJSET DELETED
IEF285I VOL SER NOS= HYPERD.
***** LKED TIMES-ELAP -----0:08.97 CPU ----0:01.983 WAIT ----0:04.417 READY ----0:02.567 RETURN CODE 0
*** EXCEP'S--UR -----59 TAPE -----00 DISK -----39 HYDISK -----714 OTHER -----00
//GO EXEC PGM=*,LKED,SYSMOD,COND=((5,LT,FORT),(5,LT,LKED)) 00003600
//FT03F001 DD SYSOUT=A,DCB=(RECFM=UA,BLKSIZE=133,LRECL=133) 00003800
//FT02F001 DD SYSOUT=B,DCB=(RECFM=FB,BLKSIZE=80,LRECL=80) 00004000
//FT01F001 DD DDNAME=SYSIN 00004200
//GO.SYSIN DD *
IEF236I ALLOC. FOR TWOAP631 GO
IEF237I PGM=*,DD ON 490
IEF237I FT01F001 ON 012

```

SIMPLE POLYNOMIAL APPROXIMATION  
MATRIX OF CONSTRAINTS, BY ROWS

-0.670000000000000D 02	-0.999999999999999D 00	0.680000000000000D 02	-0.999999999999999D 00
0.999999999999999D 00	0.0	0.0	0.0
-0.323999999999999D 03	-0.999999999999999D 00	0.324999999999999D 03	-0.999999999999999D 00
0.0	0.999999999999999D 00	0.0	0.0
0.670000000000000D 02	0.999999999999999D 00	-0.680000000000000D 02	-0.999999999999999D 00
0.0	0.0	0.999999999999999D 00	0.0
0.323999999999999D 03	0.999999999999999D 00	-0.324999999999999D 03	-0.999999999999999D 00
0.0	0.0	0.0	0.999999999999999D 00

RIGHT HAND SIDE VECTOR

-0.920000000000000D 02	-0.920000000000000D 02	0.920000000000000D 02	0.920000000000000D 02
------------------------	------------------------	-----------------------	-----------------------

OBJECTIVE FUNCTION

0.0	0.0	0.0	0.999999999999999D 00
0.0	0.0	0.0	0.0

SOLUTION

0.0	0.920000625476283D 02
-----	-----------------------

A=0 B=92

MINIMUM VALUE OF OBJECTIVE FUNCTION IS

0.4996011213124001D-15

This is equal to zero within round-off error

PRINT OUT (COL1)

TEF285I SYS69126.T122805.RPC07.TWOAPP631.LOADSET PASSED  
IEF285I VOL SER NOS= HYPERD.  
IEF285I SYSOUT  
IEF285I VOL SER NOS= .  
\*\*\*\*\* GO TIMES-ELAP ----0:02.13 CPU ----0:00.683 WAIT ----0:00.583 READY ----0:00.867 RETURN CODE 0  
\*\*\*\*\* EXCP'S--UR -----57 TAPE -----00 DISK -----13 HYDISK -----205 OTHER -----00  
// TEF285I SYS69126.T122805.RPC07.TWOAPP631.LOADSET DELETED  
IEF285I VOL SER NOS= HYPERD.  
\*\*\*\*\* TWOAPP TIMES-ELAP ----0:24.02 CPU ----0:09.367 WAIT ----0:08.600 READY ----0:06.050 COP.UNCG.B  
\*\*\*\*\* EXCP'S--UR -----375 TAPE -----00 DISK -----77 HYDISK ---1,340 OTHER -----00  
CARDS IN 00348 PAGES 0013

RELEASE 14.6

THRAPP  
(Approximation of three points by a quadratic)

In this case again we have essentially an interpolation problem, and again we expect zero error.

The original equation is  $16x^2 + 35x + 40 = y$ , and the given points are  $x_1=20$ ,  $x_2=30$ ,  $x_3=50$ .

Calculations give  $y_1=7140$ ,  $y_2=15490$ ,  $y_3=41790$

We will approximate using  $P(x)=Ax^2 + Bx + C$ . The linear programming problem is set up as follows:

$$-\epsilon \leq Ax^2 + Bx + C - y \leq \epsilon$$

or  $\begin{aligned} -Ax_2^2 - Bx_2 - C + y &\leq \epsilon \\ Ax_2^2 + Bx_2 + C - y &\leq \epsilon \end{aligned}$

and putting in the necessary positive constant

$$\begin{aligned} -(A-D)x_2^2 - (B-D)x_2 - (C-D) + y &\leq \epsilon \\ (A-D)x_2^2 + (B-D)x_2 + (C-D) - y &\leq \epsilon \end{aligned}$$

which becomes

$$\begin{aligned} -Ax_2^2 - Bx_2 - C + (x_2+1)D - \epsilon &\leq -y \\ Ax_2^2 + Bx_2 + C - (x_2+1)D - \epsilon &\leq y \end{aligned} \quad \text{for } x_1, x_2, x_3$$

and the constraint matrix becomes

$$\left[ \begin{array}{cccccc} -400 & -20 & -1 & 401 & -1 & -1 \\ -900 & -30 & -1 & 901 & -1 & -1 \\ -2500 & -50 & -1 & 2501 & -1 & -1 \\ 400 & 20 & 1 & -401 & -1 & -1 \\ 900 & 30 & 1 & -901 & -1 & -1 \\ 2500 & 50 & 1 & -2501 & -1 & -1 \end{array} \right] \begin{bmatrix} A \\ B \\ C \\ D \\ \epsilon \end{bmatrix} \leq \begin{bmatrix} -7140 \\ -15490 \\ -41790 \\ 7140 \\ 15490 \\ 41790 \end{bmatrix}$$



```

C APPROXIMATION OF THREE POINTS BY A QUADRATIC
0001      DOUBLE PRECISION A(6,11),B(6),C(11),P(6),XX(6),Y(6),PE(6),
          *X(11),E(36),DSOLN(11),JH(6),T(11),R(3),BA(3),MINOBJ
0002      DIMENSION KO(6)
0003      WRITE(3,6)
0004      READ(1,1) II,M,N,NR
0005      READ(1,4) R(1),R(2),R(3)
0006      DO 2 I=1,3
0007      2 BA(I)=R(I)*R(I)+R(I)+1.
0008      M2=M/2
0009      M21=M2+1
0010      DO 3 I=1,M2
0011      A(I,1)=- (R(I)*R(I)) } Put in A and B matrices
0012      A(I,2)=-R(I)
0013      A(I,3)=-1.0
0014      A(I,4)=BA(I)
0015      3 A(I,5)=-1.0
0016      DO 76 I=M21,M
0017      TR=I-M2
0018      A(I,1)=R(TR)*R(TR)
0019      A(I,2)=R(TR)
0020      A(I,3)=1.0
0021      A(I,4)=-BA(TR)
0022      76 A(I,5)=-1.0
0023      READ(1,77) (B(I),I=1,M)
0024      DO 5 I=1,N
0025      5 C(I)=0.0
0026      C(NR)=1.0
C PUT IN SLACK VARIABLES
0027      NR1=NR+1
0028      DO 21 I=1,M
0029      DO 21 J=NR1,N
0030      NRT=I+NR
0031      IF(NRT.EQ.J) GO TO 36
0032      A(I,J)=0.0
0033      GO TO 21
0034      36 A(I,J)=1.0
0035      21 CONTINUE
C PRINT OUT A,B,AND C VALUES
0036      WRITE(3,102)
0037      DO 20 I=1,M
0038      20 WRITE(3,100) (A(I,J),J=1,N)
0039      WRITE(3,101) (B(I),I=1,M)
0040      WRITE(3,90) (C(I),I=1,N)
0041      CALL DSIMPL(II,M,N,A,B,C,KO,X,P,JH,XX,Y,PE,E,DSOLN)
0042      NR1=NR-1
0043      NR2=NR-2
0044      DO 7 I=1,NR2 } subtract components of coefficients
0045      7 T(I)=DSOLN(I)-DSOLN(NR1)
0046      WRITE(3,97) (T(I),I=1,NR2)
0047      MINOBJ=0.0
0048      DO 13 I=1,N
0049      13 MINOBJ=MINOBJ+C(I)*DSOLN(I)
0050      WRITE(3,24) MINOBJ

```

FORTRAN IV G LEVEL 1, MOD 2

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```
0051      6 FORMAT(' QUADRATIC POLYNOMIAL APPROXIMATION')
0052      1 FORMAT(4I10)
0053      4 FORMAT(3D6.1)
0054      77 FORMAT(6D9.1)
0055      102 FORMAT(' MATRIX OF CONSTRAINTS, BY ROWS')
0056      100 FORMAT(4D28.16)
0057      101 FORMAT('// RIGHT HAND SIDE VECTOR'/(4D28.16))
0058      90 FORMAT('// OBJECTIVE FUNCTION'/(1',4D28.16))
0059      97 FORMAT('// SOLUTION'/(3D28.16))
0060      24 FORMAT('// MINIMUM VALUE OF OBJECTIVE FUNCTION IS ',D28.16)
0061      RETURN
0062      END
```

FORTRAN IV G LEVEL 1, MOD 21076 SOURCE: MAIN LIST

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SCALAR MAP

SYMBOL	LOCATION								
MINOBJ	E0	II	E8	M	EC	N	F0	NR	F4
I	F8	M2	FC	M21	100	IR	104	NR1	108
J	10C	NRI	110	NR2	114				

ARRAY MAP

SYMBOL	LOCATION								
A	118	B	328	C	358	P	380	XX	3E0
V	410	PE	440	X	470	E	4C8	DSOLN	5E8
JH	640	T	670	R	6C8	BA	6E0	KO	6F8

SUBPROGRAMS CALLED

SYMBOL	LOCATION								
TRCOM#	710	DSIMPL	714						

FORMAT STATEMENT MAP

SYMBOL	LOCATION								
6	754	1	77B	4	781	77	788	102	78F
100	7B2	101	7E9	90	7DE	97	802	24	819

TOTAL MEMORY REQUIREMENTS 000D62 BYTES

E-LEVEL LINKAGE EDITOR OPTIONS SPECIFIED MAP, LIST  
 \*\*\*\*USERPROG DOES NOT EXIST BUT HAS BEEN ADDED TO DATA SET

MODULE MAP

CONTROL SECTION			ENTRY		PROCESSING				RETURN CODE	
NAME	ORIGIN	LENGTH	NAME	LOCATION	NAME	LOCATION	NAME	LOCATION	NAME	LOCATION
MAIN	00	D62								
DSIMPL	D68	1590								
IHCFCOMH*	22F8	F00	TBCOM#	22F8	FDI0CS#	23B4	INTSW	30B4		
IHCUOPT *	31F8	8								
IHCCTRCH *	3200	2C8								
IHCFRXPT*	34C8	94	FRXPT#	34C8						
IHCFCMAXD*	3560	6D	DMAX1	3560	DMIN1	3576				
IHCFCVTH*	35D0	10A5	ADCON#	35D0	FCVZO	371C	FCVAO	37C2	FCVLO	3852
			FCVIO	3B88	FCVRO	408A	FCVCO	42A4	INT6SW	4660
IHCFIOSH*	4678	DAA	FTOCS#	4678						
IHCNATBL*	5428	638								
IHCFINTH*	5460	3A6	ARITH#	5A60	ADJSW	5D25				
ENTRY ADDRESS	00									
TOTAL LENGTH	5E06									

\*\*\*\*\* LKED ELAPSED TIME ----- TASK PROCESSING TIME -----:01.510 RETURN CODE 0

//GO.SYSIN DD \*

QUADRATIC POLYNOMIAL APPROXIMATION

MATRIX OF CONSTRAINTS, BY ROWS

Row 1	-0.4000000000000000D 03	-0.1999999999999999D 02	-0.9999999999999990D 00	0.4209999999999999D 03
	-0.999999999999990D 00	0.999999999999990D 00	0.0	0.0
	0.0	0.0	0.0	
Row 2	-0.9000000000000000D 03	-0.3000000000000000D 02	-0.999999999999990D 00	0.9310000000000000D 03
	-0.999999999999990D 00	0.0	0.999999999999990D 00	0.0
	0.0	0.0	0.0	
Row 3	-0.2499999999999999D 04	-0.5000000000000000D 02	-0.999999999999990D 00	0.2550999999999999D 04
	-0.999999999999990D 00	0.0	0.999999999999990D 00	
	0.0	0.0	0.0	
Row 4	0.4000000000000000D 03	0.1999999999999999D 02	0.999999999999990D 00	-0.4209999999999999D 03
	0.999999999999990D 00	0.0	0.0	
	0.999999999999990D 00	0.0	0.0	
Row 5	0.9000000000000000D 03	0.3000000000000000D 02	0.999999999999990D 00	-0.9310000000000000D 03
	-0.999999999999990D 00	0.0	0.0	
	0.0	0.0	0.0	
Row 6	0.2499999999999999D 04	0.5000000000000000D 02	0.999999999999990D 00	-0.2550999999999999D 04
	-0.999999999999990D 00	0.0	0.0	
	0.0	0.0	0.999999999999990D 00	

RIGHT HAND SIDE VECTOR

-0.7139999999999999D 04	-0.1548999999999999D 05	-0.4178999999999999D 05	0.7139999999999999D 04
0.1548999999999999D 05	0.4178999999999999D 05		

OBJECTIVE FUNCTION

0.0 0.0 0.0 0.0  
0.999999999999990D 00 0.0 0.0 0.0  
0.0 0.0 0.0

SOLUTION

0.160000000591117D 02 0.3499999958621747D 02 0.4000000650229682D 02

A= 16 B= 35 C= 40

MINIMUM VALUE OF OBJECTIVE FUNCTION IS 0.0

\*\*\* GO ELAPSED TIME ----- TASK PROCESSING TIME -----:00.970 RETURN CODE 0

\*\*\* THRAPP ELAPSED TIME ----- TASK PROCESSING TIME -----:09.08 COP.UNCG.B

RELEASE 14.6

Print 100(1)

0.0  
0.999999999999  
0.0

SOLUTION  
0.1600000005911

MINIMUM VALUE OF OBJECT

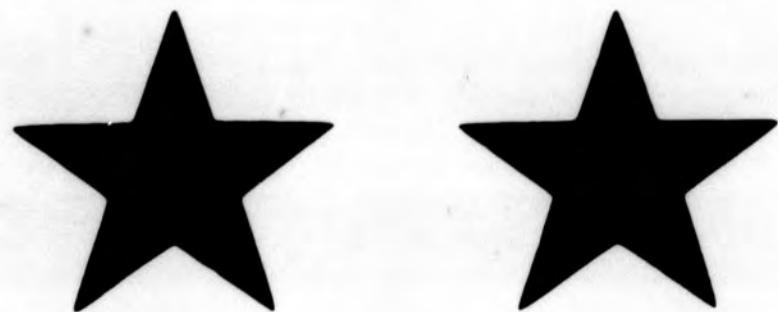
\*\*\*\*\* GO ELA

\*\*\*\*\* THRAPP ELA

RELEASE 14.6

5 C = 40

# CORRECTION



***PRECEDING IMAGE HAS BEEN  
REFILMED  
TO ASSURE LEGIBILITY OR TO  
CORRECT A POSSIBLE ERROR***

0.0 0.0 0.0 0.0  
0.999999999999999D 00 0.0 0.0 0.0  
0.0 0.0 0.0 0.0

## SOLUTION

0.160000000591117D 02

0.349999958621747D 02

0.400000650229682D 02

A = 16 B = 35 C = 40

MINIMUM VALUE OF OBJECTIVE FUNCTION IS 0.0

\*\*\*\*\* GO ELAPSED TIME ----- TASK PROCESSING TIME -----:00.970 RETURN CODE 0

\*\*\*\*\* THRAPP ELAPSED TIME ----- TASK PROCESSING TIME -----:09.08 COP.UNCG.B +

RELEASE 14.6

Print 1(6(5)

LINAPP

(Approximation of three points by a line)

The purpose of this program is to illustrate the fact that by using a polynomial of degree less than that needed for interpolation we get a less accurate approximation.

The problem is the same as that for THRAPP:

$$16x^2 + 35x + 40 = y, \text{ evaluated at } x_1=20, x_2=30, x_3=50.$$

We will approximate using  $P(x)=Ax + B$ , and therefore the linear programming set-up is the same as for TWOAPP. The constraint matrix is

$$\begin{bmatrix} -20 & -1 & 21 & -1 \\ -30 & -1 & 31 & -1 \\ -50 & -1 & 51 & -1 \\ 20 & 1 & -21 & -1 \\ 30 & 1 & -31 & -1 \\ 50 & 1 & -51 & -1 \end{bmatrix} \begin{bmatrix} A \\ B \\ C \\ \epsilon \end{bmatrix} \leq \begin{bmatrix} -7140 \\ -15490 \\ -41790 \\ 7140 \\ 15490 \\ 41790 \end{bmatrix}$$



```
C APPROXIMATION OF THREE POINTS BY A LINE
0001      DOUBLE PRECISION A(6,10),B(6),C(10),P(6),XX(6),Y(6),PE(6),
          *X(10),E(36),DSOLN(10),JH(6),T(10),MINOBJ
0002      DIMENSION KO(6)
0003      WRITE(3,6)
0004      READ(1,1) II,M,N,NR
0005      DO 2 I=1,M
0006      2 READ(1,4)(A(I,J),J=1,N)
0007      READ(1,200)(B(I),I=1,M)
0008      DO 5 I=1,N
0009      5 C(I)=0.0
0010      C(NR)=1.0
C PRINT OUT A,B, AND C VALUES
0011      WRITE(3,102)
0012      DO 20 I=1,M
0013      20 WRITE(3,100)(A(I,J),J=1,N)
0014      WRITE(3,101)(B(I),I=1,M)
0015      WRITE(3,90)(C(I),I=1,N)
0016      CALL DSIMPL(II,M,N,A,B,C,KO,X,P,JH,XX,Y,PE,E,DSOLN)
0017      NR1=NR-1
0018      NR2=NR-2
0019      DO 7 I=1,NR2
0020      7 T(I)=DSOLN(I)-DSOLN(NR1)
0021      WRITE(3,97)(T(I),I=1,NR2)
0022      MINOBJ=0.0
0023      DO 13 I=1,N
0024      13 MINOBJ=MINOBJ+C(I)*DSOLN(I)
0025      WRITE(3,24)MINOBJ
0026      6 FORMAT(' APPROXIMATION OF THREE POINTS BY A LINE')
0027      1 FORMAT(4I10)
0028      4 FORMAT(10D7.1)
0029      200 FORMAT(6D9.1)
0030      102 FORMAT(' MATRIX OF CONSTRAINTS, BY ROWS')
0031      100 FORMAT(4D28.16)
0032      101 FORMAT(' RIGHT HAND SIDE VECTOR'/(4D28.16))
0033      90 FORMAT(' OBJECTIVE FUNCTION'/(1 ',4D28.16))
0034      97 FORMAT(' SOLUTION'/(2D28.16))
0035      24 FORMAT(' MINIMUM VALUE OF OBJECTIVE FUNCTION IS ',D28.16)
0036      RETURN
0037      END
```

FORTRAN IV G LEVEL.1, MOD 2

1000 SUBROUTINE MAP LIST

DATE = 69133

11/43/00

PAGE 0002

SCALAR MAP									
SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION
MNOBJ	C0	II	C8	M	MODULE	CC	N	DO	NR
I	D8	J	DC	NR1		E0	NR2	E4	D4

ARRAY MAP									
SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION
A	E8	B	2C8	C	2F8	P	348	XX	378
Y	3A8	PE	3D8	X	408	E	458	DSOLN	578
JH	5C8	T	5F8	KO	648				

SUBPROGRAMS CALLED									
SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION
TBCOM#	660	DSIMPL	664						

FORMAT STATEMENT MAP									
SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION	SYMBOL	LOCATION
6	6A4	1	6D0	4	6D6	200	6DD	102	6E4
100	707	101	70E	90	733	97	757	24	76E

TOTAL MEMORY REQUIREMENTS 000B3A BYTES

E-LEVEL LINKAGE EDITOR OPTIONS SPECIFIED MAP, LIST  
 \*\*\*\*USERPROG DOES NOT EXIST BUT HAS BEEN ADDED TO DATA SET

MODULE MAP

CONTROL SECTION			ENTRY								
NAME	ORIGIN	LENGTH	NAME	LOCATION	NAME	LOCATION	NAME	LOCATION	NAME	LOCATION	
MAIN	00	B3A									
DSTIMPL	B40	1590									
IHCFCOMH*	20D0	F00	TBCOM#	20D0	FDIOCS#	218C	INTSW	2EBC			
IHCUOPT *	2F00	8									
IHCTRCH *	2FD8	2C8									
IHCFRXPI*	32A0	94	FRXPI#	32A0							
IHCFCMAXD*	3338	6D	DMAK1	3338	DMIN1	334E					
IHCFCVTH*	33A8	10A5	ADCON#	33A8	PCVZO	34F4	PCVAO	359A	PCVLO	362A	
			FCVIO	3960	PCVEO	3E62	PCVCO	407C	INT6SW	4438	
IHCFIOSH*	4450	DAA	FIOCS#	4450							
IHCUATBL*	5200	638									
IHCFINTH*	5838	3A6	ARTTH#	5838	ADJSW	5AFD					
ENTRY ADDRESS	00										
TOTAL LENGTH	5BDE										

\*\*\*\*\* LKED ELAPSED TIME ----- TASK PROCESSING TIME -----:01.930 RETURN CODE 0

//GO.SYSIN DD \*

APPROXIMATION OF THREE POINTS BY A LINE

MATRIX OF CONSTRAINTS, BY ROWS

-0.199999999999999D 02	-0.999999999999999D 00	0.209999999999999D 02	-0.999999999999990D 00
<u>Row 1</u> 0.999999999999990D 00	0.0	0.0	0.0
<u>2</u> 0.0	0.0		
-0.300000000000000D 02	-0.999999999999990D 00	0.309999999999999D 02	-0.999999999999990D 00
<u>Row 2</u> 0.0	0.999999999999990D 00	0.0	0.0
<u>3</u> 0.0	0.0		
-0.500000000000000D 02	-0.999999999999990D 00	0.510000000000000D 02	-0.999999999999990D 00
<u>Row 3</u> 0.0	0.0	0.999999999999990D 00	0.0
<u>4</u> 0.0	0.0		
0.19999999999999D 02	0.999999999999990D 00	-0.209999999999999D 02	-0.999999999999990D 00
<u>Row 4</u> 0.0	0.0	0.0	0.999999999999990D 00
<u>5</u> 0.0	0.0		
0.300000000000000D 02	0.999999999999990D 00	-0.309999999999999D 02	-0.999999999999990D 00
<u>Row 5</u> 0.0	0.0	0.0	0.0
0.999999999999990D 00	0.0		
0.500000000000000D 02	0.999999999999990D 00	-0.510000000000000D 02	-0.999999999999990D 00
<u>Row 6</u> 0.0	0.0	0.0	0.0
0.0	0.999999999999990D 00		

RIGHT HAND SIDE VECTOR

-0.71399999999999D 04	-0.154899999999999D 05	-0.417899999999999D 05	0.71399999999999D 04
0.15489999999999D 05	0.41789999999999D 05		

## OBJECTIVE FUNCTION

0.0	0.0	0.0	0.9999999999999990D 00
0.0	0.0	0.0	0.0
0.0	0.0		

## SOLUTION

0.1155000079472922D 04	-0.1756000241716976D 05
------------------------	-------------------------

$$A = 1155 \quad B = 17560$$

MINIMUM VALUE OF OBJECTIVE FUNCTION IS

0.1599998920360337D 04
------------------------

Note that we get an extremely large error.

\*\*\*\*\* GO ELAPSED TIME ----- TASK PROCESSING TIME -----:00.830 RETURN CODE 0

\*\*\*\*\* LINAPP ELAPSED TIME TASK PROCESSING TIME -----:09.16 COP.UNCG.B +

RELEASE 14.6

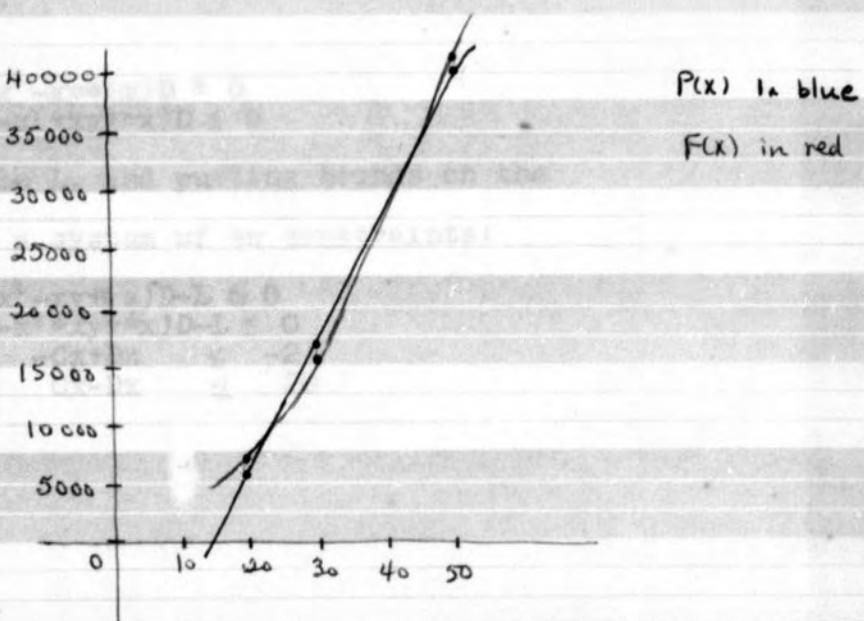
Note that the answer obtained is indeed the minimum approximation.

The values are as follows

<u>X</u>	20	30	50
F(x)	7140	15490	41790
P(x)	5540	17090	40190
E(x) = F(x) - P(x)	1600	-1600	1600

The maximum errors are equal and alternating

Finally becomes:



RATAPP  
(Approximation of a rational function by a rational function)

The original function is  $\frac{x^2-4}{2x} = y$   
evaluated at the points  $x_i$ ,  $i=1, 2, \dots, 10$

Our approximating function is  $P(x) = \frac{Ax^2+B}{Cx}$ , and we hope to  
get  $A=1$ ,  $B=-4$ ,  $C=2$ .

For linear programming, we will bound the denominator between  
2 and 20, since  $2x$  can take on only values in this range.

To set up the problem:

$$-\epsilon \leq \frac{Ax^2+B}{Cx} - y \leq \epsilon$$

$$-\epsilon Cx \leq Ax^2 + B - yCx \leq \epsilon Cx$$

$$\begin{aligned} -Ax^2 - B + yCx &\leq \epsilon Cx \\ Ax^2 + B - yCx &\leq \epsilon Cx \end{aligned}$$

$$\begin{aligned} -(A-D)x^2 - (B-D) + y(C-D)x &\leq \epsilon(C-D)x \\ (A-D)x^2 + (B-D) - y(C-D)x &\leq \epsilon(C-D)x \end{aligned}$$

which finally becomes:

$$\begin{aligned} -Ax^2 - B + (xy - \epsilon x)C + (x^2 - xy + \epsilon x)D &\leq 0 \\ Ax^2 + B - (xy + \epsilon x)C + (-x^2 + xy + \epsilon x)D &\leq 0 \end{aligned}$$

Adding the necessary variable  $L$ , and putting bounds on the  
denominator, we end up with a system of  $4n$  constraints:

$$\begin{aligned} -Ax^2 - B + (xy - \epsilon x)C + (x^2 - xy + \epsilon x)D - L &\leq 0 \\ Ax^2 + B - (xy + \epsilon x)C + (-x^2 + xy + \epsilon x)D - L &\leq 0 \\ -Cx + Dx &\leq -2 \\ Cx - Dx &\leq 20 \end{aligned}$$

```
//RATAPP JOB.COP.UNCG.B, EVANS, MSGLEVEL=1 TIME=1  
// EXEC PGLNKGO  
//FORT EXEC PGM=TKEYFORT, PARM='MAP'  
//SYSPRINT DD SYSOUT=A 00000200  
//SYSPUNCH DD DDNAME=DECK 00000400  
//DECK DD SYSOUT=B,DCB=(RECFM=F,BLKSIZE=80,LRECL=80) 00000600  
//SYSLIN DD DSNAME=6OBJSET,DISP=(MOD,PASS),SPACE=(CYL,(4,1)),  
// DCB=(RECFM=FB,BLKSIZE=400,LRECL=80),UNIT=HDSK0 XXXXX00001000  
//FORT.SYSIN DD *
```

0 \*\*\*\*\* RATAP283 RUN AT TUCC - RELEASE 14 ENTERED- 15:55:11 STARTED- 15:59:10 DATE- 5/17/69 69/137 0  
0 MAX VALUES- TIME---60 PAGES---50 CARDS---00 PLOTS---00 0  
0

0  
IEF236T ALLOC. FOR RATAP283 FORT  
IEF237I SYSLIN ON 490  
IEF237I SYSIN ON 012

```

0001      C EXAMPLE OF RATIONAL APPROXIMATION USING LINEAR INEQUALITY METHOD
0001      DOUBLE PRECISION A(40,45),A2(40,45),B(40),B2(40),C(45),C2(45),
0001      *P(40),XX(40),Y(40),PE(40),X(45),E(1600),DSOLN(45),TH(40),T1(10),
0001      *Z(75),T(45),MINOBJ,D1,D2,TMAX,DNUM,DANU
0002      DIMENSION KO(6)
0003      READ(1,1) TT,M,N,NR,D1,D2
0004      WRITE(3,15)
0005      NUM=1
0006      M4=M/4      first X4 constraint
0007      M41=M4+1
0008      M2=M/2      first Y2 constraint
0009      M21=M2+1
0010      M3=3*M4
0011      M31=M3+1

0012      C CALCULATE VALUES OF ORIGINAL FUNCTION
0012      DO 5 T=1,M4
0013      5   T1(T)=(T*T-4.0)/(2.0*T)
0014      TMAX=0.0
0015      DO 400 T=1,M4
0016      DNUM=T1(T)
0017      DANU=DAABS(DNUM)
0018      IF(DANU.LE.TMAX) GO TO 400
0019      TMAX=DANU
0020      400 CONTINUE
0021      Z(1)=TMAX

0022      C SET UP A MATRIX
0022      DO 2 T=1,M4
0023          A(T,1)=- (T*T)
0024          A(T,2)=-1.0
0025          A(T,3)=T1(T)*T-T*Z(NUM)
0026          A(T,4)=T*T+1.0-T*T1(T)+T*T2(NUM)
0027          2   A(T,5)=-1.0
0028      DO 3 T=M41,M2
0029          IR=T-M4
0030          A(T,1)=IR*IR
0031          A(T,2)=1.0
0032          A(T,3)=- (T1(IR)*IR+IR*T2(NUM))
0033          A(T,4)=- (IR*IR)-1.0+IR*T1(IR)+IR*T2(NUM)
0034          3   A(T,5)=-1.0
0035      DO 7 T=M21,M3
0036          IR=T-M2
0037          A(T,1)=0.0
0038          A(T,2)=0.0
0039          A(T,3)=-IR
0040          A(T,4)=IR
0041          7   A(T,5)=0.0
0042      DO 8 T=M31,M
0043          IR=T-M3
0044          A(T,1)=0.0
0045          A(T,2)=0.0
0046          A(T,3)=IR
0047          A(T,4)=-IR
0048          8   A(T,5)=0.0

0048      C INSERT SLACK VARIABLES

```

} Find original value of  $\epsilon$

```

0049      NR1=NR+1
0050      DO 9 T=1,M
0051      DO 9 J=NR1,N
0052      IR=T+NR
0053      IF(IR.EQ.J) GO TO 10
0054      A(I,J)=0.0
0055      GO TO 9
0056   10  A(I,J)=1.0
0057      9  CONTINUE
C SET UP RIGHT HAND SIDE VECTOR.
0058      DO 11 I=1,M2
0059      11  B(I)=0.0
0060      DO 13 I=M21,M3
0061      13  B(I)=-D1      - D1 = lower bound on denominator
0062      DO 14 I=M31,M
0063      14  B(I)=D2      - D2 = upper bound on denominator
C SET UP OBJECTIVE FUNCTION FOR EPSILON
0064      DO 15 I=1,N
0065      15  C(I)=0.0
0066      C(NR)=1.0
C PRINT OUT A,B, AND C VALUES
0067      WRITE(3,102)
0068      DO 20 I=1,M
0069      20  WRITE(3,100) (A(I,J),J=1,N)
0070      WRITE(3,101) (B(I),I=1,M)
0071      WRITE(3,90) (C(I),I=1,N)
C COPY A,B, AND C MATRICES FOR FUTURE USE
0072      DO 21 I=1,M
0073      DO 22 J=1,N
0074      22  A2(I,J)=A(I,J)
0075      21  B2(I)=B(I)
0076      DO 42 J=1,N
0077      42  C2(J)=C(J)
0078      23  CALL DSIMPL(IT,M,N,A,B,C,KO,X,P,JH,XX,Y,PE,E,DSOLN)
C CHECK FEASIBILITY AND REPORT
0079      T=NUM+1
0080      IF(DSOLN(NR).LE.0.0) GO TO 27 - Check to see if L<0
0081      WRITE(3,29)
0082      GO TO 224
0083      27  WRITE(3,28)
0084      Z(I)=Z(NUM)/2      Halve lower half of interval
0085      GO TO 95.
0086      224  Z(I)=3*Z(NUM)/2      Halve upper half of interval
0087      95  IF(NUM.EQ.1) GO TO 24
0088      IF((DABS(Z(I)-Z(NUM))).LE.10E-7) GO TO 25      Compare epsilon values
0089      IF(NUM.EQ.75) GO TO 75
0090      24  WRITE(3,26) Z(NUM),NUM
0091      NUM=T
C PUT MATRICES BACK INTO ORIGINAL FORM, MAKING ONLY CHANGES
C NECESSARY FOR NEW Z VALUE
0092      DO 32 I=1,M
0093      DO 33 J=1,N
0094      33  A(I,J)=A2(I,J)
0095      32  B(I)=B2(I)

```

16268.1

These were set at 2 and 20, which covers the whole range of X values. Formerly these were set at .5 and 1.5, but the correct answers were not obtained - perhaps the interval was too small when bounded this way.

Compare epsilon values

```
0096      DO 43 T=1,N
0097      43 C(T)=C2(T)
0098      DO 35 I=1,M4
0099      A(I,3)=T*T1(I)-Z(NUM)*T
0100      35 A(I,4)=I*T+1.0-T*T1(I)+I*Z(NUM)
0101      DO 36 I=M41,M2
0102      TR=T-M4
0103      A(I,3)=- (TR*T1(TR)+Z(NUM)*TR)
0104      36 A(I,4)=- (IR*IR)-1.0+IR*T1(TR)+IR*Z(NUM)
C GO BACK TO SUBROUTINE FOR NEXT ITERATION
0105      GO TO 23
0106      25 WRITE(3,39) NUM
0107      WRITE(3,40) (DSOLN(T),T=1,N)
0108      NR1=NR-1
0109      NR2=NR-2
0110      DO 41 I=1,NR2
0111      41 T(I)=DSOLN(I)-DSOLN(NR1)
C SUBTRACTING THE TWO POSITIVE NUMBERS GIVES US THE DESIRED ANSWER,
C WHICH MAY BE NEGATIVE
0112      WRITE(3,97) (T(I),I=1,NR2)
0113      MINOBJ=0.0
0114      DO 998 T=1,N
0115      998 MINOBJ=MINOBJ+C(T)*DSOLN(T)
0116      WRITE(3,999) MINOBJ
0117      GO TO 80
0118      75 WRITE(3,44) NUM
0119      1 FORMAT(4I5,3D4.1)
0120      16 FORMAT(' RATIONAL APPROXIMATION USING LINEAR PROGRAMMING')
0121      102 FORMAT(' MATRIX OF CONSTRAINTS, BY ROWS')
0122      100 FORMAT(4D28.16)
0123      101 FORMAT('/' RIGHT HAND SIDE VECTOR'/(4D28.16))
0124      90 FORMAT('/' OBJECTIVE FUNCTION'/(6E20.8))
0125      26 FORMAT('/' EPSILON IS ',D28.16,' IN ITERATION NUMBER ',T5)
0126      28 FORMAT(' PROBLEM IS FEASIBLE WITH THIS EPSILON')
0127      29 FORMAT(' PROBLEM IS INFEASIBLE WITH THIS EPSILON')
0128      39 FORMAT('/' OPTIMUM SOLUTION IS OBTAINED IN ITERATION ',T5)
0129      40 FORMAT(' SOLUTION'/(4D28.16))
0130      97 FORMAT('/' ANSWERS TO PROBLEM ARE'/(4D28.16))
0131      999 FORMAT('/' MINIMUM VALUE OF OBJECTIVE FUNCTION IS ',D28.16)
0132      44 FORMAT('/' OPTIMUM SOLUTION DID NOT OCCUR IN ',I5,' ITERATIONS')
0133      80 RETURN
0134      END
```

FORTRAN IV G LEVEL 1, MOD 2 107, RERADING MAIN

DATE = 69137

15/57/40

PAGE 0004

## SCALAR MAP

SYMBOL	LOCATION								
D1	180	D2	189	TMAX	190	DNUM	198	DANU	1A0
MTNOBJ	1A8	TI	1B0	M	1B4	N	1B8	NR	1BC
NUM	1C0	M4	1C4	M41	1C8	M2	1CC	M21	1D0
M3	1D4	M31	1D8	I	1DC	IR	1E0	NR1	1E4
T	1E8	NR2	1EC						

## ARRAY MAP

SYMBOL	LOCATION								
A	1F0	A2	3A30	B	7270	B2	73B0	C	74F0
C2	7658	P	77C0	XY	7900	Y	7A40	PE	7B80
X	7CC0	E	7E28	DSOLN	B028	JH	B190	T1	B2D0
Z	B320	T	B578	KO	B6E0				

## SUBPROGRAMS CALLED

SYMBOL	LOCATION								
IBCOM#	B6F8	DSTMPL	B6FC						

## FORMAT STATEMENT MAP

SYMBOL	LOCATION								
1	B744	16	B74F	102	B783	100	B7A6	101	B7AD
90	B7D5	26	B7F9	28	B826	29	B850	39	B87C
40	B8AE	97	B8C7	999	B9EF	44	B91F		

TOTAL MEMORY REQUIREMENTS 00C82E BYTES

```

IEF285I SYS69137.T092711.RP007.RATAP283.LOADSET PASSED
IEF285I VOL SER NOS= HYPERD.
IEF285I SYS1.FORTLIB KEPT
IEF285I VOL SER NOS= HYPERD.
IEF285I SYS1.SUBLIB KEPT
IEF285I VOL SER NOS= HYPERD.
IEF285I SYS69137.T092711.RP007.RATAP283.UT1 DELETED
IEF285I VOL SER NOS= HYPERD.
IEF285I SYSOUT SYSOUT
IEF285I VOL SER NOS=
IEF285I SYS69137.T092711.RP007.RATAP283.LOADSET PASSED
IEF285I VOL SER NOS= HYPERD.
IEF285I SYS69137.T092711.RP007.RATAP283.OBJSET DELETED
IEF285I VOL SER NOS= HYPERD.

***** LKED      TIMES-ELAP -----0:06.18 CPU -----0:02.150 WATT -----0:02.183 READY -----0:01.850 RETURN CODE 0
***** EXCP'S-UR -----59 TAPE -----00 DSK -----39 HYDISK -----749 OTHER -----00
//GO EXEC PGM=*.LKED.SYSLMOD,COND=((5,LT,FORT),(5,LT,LKED)) 00003600
//FT03P001 DD SYSPRINT=A,DCB=(RECFM=UA,BLKSIZE=133,LRECL=133) 00003800
//FT02F001 DD SYSPRINT=B,DCB=(RECFM=FB,BLKSIZE=80,LRECL=80) 00004000
//FT01F001 DD DDNAME=SYSTIN 00004200
//GO SYSTIN DD *

IEF236I ALLOC. FOR RATAP283 GO
IEF237I PGM=*.DD ON 490
IEF237I FT01F001 ON 012

```

## RATIONAL APPROXIMATION USING LINEAR PROGRAMMING

#### MATRIX OF CONSTRAINTS, BY ROWS











0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.9999999999999999
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0

33 0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.999999999999999D 00 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0

36 0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.999999999999990D 00  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.599999999999999D 01 -0.599999999999999D 01

*36*      0.0      0.0      0.0      0.0  
0.0      0.0      0.0      0.0  
0.0      0.0      0.0      0.0  
0.0      0.0      0.0      0.0  
0.0      0.0      0.0      0.0  
0.0      0.0      0.0      0.0  
0.0      0.0      0.0      0.0  
0.0      0.0      0.0      0.0  
0.9999999999999900 00      0.0      0.0      0.0  
0.0

37  
0.0 0.0 0.699999999999999D 01 -0.699999999999999D 01  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.999999999999990D 00 0.0 0.0

0.0 0.0 0.799999999999999D 01 -0.799999999999999D 01  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.999999999999990D 00 0.0 0.0

0.0 0.0 0.899999999999999D 01 -0.899999999999999D 01  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
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0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.999999999999990D 00 0.0 0.0

0.0 0.0 0.999999999999999D 01 -0.999999999999999D 01  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.999999999999990D 00 0.0 0.0

#### RIGHT HAND SIDE VECTOR

0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0  
-0.199999999999999D 01 -0.199999999999999D 01 -0.199999999999999D 01 -0.199999999999999D 01  
-0.199999999999999D 01 -0.199999999999999D 01 -0.199999999999999D 01 -0.199999999999999D 01  
-0.199999999999999D 01 -0.199999999999999D 01 0.199999999999999D 02 0.199999999999999D 02  
0.199999999999999D 02 0.199999999999999D 02 0.199999999999999D 02 0.199999999999999D 02  
0.199999999999999D 02 0.199999999999999D 02 0.199999999999999D 02 0.199999999999999D 02

#### OBJECTIVE FUNCTION

0.0 0.0 0.0 0.0 0.1000000D 01 0.0  
0.0 0.0 0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0 0.0 0.0

0.0 0.0 0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0 0.0 0.0  
0.0 0.0 0.0 0.0 0.0 0.0

PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.4799999237060546D-01 IN ITERATION NUMBER 1  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.2399999618530272D-01 IN ITERATION NUMBER 2  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.1199999809265136D-01 IN ITERATION NUMBER 3  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.5999999046325683D-00 IN ITERATION NUMBER 4  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.2999999523162841D-00 IN ITERATION NUMBER 5  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.1499999761581420D-00 IN ITERATION NUMBER 6  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.7499998807907100D-01 IN ITERATION NUMBER 7  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.3749999403953551D-01 IN ITERATION NUMBER 8  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.1874999701976775D-01 IN ITERATION NUMBER 9  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.9374998509883879D-02 IN ITERATION NUMBER 10  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.4687499254941939D-02 IN ITERATION NUMBER 11  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.2343749627470969D-02 IN ITERATION NUMBER 12  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.1171874813735484D-02 IN ITERATION NUMBER 13  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.5859374068677424D-03 IN ITERATION NUMBER 14  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.2929687034338712D-03 IN ITERATION NUMBER 15  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.1464843517169356D-03 IN ITERATION NUMBER 16  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.7324217585846781D-04 IN ITERATION NUMBER 17  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.3662108792923390D-04 IN ITERATION NUMBER 18  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.1831054396461694D-04 IN ITERATION NUMBER 19  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.9155271982308476D-05 IN ITERATION NUMBER 20  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.4577535991154237D-05 IN ITERATION NUMBER 21  
PROBLEM IS FEASIBLE WITH THIS EPSILON

EPSILON IS 0.2288817995577118D-05 IN ITERATION NUMBER 22  
PROBLEM IS FEASIBLE WITH THIS EPSILON

OPTIMUM SOLUTION IS OBTAINED IN ITERATION 23  
SOLUTION

0.4999994805283126D 01	0.0	0.5999995010339852D 01	0.3999994928712867D 01
0.0	0.7359047920743937D-05	0.9155136319748358D-05	0.1074194755174649D-04
0.1176185374297941D-04	0.1829452890700643D-04	0.2068402017987517D-04	0.2465237371537534D-04
0.1303345109410595D-04	0.1456931512471225D-04	0.9562162531765409D-04	0.0
0.0	0.2990824904798859D-05	0.6548554892667074D-05	0.4593515921633462D-05
0.6781660826658512D-05	0.7390943460391975D-05	0.2358750227398862D-04	0.2676110653935781D-04
0.1881910502143101D-04	0.0	0.1999999945582004D 01	0.4000000145780428D 01
0.6000000185564967D 01	0.8000000100439081D 01	0.1000000035520787D 02	0.1200000028944595D 02
0.1400000032568075D 02	0.1600000024108826D 02	0.1800000081626984D 02	0.1799999991837300D 02
0.1599999983674601D 02	0.1399999975511902D 02	0.1199999967349204D 02	0.9999999591865068D 01
0.7999999510238091D 01	0.5999999428611095D 01	0.3999999346984117D 01	0.1999999265357143D 01
0.1953990195315360D-13			

ANSWERS TO PROBLEM ARE

0.9999998765702588D 00 -0.3999994928712867D 01 0.2000000081626984D 01

A = 1 B = -4 C = 2

MINIMUM VALUE OF OBJECTIVE FUNCTION IS 0.0

#### ABSTRACT

The thermoluminescence technique was used to investigate the two types of F centers. The growth of F centers as a function of time of irradiation and the effect of thermal quenching were studied. The initial-rise method was employed to calculate the activation energy for the  $F_1$  centers and a spectral study was conducted to determine the energy difference between the excited levels for the different F centers and the recombination levels. On the basis of the result that the activation and emission energies of the two types of F centers vary by the same amount, approximately 0.10 eV, some possible energy level diagrams are suggested.