CHAPTER 21

THE WEIGHTED DISTRIBUTION PROBLEM

21-1. THE NEAR-TRIANGULARITY OF THE BASIS

The standard transportation model uses a particularly simple constraint matrix in which each variable has at most two non-zero coefficients whose values are +1 and −1. We propose to examine a model which is similar in form, for it allows at most two non-zero coefficients for each variable.

Problem 1. The Row-Column Weighted Distribution Problem.

Find nonnegative \( y_{ij} \) and \( \min z \) satisfying

1. The Row Equations:

   \[ \sum_{j=1}^{n} a_{ij} y_{ij} = a_i \quad (i = 1, 2, \ldots, m) \]

2. The Column Equations:

   \[ \sum_{i=1}^{m} b_{ij} y_{ij} = b_j \quad (j = 1, 2, \ldots, n) \]

3. The Objective Function:

   \[ \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} y_{ij} = z \]

where \( a_i \) and \( b_j \) are nonnegative, and \( a_{ij} \) is positive. Before proceeding, we will transform the variables so that all row coefficients become unity. Thus, when we replace the \( y_{ij} \) by new variables, defined as \( x_{ij} = a_{ij} y_{ij} \), the row equations take on unit coefficients in place of the \( a_{ij} \), while the coefficients of the column equations become \( p_{ij} = b_{ij}/a_{ij} \) and the cost equation becomes \( c_{ij} = c_{ij}/a_{ij} \). In this way we arrive at

The Standard Form of the Weighted Distribution Problem.

4. \[ \sum_{j=1}^{n} x_{ij} = a_i \quad (\text{Row equations, } i = 1, 2, \ldots, m) \]

5. \[ \sum_{i=1}^{m} p_{ij} x_{ij} = b_j \quad (\text{Column equations, } j = 1, 2, \ldots, n) \]

6. \[ \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij} = z \]

where \( x_{ij} \geq 0 \), and \( z \) is to be minimized.

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In a typical application, the \( a_i \) represent availabilities which must not be exceeded (as in the machine-task example to be discussed). In this case (4) is replaced by (7).

\[
\sum_{j=1}^{m} x_{ij} \leq a_i \quad \text{for } i = 1, 2, \ldots, m
\]

The theory and technique of solution are virtually the same for the system, \{(5), (6), and (7)\} as for \{(4), (5), and (6)\}.

The Dual of the Standard Weighted Distribution Problem is: Find \( u_i, v_j \) and the Maximum \( q \), such that

\[
 u_i + p_{ij}v_j \leq c_{ij} \quad \text{for } i = 1, 2, \ldots, m \\
\text{and } j = 1, 2, \ldots, n
\]

where

\[
\sum_{i=1}^{m} u_i a_i + \sum_{j=1}^{n} v_j b_j = q \quad \text{(Max)}
\]

Criterion of Optimality: A set of \( x_{ij} \) satisfying the primal problem is an optimal solution if there are \( u_i \) and \( v_j \) satisfying the dual, such that

\[
x_{ij} > 0 \Rightarrow u_i + p_{ij}v_j = c_{ij} \\
u_i + p_{ij}v_j < c_{ij} \Rightarrow x_{ij} = 0
\]

Illustrative Applications.

1. A number of different tasks can be accomplished on one of several types of available machines, some more efficiently than others. The tasks are to be assigned to machines in such a way that all tasks are completed within the machine-time available and at a minimum over-all cost.

   To set up the mathematical model, let

   \( a_i \) = number of hours available on \( i^{th} \) type machine,  
   \( b_i \) = number of units of \( j^{th} \) type task to be performed,  
   \( c_{ij} \) = cost to do one unit of the \( j^{th} \) type task on the \( i^{th} \) type machine,  
   \( p_{ij} \) = number of units of the \( j^{th} \) type task that can be processed per hour on the \( i^{th} \) type machine,  
   \( x_{ij} \) = number of hours machine \( i \) is to work on task \( j \).

2. A fleet, consisting of various types of aircraft, is to be assigned to airline routes in order to satisfy the passenger demand at the least operating costs. In this case, for some period, let

   \( a_i \) = number of aircraft of type \( i \) in the fleet,  
   \( b_i \) = number of passengers requiring passage on the \( j^{th} \) route,  
   \( c_{ij} \) = operating costs per aircraft of type \( i \) assigned to route \( j \) in the period,
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\( p_{ij} \) = the total number of passengers that can be accommodated by one aircraft of type \( i \) if assigned to route \( j \) during the period,

\( x_{ij} \) = number of aircraft of type \( i \) assigned to the \( j^{th} \) route.

Tableau and Implicit Prices for the Weighted Distribution Problem.

The tableau for a \( 2 \times 3 \) problem takes the form (11)

(11)

<table>
<thead>
<tr>
<th>( x_{11} )</th>
<th>( x_{12} )</th>
<th>( x_{13} )</th>
<th>( a_1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( c_{11} )</td>
<td>( p_{11} )</td>
<td>( c_{12} )</td>
<td>( p_{12} )</td>
</tr>
<tr>
<td>( x_{21} )</td>
<td>( x_{22} )</td>
<td>( x_{23} )</td>
<td>( a_2 )</td>
</tr>
<tr>
<td>( c_{21} )</td>
<td>( p_{21} )</td>
<td>( c_{22} )</td>
<td>( p_{22} )</td>
</tr>
<tr>
<td>( b_1 )</td>
<td>( b_2 )</td>
<td>( b_3 )</td>
<td>( v_1 )</td>
</tr>
</tbody>
</table>

One practical observation is in order: since the entries, \( x_{ij}, \), \( u_1 \), and \( v_1 \), are numerical and must be changed from one iteration to the next, it is important for hand computation that the chart be arranged in some convenient manner, as above, to facilitate the manual labor.

Finding a Starting Basic Solution.

The weighted distribution problem differs from the standard transportation problem in that no simple rule for directly obtaining an initial basic feasible solution has been found as yet. However, for the case in which all the \( p_{ij} \) are nonnegative, we shall describe and illustrate a method analogous to the rule of solution given in § 15-3, using the simple numerical problem which appears below.

(12)

<table>
<thead>
<tr>
<th>( x_{11} )</th>
<th>( x_{12} )</th>
<th>( x_{13} )</th>
<th>( a_1 = 4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( p_{11} = 1 )</td>
<td>( p_{13} = 2 )</td>
<td>( p_{12} = 2 )</td>
<td>( p_{13} = 1 )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( x_{21} )</th>
<th>( x_{22} )</th>
<th>( x_{23} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( p_{21} = 2 )</td>
<td>( p_{22} = 1 )</td>
<td>( p_{23} = 1 )</td>
</tr>
<tr>
<td>( b_1 = 5 )</td>
<td>( b_2 = 2 )</td>
<td>( b_3 = 3 )</td>
</tr>
</tbody>
</table>

Step 1. Select a basic variable by choosing a square arbitrarily (a good choice would be one having a smallest \( c_{ij} \)), and increasing the corresponding \( x_{ij} \) to the largest value consistent with its row and column totals. Delete the row or the column that becomes saturated, i.e., the one whose total has
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just been attained (should a row and a column be saturated simultaneously, delete one or the other, but not both). Now repeat this cycle as necessary.

For the example (12), squares were chosen as follows:

<table>
<thead>
<tr>
<th>Square</th>
<th>Value of the Variable</th>
<th>Saturated Row or Column</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1, 3)</td>
<td>( x_{13} = 3 )</td>
<td>col. 3</td>
</tr>
<tr>
<td>(1, 1)</td>
<td>( x_{11} = 1 )</td>
<td>row 1</td>
</tr>
<tr>
<td>(2, 2)</td>
<td>( x_{22} = 2 )</td>
<td>col. 2</td>
</tr>
<tr>
<td>(2, 1)</td>
<td>( x_{21} = 2 )</td>
<td>col. 1</td>
</tr>
</tbody>
</table>

Step 2. One column or row total, in general, will remain unsaturated.

We then introduce a new artificial variable by adding a "deficit" square, \((r, s)\), either \((0, s)\) or \((r, 0)\), to the unsaturated row or column. Next, we minimize the infeasibility form, \(\Sigma \Sigma d_{ij} x_{ij}\), where \(d_{ij} = 0\) for all \(i\) and \(j\), with one exception, for the supplementary square \(d_{rs} = 1\). If the deficit occurs in a column, we arbitrarily set \(p_{rs} = 1\), while for a row, we need not define \(p_{rs}\) at all (since there is no column equation corresponding to the deficit).

EXERCISE: Modify this rule to cover the case where some \(p_{ij}\) may be negative.

The Phase I multipliers, \(u_i\) and \(v_j\), must be such that \(u_i + p_{ij}v_j = 0\) for \(x_{ij}\) a basic variable, except that \(u_i = 1\), if the \(r^{th}\) row is left unsaturated, and \(v_j = 1\) if the \(j^{th}\) column is left unsaturated. In our example, row 2 is not saturated; the initial tableau for Phase I, therefore, takes the form (13).

\[
\begin{array}{ccccccc}
(j=1) & (j=2) & (j=3) & \alpha_i & u_i \\
1 & 1 & 2 & 3 & 4 & 5 \\
1 & \bullet & 2 & 2 & 1 & 0 & 0 & 1 \\
1 & 0 & 0 & 1 & 1 & 0 & 0 & 1 \\
b_i & 5 & 2 & 3 & -4 & -1 & -1 & \text{implicit prices} \\
v_j & & & & & & & \\
\end{array}
\]

The dot in square \((2, 0)\) is to indicate that \(p_{ij}\) is undefined (i.e., there is no equation for column 0). Because of the deficit the price of \(u_2 = 1\); the remainder of the prices, \(u_i\) and \(v_j\), are computed using equation (10) with \(c_{ij}\) replaced by \(d_{ij}\). Since \(d_{23} - (u_2 + p_{23}v_3) = 0 - [1 + 1 \cdot (-1/2)] = -(1/2)\), the infeasibility can be diminished by increasing \(x_{23}\) and adjusting the basic variables to compensate for this increase; see (14).
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\begin{align*}
\begin{array}{|c|c|c|c|c|}
\hline
\text{Deficit} & 1 + \theta & 2 & 3 - \theta & 4 \\
1 - (1/2)\theta & \theta^* & 5 \\
1 & 2 - (1/2)\theta & 1 & 0 & 0 \\
\hline
\end{array}
\end{align*}

It is clear that Max \( \theta = 2 \), and that the infeasibility vanishes at this value. Thus, \( x_{10} \) becomes a new basic variable replacing the deficit variable, \( x_{20} \), and Phase I is already complete; we drop the deficit box. The starting tableau for Phase II, showing the \( u_i \) and \( v_j \) as well as \( \theta \) entries, both of which we shall explain in a moment, is (15).

\begin{align*}
\begin{array}{|c|c|c|c|c|}
\hline
1 + 2\theta & \theta^* & 1 - 3\theta & 4 \\
1 & 2 & -3 & 3 \\
2 & 2 - 3\theta & 1 & 7 \\
5 & -2 & -3 & \leftarrow v_j \\
\hline
\end{array}
\end{align*}

Computing Implicit Prices (Simplex Multipliers).

The values of \( u_i \) and \( v_j \) from (10), must satisfy a system of five equations in the five unknowns, \( u_1, u_2, v_1, v_2, \) and \( v_3 \):

\begin{align*}
\begin{align*}
(16) & \quad u_1 + v_1 = 4 \\
& \quad u_1 + v_3 = 3 \\
& \quad u_2 + 2v_1 = 6 \\
& \quad u_2 + v_2 = 4 \\
& \quad u_2 + v_3 = 7 \\
\end{align*}
\end{align*}

In contradistinction to the standard transportation model, there need not be a redundancy in the system of equations \{(1), (2)\}. In general, therefore, it is not possible to choose one of the prices arbitrarily. Similarly, the bases of system \{(1), (2)\} need not be triangular. Nevertheless, the system is nearly triangular in the following sense: Choose any variable, say \( u_2 \), and treat it as a parameter in terms of which the other variables are to be evaluated.
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This leads to equations in a single variable, which can be immediately evaluated in terms of the parameter. From (16), we get

\[ v_1 = 3 - \frac{1}{2} u_2, \quad v_2 = 4 - u_2, \quad v_3 = 7 - u_2 \]

\[ u_1 = 4 - (3 - \frac{1}{2} u_2) \]
\[ = 1 + \frac{1}{2} u_2 \]

\[ u_1 = 3 - (7 - u_2) \]
\[ = -4 + u_2 \]

We have arrived at two expressions for \( u_1 \) in terms of the parameter \( u_2 \). Equating them leads to a numerical evaluation of \( u_2 \) and, hence, of all the variables it defines. Thus, since \( 1 + \frac{1}{2} u_2 = -4 + u_2 \), we have \( u_2 = 10 \) whence \( v_1 = -2, v_2 = -6, v_3 = -3, \) and \( u_1 = 6 \).

A complete set of prices for our example has now been brought to hand. However, in certain other cases, some implicit prices might still remain unevaluated after such a procedure. In that event, any unevaluated price may, as before, be treated as a parameter and additional variables evaluated in terms of it by successive substitution until two equations in two variables appear which allow its evaluation. We now generalize these remarks.

**Theorem 1:** Assuming a basis of rank \( n + m \), implicit prices can be evaluated by treating any one of them as a parameter, and solving a sequence of equations in one unknown, repeating the procedure as necessary for any residual set of unevaluated prices.

**Proof:** Each equation of (10) contains two prices. If one of them is selected as a parameter, several others can be expressed in terms of it. By successive substitutions this leads to a set of variables evaluable in terms of this parameter, which have no variable in common with any equation still containing an unevaluated variable (for this in turn could be immediately evaluated in terms of the parameter and added to the set). We shall show in this set that there is just one variable that is linearly expressed in exactly two different ways. By equating the two expressions, we can determine the value of the parameter. If more than one price in the set were doubly expressed (i.e., if one variable could be evaluated in more than two ways), this would mean that the equations contain either a redundancy or an inconsistency. On the other hand, if no variable were doubly evaluable, then the value of the parameter could be chosen arbitrarily. If the basis is of rank \( n + m \), however, neither one of these situations is possible, for the set of equations associated with the transpose of a basis must always lead to a unique solution.

**Improving the Basic Solution.**

The implicit prices, computed as above, are used to determine whether the current solution is minimal, according to condition (10), and to compute
an improved solution if it is not. The solution we have computed for our example is not yet optimal, since

\[ c_{12} = a_4 - p_{12}v_2 = -8 - 6 - 2(-6) = -2 \]

Accordingly, set \( x_{12} = \theta \), and adjust the basic variables. In our example, we compute the values of the basic variables, which result by changing the constant terms to

\[ a'_4 = 4 - \theta, \quad a'_4 = 5, \quad b'_4 = 5, \quad b'_4 = 2 - 2\theta, \quad \text{and} \quad b'_4 = 3 \]

The new values of the basic variables are expressed linearly, in the form \( \alpha + \beta \theta \), where \( \alpha \) is the old value and \( \beta \theta \) is the compensatory change necessitated by the increase of \( \theta \) in the value of the non-basic variable coming into the basic set. The old values, \( \alpha \), are known, and therefore only the amount by which basic variables change, \( \Delta x_{i\ell} \), need be computed. They must satisfy five equations in five unknowns:

\[
\begin{align*}
\Delta x_{11} + \Delta x_{13} &= -\theta \\
\frac{1}{2} \Delta x_{21} + \Delta x_{22} + \Delta x_{23} &= 0 \\
\Delta x_{11} + 2\Delta x_{21} &= 0 \\
\Delta x_{13} + \Delta x_{22} &= 0 \\
\Delta x_{23} &= 0
\end{align*}
\]

(18)

This, of course, is the transpose of the system used earlier for evaluating the implicit prices. After we evaluate \( \Delta x_{23} \) from the fourth equation and substitute its value in the others, each of the remaining equations has precisely two variables that are still unknown. Moreover, it is clear that if one unknown is introduced parametrically, the others may be evaluated in terms of it. Thus, if \( \Delta x_{11} \) is chosen as a parameter, it can be used in turn to express \( \Delta x_{13}, \Delta x_{23}, \Delta x_{21} \), and then back to \( \Delta x_{11} \). This gives an equation in \( \Delta x_{11} \) alone, and the latter can therefore be numerically evaluated. The cycle of dashes in (18) indicates this order of expression. Explicitly,

\[
\begin{align*}
\Delta x_{22} &= -2\theta \\
\Delta x_{13} &= -\theta - \Delta x_{11} \\
\Delta x_{23} &= -\Delta x_{13} = \theta + \Delta x_{11} \\
\Delta x_{21} &= -\Delta x_{22} - \Delta x_{23} = +\theta - \Delta x_{11} \\
\Delta x_{11} &= -2\Delta x_{21} = -2\theta + 2\Delta x_{11} \text{ or } \Delta x_{11} = 2\theta.
\end{align*}
\]

Substituting the value \( \Delta x_{11} = 2\theta \) in the remaining equations yields \( \Delta x_{13} = -3\theta, \Delta x_{23} = 3\theta, \) and \( \Delta x_{21} = -\theta \).

This method of evaluating changes in the basic variables is perfectly general. Indeed, the procedure applied here to nearly triangular bases is an analogue of the process by which one exploits the basic triangularity which occurs in transportation problems.

**Theorem 2:** Given any basis of rank \( n + m \) for a weighted distribution
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problem, either (a) there exists a row or column with just one basic variable, or
(b) each row and column has precisely two basic variables and \( m = n \). If (a)
is true, then the sub-basis, resulting by deletion of the row or column which
contains only this basic variable, has the same properties.

PROOF: Each row and column has at least one basic variable. If none
of them have precisely one, then every row and column has two or more.
In the latter case, the number of basic variables, \( n + m \), cannot be less
than twice the number of rows or twice the number of columns; hence,

\[
\begin{align*}
n + m & \geq 2m \quad \text{and} \quad n + m \geq 2n \\
\end{align*}
\]

or, by adding,

\[
2(n + m) \geq 2m + 2n
\]

where equality holds only if equality holds in both expressions \((20)\), i.e.,
if each row and each column has precisely two basic variables, and \( m = n \).
But the equality must hold. This argument can be repeated for the sub-basis
if there is one equation having a single variable and if the row and column
in which it occurs have been deleted.

21-2. LINEAR GRAPH STRUCTURE OF THE BASIS

When the weighted distribution problem is interpreted in the context of
a linear network, the linear graph whose arcs correspond to the variables of
a basic set possesses a characteristic structure.

The discussion will be facilitated if we consider the model simply as a
set of equations having certain well-defined properties, and for this purpose
it will be convenient to make use of single-subscripted letters to represent
the variables involved. It will be recalled that the classical transportation
model, § 14-2, had a system of constraints composed of two subsystems, one
of which (with row equations) referred to \( \text{exports from} \) each source to the
various destinations, while the second subsystem (with column equations)
dealt with \( \text{imports to} \) each destination from the various sources. In the trans-
shipment model, § 16-1, each variable had at most two non-zero coefficients
\( \pm 1 \). In the weighted model, we remove the restriction \( \pm 1 \) and consider a
class of problems in which at most two coefficients of each variable \( x \) are
non-zero, one in equation \( i = g(j) \) and the other in \( i = h(j) \). When \( x \) has only
one non-zero coefficient \( g(j) = h(j) \).

Problem 2. The General Weighted Distribution Problem.

Choose a set of nonnegative numbers, \( x_{ij} \), and the Minimum \( z \), such that

\[
\begin{align*}
\sum_{j=1}^{n} a_{ij} x_{ij} &= b_i \quad (i = 1, 2, \ldots, m) \\
\sum_{i=1}^{m} c_i x_{ij} &= z \quad (\text{Min})
\end{align*}
\]

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21.2. \textit{Linear Graph Structure of the Basis}

where \( a_{ij} = 0 \) unless \( i = g(j) \) or \( i = h(j) \). We will refer to any \( x_j \) having either \( a_{ij} \) or \( a_{kj} \) zero (but not both) as a \textit{slack variable}.

Each equation of (1) corresponds to a node in the network form of the model, while each non-slack variable, \( x_i \), corresponds to an undirected arc joining node \( g(j) \) to node \( h(j) \). Slack arcs may be considered (as pointed out by F. Harary) as arcs which connect two nodes that are identical.

In drawing a linear graph, the nodes may be placed in any convenient position. Thus Fig. 21.2-I and Fig. 21.2-II are pictures of the same network, but the nodes in Fig. 21.2-II have been repositioned, so as to illustrate more clearly its essential structure. If slack variables are to be admissible, then the network must also include \textit{slack arcs}, associated with these variables, each having only a single node.

\begin{center}
\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure1.png}
\caption{Graph of a weighted distribution problem.}
\end{figure}
\end{center}

\begin{center}
\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure2.png}
\caption{Rearranged graph of a weighted distribution problem.}
\end{figure}
\end{center}

In Fig. 21.2-III is depicted a linear graph whose arcs correspond to the variables of a basis. This graph is composed of four isolated, connected subgraphs.

\textbf{Theorem 1:} Each connected subgraph of a basic graph for system (1) has precisely one loop.

\textbf{Proof:} It is clear that each connected part consists of an equal number of nodes and arcs, for the variables associated with the arcs appear only in the equations associated with the nodes of the subgraph, and these equations could not, in general, be satisfied by fewer variables than equations. On the other hand, the total number of basic variables equals the total number
of equations, so equality must hold for each isolated subgraph in the network.

Now a connected subgraph having no slack arc(s) must contain at least one loop, since it would otherwise have fewer arcs than nodes. If we were to delete an arc belonging to a loop in this part, we would be left with a connected subgraph in which the number of arcs would be one less than the number of nodes, which therefore (Theorem 1, § 17.12) constitutes a tree. But a tree contains no loops; hence, the subgraph must initially have had exactly one loop.

On the other hand, if a connected subgraph has one or more slack arcs, then the graph formed by deleting them has a smaller number of arcs than nodes, the difference being equal to the number of arcs deleted. But since only the slack arcs (i.e., arcs having one node) were deleted, the resulting subgraph is still connected, and this is possible only if the number of slack arcs was one and the remaining subgraph, a tree. The proof is completed by defining an arc as a one-arc loop.

Computing an Associated Solution.

To evaluate the variables of a basis, one may begin with nodes having exactly one arc. Thus, for Fig. 21.2-II, we have

\( a_{1,0}x_0 = b_1 \)
\( a_{6,1}x_7 = b_6 \)
\( a_{10,9}x_8 = b_{10} \)
\( a_{5,10}x_{10} = b_5 \)

If a node has several arcs, all but one of whose variables have been evaluated, then the excepted variable can be evaluated immediately. Thus, after \( x_{10} \) is determined as above, \( x_9 \) can be evaluated at node 6 from the equation,

\( a_{6,9}x_9 + a_{6,10}x_{10} = b_6 \)

By this means, all variables, except those corresponding to arcs of the
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loop, can successively be evaluated. The evaluation of such loop variables may proceed by the method we shall now illustrate.

\[ (4) \]
\[ a_{34}x_1 + a_{32}x_2 = \delta_3 \]
\[ a_{46}x_2 + a_{43}x_3 = \delta_4 \]
\[ a_{76}x_3 + a_{74}x_4 = \delta_7 \]
\[ a_{94}x_4 + a_{92}x_5 = \delta_9 \]
\[ a_{21}x_1 + a_{25}x_5 = \delta_2 \]

The number \( \delta_i \) is the value of \( \delta_i \) adjusted by subtraction of such terms in the original array as are missing from \( (4) \). These missing terms belong to arcs, whose numerical values have already been determined by the foregoing procedure. Because of the nearly triangular structure of system \( (4) \), we may treat one variable of the loop as the parameter and then evaluate all the others in terms of it as we proceed around the loop. Upon completion of this circuit, a second expression for the parameter will result, and by equating the two expressions we may evaluate it numerically.

Thus, by proceeding clockwise about the loop in network Fig. 21-2-II, one arrives at the following explicit formula for \( x_1 \):

\[ (5) \]
\[ x_1 = \frac{1}{a_{21}} \left[ \frac{\delta_2 - a_{25} \left( \delta_9 - a_{91} \left( \delta_4 - a_{43} \delta_9 \right) \right)}{1 - \frac{-a_{25}}{a_{95}} \cdot \frac{-a_{25}}{a_{74}} \cdot \frac{-a_{32}}{a_{22}} \cdot \frac{-a_{31}}{a_{21}}} \right] \]

**Exercise:** Derive an equivalent expression by proceeding counterclockwise about the loop, and then show algebraically that the two formulas are identical.

**Evaluation of the Implicit Prices Associated with a Basis.**

If the basis includes slack variables, then the implicit price for any equation associated with the single node of a slack arc can, of course, be immediately evaluated, and, from this, all the prices for the entire subgraph.

If, on the other hand, an isolated subgraph contains a loop, then the prices may first be determined at nodes sequenced around the loop, and the remainder evaluated by successively proceeding to nodes which have an arc in common with nodes whose prices have already been determined. If \( x_i \) is a basic variable and \( \pi_i \) is the price associated with the \( i \)th equation, then

\[ (6) \]
\[ a_{34}x_1 + a_{94}x_5 = c_j \]

where \( g = g(j) \) and \( h = h(j) \) are the node designations of the equations corresponding to the non-zero coefficients of \( x_j \).
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For Fig. 21-2-II the arcs around the loop give rise to the system:

\[
\begin{align*}
    a_{21} \pi_3 + a_{31} \pi_2 &= c_1 \\
    a_{22} \pi_2 + a_{42} \pi_4 &= c_2 \\
    a_{43} \pi_4 + a_{73} \pi_7 &= c_3 \\
    a_{44} \pi_7 + a_{94} \pi_9 &= c_4 \\
    a_{95} \pi_9 + a_{25} \pi_3 &= c_5
\end{align*}
\]

Moreover, since the coefficient matrix in (7) is the transpose of the one in (4), the systems have analogous structures, and the same technique of evaluation may be used for the implicit pricing as for the basic solution itself.

21-3. A SUBCLASS WITH TRIANGULAR OPTIMUM BASES

The technique we have described for exploiting near-triangularity of the basis structure is a little more complex than the methods we have applied to the standard transportation problem. This is partly because the equations of the weighted distribution can have non-triangular bases.

However, even though non-optimal bases need not be triangular, H. Markowitz [1954-2] found that, for an important class of these problems, any basis corresponding to an optimal solution is triangular, regardless of the values of the constant terms [Theorem 1, below]. Unfortunately, if the usual simplex process is employed, no computational advantage results from the fact that the final basis is triangular. Markowitz’s idea was to vary the procedure, so that each basis occurring in the course of the algorithm would be made triangular. He noted that, for certain values of the constant terms, an optimal basic solution is immediately available, and, by parametrizing these terms, one could subsequently adjust them to any desired values. Since the bases are, in this way, kept both feasible and optimal throughout the process, they must remain triangular. This is the idea we will develop in the present section.

Two forms of the problem were considered by Markowitz; the first appears below and the second will be discussed later under (3).

Determine nonnegative numbers and the minimum \( z \) satisfying

\[
\begin{align*}
    \sum_{j=1}^{n} a_{ij} x_{ij} + x_i &= a_i & \text{for } i = 1, 2, \ldots, m \\
    \sum_{i=1}^{n} b_{ij} x_{ij} &= b_j & \text{for } j = m + 1, m + 2, \ldots, m + n \\
    - \sum_{i=1}^{n} c_i x_i &= z & (c_i > 0)
\end{align*}
\]
where \( a_{ij} \) and \( b_{ij} \) are nonnegative, while \( a_i \) and \( b_i \) are positive. The \( n \) column equations have been numbered \( j = m + 1, m + 2, \ldots, m + n \), to bring out the one-to-one correspondence between the \( m + n \) nodes and the \( m + n \) equations. Problems of this kind first came to light in attempts to assign machines to a fixed set of tasks in such a way as to minimize the use of machine time by maximizing the total value of the machine time left unused after the tasks have been completed; that is, by building up certain of the slack variables, \( x_r \). (See illustrative applications in § 21-1.)

**Theorem 1.** Every optimal basis for \((1), (2)\) is triangular.

**Proof:** If, on the contrary, a basis is not triangular, there is a subset of the equations whose linear subgraph is connected, contains one loop, and has no slack variable arcs, by Theorem 1 of § 21-2. The prices corresponding to nodes about the loop may be evaluated by means of equations, such as § 21-2-(7). However, since there are no slack variables, the coefficients in the objective form are all zero for the subset of the basic variables contained in these equations. Hence, the implicit prices must all vanish for this subset of equations. In particular, if \( x_{ri} \) is one of the basic variables in the subset, then \( u_r = 0 \). However, the conditions for an optimal basis are that

\[
\begin{align*}
  a_{ij}u_i + b_{ij}v_i & \leq 0 \\
  -u_i & \geq c_i > 0 \\
  \quad \text{for } i = 1, 2, \ldots, m \\
  \quad \text{and } j = m + 1, m + 2, \ldots, m + n
\end{align*}
\]

which contradicts the assertion that \( u_r = 0 \). Hence, loops are not possible (except slack-arc loops) and the basis must be triangular.

**Finding an Initial Feasible Dual Solution.**

If the \( a_i \) are replaced by sufficiently large values \( a_i^* \), a starting solution with a triangular basis is immediately available. As basic variables, choose the slacks and one variable, \( x_{ri} \), from each column \( j \), such that

\[
\Min_{i} \frac{a_{ij}c_i}{-b_{ij}} = \frac{a_{rij}c_r}{-b_{rij}} = v_j \quad (b_{ij}, b_{ij} \neq 0)
\]

Then (assuming that all \( b_{ij} \) are nonnegative), it is easy to see that the prices \( u_i = c_i \) and \( v_j \) above satisfy (3), so that the basic solution is both feasible and optimal.

**Exercise:** Determine explicitly how large to make \( a_i^* \) in order to guarantee feasibility.

The next step is to replace the constants \( a_i \) by \( a_i + \lambda(a_i^* - a_i) \) and determine the values of the basic variables as a function of \( \lambda \). The solution is feasible and optimal when \( \lambda = 1 \). Finally, the parametric linear programming algorithm (§ 11-3) can be applied to reduce \( \lambda \) to zero. At the end of this section we will describe an adaptation of the algorithm to this problem.
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The second form of the problem, considered by Markowitz, is as follows: determine numbers $x_i \geq 0$ and maximum $\lambda$, such that

\[
\sum_j a_{ij}x_{ij} + x_i = a_i \quad (i = 1, 2, \ldots, m)
\]
\[
\sum_i b_{ij}x_{ij} = \lambda b_i \quad (j = m + 1, m + 2, \ldots, m + n)
\]

In the previous formulation we sought to maximize the unused machine time after performing a fixed set of tasks, but here we seek that allocation which will turn out the most work when the proportion $b_j$ of each type task is fixed. This type of problem arises naturally if the different type tasks are combined in fixed proportions to form completed assemblies (e.g., parts of a calculator to be used for completed machines).

**Theorem 2:** For any fixed $\lambda$, a basis can be determined that is triangular.

**Proof:** Let $\lambda$ be any fixed value in (5). Maximize $\Sigma c_i x_i$. By Theorem 1, the final basis is triangular, completing the proof. To solve (5), one can proceed as follows: for $\lambda = 0$, use the same basic set as found by (4). The corresponding basic solution, $x_{ij} = 0, x_i = a_i$ for all $i, j$ is feasible and optimal for (5). Apply the parametric linear programming algorithm to increase $\lambda$ to a maximum. The successive bases will be triangular.

**Iterative Procedure.** To simplify the calculations, we assume $a_{ij} > 0$; it is convenient to consider system \{(1), (2)\} in the form:

Find $x' \geq 0, x'_i \geq 0$, Max $z'$ satisfying

\[
\begin{cases}
\sum_{i=1}^{n} x'_{ii} + x'_i = a'_i, \\
- \sum_{i=1}^{m} b_{ij}x'_{ij} = -b_j, \\
\sum_{i=1}^{m} x'_i = z' \quad \text{(Max)}
\end{cases}
\]

where we have chosen to maximize instead of minimize. This can be done by a simple transformation of variables $x'_{ij} = c_{ij}a_{ij}x_{ij}$ ($x_{ij} = x'_{ij}$ if $a_{ij} = 0$) and $c_i x'_i = x'_{i}$, and by setting $\beta_{ij} = b_{ij}/c_{ij} a_{ij}$ ($\beta_{ij} = b_{ij}$, if $a_{ij} = 0$) and $c_i a_i = a'_i$. We have assumed $a_{ij} \neq 0$ in (6).

**Exercise:** Explain why in practice $a_{ij} = 0$ usually implies $b_{ij} = 0$.

The dual of (6) is: Find $u_i, v_j$, Min $z'$ satisfying:

\[
\begin{align*}
    u_i - \beta_{ij}v_j & \geq 0 \\
u_i & \geq 1 \\
    a'_i u_i - b_j v_j & = z' \quad \text{(Min)}
\end{align*}
\]

where $i = 1, 2, \ldots, m; j = 1, 2, \ldots, n$. 

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Replacing $a'_i$ by $0a'_i$: Let us suppose that the $a'_i > 0$ have been replaced by $0a'_i$ for $i = 1, 2, \ldots, m$ and that for $\theta$ sufficiently large, we have at hand an optimal basic solution to (6). Then the basis is triangular and consists of a number of trees each connected to a slack arc, as shown in Fig. 21-3-I, which we will refer to as an sl+tree where sl is short for slack arc.

![Figure 21-3-I](image)

Figure 21-3-I. Improving a basic solution.

However, if $\theta$ is reduced, the value of some basic variable associated with an arc of some sl+tree may become negative. By the rules of the parametric programming algorithm (§11-3), the first basic variable to change sign below a critical value $\theta = \theta^*$ will be dropped from the basic set in the next iteration. In case the variable to be dropped is not a slack, say $x_{pq}$ as in Fig. 21-3-I, then the removal of the arc $(p, q)$ from the sl+tree separates it into parts $(F)$ and $(G)$. We assume for convenience that node $p \in F$ and that nodes $k, q \in G$. Now $(F)$, containing no slack variables, must join in the graph of the new basis with either $(G)$ or some other sl+tree by an arc $(r, s)$ associated with the new basic variable. In case $x_k$, the slack variable, is dropped, then, of course, $(G)$ is vacuous and $(F)$ must join up with some other sl+tree.

We shall now determine which basic variable to introduce into the basic set. We note that the prices on all nodes on all other sl+trees do not change with the change in basis, nor is there any change on the nodes of $(G)$. Hence, the only changes are the prices on the nodes of $(F)$. However, the prices on the nodes of $(F)$ were determined before a change of basis by a set of relations:

$$u_i - \beta_{ij}u_j = 0 \quad (i, j \in F) \tag{8}$$

where $(i, j)$ is an arc of $(F)$ and the price $u_p$ on the node $p$ where $u_p$ was determined via similar relations on $(G)$ and $u_k = 1$. Relations (8) still hold after a change of basis, but the price on $p$ can change from $u^*_p$ to, say, $\mu u^*_p$. Since relations (8) are homogeneous, it follows that the prices on all nodes $i$ of $(F)$ will all change proportionally from $u^*_i$ to $\mu u^*_i$. We have assumed $p \in F$ and $q, k \in G$; similar remarks hold if $q \in F$ and $p, k \in G$.

**Exercise:** Show that all implicit prices are nonnegative.

From these observations it is easy to put together the following rules for
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deciding the factor, \( \mu \), of proportionality and the variable, \( x_{rs} \) or \( x_r \), to introduce into the basic set:

Case I: If \( x_{pq} \) is dropped, where \( p \) is in \( F \) and \( q \) is not in \( F \), or if a slack variable \( x_r \) is dropped, then \( \mu > 1 \). If it exists, choose \( x_{rs} \) to enter where \( r \) is not in \( F \) and \( s \) is in \( F \), such that

\[
\mu = \frac{u_r}{\beta_{rr} v_r} = \min \frac{u_i}{\beta_{ii} v_j} > 1 \quad (j \text{ in } F, \ i \text{ not in } F).
\]

If no such \((r, s)\) exists, terminate.

Case II: If \( x_{pq} \) is dropped, where \( p \) is not in \( F \) and \( q \) is, then \( \mu < 1 \). If it exists, choose \( x_r \), to enter where \( r \) is in \( F \) and \( s \) is not in \( F \), such that

\[
\mu' = \frac{\beta_{rr} v_r}{u_r} = \max \frac{\beta_{ij} v_j}{u_i} < 1 \quad (i \text{ in } F, j \text{ not in } F)
\]

or choose slack variable \( x_r \), to enter, where \( r \) is in \( F \)

\[
\mu^* = \frac{1}{u_r} = \max \frac{1}{u_i} < 1 \quad (i \text{ in } F)
\]

depending on which ratio, \( \mu = \mu' \) or \( \mu = \mu^* \), is the larger. If no such \((r, s)\) exists, terminate.

The following can easily be shown:

Exercise: If the \( x_{rs} \) or \( x_r \), chosen above is introduced into the basic set in the place of \( x_{pq} \) or \( x_p \), show that the new solution (if non-degenerate) will be feasible in some range of values \( \theta < \theta^* \).

Exercise: If it is not possible to find an \( i \) not in \( F \), \( j \) in \( F \) for Case I or an \( i \) in \( F \), \( j \) not in \( F \) for Case II, show that there can be no feasible solution for \( \theta < \theta^* \).

Example: Consider the array:

\[
\begin{array}{cccccc}
(j = 3) & (j = 4) & (j = 5) & \text{(slack)} & a_j \\
(i = 1) & x_{13} & x_{14} & x_{15} & x_1 & 8 \\
& \beta_{13} = 1 & \beta_{14} = 2 & \beta_{15} = 3 & & \\
(i = 2) & x_{23} & x_{24} & x_{25} & x_2 & 2 \\
& \beta_{23} = 4 & \beta_{24} = 3 & \beta_{25} = 6 & & \\
& b_j & 8 & 6 & 12 &
\end{array}
\]
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which represents the equations

(13) Row Equations: \[ x_{13} + x_{14} + x_{15} + x_1 = 8 \quad (= 8\theta \text{ when right-hand side is parametrized}) \]
\[ x_{23} + x_{24} + x_{25} + x_2 = 2 \quad (= 2\theta \text{ when right-hand side is parametrized}) \]

(14) Column Equations:
\[ x_{13} + 4x_{23} = 8 \]
\[ 2x_{14} + 3x_{24} = 6 \]
\[ 3x_{15} + 6x_{25} = 12 \]
\[ x_1 + x_2 = z \quad (\text{Max}) \]

To construct a starting solution choose for basic variables the variable in each column \( j \) corresponding to \( \max \beta_{ij} \) and the slack variables. For the example the basic variables are \( x_{23}, x_{24}, x_{25}, x_1, x_2 \). The graph of the basis, the prices, and the values of the basic variables are shown in Fig. 21.3-II.

\[ u_1 \quad v_3 = 1/4 \quad v_4 = 1/3 \quad v_5 = 1/6 \]

\[ x_{23} = 2 \quad x_{24} = 2 \quad x_{25} = 2 \]

\[ u_2 - \beta_{23} v_3 = 0 \]
\[ u_2 - \beta_{24} v_4 = 0 \]
\[ u_2 - \beta_{25} v_5 = 0 \]

Figure 21.3-II. Graph of basis for cycle 0.

It is easy to verify \( u_i - \beta_{ij} v_j \geq 0 \) for \( j = 3, 4, 5 \), so that the solution is optimal and feasible for \( \theta \geq 3 \). Reducing \( \theta \) below the critical value \( \theta^* = 3 \), \( x_3 \) changes sign; hence \( x_3 \) is to be dropped as basic variable. To do this, prices are modified as shown in Fig. 21.3-III. By the calculation shown at the right of the figure, \( x_{14} \) becomes the new basic variable to replace \( x_3 \). The graph of the new basis, the prices, and the values of basic variables are given in Fig. 21.3-IV.

When \( \theta \) is reduced below the critical value \( \theta^* = 2 \), \( x_{24} \) changes sign and accordingly will be dropped on the next iteration. Hence, prices are modified as shown in Fig. 21.3-V, and by the calculation shown at the right, \( x_{15} \) will be the new basic variable.
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Figure 21.3-III. Graph of basis for cycle 1.

Figure 21.3-IV. Graph of basis for cycle 2 (start).

Figure 21.3-V. Graph of basis for cycle 2 (end).
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The graph of the new basis is given by Fig. 21-3-VI.

Figure 21-3-VI. Graph of basis for cycle 3 (optimum).

The value of \( \theta \) can be reduced to 1 without affecting feasibility. At \( \theta = 1 \) the parametrized right-hand side of (1) attains the desired \( a_i \) values, hence the optimal solution is given by (15) for \( \theta = 1 \). This solution is recapped below (boxes indicate position of basic variables).

\[
\begin{align*}
  x_{13} &= 0 & x_{14} &= 3 & x_{15} &= 4 & x_1 &= 1 \\
  x_{23} &= 2 & x_{24} &= 0 & x_{25} &= 0 & x_2 &= 0
\end{align*}
\]

21-4. PROBLEMS

1. (Review.) What is the change of variables referred to in the second paragraph of § 21-1? Why does it fail if a coefficient is negative in a row equation? How would you work the simplex method if some variables were allowed to be negative? How is \( p_{ij} \) related to the previous coefficients?

2. What is the dual for the system of equations (4), (5), and (6) of § 21-1?

3. Change the constants \( a_i \) and \( b_j \) in such a way that more than one iteration is needed in Phase I of the example in § 21-1.

4. (Review.) In § 21-3, show how to choose \( a_i^c \) sufficiently large so that the basic solution will also be feasible. Interpret the meaning of the optimal solution in this case.

5. How is the selection made if some \( \beta_{ij} \) is negative?

6. Apply the procedure and solve a 3 \( \times \) 4 example. Use linear graphs to guide computation of prices and adjustments in the values of basic variables.

7. Solve the 3 \( \times \) 4 example as in Example 1, § 21-1, where \( b_i \) are replaced by \( \lambda b_i \). Choose \( \lambda \) initially sufficiently small so that feasibility is attained, and then parametrically increase \( \lambda \) to 1.

8. Set up a machine-task model in the standard form of the weighted distribution problem, § 21-1-(4), (5), (6). Assume the cost per hour, \( c_{ij} \), for the \( i \)th machine is the same, regardless of the task, and \( c_i \) is the revenue per hour derived from other uses of the left-over machine time. If the
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objective is to minimize net costs, show for such a model that system (6) of § 21-3 can be obtained from system ((1), (2)) of § 21-3.

9. If $u_i$ and $v_j$ are the prices associated with the $i^{th}$ row equation and the $j^{th}$ column equation of § 21-3-(6) respectively, show that the prices of an optimal solution satisfy $u_i \geq 0, v_j > 0$.

10. Starting from (15) of § 21-3, continue to reduce $\theta$ and find the value of $\theta$ below which there is no feasible solution. Show that, in this case, it is not possible to determine which variable is to enter the basic set.

11. Review problems and illustrative examples in Chapters 3, 4, 5 and determine which ones are weighted distribution problems. Solve those which are numerical.

12. (Unsolved.) Does there exist a transformation of variables and constants that will convert the first type of system considered by Markowitz § 21-3-(1), (2) to his second type § 21-3-(5) ?

REFERENCES

Eisemann and Lourie, 1959-1
Ferguson and Dantzig, 1954-1, 1956-1
Hadley, 1962-2
Jewell, 1960-1
Kantorovich, 1939-1
Markowitz, 1954-2

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CHAPTER 22

PROGRAMS WITH VARIABLE COEFFICIENTS

22-1. WOLFE'S GENERALIZED PROGRAM\(^1\)

In this chapter, we will consider problems in which there is some freedom in the choice of coefficients of an activity. Such problems arise when a system is being designed or when the input and output characteristics of a process depend on one or more parameters, such as temperature, which can be regulated.

First, a matter of notation; it will be convenient to consider the linear programming problem in vector form: Find \( x_j \geq 0 \) for \( j \neq 0 \) and \( \text{Max } x_0 \) satisfying

\[
P_0 x_0 + P_1 x_1 + P_2 x_2 + \ldots + P_n x_n = Q
\]

For example, if we had to find \( x_j \geq 0 \) and \( \text{Min } z \) satisfying

\[
\begin{align*}
  x_1 + x_2 - 4x_3 + 2x_4 &= 5 \\
  -x_1 + x_2 - x_3 + 3x_4 &= 1 \\
  6x_1 + 4x_2 + x_3 - 2x_4 &= z
\end{align*}
\]

we would set \( z = -x_0 \), obtaining

\[
\begin{bmatrix}
  0 \\
  1 \\
  -1 \\
  6
\end{bmatrix}
\begin{bmatrix}
  x_0 \\
  x_1 \\
  x_2 \\
  x_3 \\
  x_4
\end{bmatrix}
\begin{bmatrix}
  1 \\
  1 \\
  -1 \\
  4 \\
  -1
\end{bmatrix}
\begin{bmatrix}
  -4 \\
  3 \\
  -2 \\
  -1 \\
  0
\end{bmatrix}
\begin{bmatrix}
  1 \\
  0
\end{bmatrix}
\begin{bmatrix}
  5 \\
  1
\end{bmatrix}
\]

We will also be convenient to redefine the simplex multipliers \( \pi = (\pi_1, \pi_2, \ldots, \pi_m, \pi_{m+1}) \), so that

\[
\begin{align*}
  \pi P_j &= 0 & \text{if } x_j = x_0 \text{ is a basic variable} \\
  \pi P_0 &= 1
\end{align*}
\]

The last of these multipliers, \( \pi_{m+1} \), is always 1 because \( P_0 = U_{m+1} \) is a unit

\(^1\) The approach to this class of problems was first developed in the joint work of Philip Wolfe and the author on a decomposition principle for large-scale programs (discussed in Chapter 23); because it was Wolfe who suggested that the procedure developed there could be formalized as a special case of a “Generalized Linear Program,” we associate his name with it here [Dantzig and Wolfe, 1960-1; Gomory and Hu, 1960-1].
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vector and \( x_0 \) is unrestricted in sign. Hence these multipliers would generate a modified cost equation \( \sum \xi_i x_i \) where (referring to a standard linear program)

\[
\xi_i = \pi P_i = \sum_{i=1}^{m} \pi a_{ij} + 1 \cdot c_i
\]

It is now evident, since we are adding the sum term to \( c_i \) instead of subtracting, that the multipliers \( \pi_1, \pi_2, \ldots, \pi_m \) will have the opposite sign to those in § 9.2. As usual, in order for a basic feasible solution to be optimal \( \xi_i = \pi P_i \geq 0 \) for all \( i \).

DEFINITION: A Generalized Linear Program is a linear programming problem with variable coefficients as follows: Find \( x_i \geq 0 \) for \( j \neq 0 \) and Max \( x_0 \) satisfying

\[
P_0 x_0 + P_1 x_1 + \ldots + P_n x_n = Q
\]

where each \( P_j \) for \( j \neq 0 \) may be freely chosen to be any \( P_j \in C_j \), where each \( C_j \) is a convex set. By simple extension the fixed vectors in (5), \( P_0 \) and \( Q \), may be replaced by any vectors \( P_0, Q \) drawn from convex sets \( C_0 \) and \( C_0 \). This is further discussed in the subsection on "Equivalent Formulations" at the end of this section. The convex sets we shall consider here are defined by systems of linear inequalities. However, the methods of Chapter 24 can be used to extend the results to general convex sets.

For example, (3) becomes a program with variable coefficients if we generalize it to the following form: Find \( x_i \geq 0 \) for \( j \neq 0 \), Max \( x_0 \) satisfying

\[
\begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \\ 1 \\ 6 \\ 4 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} x_0 + \begin{bmatrix} 1 \\ -1 \\ 1 \\ -1 \\ 1 \\ 4 \\ 1 \end{bmatrix} x_1 + \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} x_2 + \begin{bmatrix} 6 \\ -1 \\ -1 \\ 1 \end{bmatrix} x_3 + \begin{bmatrix} 4 \\ 1 \end{bmatrix} y_1 + \begin{bmatrix} 1 \end{bmatrix} y_2 + \begin{bmatrix} 1 \end{bmatrix} y_3 = \begin{bmatrix} 1 \\ 5 \\ 0 \end{bmatrix}
\]

where \( y_i \) may be chosen as any values satisfying

\[
y_1 + 2y_2 + 3y_3 = 2 \quad (y_i \geq 0)
\]

One may wonder whether a system such as (6), (7) is formally a linear programming system. However, if we set \( y_1 x_4 = u_1 \), \( y_2 x_4 = u_2 \), \( y_3 x_4 = u_3 \) and multiply (7) by \( x_4 \), it is easily seen that the system may be re-expressed linearly in \( x_i \) and \( u_i \) (see Problem 2). In general we have:

COMMENT: A system (5) in which some column \( P_i = (y_1, y_2, \ldots, y_m) \) must satisfy a system \( S_i \) of linear inequalities in variables \( y_i \) for \( i = 1, 2, \ldots, m \), and auxiliary variables \( y_{m+1}, \ldots, y_{m+k} \) independent of the rest of the system, can be replaced by a linear inequality system by multiplying the relations of \( S_i \) by \( x_i \geq 0 \) and substituting new variables \( u_i = y_i x_i \).

While the above remark permits us formally to expand the system to make it linear, this expansion does not necessarily lead to a linear program which is equivalent to the original system because it is possible for the
linear program to have a solution such that \( x_i = 0 \) and \( u_{i+} \neq 0 \) at the same time. For further discussion of this point, see Problem 2. Great advantage accrues by not using this approach. Using instead the variable coefficient concept, the general program is solved by a series of adjustments of the values of \( y_i \) obtained by solving an auxiliary program or subprograms in the \( y_i \) above. In effect, a large linear program is decomposed into smaller linear programs.

The Method Illustrated.

The working out of example ((6), (7)) will illustrate clearly the general procedure. Suppose we initiate the computation with the basic set of variables \( x_0, x_1, x_2 \). We wish to ascertain whether or not the basic feasible solution \( x_0 = -24, x_1 = 2, x_2 = 3, x_3 = x_4 = 0 \) is optimal for (6), which we will refer to as a master program. The simplex multipliers

\[
\pi = [-5, 1, 1]
\]

are defined so that \( \pi P_0 = 1, \pi P_1 = 0, \pi P_2 = 0 \). Multiplying equations (6) on the left by \( \pi \), we obtain

\[
x_0 + (\pi P_0)x_0 + (\pi P_4)x_4 = (\pi Q)
\]

where

\[
\pi P_2 = 20, \quad \pi Q = -24
\]

\[
\pi P_4 = -5y_1 + y_2 + y_3
\]

It is clear that the test for maximum \( x_0 \) is \( \pi P_j \geq 0 \) for all \( j \). On the other hand, if \( \pi P_4 < 0 \), it is possible to find a better solution by increasing the value of \( x_4 \). Therefore, let us set \( z_4 = \pi P_4 \) and consider the auxiliary linear programming problem of finding \( y_i \geq 0 \), and Min \( z_4 \) satisfying

\[
y_1 + 2y_2 + 3y_3 = 2 \quad (y_i \geq 0)
\]

\[
-5y_1 + y_2 + y_3 = z_4 (\text{Min}) \quad (z_4 = \pi P_4)
\]

What we are doing is in keeping with the usual simplex procedure of bringing into the basis that column which prices out the least. The solution yielding minimal \( \pi P_4 \) is immediate, namely, \( y_1 = 2, y_2 = 0, y_3 = 0; \pi P_4 = -10 \).

We can now obtain an improved solution by introducing the column \( (y_1, 0, y_2, 0) \) into the basis of the master program. However, we must allow for the possibility of revising later the values of \( y_i \). We can do both by rewriting the problem in the form

\[
\begin{bmatrix}
0 \\
1 \\
\end{bmatrix} x_0 + \begin{bmatrix}
-1 \\
4 \\
\end{bmatrix} x_1 + \begin{bmatrix}
1 \\
6 \\
\end{bmatrix} x_2 + \begin{bmatrix}
-4 \\
1 \\
\end{bmatrix} x_3 + \begin{bmatrix}
2 \\
0 \\
\end{bmatrix} x_4 + \begin{bmatrix}
y_1 \\
y_2 \\
\end{bmatrix} x_4 = \begin{bmatrix}
5 \\
0 \\
\end{bmatrix}
\]

\[
\bullet \quad \bullet \quad \bullet \quad *
\]

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where the $y''_i$ satisfy the same relations as the $y_i$:

(15) \[ y''_1 + 2y''_2 + 3y''_3 = 2 \quad (y''_i \geq 0) \]

We shall refer to the column $\langle y'_1, y'_2, y'_3 \rangle$ as the generic column. It appears we have changed our original problem; they are equivalent, however. To see this we rewrite any solution to (14) back in the form (6) by setting $x_4 = x'_4 + x''_4$ and letting the coefficients of $x_4$ be given by:

(16) \[
\begin{bmatrix}
  y_1 \\
y_2 \\
y_3
\end{bmatrix}
= \begin{bmatrix}
  2 \\
  0 \\
  0
\end{bmatrix}
\frac{x'_4}{x'_4 + x''_4} + \begin{bmatrix}
  y'_1 \\
y'_2 \\
y'_3
\end{bmatrix}
\frac{x''_4}{x'_4 + x''_4} \quad (x'_4 + x''_4 > 0)
\]

The right-hand side is clearly a convex combination of two points lying in a convex set defined by (12); as a consequence the point $(y_1, y_2, y_3)$ must lie in the convex set also. Conversely, to any solution of (12) we can associate a solution of (16), for example, set $x'_4 = 0$; in this case $x_4 = x'_4$, $y_i = y'_i$.

When $x'_4$ is introduced into the basic set of the master program, $x_1$ will be found to drop out. The new basic solution is $x_0 = -4$, $x_1 = 1$, $x'_4 = 2$; $x_1 = x_3 = x'_4 = 0$. The corresponding simplex multipliers are

(17) \[ \pi = [0, -4, 1] \]

where $\pi$ is defined by (4), so that $\pi P_0 = 1$, $\pi P_2 = 0$, $\pi P'_4 = 0$. To test for maximum $x_0$ we form

(18) \[
\begin{align*}
\pi P_1 &= 10 \\
\pi P_2 &= 5 \\
\pi P'_4 &= -4y''_2 + y''_3
\end{align*}
\]

The only possibility for increasing values of $x_0$ is to find values of $y''_i$ so that $\pi P'_4 < 0$. Accordingly, we consider the new subprogram

(19) \[ y''_1 + 2y''_2 + 3y''_3 = 2 \quad (y''_i \geq 0) \]

This yields $y''_1 = 0$, $y''_2 = 1$, $y''_3 = 0$ and $\pi P'_4 = -4$.

Our augmented master problem now becomes

(20) \[
\begin{bmatrix}
0 \\
1
\end{bmatrix}
x_0 + \begin{bmatrix}
-1 \\
6
\end{bmatrix} x_1 + \begin{bmatrix}
1 \\
4
\end{bmatrix} x_2 + \begin{bmatrix}
-4 \\
1
\end{bmatrix} x_3 + \begin{bmatrix}
2 \\
0
\end{bmatrix} x'_4 + \begin{bmatrix}
0 \\
1
\end{bmatrix} x''_4 + \begin{bmatrix}
y'_1 \\
y'_2 \\
y'_3
\end{bmatrix} x''_4 = \begin{bmatrix}
5 \\
1 \\
0
\end{bmatrix}
\]

\[ \bullet \quad \bullet \quad \bullet \quad \bullet \quad \ast \]

where again we have allowed for the possibility that we may again revise the values of $y_i$ by the introduction of the "generic" column $y''_i$ and variable $x''_i$.
22.1. WOLFE'S GENERALIZED PROGRAM

Introducing $x_i^*$ into the basic set, $x_2$ drops out and the new basic solution is $x_0 = 0$, $x_2^* = \frac{1}{2}$, $x_3^* = 1$; $x_1 = x_2 = x_3 = 0$; the new simplex multipliers are defined by $\pi P_0 = 1, \pi P_1^* = 0, \pi P_3^* = 0$. We now have

$$\pi P_1 = 6$$

$$\pi P_2 = 4$$

$$\pi P_3 = 1$$

$$\pi P_3^* = y_3^m$$

The auxiliary linear program is: Find $y_i^m$ and Min $\pi P_4^m$ satisfying

$$y_1^m + 2y_2^m + 3y_3^m = 2$$

$$(y_i^m \geq 0)$$

$$y_3^m = \pi P_4^m \text{ (Min)}$$

But this yields as one optimal solution $y_1^m = 2$, $y_2^m = 0$, and $y_3^m = \text{Min } \pi P_4^m = 0$. Thus, at this stage, no improved solution to (20) can be found modifying the values of $y_i$. Since all other $\pi P_j \geq 0$ the basic solution is optimal.

**Exercise:** From the optimal solution to (20), (23) derive the optimal solution to (6), (7).

It would appear that this process, iterated many times, could expand the problem by an indefinite number of columns. Such is not the case, however, since no more of these added columns need be retained than are currently used in the basis. We shall show that any column which drops out of the basis may be “dropped” because it is included in the convex sets defining the generic columns associated with the master program and these convex sets are each defined by a system of linear inequalities. We now formalize some of the terms and concepts used so far.

**Definition:** A restricted master program (at the $k$th stage of the algorithm) consists of variables $x_i^{(k)}$ with specified columns of coefficients $P_i^{(k)}$ drawn from the convex sets $C_j$. Its optimal solution determines values for the simplex multipliers, $\pi = \pi^k$, for use in the subprograms.

**Definition:** The $jth$ subprogram is: Find $P_j \in C_j$ which minimizes the linear form, $\pi^k P_j$ (in the unknown components of $P_j$), where $\pi = \pi^k$ is known. Its optimal solution $P_j = P_j^*$ generates an additional specified column of coefficients $P_j^*$ for the next restricted master program.

**Theorem 1:** If terms $\sum P_j x_j$ are added to a restricted master program, where the “generic columns,” $P_j$, are general elements of convex sets $C_j$, the new problem is equivalent to the original generalized linear program.

The General Theory for Polyhedral $C_j$

We assume here that each convex set $C_j$ is polyhedral, i.e., defined by a system of linear inequalities. In this case a general $P_j$ can be represented
by a convex linear combination of a finite set of extreme points of\( C_j \) plus a nonnegative linear combination of a finite set of homogeneous solutions (in case \( C_j \) is unbounded).

**Definition:** By a homogeneous solution \( P_j \), it is meant one with the property that if \( P_j \in C_j \), then \( P_j + kP_j \in C_j \) for all \( k \geq 0 \).

**Theorem 2:** A solution \((x_j^*, P_j^*)\) for \( j = 0, 1, 2, \ldots, n \), is optimal if there exists a \( \pi \), such that \( \pi P_0 = 1 \), \( \pi P_j \geq 0 \) for all \( P_j \in C_j \) and \( \pi P_j^* = 0 \) for all \( j \) for which \( x_j^* > 0 \), \( j \neq 0 \).

**Theorem 3:** Only a finite number of iterations of the simplex algorithm is required if each basic feasible solution is improved by introducing into the basis either an extreme point \( P_j^* \in C_j \) chosen so that

\[
\pi P_j^* = \min_{P_j \in C_j} \pi P_j < 0 \quad (j = 1, 2, \ldots, n)
\]

where \( \pi \) are the simplex multipliers of the basis or by introducing into the basis any homogeneous solution \( P_j^* \) from a finite set such that \( \pi P_j^* < 0 \).

**Proof:** From our earlier remarks, Theorem 2 is obvious. With regard to Theorem 3, finiteness of the algorithm is also obvious if we can show that columns of any basis must be drawn from a finite class. Since \( C_j \) is a convex set defined by a set of inequalities, each \( P_j^* \) is obtained by solving a linear program which minimizes the linear form \( \pi P_j \) where \( \pi \) is fixed and the components of \( P_j \) are unknown.

If \( C_j \) is bounded, \( P_j^* \) will be one of a finite number of basic solutions. If \( C_j \) is unbounded, then it may happen that \( \pi P_j \) has no lower bound. In this case, on some iteration of the simplex method a homogeneous solution will be obtained (see Chapter 6, Problem 19). In the notation of the standard simplex method as applied to the canonical form for the subproblem for \( C_j \), on some iteration a column will be found such that all coefficients, say \( \bar{a}_i \), will be nonpositive and the relative cost factor \( \bar{c}_i < 0 \). In this case, letting \( y_i \) represent the \( i \)th basic variable of the subproblem, the set of values \( y_i = -\bar{a}_i \geq 0, y_1 = 1 \), and all other \( y_i = 0 \) forms a homogeneous solution \( P_j \) for \( C_j \) with the requisite property; namely \( \bar{c}_i = \pi P_j \leq 0 \), where \( \pi \) is the set of simplex multipliers for the basis of the master program. Since the number of canonical forms for the various subprograms (omitting the objective equation) is finite, the number of columns with the property \( \bar{a}_i \leq 0 \) for all \( i \) is finite. Hence the set of \( P_j \) is also finite.

**Equivalent Formulations.**

It was assumed in (5) that \( P_0 \) and \( Q \) were fixed vectors. However, if it is desired to have \( Q \) freely chosen from a convex set \( C_0 \), it is possible to do so by considering the system

\[
P_0 x_0 + P_1 x_1 + \ldots + P_n x_n - Q x_{n+1} = 0
\]

\[
x_{n+1} = 1
\]
22.1. WOLFE'S GENERALIZED PROGRAM

EXERCISE: Extend the results so that $P_0$ can be drawn from a convex set $C_0$.

EXERCISE: Reduce the following problem to a generalized linear program: Find vectors $P_1 \in C_1, Q \in C_q$ such that

$$ P_1 + P_2 + \ldots + P_n = Q $$

(26)

EXERCISE: Suppose in place of condition (7), we have $y_1^2 + y_2^2 + y_3^2 \leq 1$. Show that this is a generalized linear program. Apply methods of this section and contrast with the polyhedral case.

Convex Programs. (See Chapter 24.)

Kuhn and Tucker [1950-2] considered a broad class of problems of the form: Find $z = (x_1, x_2, \ldots, x_n)$ and Min $z$ satisfying

$$ G_i(x) \leq 0 \quad (i = 1, 2, \ldots, m) $$

$$ G_0(x) = z \quad (\text{Min}) $$

(27)

where $G_i(x)$ are convex functions and $x$ is restricted to a convex set $R$.

We replace this by the equivalent problem: Find $\lambda, \lambda_0, y_i$, satisfying

$$ \lambda = 1 \quad (\lambda_i \geq 0, \lambda_2 \geq 0, \ldots, \lambda_m \geq 0) $$

$$ y_1 \lambda + \lambda_1 = 0 $$

$$ y_2 \lambda + \lambda_2 = 0 $$

$$ \ldots $$

$$ y_m \lambda + \lambda_m = 0 $$

$$ y_0 \lambda = z \quad (\text{Min}) $$

(28)

where $y_i \geq G_i(x)$ for some $x \in R$. To show that the set of possible $y = (y_0, y_1, \ldots, y_m)$ forms a convex set, $C_y$, suppose $y_i' \geq G_i(x')$, $y_0' \geq G_0(x')$, and let $\lambda + \mu = 1$ and $\lambda \geq 0, \mu \geq 0$. Then

$$ y_i = \lambda y_i' + \mu y_i' \geq \lambda G_i(x') + \mu G_i(x') \geq G_i(\lambda x' + \mu x') $$

(29)

where $(\lambda x' + \mu x') \in R$ because $R$ is convex. The methods of Chapter 24 can be used to extend the results to solve in general this essentially one variable linear program with coefficients generated by a set of general convex functions of a point $x$ in $n$ dimensions.

EXERCISE: Prove that if $y_i' \geq G_i(x')$ solves the linear program with $\lambda = \lambda_i, \lambda_0 = \lambda_0'$, then $y_i = G_i(x)$ also solves the program and $G_0(x) \leq y_0'$.

EXERCISE: Suppose a feasible solution to (28) exists with $y = y^*$, where $y^*$ is a convex combination of several $y^k$ such that for each $k$, $y_k^* \geq G_i(x^k)$, and suppose that feasible solutions may or may not exist for these $y^k$, prove there exists an $x^*$ such that $y_k^* \geq G_i(x^*)$ where $y^* = (1, y_2^*, \ldots, y_m^*, y_0^*)$.

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EXERCISE: Prove that the simplex multipliers \( \pi_i \) of the optimal solution of each master program for (28) are nonnegative. Show that the subprogram can be stated: Find \( x \in R \) such that \( F(x) \) is minimum where

\[
F(x) = \sum \pi_i G_i(x)
\]

Prove that \( F(x) \) is convex. Relate this to the method of Lagrange multipliers, § 6-5.

22-2. NOTES ON SPECIAL CASES

The Case of One Control Parameter \( T \).

Many industrial processes have a continuous spectrum of alternative activities depending on the settings of certain controls such as temperature \( (T) \), pressure \( (P) \), recycle ratio \( (R) \), etc. This is particularly true in refinery applications where, to keep things simple, only one standard way to operate the equipment is often assumed in any one problem; or sometimes a few typical sets of values are selected that "span" the range of possibilities.

Suppose there is one control \( T \), whose range of settings is \( T_1 \leq T \leq T_2 \); let \( j = 1 \) be a single activity whose technological coefficients depend on \( T \).

Its coefficients for \( T = T_1 \) and \( T = T_2 \) and general \( T \) are

\[
\begin{array}{ccc}
T_1 & T_2 & T \\
\hline
a^{(1)}_{11} & a^{(2)}_{11} & y_1 \\
a^{(1)}_{21} & a^{(2)}_{21} & y_2 \\
\vdots & \vdots & \vdots \\
a^{(1)}_{m1} & a^{(2)}_{m1} & y_m \\
c^{(1)}_{1} & c^{(2)}_{1} & y_{m+1}
\end{array}
\]

where \( y_i = y_i(T) \) for \( i = 1, 2, \ldots, m, m + 1 \) are functions of \( T \).

In many applications a linear interpolation between the first two columns of coefficients is a satisfactory approximation for a general \( T \). If this is the case, the equivalent linear programming problem becomes:

\[
\begin{align*}
a^{(1)}_{11}x_{11} + a^{(2)}_{11}x_{21} + a_{12}x_2 + \ldots + a_{1m}x_m &= b_1 \\
a^{(1)}_{21}x_{11} + a^{(2)}_{21}x_{21} + a_{22}x_2 + \ldots + a_{2m}x_m &= b_2 \\
\vdots & \vdots & \vdots \\
a^{(1)}_{m1}x_{11} + a^{(2)}_{m1}x_{21} + a_{m2}x_2 + \ldots + a_{mm}x_m &= b_m \\
c^{(1)}_{1}x_{11} + c^{(2)}_{1}x_{21} + c_{2}x_2 + \ldots + c_{m}x_m &= z
\end{align*}
\]

where \( x_i = x_{11} + x_{21} \) is the level of the first activity. It is clear we are assuming that the variable coefficients \( y_i \) are given by the linear interpolation (3), where \( \lambda = x_{11}/x_1 \) corresponds to some temperature setting \( T \).
22.2. NOTES ON SPECIAL CASES

\[ \lambda_1 + \lambda_2 = 1, \]
\[ \lambda_i a^{(1)}_{ii1} + \lambda_{m+1} a^{(2)}_{i11} = y_i \quad (\lambda_i \geq 0; \ i = 1, 2, \ldots, m) \]
\[ \lambda_i c^{(1)}_1 + \lambda_{m+1} c^{(2)}_1 = y_{m+1} \]

In particular, if the temperature setting \( T \) has also the same linear interpolation, then

\[ \frac{x_{11}T_1 + x_{11}T_2}{x_{11} + x_{21}} = T \]

The set of relations (3) defines a convex set of possible values for \((y_1, y_2, \ldots, y_m)\). The method of \(\S\ 22.1\) is therefore applicable. If \(\pi\) is the set of multipliers associated with a basis and \(c^{(1)}_1 = c^{(1)}_1 - \sum \pi_c a^{(1)}_{1i}\) and \(c^{(2)}_1 = c^{(2)}_1 - \sum \pi_c a^{(2)}_{1i}\), then the subprogram reduces to

\[ \lambda_i + \lambda_2 = 1 \quad (\lambda_i \geq 0) \]
\[ c^{(1)}_1 \lambda_1 + c^{(2)}_1 \lambda_2 = \pi P_1 \ (\text{Min}) \]

The extreme point solutions for \((\lambda_1, \lambda_2)\) are either \((1, 0)\) or \((0, 1)\). Thus either the first or the second column of (2) would be introduced into the basis. Because of this small number of possible extreme points of the subprogram (two in this case), it does not pay to use the method of \(\S\ 22.1\).

In order to interpolate between several possible values of \( T \), say \( T_1, T_2, \ldots, T_k \), let us consider the linear program

\[ a^{(1)}_{11} x_{11} + a^{(2)}_{11} x_{21} + \cdots + a^{(k)}_{11} x_{k1} + \sum_{j=2}^{n} a_{1j} x_j = b_1 \]
\[ a^{(1)}_{21} x_{11} + a^{(2)}_{21} x_{21} + \cdots + a^{(k)}_{21} x_{k1} + \sum_{j=2}^{n} a_{2j} x_j = b_2 \]
\[ \vdots \]
\[ a^{(1)}_{m1} x_{11} + a^{(2)}_{m1} x_{21} + \cdots + a^{(k)}_{m1} x_{k1} + \sum_{j=2}^{n} a_{mj} x_j = b_m \]
\[ c^{(1)}_1 x_{11} + c^{(2)}_1 x_{21} + \cdots + c^{(k)}_1 x_{k1} + \sum_{j=2}^{n} c_j x_j = z \]

where \(a^{(r)}_{1i}\) is the value of \(y_i = y_r(T)\) for \( T = T_r, r = 1, 2, \ldots, k \). In general, letting

\[ x_1 = x_{11} + x_{21} + \cdots + x_{k1} \]

it is clear that we are assuming the linear interpolations

\[ \frac{x_{11}}{x_1} a^{(1)}_{11} + \frac{x_{21}}{x_1} a^{(2)}_{11} + \cdots + \frac{x_{k1}}{x_1} a^{(k)}_{11} = y_1 \]

and a similar expression for \(c_1\).
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However, in some applications a linear interpolation between two columns of coefficients is satisfactory, providing the range of their \( T \) values is sufficiently small. If not, then it is necessary to break up the range into several parts \( T_1 \leq T_2 \leq \ldots \leq T_r \leq \ldots \leq T_k \), so that a linear interpolation between the vectors \([y_1(T), y_2(T), \ldots, y_{m+1}(T)]\) for adjacent pairs \( T = T_i \) and \( T = T_{i+1} \) is an acceptable approximation. For this situation, an optimal solution to system (5) is acceptable only if the positive \( x_i \) occur in adjacent pairs as underlined in (8):

\[
\begin{align*}
\text{either} & \quad (a) \quad x_{11} \geq 0, \quad x_{21} \geq 0, \quad x_{31} = 0, \quad x_{41} = 0, \ldots \\
& \quad \text{or} \quad (b) \quad x_{31} = 0, \quad x_{21} \geq 0, \quad x_{31} \geq 0, \quad x_{41} = 0, \ldots \\
& \quad \text{or} \quad (c) \quad x_{31} = 0, \quad x_{21} = 0, \quad x_{31} \geq 0, \quad x_{41} \geq 0, \ldots
\end{align*}
\]

The following results can be established: (a) If the coefficients \( y_i \) except \( y_{m+1} \) are linear in \( T \) and \( y_{m+1} \) is a strictly convex function of \( T \), then (8) will hold. (b) Let \( T' \) be some strictly monotonic function of the control parameter \( T \); if the coefficients \( y_i, i \neq m + 1 \), are linear functions of \( T' \) and \( y_{m+1} \) is a strictly convex function of \( T' \), then (8) must hold. (c) If \( y_{m+1} \) is just a convex (but not necessarily strictly convex) function of \( T' \), then (8) need not hold, but if not, then the average values \( a_{i1} \) and \( c_{i1} \) obtained at the minimum are the coefficients \( y_i \) corresponding to some fixed \( T' \) and the optimum solution to (5) is exact—not an approximation to the original nonlinear problem. (d) Suppose the system has the property that the optimal prices \( \pi_i \leq 0 \) for some subset of the items (where \( \pi_i \) are defined so that \( \Sigma a_{ii} \pi_i = c_i \) for basic \( x_i \)); suppose that \( y_i \) depend on \( T' \) only for these items and these are convex functions of \( T' \), then either property (8) holds for an optimum solution or the average solution is exact for some fixed \( T' \).

Interpreting a Mixed Solution.

An interesting question arises if (8) does not hold and moreover any adjustment of the solution so that it does hold only increases the value of \( z \). In this situation we have no physical interpretation of the solution in the sense there are values \( x_i \) given by (6) and \( a_{i1}, c_1 \) given by (7) which correspond to some value of \( T \). This may or may not be acceptable. If the activity is such that \( T \) is not an adjustable control, but rather a design characteristic that once settled for some value cannot be changed, then the answer is, of course, not acceptable. (We shall discuss what to do in this case in a moment.)

If \( T \) is easily adjustable, there may be an "out." Let us suppose the optimal solution yields \( x_{11} > 0, x_{12} = x_{13} = 0, x_{14} > 0 \). We may interpret this to mean that it pays to use more than one setting for \( T \). Thus, if the activity is actually performed with several pieces of equipment, some can be
set for the value \( T = T_1 \) and the others for \( T = T_4 \). Or, if only one piece of equipment is used, it may be set part of the time at \( T_1 \) and the rest of the time at \( T_4 \).

**If Only One Value of \( T \) Is Acceptable.**

This case can be treated by limiting the number of alternative \( T \) values. For example, suppose a basic solution is at hand using a fixed value \( T = T_r \). There are no alternative columns for the moment corresponding to other values of \( T \). It is now desired to see if the solution can be improved by changing the value of \( T \). Accordingly, new columns are introduced corresponding to adjacent values of \( T \), say \( T_{r-1} \) and \( T_{r+1} \), these being selected sufficiently close that linear interpolation of their \( a_{it} \) values is acceptable. These columns are then priced out; and, if it pays to do so, one of the alternative \( T \) columns is introduced. If, as a result, \( T_r \) is replaced in the basis by, say \( T_{r+1} \), then \( T_{r+2} \) is added as a possible alternative column and \( T_{r-1} \) is dropped from consideration in the next iteration. The new solution is then priced out on the added column and on all \( P_j \), \( j = 2, \ldots, n \), since the shift in \( T \) may make it profitable to make other choices for the basic variables. On the other hand if the introduction of the alternative column \( T_{r+1} \) causes not the \( T_r \) column, but some other column to drop, then a \( T_{r+2} \) column is added as a possible alternative and the \( T_{r-1} \) column is retained and both are priced out along with the other columns; if \( T_{r+2} \) becomes a candidate by the pricing out procedure, it is allowed to enter the basis only if it replaces \( T_r \), if not it is dropped as a candidate in the next iteration; similarly \( T_{r-1} \) is allowed to be a candidate only if it replaces \( T_{r+1} \).

This procedure will eventually arrive at a value of \( T = T_r^* \), such that the alternatives \( T_{r-1}^* \) or \( T_{r+1}^* \) result in no admissible improvement, or it will eventually arrive at an interpolation between two \( T \) values \( T_r, T_{r+1} \). This does not mean that this \( T \) is best; all that has been found is a \( T \) that is locally best. If there is any suspicion that there may be other local optima that are superior, it is necessary to revise the procedure so as to drive \( T \) in turn through all values \( T = T_1, T_2, \ldots, T_k \). If there are other local optima superior to \( T = T_r \), their \( z \) values must lie between the \( z \) value for \( T = T_r \) and the \( z \) value obtained by allowing free choice among all alternative \( T \) columns. From a practical point of view, it might be best to allow unrestricted choice initially. If the solution satisfies (8), then of course the solution admits physical interpretation and is optimal. If not, it is often feasible to use the average \( T \) value

\[
T = \sum_r x_r T_r / x_r
\]

as a starting value for the above procedure. For example, in gasoline blending problems there is a nonlinear "octane change" as a function of the amount
Programs with Variable Coefficients

$T$ of tetraethyl lead added to a mixture of blending stocks whose proportions are also to be determined. While the structure of such a problem is more complex than that described here, a linear programming solution can arise for which there is no physical interpretation. This is due to a lack of convexity of a certain octane "response surface." However, it is so slight that the approximation (9) gives excellent results and no further iterations are used in practice [Kawarataki, Ullman, and Dantzig, 1960-1].

The Case of Several Independent Control Parameters, Each Affecting a Different Activity.

While the discussion so far has centered about one control $T$ and one activity $j = 1$, it should be noted that, if there were several independent control parameters, each affecting a different activity, the values of all the parameters could be determined simultaneously by splitting up each such activity column into parts corresponding to the different control settings.

The Case of Several Control Parameters Applying to the Same Activity.

For the case of only two control parameters whose range is $T_1 \leq T \leq T_2$ and $S_1 \leq S \leq S_2$, one can introduce the four extreme cases $(T_1, S_1), (T_1, S_2), (T_2, S_1)$ and $(T_2, S_2)$ as four alternative columns. Thus in (5) the coefficients of $x_{ij}$ could be interpreted as those obtained by setting $(T, S) = (T_1, S_1)$, etc. Again, if the resulting linear interpolations given by (6) and (7) are acceptable, the problem may be solved in this manner. Nothing prevents the introduction of any number of alternative columns corresponding to a grid of $(T_i, S_j)$ values in order to obtain a more accurate approximation.

\[(10)\]

Again the only difficulty that can arise is one of physical interpretation if the optimal solution chooses non-adjacent grid points with positive weights.

When there are more than two control parameters associated with an activity, it is recommended that variables be used that measure the change in the value of the parameters. To illustrate, let the coordinates of $P_1$, the first activity, be some function of the three control parameters, $R, S, T$ (for each component of the vector $P_1$) which we denote by $P_1 = P_1(R, S, T)$. Let us
suppose that for \((R, S, T) = (R_0, S_0, T_0)\) a solution to the linear programming problem is known, and that the linear approximation,

\[(11) \quad P_1(R_0 + \Delta R, S_0 + \Delta S, T_0 + \Delta T) = P_1' + \Delta R \cdot E^o + \Delta S \cdot F^o + \Delta T \cdot G^o\]

where \(P_1', E^o, F^o, G^o\) are fixed vectors, is acceptable within the ranges

\[(12) \quad -\alpha^o_1 \leq \Delta R \leq \alpha_1, \quad -\alpha^o_2 \leq \Delta S \leq \alpha_2, \quad -\alpha^o_3 \leq \Delta T \leq \alpha_3\]

This formulation permits immediate and easy solution via the methods of § 22-1 and the upper bounding methods of § 18-1.

Let \(\pi\) be the simplex multipliers associated with the known basis of the master program. By Theorem 3, § 22-1, we set up the subprogram: Minimize \[
\pi P_1 = \pi P_1' + \Delta R \pi E^o + \Delta S \pi F^o + \Delta T \pi G^o \text{ subject to the constraints (12)}.
\]

This subprogram divides into three independent linear programs:

\[
-\alpha^o_1 \leq \Delta R \leq \alpha_1 \quad (\pi E^o) \Delta R = z_R (\text{Min})
\]

\[-\alpha^o_2 \leq \Delta S \leq \alpha_2 \quad (\pi F^o) \Delta S = z_S (\text{Min})
\]

\[-\alpha^o_3 \leq \Delta T \leq \alpha_3 \quad (\pi G^o) \Delta T = z_T (\text{Min})
\]

These are readily solved; for example, setting \(\hat{\epsilon} = \pi E^o\), the solution for \(\Delta R\) is \(\Delta R = -\alpha^o_1, 0, \alpha_1\), or \(\alpha_1\) according as \(\hat{\epsilon} > 0, \hat{\epsilon} = 0, \hat{\epsilon} < 0\). Substituting these values into (11) yields a new column, \(P_1'\), to be introduced into the basis in the next iteration. After that iteration, expression (11) may be retained for further iterations, or it may be replaced by a new linear approximation about the new values of \(R, S, T\) determined by the iteration. If, however, expression (11) is changed while \(P_1'\) vector is still in the basis, we may encounter difficulties in physical interpretation of the results.

As an alternative to the subprogram of § 22-1, an equivalent linear program can be obtained by multiplying all expressions in (11) and (12) through by \(x_i\) and introducing new variables \(x_i \Delta R = x_{11}, x_i \Delta S = x_{21}, x_{11} \Delta S = x_{31}\). This yields, setting \( \Pi = \langle a_{11}, a_{12}, \ldots, a_{1m}, c_i \rangle \),

\[(13) \quad a_{11} x_1 = a_{11} x_{11} + e_{11} x_{11} + f_{11} x_{21} + g_{11} x_{31}
\]

\[-\alpha_1 x_1 \leq \alpha x_{11}, \quad -\alpha_2 x_1 \leq x_{21} \leq \alpha_2 x_1, \quad -\alpha_3 x_1 \leq x_{31} \leq \alpha_3 x_1\]

Thus the final linear programming problem requiring solution becomes

\[(14) \quad a_{11} x_1 + e_{11} x_{11} + f_{11} x_{21} + g_{11} x_{31} + (a_{12} x_2 + \ldots + a_{1m} x_m) = b_1
\]

\[a_{21} x_1 + e_{21} x_{11} + f_{21} x_{21} + g_{21} x_{31} + (a_{22} x_2 + \ldots + a_{2m} x_m) = b_2\]

\[a_{31} x_1 + e_{31} x_{11} + f_{31} x_{21} + g_{31} x_{31} + (a_{32} x_2 + \ldots + a_{3m} x_m) = b_m\]

\[c_i x_1 + e x_{11} + f x_{21} + g x_{31} + (c_2 x_2 + \ldots + c_m x_m) = z (\text{Min})\]

where \(x_i \geq 0\), and \(x_{11}\) and \(x_1\) are subject to (13).
22-3. PROBLEMS

1. Review: Extend the theory of § 22-1 to cover the case where \( C_a \) and \( C_b \) are general convex sets instead of convex sets each consisting of one fixed vector.

2. (a) In system § 22-1-(6) and (7), replace each \( y_i \) by \( u_i \) and reduce to a linear inequality system and solve numerically. Can this solution be used to solve the original system?

(b) Review § 22-1, Comment, in general. Suppose a solution is obtained for the new system with \( x_i = 0 \); show that \( y_i x_i \neq 0 \) may be possible. Construct an example where this is the case.

(c) Show that the linear program is equivalent to the original generalized program for the system (6) and (7).

(d) Show in general that the linear program is equivalent to the original generalized program if the linear program implies a relation \( \Sigma a_i u_i \leq a_i x_i \) with positive \( a_i \), where \( u_i = y_i x_i \).

(e) Consider the general problem of the existence of \( a_i > 0 \) such that \( \Sigma a_i u_i \leq a_i x_i \) for all \( x_i \geq 0 \) and \( u_i \geq 0 \) satisfying a linear inequality system \((x, u) D \geq d\). Set up a linear program for finding such \( a_i \) if they exist.

Hint: Because of homogeneity, let \( a_i = v_i + 1 \) where \( v_i \geq 0 \). Then the problem is equivalent to finding \( u_i \), \( x_i \), and \( v_i \) such that

\[
\begin{align*}
x &\geq 0, \quad u \geq 0 \\
(x, u) D &\geq d \\
\Sigma u_i - x_i &= \bar{x}_i
\end{align*}
\]

\[
\theta = \min \max_{v \geq 0} \left[ \sum v_i u_i - v_i \bar{x}_i + v_i \bar{x}_i \right]
\]

If \( \theta \leq 0 \), then \( a_i > 0 \) exists. Use Problem 2 of Chapter 13 to complete this discussion.

3. Complete the exercises given in § 22-1.

4. Simplify (13) of § 22-2 by substituting \( \bar{x} \):

\[
\bar{x}_r = x_r + a_r \bar{x}_r \quad (r = 1, 2, 3)
\]

5. (Unsolved.) Develop a theory for the case of one control parameter affecting simultaneously several activities.

6. (Unsolved.) In connection with (d) following § 22-2-(8), devise a procedure for converting \( k \) given functions, \( F_i(T) \), to convex functions of a parameter \( T' \) where \( T' \) is a monotonic function of \( T \), providing such a conversion is possible. (See Problem 7.)

7. Formulate Problem 6 as a linear program if the \( k \) given functions are defined for discrete \( T \), and it is desired to find increasing \( T' \) corresponding
REFERENCES

to increasing $T$, such that the broken line fit through the discrete points $[T', P(T)]$ is a convex function of $T'$.

8. Establish the assertions (a), (b), (c), (d) following § 22-2-(8).

REFERENCES

Dantzig, 1957-3
Dantzig and Wolfe, 1960-1
Ford and Fulkerson, 1953-1

Gomory and Hu, 1960-1, 2
Kawarazaki, Ullman and Dantzig, 1960-1
Kuhn and Tucker, 1950-2
CHAPTER 23

A DECOMPOSITION PRINCIPLE FOR
LINEAR PROGRAMS

23-1. THE GENERAL PRINCIPLE

To introduce a typical situation that suggests the application of the decomposition principle, consider the problem facing a manager of a plant with two almost independent shops. Within each shop, there are many constraints which are unaffected by the activities of the other shop, but there are a few constraints and a common objective that tie the two shops together. The manager’s problem may be formulated in linear programming terms as follows: Find \( X \geq 0, \ Y \geq 0 \), and \( \text{Max} \ x_0 \) satisfying

\[
\begin{align*}
A_1X &= b_1 \\
A_2Y &= b_2 \\
P_0x_0 + \bar{A}_1X + \bar{A}_2Y &= \bar{b}
\end{align*}
\]

We are using an extension of the notation set up at the beginning of Chapter 22. \( X \) is the vector of activity levels in the first shop; \( Y \), that in the second. The first line of (1) expresses the constraints which involve directly only the first shop; the second line does the same for the second shop; the last line expresses the objective function and those constraints which bind together the shops.

On looking at (1), the manager feels that the size of the problem has gotten out of hand. Both \( A_1 \) and \( A_2 \) are moderately large, and together they make a problem that exceeds the capacity of available computers. "But what I really have," reflects the manager, "is not this one big problem but two moderate sized ones, one for each shop. All I need is a way to break the problem into two parts and still take account of their interconnections."

In this chapter we will follow through on the manager’s hunch by developing a technique which decomposes linear programs similar to (1) into

(a) subprograms corresponding to its almost independent parts, and
(b) a master program which ties together the subprograms.

The price paid for this decomposition is that the master program and the subprogram may have to be solved several times. First the master program is solved, and from its solution, objective functions are generated for each of the subprograms. Then these are solved, and from their solution new columns are generated to be added to the master program. The process is
23.1. THE GENERAL PRINCIPLE

then repeated until, after a finite number of cycles, an optimality test is passed.¹ In the next section we will show how this technique can be applied to certain problems arising in dynamic systems, and in the last section it will be used to show how central planning can be accomplished without complete information at the center.

For our discussion it will be convenient to think of problem (1) in the following form: Solve the linear program

\[ P \geq x_0 + \sum_{i=1}^{K} \lambda_i x_i + \sum_{j=1}^{L} \mu_j y_j = 0 \]

subject to the additional constraints

\[ X \geq 0 \]

\[ Y \geq 0 \]

The \( A_i, \tilde{A}_i \) are, of course, matrices; \( P, \tilde{b}, \) and \( b_i \) are vectors.

It will simplify the discussion to assume the feasible sets for \( L_1 \) and \( L_2 \) to be bounded convexes and to indicate later the minor modifications in the formulas needed to take care of the unbounded case. Under this assumption, any \( X \geq 0 \) solving \( A_1 X = b_1 \) can be represented by a convex combination of the extreme points of the set of feasible solutions of \( L_1 \). Since the set of different basic feasible solutions \( X = X_1, X = X_2, \ldots, X = X_K \) defines the finite set of extreme points, we can represent any solution \( X \) by

\[ X = \sum_{i=1}^{K} \lambda_i x_i \quad \left( \sum_{i=1}^{K} \lambda_i = 1; \lambda_i \geq 0 \right) \]

Conversely, any \( X \) represented by (4) is feasible for \( L_1 \). Similarly, any \( Y \geq 0 \) solving \( A_2 Y = b_2 \) can be represented by

\[ Y = \sum_{j=1}^{L} \mu_j y_j \quad \left( \sum_{j=1}^{L} \mu_j = 1; \mu_j \geq 0 \right) \]

where \( Y_1, Y_2, \ldots, Y_L \) are the finite set of basic feasible solutions of \( L_2 \). Hence, any solution \( X \) and \( Y \) solving (1) can be re-expressed in terms of \( \lambda_i, \mu_j \); thus

\[ P \geq x_0 + \sum_{i=1}^{K} \lambda_i (A_1 x_i) + \sum_{j=1}^{L} \mu_j (A_2 y_j) = 0 \quad \left( \lambda_i \geq 0; \mu_j \geq 0 \right) \]

\[ \sum_{i=1}^{K} \lambda_i = 1 \]

\[ \sum_{j=1}^{L} \mu_j = 1 \]

¹ Historically, it was this special case that first gave rise to the more general concept of a generalized linear program developed in § 22.1 [Dantzig and Wolfe, 1960-1]. The decomposition principle approach was inspired by the proposals of Ford and Fulkerson [1958-1] for solving multistage commodity network problems. W. S. Jewell [1958-1] should also be credited with using a similar approach for the latter.
A DECOMPOSITION PRINCIPLE FOR LINEAR PROGRAMS

and, conversely, any \( \lambda \) and \( \mu \) satisfying (6), determine an \( X \) and \( Y \) by (4) and (5), and give a feasible solution to (1). Denoting, in general, the linear transforms of \( X \) and \( Y \),

\[
S = \bar{A}_1 X, \quad T = \bar{A}_2 Y
\]

and, in particular,

\[
S_i = \bar{A}_1 X_i, \quad T_j = \bar{A}_2 Y_j \quad (i = 1, 2, \ldots, K; j = 1, 2, \ldots, L)
\]

the original linear program is equivalent to the problem:

Find \( \lambda_i \geq 0, \ldots, \lambda_K \geq 0; \mu_1 \geq 0, \ldots, \mu_L \geq 0 \) and \( \text{Max } z_0 \) satisfying

\[
P_0 x_0 + \sum_{i=1}^{K} S_i \lambda_i + \sum_{j=1}^{L} T_j \mu_j = b \quad (\lambda_i \geq 0; \mu_i \geq 0)
\]

\[
\sum_{i=1}^{K} \lambda_i = 1
\]

\[
\sum_{j=1}^{L} \mu_j = 1
\]

**Definition:** The linear program (9) generated from the extreme point solutions of \( L_1 \), by (8) is called the equivalent extremal problem, or the full master program.

The basic solutions of \( L_1 \) and \( L_2 \) are probably far too numerous for us ever to express this extremal problem explicitly; rather, we propose to solve it by generating only those columns \( S_i \) and \( T_j \) which the simplex method brings into the successive bases.

Let us suppose that we have at hand an initial, basic feasible solution \( \lambda_i = \lambda_i^* \) and \( \mu_i = \mu_i^* \) to the extremal problem. If \( b \) has \( m \) components, then there will be \( m + 2 \) columns, say \( S_1, S_2, \ldots, S_k; T_1, T_2, \ldots, T_l \) in the corresponding basis, where \( k + l = m + 2 \). Corresponding to this basic feasible solution to the extremal problem, is the solution \( X = X^0, Y = Y^0, x_0 = x_0^0 \) to (1) given by

\[
X^0 = \lambda_1^* X_1 + \lambda_2^* X_2 + \ldots + \lambda_k^* X_k \quad (\Sigma \lambda_i^* = 1; \lambda_i^* \geq 0)
\]

\[
Y^0 = \mu_1^* Y_1 + \mu_2^* Y_2 + \ldots + \mu_l^* Y_l \quad (\Sigma \mu_i^* = 1; \mu_i^* \geq 0)
\]

At the end of this section we will give a Phase I procedure by which such a starting solution and representation may be found.

In order to test optimality of the basic solution or to generate a better solution to the master program, let the row vector \((\pi^*; -s^*; -\pi^0)\) denote the simplex multipliers associated with starting basis

\[
B = \begin{bmatrix}
P_0 & S_1 & S_2 & \ldots & S_k & T_1 & T_2 & \ldots & T_l \\
0 & 1 & 1 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 1
\end{bmatrix}
\]

\[
\begin{array}{c}
\pi^* \\
s^* \\
\pi^0
\end{array}
\]
where \( s^* \), \( t^* \) correspond to the last two rows of \( B \). As discussed in § 22-1, 
\[
\pi^* P_0 = 1, \quad \pi^* S_i = s^*, \quad \pi^* T_j = t^*
\]
for \( i = 1, 2, \ldots, k; j = 1, 2, \ldots, l \).

The standard simplex method now requires us to bring into the basis that column of (9) which has the lowest relative cost, \( \pi^* S_i - s^* < 0 \) or \( \pi^* T_j - t^* < 0 \), if any. That is, we must determine \( S_* \) and \( T_* \) such that
\[
\pi^* S_* = \min_i \pi^* S_i, \\
\pi^* T_* = \min_j \pi^* T_j.
\]
But
\[
\min \pi^* S_i = \min (\pi^* A_1) X_i = \min_{x \geq 0} \frac{\gamma^*_i X}{A_1 x = b_1}
\]
where \( \gamma^*_i = \pi^* A_1 \). That is, we determine \( S_* \) by finding the solution, \( X_* \), to

**The Subprogram \( P_1 \):**
\[
A_1 X = b_1 \quad \quad (X \geq 0) \\
\gamma^*_i X = \gamma^*_i (\min) \\
\]
If the simplex method is used on the subprogram, \( X_* \) will always be one of the \( X_1, \ldots, X_K \). We can then form \( S_* = A_1 X_* \) and bring it into the basis. If
\[
\min \gamma^*_i X_* < s^*
\]
then the relative cost factor for \( S_* \), \( \pi^* S_* - s^* = \gamma^*_i X_* - s^* \), is negative and the introduction of \( S_* \) into the basis will (assuming nondegeneracy) bring about a finite increase in \( x_* \).

Likewise, we can determine \( T_* \) from the \( Y_* \) which solves

**The Subprogram \( P_2 \):**
\[
A_2 Y = b_2 \quad \quad (Y \geq 0) \\
\gamma^*_2 Y = \gamma^*_2 (\min) \\
\]
If \( \min \gamma^*_2 < t^* \), then introducing \( T_* = A_2 Y_* \) into the basis will (assuming nondegeneracy) increase \( x_* \) by a finite amount. We introduce \( S_* \) or \( T_* \), whichever has the lower relative cost factor.

On the other hand, if \( \min \gamma^*_2 = s^* \) and \( \min \gamma^*_2 = t^* \), then all the relative cost factors for (9) are nonnegative. Consequently, we are at the optimal solution of the equivalent extremal problem, and therefore, \( X^* \) and \( Y^* \) given by (10) constitute an optimal solution to (1).

**Definition:** The program obtained from the full master program (9) by dropping all the columns except those in the basis and the new \( S_* \) (or \( T_* \))
A Decomposition Principle for Linear Programs

about to be introduced, is known as The Restricted Master Program:
Find \( \lambda, \mu \geq 0 \), and Max \( x_0 \) such that

\[
\begin{align*}
px_0 + \sum_{k} s_k \lambda_k + \ldots + s_e \lambda_e + T \mu & = b \\
\lambda_1 + \ldots + \lambda_e + \ldots + \lambda_m & = 1 \\
\mu_1 + \ldots + \mu_l & = 1
\end{align*}
\]

Iterative Process and Final Solution.

We now proceed to solve the restricted master program. The resulting optimal solution yields a new \((\pi, s, t)\); these, in turn, determine new \( \gamma_1 \) and \( \gamma_2 \), which constitute new objective forms for \( \mathcal{L}_1 \) and \( \mathcal{L}_2 \). The subprograms are then solved with the new objective forms, and the optimality test above is applied. If the test fails, a new column is added to the restricted master program, corresponding to the subprogram failing the test. The whole process is then repeated, and the cycle continued until the optimality test is passed. The optimal solution is then given by \( X = \sum \lambda X_i \) and \( Y = \sum \mu Y_i \), where the \( \lambda_i \) and \( \mu_i \) are the solution to the final restricted master program and the \( X_i \) and \( Y_i \) are the solutions of \( \mathcal{L}_1 \) and \( \mathcal{L}_2 \) corresponding to columns in the final basis of the last restricted master program. If the restricted master programs are nondegenerate (or \( \varepsilon \)-perturbed), the introduction of each \( S \) or \( T \) will, as we remarked, increase \( x_0 \) by a finite amount. Hence, none of the finite number of bases of (8) can reappear, so the iterative procedure is finite. We have established

**Theorem 1:** The solution \( X = X^*, Y = Y^* \) corresponding to a basic solution of the master program is optimal if there exist no solutions to the subprograms with \( z_1, z_2 \) values less than those of the solutions which were used to generate the basis of the master program, i.e., it is optimal if

\[
\begin{align*}
\text{Min } z_1 & = s^* \quad \text{Min } z_2 = t^*
\end{align*}
\]

If the restricted master programs are nondegenerate (or \( \varepsilon \)-perturbed) such an optimum will be reached in a finite number of iterations.

**Theorem 2:** An upper bound for the values \( x_0 \) is

\[
\begin{align*}
\text{Max } x_0 & \leq x_0^* + (s^* - \text{Min } z_1) + (t^* - \text{Min } z_2) \\
& \leq x_0^* + (s^* - \pi^* S) + (t^* - \pi^* T)
\end{align*}
\]

**Proof:** Multiply (9) by the multipliers, \((\pi^*, -s^*, -t^*)\), and sum. The constant term is \( x_0^* \), which is the value of \( x_0 \) for the basic solution. We have, therefore,

\[
\begin{align*}
x_0 + \sum_{i = 1}^{k} (\pi^* s_i - s^*) \lambda_i + \sum_{j = 1}^{l} (\pi^* t_j - t^*) \mu_j & \leq x_0^* \\
x_0 + \sum_{i = 1}^{k} (\text{Min } z_1 - s^*) \lambda_i + \sum_{j = 1}^{l} (\text{Min } z_2 - t^*) \mu_j & \leq x_0^*
\end{align*}
\]

and the result follows.

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Computational Remarks.

The change of basis in the restricted master program is performed, of course, by the simplex method using multipliers (Chapter 9). In this format, the lexicographic ordering rule may be used to resolve degeneracy and assure that no basis is repeated (Chapter 10). As various columns of the master program are generated during the iterative process, one of the following three variants is customarily used:

1. The restricted master program is augmented by each new column, but each column that drops out of the basis is dropped from the current restricted master.
2. The restricted master program is augmented by more and more columns and those dropping out of the basis are retained as supplementary columns.
3. The restricted master program is augmented by more and more columns, and those dropping out of the basis are retained up to the available memory capacity within the electronic computer; at this point columns that price out most positive are dropped.

Observe also that on each cycle after the first we can start the solution of a subprogram or the master program from the basic solution which was optimal on the preceding cycle. Thus, no Phase I procedures are necessary except before the first cycle, and there is a good chance that only a few pivot operations will be necessary for the re-solution of the subprograms and master program.

Modifications Necessary for Unbounded $\mathcal{L}_i$.

Even though the set of feasible solutions to the entire problem (1) is bounded, it is quite possible that the sets of solutions for some $\mathcal{L}_i$ are unbounded. In this case, there may be no lower bound for $z_i$, and the minimization of $z_i$ via the simplex procedure will result in a homogeneous solution $X_*, Y_*$, satisfying

$$A_iX_* = 0 \text{ or } A_iY_* = 0$$
$$\gamma_iX_* < 0 \text{ or } \gamma_iY_* < 0$$

These $X_*, Y_*$ as pointed out in a similar discussion at the end of § 22-1, belong to a finite class (extreme rays, Chapter 7). In this case we can generate the full class of solutions to $\mathcal{L}_i$ by considering solutions that are convex combinations of the nonhomogeneous solutions and nonnegative combinations of the homogeneous solutions. Thus, in place of (4) and (5)

$$X' = X_1\lambda_1 + X_2\lambda_2 + \ldots + X_K\lambda_K$$
$$Y' = Y_1\mu_1 + Y_2\mu_2 + \ldots + Y_L\mu_L$$

where $\lambda_i \geq 0, \mu_i \geq 0$, satisfy a condition that the $\lambda_i$ and $\mu_i$ must each sum

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to unity when restricted to those \( i \) and \( j \) corresponding to nonhomogeneous solutions, i.e.,

\[
\begin{align*}
\delta_1 \lambda_1 + \delta_2 \lambda_2 + \ldots + \delta_K \lambda_K &= 1 \\
\delta_1 \mu_1 + \delta_2 \mu_2 + \ldots + \delta_L \mu_L &= 1
\end{align*}
\]

where

\[
\delta_i = 1 \text{ if } X_i \text{ is a basic feasible solution,} \\
\delta_i = 0 \text{ if } X_i \text{ is a homogeneous solution,} \\
\delta'_i = 1 \text{ if } Y_i \text{ is a basic feasible solution,} \\
\delta'_i = 0 \text{ if } Y_i \text{ is a homogeneous solution}
\]

This means that the basis \( B \) is redefined to be

\[
B = \begin{bmatrix}
P_0 & S_1 & \ldots & S_k & T_1 & \ldots & T_l \\
0 & \delta_1 & \ldots & \delta_k & 0 & \ldots & 0 \\
0 & 0 & \ldots & 0 & \delta'_1 & \ldots & \delta'_l
\end{bmatrix}
\]

In the event \( b_1 = 0 \) or \( b_k = 0 \), only homogeneous solutions are of interest. In this case the corresponding restrictions \( (25) \) can be dropped from the master program.

Since there is only a finite number of homogeneous solutions generated by the simplex process, the proof of the finiteness of the iterative procedure remains valid.

Initiating the Algorithm.

We assumed in \((10)\) an initial solution \( X^o, Y^o \) represented in terms of basic feasible solutions \( X_i, Y_i \) and—we may now add—homogeneous solutions of \( L^o \) and \( L^y \), respectively. Such an initial solution can be obtained by a Phase I procedure.

Let \( X_i \) and \( Y_i \) be any arbitrary solution to \( L^x \) and \( L^y \), and \( S_1, T_1 \) their transforms under \((7)\). Let the starting basis of the master program of Phase I be

\[
\begin{align*}
\mu_1 \\
\lambda_1 \\
\varepsilon_1 + \varepsilon_2 + \ldots + \varepsilon_m - w &= 0
\end{align*}
\]

where \( U_i \) is an \( m + 1 \) component unit vector with 1 in row \( i \), where \( m + 1 \) is the number of rows in \( [A_1, A_k] \). The variables \( \varepsilon_1, \varepsilon_2, \ldots, \varepsilon_m; x_0, \lambda_1, \mu_1, \) and \( w \) form a basic set. The signs of the \( U_i \) are chosen so that the artificial variables \( \varepsilon_i \) are nonnegative in the basic solution. During Phase I, the objective is to minimize \( w \). Accordingly, the simplex multipliers are defined so that all columns price out to zero except the \((-w)\) column, which prices out to unity. From the Phase I-Phase II process, we deduce:

**Theorem 3:** An optimal basic feasible solution to the original system can be represented as the sum of at most \( m + 2 \) basic feasible solutions of the two
23-2. DECOMPOSITION PRINCIPLE, ANIMATED

parts where \( m \) is the number of equations in the interconnecting part (2) exclusive of the objective form.

23-2. DECOMPOSITION PRINCIPLE, ANIMATED

PROLOGUE

The coordinator, "Staff," of the Central Agency must procure tankers to assist his distributor, "Sub," in the shipping of their product from two plants to four terminals. Staff hates details and has asked Sub to furnish him with only two numbers, the cost, \( c \), of the proposed shipping plan, and the number of tankers, \( t \), required to support it.

Distributor, Sub, has two arrays, a unit cost matrix \([c_{ij}]\), and a unit tanker requirement matrix \([t_{ij}]\) (tankers required per unit shipped):

\[
[c_{ij}] = \begin{bmatrix} 3 & 6 & 6 & 5 \\ 8 & 1 & 3 & 6 \end{bmatrix}; [t_{ij}] = \begin{bmatrix} 0 & 0 & 2 & 0 \\ 0 & 2 & 0 & 0 \end{bmatrix}
\]

(The zeros in the \([t_{ij}]\) array indicate shipments by pipeline instead of by boat.) Since the general objective is to minimize costs, Sub sets out to solve the transportation problem, below, where \( a_i \) are the known availabilities at the plants and \( b_j \) are the known requirements at the terminals.

\[
\begin{array}{ccccccc}
 & x_{11} & x_{12} & x_{13} & x_{14} & & \\
\hline
x_{21} & 3 & 6 & 6 & 5 & & \\
x_{22} & 8 & 1 & 3 & 6 & & \\
\end{array}
\]

Available \( 9 = a_1 \)

Required: \( 2 = b_1 \), \( 7 = b_2 \), \( 3 = b_3 \), \( 5 = b_4 \)

Having taken a ten-day operations research course where he learned how to solve small transportation problems, Sub soon discovers the minimum cost solution to this problem to be

\[
[x_{ij}] = \begin{bmatrix} 2 & 0 & 2 & 5 \\ 0 & 7 & 1 & 0 \end{bmatrix}
\]

In this case \( c = \Sigma c_{ij} x_{ij} = 53 \), \( t = \Sigma t_{ij} x_{ij} = 18 \). Hence, the two numbers that Sub furnishes Staff, in his proposed plan, are

\[
P_1 = \begin{bmatrix} c_1 \\ t_1 \end{bmatrix} = \begin{bmatrix} 53 \\ 18 \end{bmatrix}
\]

where \( P_1 \) represents the vector made up of the components of his first plan.

\[ [455] \]
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Staff discovers, however, that a sudden shortage of tankers has developed, and the most he can muster for Sub is 9 tankers. Noting that two out of Sub’s eight possible shipping activities have to use tankers, Staff requests Sub to find a solution that “goes easy on the use of tankers.” Sub, being literal, forgets costs and immediately comes up with the following solution that minimizes the use of tankers

\[
[x_{ij}]_2 = \begin{bmatrix} 0 & 7 & 0 & 2 \\ 2 & 0 & 3 & 3 \end{bmatrix}
\]

In this case \(\Sigma_i c_{ij} x_{ij} = 95 = c_2, \ \Sigma_i t_{ij} x_{ij} = 0 = t_2\). Hence, Sub’s new proposed plan is

\[
P_2 = \begin{bmatrix} c_2 \\ t_2 \end{bmatrix} = \begin{bmatrix} 95 \\ 0 \end{bmatrix}
\]

ACT I.

STAFF: Well, whatever else one might say about Sub’s new plan, it certainly has gone easy on the use of tankers; in fact, none are used. But look what has happened to costs—they have nearly doubled! I just can’t tell Sub that he can have only 9 tankers and let him find his own least-cost solution; I tried that the last time there was a tanker shortage, and costs soared. Somehow I wish I had sent Sub to that six-week operations research course, instead of the ten-day one. It would probably have been a lot cheaper in the long run.

Note: At this point, Staff has decided to call in his economist friend, F. M. Dalke, as a consultant.

DALKE: According to good economic theory, what you should do is to tell Sub that there may be an extra premium charge for the use of tankers. This will teach Sub to keep the costs down and at the same time not use tankers excessively, because they are now part of the charges in the total bill.

STAFF (Enthusiastic and not above a bit of subterfuge if it gets results): Let’s do just that. (F.M. is crestfallen; theory is theory, but putting it into practice is another matter.)

DALKE: Let’s go a little more slowly. It is not always easy to calculate what the prices should be on scarce commodities. It depends on many factors. But let me assure you it has been rigorously established, beyond any doubt, that such prices always exist. (Seeing distrust creep into Staff’s eyes, F.M. begins to toy with the idea of coming down out of the “ivory tower.”) In this case, however, we have only one scarce commodity, tankers, and we could try various premium charges for tankers and see what happens to Sub’s use of them. This way we could eventually get Sub to come up with a plan that offers both feasibility and least-cost.

\(^1\) F. M. Dalke, like the letters of his name, is a composite of leading mathematical economists of his time, who have applied linear programming to economic theory.
Staff: Sounds like a good approach.

Dalks: According to theory, if tankers are in surplus, the price on tankers should be zero. Since Sub’s latest plan, \( P_2 \), doesn’t use any tankers at all, this is certainly the case. As a start, we can tell Sub the price, \( \pi = 0 \), on tankers. How’s that?

Staff (Sarcastically): Terrific! The only trouble with it is that we have already tried placing no value on tankers, and Sub came up with some plan or other which we couldn’t use. I threw it away, but maybe Marge saved a copy. . . . Ah! See how valuable a secretary can be; here is a copy. See Sub’s old plan: \( P_1 = (53, 18) \). It isn’t feasible, so what good is it?

Dalks: I have another idea. I was reading an O.R. journal the other day. Of course, I don’t usually read that kind of journal, but when I do, I find it is not so peripheral to econometrics as some people think. Anyway, a friend wanted my opinion about an article on a “decomposition principle.” He thought it might throw some light on how to handle price problems when there are breakpoints due to discontinuity in the derivatives of the underlying production functions. But this is beside the point. The article suggests that we should take a weighted average of the two plans (as moves to the blackboard) like this:

\[
P_1 \lambda_1 + P_2 \lambda_2 = \begin{bmatrix} 53 \\ 18 \end{bmatrix} \lambda_1 + \begin{bmatrix} 95 \\ 0 \end{bmatrix} \lambda_2
\]

where \( \lambda_1 + \lambda_2 = 1 \), and, of course, \( 0 \leq \lambda_1 \leq 1 \). For example, we could try \( \lambda_1 = \frac{1}{3}, \lambda_2 = \frac{2}{3} \). Say, this gives

\[
\frac{1}{3}(53 + 95) = 74
\]

\[
\frac{2}{3}(18 + 0) = 12
\]

which is a lot cheaper than 95 and happens to use up the available tankers. How’s that?

Staff: That’s splendid, simply splendid! But how do we know that we can average Sub’s proposals in this way? How will Sub know what to do? I don’t want to get into the details of Sub’s shipping schedule, you know.

Dalks: Oh! Don’t worry about that. Just tell Sub to average the detailed schedules he used for generating plans \( P_1 \) and \( P_2 \), and he has the answer.

Staff: That is a neat trick—averaging the old and new plans—and to think I was smart enough not to throw away that old plan. The boss is going to be very pleased when I tell him how we figured this one out. Before doing so, let’s study this average plan of yours a little to make sure it’s okay. Let’s see, 9 tankers and an over-all transportation cost of 74. Isn’t 74 rather high, considering that the
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least-cost solution might have been 53, if it were not for the tanker shortage?

Dalks: Well, according to the article, this does not necessarily give the best solution. What we are supposed to do is set up a little linear program that tells us how to “blend” old and new plans in the best way. Here it is.

$$53\lambda_1 + 95\lambda_2 + (-z) = 0$$  \hspace{1cm} (\lambda_i \geq 0)

$$\lambda_0 + 18\lambda_1 + 0\lambda_2 = 9$$

$$\lambda_1 + \lambda_2 = 1$$

where $\lambda_0$ is the slack (if any) in the use of tankers. It's fairly obvious, in this case, that $\lambda_0 = 0$, $\lambda_1 = \frac{1}{9}$, $\lambda_2 = \frac{1}{9}$, with a cost $z^1 = 74$ so that we don't learn anything we don't already know. The important thing is that it gives us an idea of what price we should tell Sub to set on tankers. We do this by solving the dual linear program.

Staff: I'm afraid you are in over my head. What's the solution?

Dalks: Well, the dual solution is very interesting. It works out this way. You see, the basic variables associated with the optimal primal solution are indicated by the three dots $\bullet \bullet \bullet$ under the $\lambda_1, \lambda_2$, and $-z$ columns. It means we should choose multipliers $(1, \pi^1, -s^1)$ for the three equations in such a way that when we multiply and sum, the $\lambda_1$ and $\lambda_2$ terms vanish. It is easy to see that the following conditions must hold:

$$53 + 18\pi^1 - s^1 = 0 \quad \text{(coefficient of } \lambda_1)$$

$$95 + 0\pi^1 - s^1 = 0 \quad \text{(coefficient of } \lambda_2)$$

or $s^1 = +95$ and $\pi^1 = +\frac{9}{8} = 2\frac{1}{8}$.

Staff: I don't understand why $\pi^1 = 2\frac{1}{8}$ is positive. As I understand linear programming price-conventions, this means Sub is paid to use tankers, instead of having to pay a premium for their use (§12-3).

Dalks: Yes, but not in this case. For once, for this kind of problem, the linear programmers have set up their sign conventions sensibly, just as we economists do. So, in this case, $\pi$ means what it says. In other words, we tell Sub that the premium charge on tankers might be $2\frac{1}{8}$ units per tanker. Let's try this and see what happens.

Staff: Quite an interesting game we are playing with Sub. What is this $s^1 = +95$?

Dalks: Oh, that is to see whether or not we should try to blend Sub's proposal number three (when it comes in) with $P_1$ and $P_2$. But we can talk more about this later (§23-1, Theorem 1).

Staff: But I don't understand. Does that mean that Sub is going to send
23.2. Decomposition Principle, Animated

us another "infeasible" proposal, and we will have to do some more combining of proposals?

Dalks: Yes, I am afraid it does, unless we are awfully lucky!

Note: At this point Sub is instructed to set up a new unit cost matrix,

\[ [c_{ij}] + 2\frac{1}{2}[t_{ij}] = \begin{bmatrix} 3 & 6 & 6 + 4 \frac{1}{2} & 5 \\ 8 & 1 + 4 \frac{1}{2} & 3 & 6 \end{bmatrix} \]

In due course, Sub arrives at the following optimal solution to his transportation problem:

\[ [x_{ij}]_3 = \begin{bmatrix} 2 & 2 & 0 & 5 \\ 0 & 5 & 3 & 0 \end{bmatrix} \]

In this case, \( \sum c_{ij}x_{ij} = 57 \), and \( \sum t_{ij}x_{ij} = 10 \). Therefore, the third plan he submits, is

\[ P_3 = \begin{bmatrix} c_2 \\ t_2 \end{bmatrix} = \begin{bmatrix} 57 \\ 10 \end{bmatrix} \]

ACT II.

Staff: I begin to understand it now. What we do is set up a new little linear program. Is there some special name by which we can refer to it?

Dalks: It is called a "restricted master." But first, we want to test to see if \( P_3 \) is worth considering. Remember \( s^1 = 95 \)? What we do is "price out" the new proposal and compare it with 95, the "break-even value." Since the new plan has a transportation cost of 57 and there will be a charge of \( 2\frac{1}{2} \) units for each of the 10 tankers used, we have \( 57 + 23 \frac{1}{2} = 80 \frac{1}{2} \). This is less than \( s^1 = 95 \), so we can now go ahead with the restricted master. Here it is:

\[
\begin{align*}
53\lambda_1 + 95\lambda_2 + 57\lambda_3 + (-z) &= 0 \\
\lambda_1 + 18\lambda_2 + 0\lambda_3 + 10\lambda_4 &= 9 \\
\lambda_1 + \lambda_2 + \lambda_3 &= 1
\end{align*}
\]

Staff: Does it take very long to solve? I'm curious to see what the answer is.

Dalks: Well, in this case, no! According to linear programming theory, only two of the three plans that Sub submitted are going to be used. Since no average of plans No. 1 and 3 will have less than 10 tankers, this leaves only one new possibility, a combination of \( P_2 \) and \( P_3 \). The new solution is easy. It is obviously \( \lambda_2 = y_8 \), \( \lambda_3 = y_6 \). This gives a cost of \( z^* = 95(y_6) + 57(y_8) = 60.8 \).

Staff: That's a big improvement! We have cut the cost from \( z^1 = 95 \) to \( z^1 = 74 \) and now to \( z^* = 60.8 \). How much more do you think we can reduce it if we keep this up?

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DALKS: Well, not too much. It can't go any lower than 53, because we know that the value of z for the cheapest cost solution is 53 when there is no restriction on tankers. But perhaps we can do a little better. According to decomposition theory, we can always get an estimate of a lower bound by going back to the previous basic solution. Here is the formula (§23-1, Theorem 2):

\[
\min z \geq z^1 - s^1 + c_3 + \pi^1 a_3 = 74 - 95 + 57 + 23\frac{1}{2} = 59\frac{1}{2}
\]

STAFF: Fantastic! If you are right, very little saving below \( z^2 = 60.8 \) is possible. I would like to see what the true minimum is and see how good your guess really is.

DALKS: Okay, but it is not really a guess. Let us determine a new price on tankers. Since \( \lambda_2 \) and \( \lambda_3 \) are new basic variables, we have

\[
95 + 0\pi^2 - s^2 = 0
\]
\[
57 + 10\pi^2 - s^2 = 0
\]

or \( s^2 = 95 \) and \( \pi^2 = \frac{95}{10} = 3.8 \). It shows we should raise the ante on tankers from \( \pi^1 = 2\frac{1}{2} \) to \( \pi^2 = 3.8 \).

STAFF: I hope Sub won't become too unhappy with our changing our minds so often. He might start complaining to the big boss before this noble experiment is finished.

Note: In due course, Sub sets up his new array

\[
[c_{ij}] + 3.8t_{ij} = \begin{bmatrix} 3 & 6 & 6 + 7.6 & 5 \\ 8 & 1 + 7.6 & 3 & 6 \end{bmatrix}
\]

and derives a new optimal solution

\[
[x_{ij}] = \begin{bmatrix} 2 & 7 & 0 & 0 \\ 0 & 0 & 3 & 5 \end{bmatrix}
\]

\[(c_{ij})_a = \begin{bmatrix} 87 \\ 0 \end{bmatrix}
\]

Here \( \Sigma x_{ij} = 87 \) and \( \Sigma \Sigma t_{ij} = 0 \). So this, Sub's fourth plan becomes

\[
P_4 = \begin{bmatrix} c_4 \\ t_4 \end{bmatrix}
\]

ACT III.

STAFF: This gets better and better. Obviously we can substitute \( y_0 \) of \( P_4 \) for the \( y_0 P_2 \) that we used earlier and get a better solution. So, let's go ahead with the restricted master. Here it is.

\[
53\lambda_1 + 95\lambda_2 + 57\lambda_3 + 87\lambda_4 + (-z) = 0
\]
\[
\lambda_0 + 18\lambda_1 + 0 \cdot \lambda_2 + 10\lambda_3 + 0 \cdot \lambda_4 = 9
\]
\[
\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1
\]

Let us see what the new value of z is. Not much improvement, \( z^3 = 57(\frac{y_0}{9}) + 87(\frac{y_0}{9}) = 60 \). Maybe your lower bound of 59\frac{1}{2} is not so bad after all. Let's try your formula again for the lower bound.

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For this purpose, we go back to the previous basic solution. Is that not so? That's funny! This time don't we get

\[ \text{Min } z \geq z^2 - s^2 + c_4 + \pi t_4 = 60.8 - 95 + 87.0 = 52.8? \]

Dalks: It appears that our previous estimate of 59 1/2 was just a very lucky one. I guess we should make the lower bound estimate each cycle, because some are better than others.

Staff: I suppose now we will have to get a new price

\[ 57 + 10\pi^3 - s^3 = 0 \]
\[ 87 + 0t^3 - s^3 = 0 \]

or \[ s^3 = 87 \text{ and } \pi^3 = 3. \] This time we tell Sub the price on tankers has dropped to 3.

Note: Sub's new problem becomes

\[ [c_{ij} + 3t_{ij}] = \begin{bmatrix} 3 & 6 & 6 & 6 & 5 \\ 8 & 1 & 6 & 3 & 6 \end{bmatrix} \]

which he quickly solves because his last solution, \([x_{ij}], \) is still optimal. Also he finds that his previous one, \([x_{ij}], \) is also optimal.

ACT IV.

Staff: What does this mean? Sub has come up with the same solution as last time.

Dalks: It means that there is no improvement. Let us try our lower bound estimate and see what it says. If we use \( c_4 = 87, t_4 = 0 \) in the formula, then

\[ \text{Min } z \geq z^2 - s^2 + c_4 + \pi t_4 = 60 - 87 + 87 + 0 = 60 \]

If we use \( c_4 = 57, t_4 = 10, \) instead of \( c_4, t_4, \) which is Sub's other optimum solution, we also get

\[ z \geq 60 - 87 + 57 + 3(10) = 60 \]

Since our lower bound 60 is the same as our value of \( z, \) this proves we are done.

Staff: I must tell the boss about our new decentralized decision process and send out orders to Sub to form the weighted average of his plans, namely, \(.9P_3 + .1P_4.\)

Note: When Sub carries out his orders he finds his optimal plan to be

\[ .9[x_{ij}] + .1[x_{ij}] = \begin{bmatrix} 2 & 2 & 0 & 4 & 1 \\ 0 & 4 & 3 & 1 \end{bmatrix} \]

Dalks: Technically, this is not exactly what we economists mean when we say "decentralized planning." A better term would be "central planning without full information at the center." A very interesting experiment! I may write a paper on how for the first time prices were used to control, in a precisely defined way, a real life situation.

The End

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23-3. CENTRAL PLANNING WITHOUT COMPLETE INFORMATION AT THE CENTER

The theory developed in §23-1 makes it possible to plan the over-all operation of an organization without the central staff having full knowledge of the technology of each part. We shall deal with the case in which the technology matrix is constant over time and there is no capital expansion except for current needs.

Consider, then, an economy or industrial complex with \( T \) plants and \( m \) items which are traded between plants. Plant \( p \) has a technological matrix, \( A_p \), of \( m \) rows expressing constraints on intermediate products, plant capacity, and local demands. In addition to \( A_p \), each plant has a trade matrix, \( \bar{A}_p \), which has \( m \) rows that correspond to \( m \) commodities traded between plants or supplied to the consumption sector of the economy. Plant \( p \) also has a vector of constraint constants, \( b_p \). The constraints for plant \( p \) are then

\[
A_p X_p = b_p, \quad X_p \geq 0 \quad (p = 1, 2, \ldots, T)
\]

where \( X_p \) is the vector of its activity levels.

The Central Trade Agency has constraints specifying that the amounts of item \( j \) procured from various plants minus the amounts supplied to them be greater than or equal to the amount it turns over to final \textit{minimum basic demand} (consumption, defense, exports, and the like). Using \( I \) to denote the identity matrix, these constraints may be written

\[
\bar{A}_1 X_1 + \bar{A}_2 X_2 + \ldots + \bar{A}_T X_T + I Y = \delta \quad (Y \geq 0)
\]

\( Y \) being the vector of final incremental demands in excess of the minimum basic demand \( \delta \). (With our sign conventions the components of \( \delta \) are all negative.)

The planners attach a certain set of values, specified by the row vector \(-c\), to final incremental demands so that \(-cY\) represents the value of the plan to them. The total problem facing the economy may then be written

\[
\begin{align*}
A_1 X_1 & = b_1 \\
A_2 X_2 & = b_2 \\
& \vdots \\
A_p X_p & = b_p \\
& \vdots \\
A_T X_T & = b_T \\
\bar{A}_1 X_1 + \bar{A}_2 X_2 + \ldots + \bar{A}_T X_T + I Y & = \delta \\
-c Y & = z \text{ (Min)}
\end{align*}
\]

\(^2\) This section was also contributed by C. Almon to bring out some of the potentialities of the decomposition principle for decentralized planning.
23-3. CENTRAL PLANNING. INCOMPLETE INFORMATION AT CENTER.

This is an angular system which the theory of § 23-1 will decompose into 
T subprograms and one master program. If the \( A_p \) matrices were all available 
they could be sent to the Central Planning Agency where a large computer, 
programmed to use our decomposition principle, would soon produce the 
optimal solution.

In reality, however, the \( A_p \) matrices are hard to compose. It may require 
substantial engineering time to specify each new activity even though no 
real technological change, or basic innovation is involved. There may be 
many things which no one doubts could be done, but which it would require 
much valuable time to specify in detail. For instance, no engineer would, 
just for the sake of adding an activity to the \( A_p \) matrix, spend a week to 
carefully specify the characteristics of a transformer using copper wire 
instead of aluminum if a few rough calculations showed that the resulting 
product would cost about twice what the present one does and offer no 
compensating advantages.

For such reasons, the complete \( A_p \) are probably not explicitly known; 
rather we may regard them as potentially known to the plants, with some 
effort being required to make them explicit. Since potential knowledge can 
hardly be sent to the Central Planning Agency, this Agency lacks complete 
information. It does not, however, completely lack information, for it has 
available the records of Central Trade which show how much each plant 
used and supplied of each common item for several preceding years, say two 
for simplicity. Thus it knows the values of \( S_p = \tilde{A}_pX_p \) determined by two 
feasible solutions to the entire program and hence to each subprogram:

\[
\begin{align*}
A_pX^0_p &= b_p; \quad S^0_p = \tilde{A}_pX^0_p \\
A_pX^1_p &= b_p; \quad S^1_p = \tilde{A}_pX^1_p
\end{align*}
\tag{4}
\]

\(p = 1, \ldots, T\)

(If there was no capital expansion, the \( b_p \) are the same in the two years.
If there was capital expansion, the first year’s plan could be converted into 
a feasible plan for the second year and used in (4.).)

The Central Planning Agency uses this data to make up a master program 
with \( m + T \) constraints as follows:

\[
\begin{align*}
S_1^2\lambda_1 + S_1^3\lambda_2 + S_2^3\lambda_2 + S_3^3\lambda_2 + \ldots + S_T^2\lambda_T + S_T^3\lambda_T + IY &= b \\
\lambda_1 + \lambda_T &= 1 \\
\lambda_2 + \lambda_T &= 1 \\
\vdots \\
\lambda_T + \lambda_T &= 1 \\
\end{align*}
\]

\[cY = \varepsilon \ (\text{Min})\]

The planners then solve this master program and come up with simplex 
multipliers \((\pi; -s)\), \(\pi\) having \( m \) elements, and \( s \) having \( T \). Economically
speaking, \( \pi \) is, of course, a vector of prices. For each plant we can then make an objective form

\[
\text{Minimize } z_p = \pi S_p = (\pi \bar{A}_p)X_p
\]

In words, this objective form states: Minimize the excess of the cost of purchases over the value of sales, i.e., minimize losses or, what comes to the same thing, maximize profits.

The planners then announce these prices, \( \pi \), and instruct all plant managers to propose plans for the operation of their plant in the next year. Specifically, the plan is to state how much of each item they will buy and sell to Central Trade. In making these proposals, they are to assume that they can buy, at the announced prices, all they need of any of the \( m \) items and likewise sell all they produce. They are further instructed to propose the plan which will maximize their profits.

On receipt of these instructions, the managers call in their engineers, give them the prices, and tell them to leave no stone unturned in looking for ways to cut costs and increase profits at these prices. The engineers now have the guidance they need to set about making explicit a portion of their potential knowledge. In a month or so they produce what they believe to be their optimal plans, and the managers give the plans to Central Planning.

It would be extraordinary good luck if these plans will satisfy (2) and constitute a feasible program for the whole economy; usually Central Planning will have to coordinate them. For each plant \( p \) for which the proposed profits exceed \( s_p \), the Agency adds an activity, \( S'_p \), to the master program (5). Then it re-solves this program, obtaining a new \((\pi^*; -s^*)\), say \((\pi^*; -s'^*)\) and also a \( \lambda \) solution. The \( \lambda \) are used to combine the new proposals with the previous solutions to get what we may call the optimal feasible plan, given the information possessed by the Central Planning Agency.

In principle, the planners could then announce \( \pi^* \), get new proposals, and repeat the process until the optimal is found. In practice, planning takes time, production must go on, and the planners reason that consistent plans that get better and better are to be preferred over no plans. Hence, they announce in quantitative terms their feasible plan. They tell each plant manager how much of each traded commodity he must produce and how much he is allowed to purchase; this information is summarized for plant \( p \) in the column vector \( S_p = \sum \lambda^*_p S'_p \) where the values of \( \lambda^*_p \) are those of the optimum solution of the restricted master. They also announce the prices \((\pi^*; -s'^*)\) and direct that trade be conducted at these prices. They may also instruct the managers that, subject to their meeting the quantitative goals \( S_p \), they should also maximize profits. Such a rule is intended as a guide to avoid possible waste in the event that \( S \) is not precisely achieved for one reason or another. It is important to note that they cannot tell the manager simply to maximize the profits (omitting production goals, \( S_p \)) for
if they did, Central Trade would almost certainly have difficulty with its constraints (2).

Toward the end of the period for which production was planned, the order again goes out to propose plans for the next period, this time using $\pi'$ as a guide. The managers, knowing that this order was coming, have been at work all year looking for ways to make profits, and they soon have their proposals. From these, Central Planning makes up new activities to add to the master program and matters proceed as before, the values of the plans always increasing. The essential point to bear in mind is that the master program remembers all previous proposals, except those which it is no longer using at all.

We leave to the reader's judgment the problem of the economic significance of the finiteness proposition of § 23-1. He should also consider the related, though not identical, question of whether it will ever be possible for the planners to abandon the quota and allotment system and simply direct the managers to maximize their profits.

Concluding Remark.

Our discussion has been intended to elucidate the workings of the decomposition principle as a planning tool, rather than to explain the methods actually used by a present-day industrial complex or by a socialist economy. We have shown that there exists a special method of allocation by a central authority and a specially devised system of prices that can induce the separate plants to submit summarized proposals, which can be combined into better and better over-all plans. Whether or not the system of allocation, prices, and proposals used by a particular economy or complex approximate those envisaged by our method, we cannot say. Our iterative process can be diagrammed as follows:

![Diagram](image)

Figure 23-3.1. Decentralized planning using the decomposition principle.

Many people familiar with planning in large organizations are conscious of a flow of information similar to the above. *The difference is that the*
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decomposition principle replaces the not-too-well-understood procedure by one
that is rigorous and well-defined.

23-4. Decomposing multi-stage programs

The methods developed in § 23-1 extend immediately to problems where
there are more than two subprograms, the so-called "angular" systems of
the form:

\[(1) \quad A_1 X_1 = b_1 \]
\[\ldots\]
\[A_r X_r = b_t \]
\[A_T X_T = b_T \]
\[\bar{A}_1 X_1 + \ldots + \bar{A}_s X_s + \ldots + \bar{A}_T X_T = b \]
\[C_1 X_1 + \ldots + C_s X_s + \ldots + C_T X_T = z \text{ (Min)} \]

where the \( A_i \) and \( \bar{A}_i \) are matrices, and \( X_i \) and \( C_i \) are vectors.

Let us now consider another important class of structures, those of the
form: Find \( X_i \) and Max \( x_0 \) satisfying

\[(2) \quad A_1 X_1 = e_1 \quad (X_i \geq 0) \]
\[\bar{A}_1 X_1 + A_2 X_2 = e_2 \]
\[\bar{A}_2 X_2 + A_3 X_3 = e_3 \]
\[\bar{A}_3 X_3 + A_4 X_4 + P_0 x_0 = e_4 \]

where \( X_i \) are vectors, \( A_i \) matrices, \( e_i \) and \( P_0 \) vectors. These are called multi-stage systems (so-called "staircase" systems) and often arise in the study of
processes through time in which the activities of one period are directly
connected with those of the preceding and following periods but with no
others. In such cases, the several \( A_i \) may all be the same, as may be the \( \bar{A}_i \).
Although our results would permit computational advantage to be taken of
such constancy, we shall not assume it.

Following the general lines of what we did in § 23-1, we begin by making
a subprogram out of every other stage by rewriting (2) in the following form:
Solve the program: Find \( X_i \geq 0 \) and Max \( x_0 \) satisfying

\[(3) \quad \bar{A}_1 X_1 + A_2 X_2 = e_2 \]
\[\bar{A}_2 X_2 + A_4 X_4 + P_0 x_0 = e_4 \]

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subject to the constraints

\[ \mathcal{L}_1: A_1X_1 = e_1 \quad \mathcal{L}_2: A_2X_2 + A_3X_3 = e_3 \]

Thus, equations (4) have been selected to play the role of the independent parts, while equations (3) that of the binding constraints. The reader, of course, recognizes that the roles of (3) and (4) could be interchanged and that there are several other ways we could choose the subprograms.

We denote the extreme points of \( \mathcal{L}_1 \) by \( X_i = X_{i1} \) for \( i = 1, 2, \ldots, K \) and those of \( \mathcal{L}_2 \) by \([X_{2j}, X_{3j}]\) for \( j = 1, 2, \ldots, L \) and denote their transforms by

\[ S_i = A_1X_{i1}, \quad T_j = A_2X_{2j}, \quad \bar{T}_j = A_3X_{3j} \]

In this case the master program takes the form: Find Max \( x_0 \), \( \lambda_i \geq 0, \mu_j \geq 0 \) satisfying

\[
\begin{align*}
\sum_{i=1}^{K} S_i \lambda_i + \sum_{j=1}^{L} T_j \mu_j &= e_2 \\
\sum_{i=1}^{K} \lambda_i &= 1 \\
\sum_{j=1}^{L} T_j \mu_j + A_4X_4 + P_0x_0 &= e_4 \\
\sum_{j=1}^{L} \mu_j &= 1
\end{align*}
\]

Starting with some basic set of variables \( \lambda_i, \mu_j \) and components \( X_{ip} \) of \( X_4 \) of the master program, we can solve for simplex multipliers, derive objective forms for \( \mathcal{L}_1 \) and \( \mathcal{L}_2 \), solve, use transforms of their solutions to add columns to the restricted master, re-solve, and repeat the process until the optimality test is passed.

When we set about to solve (5), however, the first thing we observe is that the master program itself is of the staircase form (2), but with half the number of stages. Hence, the logical thing to do is to decompose this master program. Accordingly, let us refer to (5) as the first level master program and proceed to its decomposition. We rewrite (5) in the form:

Find Max \( x_0 \) such that

\[ \sum_{j=1}^{L} T_j \mu_j + A_4X_4 + P_0x_0 = e_4 \quad (\mu_j \geq 0; \ X_4 \geq 0) \]
A Decomposition Principle for Linear Programs

subject to

\[ \mathcal{L}_2: \sum_{i=1}^{K} S_i \lambda_i + \sum_{j=1}^{L} T_j \mu_j = e_2 \quad (\lambda_i \geq 0) \]
\[ \sum_{i=1}^{K} \lambda_i = 1 \]
\[ \sum_{j=1}^{L} \mu_j = 1 \]

We denote the extreme points of \( \mathcal{L}_2 \) by \( \lambda_i = \lambda_i^q, \mu_j = \mu_j^q \) for \( q = 1, 2, \ldots, Q \), and denote for the latter its transform \( \sum_{j=1}^{L} T_j \mu_j^q = R_q \). Substituting in (6) we get the second level master program:

\[ \sum_{q=1}^{Q} R_q v_q + A_4 X_4 + P \phi x_0 = e_4 \quad (v_q \geq 0; X_4 \geq 0) \]
\[ \sum_{q=1}^{Q} v_q = 1, \quad \text{where} \quad R_q = \sum_{j=1}^{L} T_j \mu_j^q \]

We have now decomposed the four-stage program into four programs, \( \mathcal{L}_1, \mathcal{L}_2, \mathcal{L}_3 \) and (8), whose total number of equations is three more than the corresponding number of equations of the four original stages.

Let us now outline the iterative procedure by which these programs are solved. First, we solve a restricted second level master program (8) and determine, in addition to \( v_q \), the simplex multipliers \( (\pi_2^q, w_2^q, v_2^q) \) such that \( \pi_2^q P_0 = 1 \), the basis columns \( R_q \), price out to \( w_2^q \), and those of \( A_4 \) price out nonnegative. (Compare with § 23-1.(12).) Next, we determine an objective form for \( \mathcal{L}_3 \), namely

\[ \text{Minimize } z_4 = \sum_{j=1}^{L} (\pi_4 T_j) \mu_j \]

We assume we have at hand some feasible basis for \( \mathcal{L}_2 \). The values of simplex multipliers \( (\pi_2^q, w_2^q, v_2^q) \) for this basis can now be determined using the values of \( (\pi_4 T_j) \) pertaining to basis columns. We now wish to test \( \mathcal{L}_3 \) for optimality by pricing out (using these multipliers) all columns \( i = 1, 2, \ldots, K \) and \( j = 1, 2, \ldots, L \). However, since \( K \) and \( L \) can be large, we wish to discover the columns \( i = i_0 \) and \( j = j_0 \) that price out the least without actually generating all the columns in advance; we note by (4.1)

\[ \pi_4 T_{i_0} - \pi_2^q T_{j_0} = \min \{ \pi_4 T_j - \pi_2^q T_j \} \]
\[ = \min \{ \{-\pi_2^q A_4 X_4 + (\pi_4 A_4) X_3 \} \leq v_2^q, \quad ((X_2, X_3) \in \mathcal{L}_2) \]
and

\[ -\pi_0 S_n = \min_i [ -\pi_0^i S_i ] = \min \{ - (\pi_0^i A_i) X_1 \} \leq u_n^* \quad (X_1 \in \mathcal{L}_1) \]

Hence, the problem reduces to minimizing the two linear objective forms; the first, (10), in variables \((X_1, X_2, X_3)\), where \((X_2, X_3) \in \mathcal{L}_2\), and the second, (11), linear in \(X_1\), where \(X_1 \in \mathcal{L}_1\). If the solutions to these two linear subprograms yield equality, then subprogram \(\mathcal{L}_3\) was optimum and the problem terminates. If not, then the transforms of the extreme point solution \(X_1 = X_{1*}\) or \((X_2, X_3) = (X_{2*}, X_{3*})\) associated with the most negative one is adjoined to the restricted \(\mathcal{L}_3\) problem and used, in turn, to generate a new extreme solution for the second-order master problem.

As in § 23-1, we note that it is not necessary to carry over from one cycle to the next any columns of (7) or (8) not in the basis. Non-basic columns in these programs may be dropped and forgotten; they will be generated again if needed.

Although we have been working with a four-stage program, our procedure has been perfectly general. Letting \([p]\) mean the largest integer not exceeding \(p\), we can see the following:

**Theorem 1:** A \(K\)-stage problem can be decomposed into \(K\)-subprograms; one corresponding to each stage, the total number of equations in the set of subprograms is \(K - 1\) more than the total number of equations of the original problem; the subprograms form a hierarchy with \([K/2]\) or \([K/2] + 1\) in the lowest rung, \([K/4]\) or \([K/4] + 1\) in the next, etc.

It will be noted that the procedure yields the *optimal multipliers*, but it was necessary to do some side calculations to get the optimal values of the primal variables. It may be useful to consider the *dual* of a multi-stage program, for it has the same structure. The calculations carried out on the dual permit direct evaluation of the primal variables and indirect evaluation of the multipliers.

### 23-5. PROBLEMS

1. Consider the method used of decomposing the multi-stage system § 23-4-(2); develop the analogous method for decentralized planning in such a structure. Generalize.
2. With reference to Problem 1, develop alternative methods corresponding to other ways to decompose such a system.
3. With reference to the discussion following § 23-4, Theorem 1, dualize § 23-4-(2) and develop a method based on the decomposition principle that will evaluate directly the primal variables.
4. Establish in general the statement in § 23-4, Theorem 1, that there are \(K - 1\) more equations in the set of subprograms than in the original system.
A DECOMPOSITION PRINCIPLE FOR LINEAR PROGRAMS

5. Analogous to § 23.1-(20), develop a lower bound for $z$ for the simplex method for the case where one of the equations is of the form $\sum_1^n x_i = 1$.

6. Let $x_i$ be an upper bound for $x_i$ and let $x_0 + \sum_1^n \xi x_j = x_0^0$; show, in general, that another upper bound for $x_0$ is $x_0^0 - \sum \xi_j x_j$, where the summation is restricted to those $j$ such that $\xi_j < 0$.

REFERENCES

Dantzig, 1957-3
Dantzig and Wolfe, 1960-1
Ford and Fulkerson, 1958-1

Gomory and Hu, 1960-2
Jewell, 1958-1
Kawarazaki, Ullman, and Dantzig, 1960-1
Kuhn and Tucker, 1950-2
CHAPTER 24

CONVEX PROGRAMMING

24-1. GENERAL THEORY

Kuhn and Tucker in their paper on "Nonlinear Programming" [1950-2] [Tucker, 1957-1] considered the problem of minimizing a convex function with variables $x_1, x_2, \ldots, x_n$ subject to the condition that the values assumed by a system of concave functions in these variables be nonnegative. They showed that if the concave functions were differentiable, the method of Lagrange multipliers could be appropriately extended to inequality restrictions on concave functions (see discussion in § 6-5). Instead of concave functions, their negative, convex functions (for definition, see § 7-1 and Fig. 7-1-VIII) will be used whose values must be nonpositive. Following Slater [1950-1] and Uzawa [1958-1], our object will be to show that their results hold even if the functions are not differentiable, provided: (a) the domain of variation is restricted to a closed bounded convex set $R$; (b) there exists at least one point where the convex functions are all negative; and, (c) the convex functions are continuous\(^1\) in $R$. We shall also give a constructive procedure for solving such systems using the generalized programming approach.

Philip Wolfe first discussed this idea at the RAND Symposium on Mathematical Programming, 1959, for convex objectives; at the same meeting, H. O. Hartley discussed the case of variable coefficients in a column of a special form. The first proof of convergence can be found in Dantzig [1960-3]; see also A. C. Williams [1960-1].

**Problem A:** Find a point $x = (x_1, x_2, \ldots, x_n)$ in a closed bounded convex set $R$ and the minimum value of $z$ satisfying

\[
\begin{align*}
\phi_i(x) &\leq 0 \quad (i = 1, 2, \ldots, m) \\
\phi_0(x) &= z \quad (\text{Min})
\end{align*}
\]

where the $\phi_i(x)$ are continuous convex functions.

**Theorem 1:** If there exists $x^0 \in R$ such that $\phi_i(x^0) < 0$ for $i = 1, 2, \ldots, m$, then there exist multipliers $\bar{\alpha}_1 \geq 0, \bar{\alpha}_2 \geq 0, \ldots, \bar{\alpha}_m \geq 0$ and an $\bar{x} \in R$ which solves (1) with $\text{Min in } z$ and satisfies

\[
F(\bar{x}) = \text{Min } F(x) = \text{Min }_{x \in R} \left[ \phi_0(x) + \sum_{i=1}^{m} \bar{\alpha}_i \phi_i(x) \right]
\]

\(^1\) Since a general convex function is always continuous in the interior of the domain of definition, $R$, we are essentially assuming that this continuity extends to the boundary.

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or, if the \( \phi_i(x) \) are differentiable, satisfies the Kuhn-Tucker condition,

\[ \sum_{j=1}^{n} (x_j - \bar{x}_j) \frac{\partial F}{\partial x_j} |_{x = \bar{x}} \geq 0 \quad \text{for all } x \in R, \]

where \( F(x) \) is defined by the bracket term in (2a).

**Exercise:** Show that a convex differentiable function \( F(x) \) defined over a closed bounded convex set \( R \) attains a minimum at \( x = \bar{x} \) if and only if (2b) is satisfied.

**Exercise:** Show that the usual primal-dual complementary slackness for optimality is a special case of (2b).

We shall consider Problem A in a slightly more general form.

**Problem B:** Find a point \( x = (x_1, x_2, \ldots, x_n) \) in a closed bounded convex set \( R \) and Min \( z \) satisfying

\[ L_i(x) = 0 \quad \text{for } i = 1, 2, \ldots, r \\
\phi_i(x) = 0 \quad \text{for } i = r + 1, \ldots, m \\
\phi_i(x) = z \quad \text{(Min)} \]

where \( \phi_i(x) = L_i(x) \), for \( i = 1, 2, \ldots, r \), are linear, and \( \phi_i(x) \), for \( i = 0 \) and \( r + 1, \ldots, m \), are continuous convex functions.

As noted in § 22-1, we may rewrite (3) in the form

\[ y^* \lambda = 1 \quad (\mu_i \geq 0) \\
y_1 \lambda_0 = 0 \\
\vdots \\
y_r \lambda_0 = 0 \\
y_{r+1} \lambda_0 + \mu_{r+1} = 0 \\
\vdots \\
y_m \lambda_0 + \mu_m = 0 \\
y_n \lambda_0 = z \quad \text{(Min)} \]

where \( y_i \) are variable coefficients that may be freely chosen subject to the conditions that \( y_i = L_i(x) \) for \( 1 \leq i \leq r \) and \( y_i \geq \phi_i(x) \) for \( r + 1 \leq i \leq m \) for some \( x \in R \).

**Exercise:** Show that the set of possible \( P = (1, y_1, y_2, \ldots, y_m, y_0) \) is a convex set and that (4) is a generalized program; see § 22-1 (27), (28).

**Nondegeneracy Assumption.** There exists at least one nondegenerate basic feasible solution to a restricted master problem, (5), generated by some \( p \) choices of admissible \( P \):

\[ \lambda_1 P_1 + \ldots + \lambda_p P_p + \mu_{r+1} U_{r+1} + \ldots + \mu_m U_m + (-z) U_{m+1} = U_0 \]

\[ (\lambda_i \geq 0, \mu_i \geq 0) \]
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where \( U_i \) denotes the unit vector with its unit component in equation \( i \) of (4), where \( i \) may range from \( i = 0 \) to \( i = m + 1 \). This restricted master, which we assume for convenience to be the initial restricted master, whose columns form a basis, is shown explicitly in detached coefficient form and in greater detail in (6). Because the basic solution is nondegenerate, the values of \( \lambda_i \) and \( \mu_{r+1} \) are positive.

(6)

| Table: Initial Restricted Master Program for Problem B, Cycle \( k \) |
| (for Initial Basis set \( k = 0, p = r + 1 \)) |
| \( \lambda_1 \geq 0 \ldots \lambda_p \geq 0 \ldots \lambda_{p+r} \geq 0 \mu_{r+1} \geq 0 \ldots \mu_m \geq 0 \) |

| \( ( -z ) \) |

| Constants |

| Multipliers |

<table>
<thead>
<tr>
<th>( \lambda_1 )</th>
<th>( \lambda_2 )</th>
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<th>( \lambda_p )</th>
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<th>( \lambda_{p+r} )</th>
<th>( \mu_{r+1} )</th>
<th>( \ldots )</th>
<th>( \mu_m )</th>
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<td>( y_{n+3} )</td>
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<td>( y_{n+b} )</td>
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**Exercise:** Show that the nondegeneracy assumption implies the existence of a point \( x^* \) such that \( L_i(x^*) = 0 \) for \( i = 1, 2, \ldots, r \) and \( \phi_i(x^*) < 0 \) for \( i = r+1, \ldots, m \).

**Exercise:** Show that if there exists a point \( x^* \) satisfying the above conditions and a nondegenerate basis for the system of \( r \) linear equations \( L_i(x) = 0 \) above, then there exists a nondegenerate basis for the system as a whole.

Since we have shown that (4) is a generalized program, we are in a position to apply the methods of §22.1 to affect a solution. This is an iterative procedure that was shown to converge in a finite number of steps when the variable coefficients associated with any column are drawn from a convex polyhedron. However, in both Problems A and B we are dealing with general convex sets and our purpose is to show that the process, if infinite, converges to a solution.

**Exercise:** Assuming that the iterative procedure converges, formulate a "Phase I" type problem that will yield, in a finite number of iterations, a nondegenerate basic feasible solution satisfying (5), if one exists. *Hint:* Make use of the two previous exercises.

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Finding an Initial Nondegenerate Basic Feasible Solution to a Restricted Master Program.

Under the hypothesis of Theorem 1, where there are no linear equations $L_i(x)$ to be satisfied, there exists an $x = x^*$ such that $\phi_i(x^*) < 0$ for $i = 1, 2, \ldots, m$. The nondegeneracy condition is then satisfied by the basic solution formed by using $m$ slack variables and the variable $\lambda_1 = 1$, where the coefficients of $\lambda_1$ are $y^*_1 = \phi_1(x^*)$ [see (7)]. Hence for Problem A, there always exists at least one nondegenerate basic feasible solution.

(7)

<table>
<thead>
<tr>
<th>Initial Restricted Master (and Basis) for Problem A</th>
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<tbody>
<tr>
<td>$\lambda_1$</td>
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<tr>
<td>1</td>
</tr>
<tr>
<td>$\phi_2(x^*)$</td>
</tr>
<tr>
<td>$\vdots$</td>
</tr>
<tr>
<td>$\phi_m(x^*)$</td>
</tr>
<tr>
<td>$\phi_b(x^*)$</td>
</tr>
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</table>

For Problem B, we assume that we have at hand a nondegenerate basic feasible solution to some restricted master with which to initiate the algorithm. See the first and second exercises above.

Iterative Procedure.

We now review the iterative procedure given in Chapter 22 for a generalized program. The restricted master (5) for some cycle $k$ is optimized, yielding a new basic feasible solution $\lambda^k$, and a new set of simplex multipliers $\pi^k$. These multipliers are used to generate a new column $P_{p+k+1}$ for the restricted master for cycle $k + 1$ where all columns of the master program for cycle $k$ are retained and used in cycle $k + 1$. (Note that retention of the columns was optional in Chapter 22, but here it is required for the proof of convergence.)

The components of $\lambda^k$, the $k^{th}$ basic feasible solution, will be denoted by

$\lambda^k_1, \lambda^k_2, \ldots, \lambda^k_{p+k}, \mu^k_{r+1}, \ldots, \mu^k_m \geq 0$

and

$z^k = \sum_{j=1}^{p+k} \lambda^k_j y^*_j$

In order to express conveniently the $k^{th}$ approximation, $z^k$, to a minimizing solution of Problem B, we will assume that each column $P_j$ of the master program is defined by choosing some value $x = x'$ and setting

$P_j = \langle 1, \phi_1(x'), \phi_2(x'), \ldots, \phi_m(x'); \phi_b(x') \rangle \quad (j = 1, 2, \ldots, p + k)$
24.1. **General Theory**

In this case the $k^{th}$ approximation to the minimizing solution of (3) is

$$\hat{x}^k = \sum_{j=1}^{p+k} \lambda_j^k x_j^i; \quad \hat{x}^k = \phi_0(\hat{x}^k)$$

The simplex multipliers for cycle $k$ satisfy the following conditions:

$$\begin{align*}
\pi^k U_{m+1} &= 1 \\
\pi^k P_j &= 0 \quad \text{if } \lambda_j \text{ or } \mu_i \text{ is a basic variable} \\
\pi^k U_i &= 0 \\
\pi^k P_j \geq 0 \quad \text{if } \lambda_j \text{ or } \mu_i \text{ is a nonbasic variable} \\
\pi^k U_i \geq 0
\end{align*}$$

It follows that the components $i = r + 1, \ldots, m$ of $\pi^k = [\pi^k_0, \pi^k_1, \ldots, \pi^k_m; 1]$ are nonnegative because $\pi^k_i = \pi^k U_i \geq 0$ for these $i$.

To test whether or not the $k^{th}$ approximate solution (8) is optimal, the function

$$\Delta(x|\pi^k) = \phi_0(x) + \sum_{i=1}^m \pi^k_i \phi_i(x) + \pi^k_0$$

is minimized over all $x \in R$.

**Theorem 2:** If $\min \Delta(x|\pi^k) \geq 0$ for $x \in R$, then $\hat{x}^k$ is optimal.

**Proof:** Let $x \in R$ satisfy

$$\begin{align*}
L_i(x) &= 0 \quad (i = 1, 2, \ldots, r) \\
\phi_i(x) &\leq 0 \quad (i = r + 1, \ldots, m)
\end{align*}$$

Multiplying the $i^{th}$ relation by $\pi^k_i$, where $\pi^k_i \geq 0$ for $i = r + 1, \ldots, m$, and adding gives

$$\sum_{i=1}^m \pi^k_i \phi_i(x) \leq 0$$

Adding $\phi_0(x) + \pi^k_0$ to both sides of this inequality yields

$$\Delta(x|\pi^k) \leq \phi_0(x) + \pi^k_0$$

Setting $\lambda = \lambda^k$ in the master program (6), multiplying its rows by the corresponding components of $\pi^k$, and summing yield, by the complementary slackness conditions (9) of the optimal solutions to the primal and dual systems,

$$-z^k = \pi^k_0$$

So that

$$\Delta(x|\pi^k_0) + z^k \leq \phi_0(x)$$

On the other hand, for the approximate solution $\hat{x}^k = \sum \lambda^k_j x^j$, it follows from the convexity of $\phi_0(x)$ that

$$\phi_0(\hat{x}^k) \leq \sum_{j=1}^{p+k} \lambda^k_j \phi_0(x^j) = \sum_{j=1}^{p+k} \lambda^k_j y^j = z^k$$

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CONVEX PROGRAMMING

By first selecting that \( x \) which minimizes \( \phi_0(x) \) in (15) and then that \( x \) which minimizes \( \Delta(x|\pi_0^k) \), it is easy to see that

**Theorem 3:** Lower and upper bounds for \( \min \phi_0(x) \) are

\[
\begin{align*}
\min_{x \in R} \Delta(x|\pi^k) + z^k \leq \min_{x \in R} \phi_0(x) & \leq \phi_0(\hat{x}^k) \leq z^k \\
\end{align*}
\]

Continuing with the proof of Theorem 2, setting \( x = \hat{x} \) in (13), noting (16),

\[
\begin{align*}
\min_{x \in R} \Delta(x|\pi^k) \leq \Delta(\hat{x}|\pi^k) \leq \phi_0(\hat{x}^k) + \pi_0^k = \phi_0(\hat{x}^k) - z^k \leq 0
\end{align*}
\]

If now we employ the hypothesis \( \min \Delta(x|\pi^k) \geq 0 \), the above implies

\[
\begin{align*}
\min_{x \in R} \Delta(x|\pi_0^k) = 0
\end{align*}
\]

and, by Theorem 3,

\[
\begin{align*}
-\pi_0^k = z^k = \phi_0(\hat{x}^k) = \min \phi_0(x)
\end{align*}
\]

which establishes Theorem 2.

**Exercises:**

(a) Prove Theorem 3 in detail.

(b) Show that a nonnegative weighted sum of convex functions is a convex function.

(c) Show that \( \Delta(x|\pi^k) \) is a continuous convex function on \( R \).

(d) Show that there exists an \( \hat{x} \in R \), such that \( \Delta(\hat{x}|\pi^k) = \min \Delta(x|\pi^k) \).

**Generating a New Column for the Master Program.**

If \( \min \Delta(x|\pi^k) < 0 \), define \( x^{k+1} \in R \) and \( P_{x^{k+1}} \) by

\[
\begin{align*}
\Delta(x^{k+1}|\pi^k) = \min_{x \in R} \Delta(x|\pi^k) < 0
\end{align*}
\]

\[
\begin{align*}
P_{x^{k+1}} = \langle 1, \phi_1(x^{k+1}), \ldots, \phi_m(x^{k+1}) ; \phi_0(x^{k+1}) \rangle
\end{align*}
\]

It follows from the definitions (10), (21), and (22), that

\[
\begin{align*}
\pi^k P_{x^{k+1}} = \Delta(x^{k+1}|\pi^k) < 0
\end{align*}
\]

If we could now show that \( \min \Delta(x|\pi^k) \) tends to zero as \( k \to \infty \), it would be easy to show convergence of \( \phi_0(x^k) \) from Theorem 3, since \( z^k \) forms a monotonically decreasing sequence bounded from below [see Exercise (d)]. However, note that convergence can also be established if \( \min \Delta \) tends to zero on some subset of the \( k \)'s; indeed, the latter is all we shall be able to prove. For this purpose we first show

**Theorem 4:** If a nondegenerate basic feasible solution exists for some master program, there is an infinite subset \( K \) of values of \( k \), such that \( \lim_{k \to \infty} \pi^k \exists k \in K \).

**Proof:** Let \( B \) be the basis of some master program associated with the
nondegenerate basic feasible solution. For convenience, let this be the solution for (6), the initial master program \( k = 0 \), and let

\[
B = [P_1, P_2, \ldots, P_{m+1}, U_{m+1}]
\]

where some of the \( P_i \) may be the \( U_i \) associated with the slack variables. Thus \( \lambda^0 = (\lambda^0_1, \lambda^0_2, \ldots, \lambda^0_{m+1}, -z^0) \) satisfies

\[
B\lambda^0 = U_0
\]

and, by nondegeneracy, the components \( \lambda^0_i \) are positive. Thus

\[
\lambda^0 = B^{-1}U_0 = [\lambda^0_1, \lambda^0_2, \ldots, \lambda^0_{m+1}, -z^0]^T \quad \text{where } \lambda^0_i > 0
\]

On the other hand, any \( \pi^k \) solving the dual master program for cycle \( k \) satisfies \( \pi^k P_i \geq 0 \), \( \pi^k U_{m+1} = 1 \) by (9), and therefore the components of a vector \( \gamma^k = (\gamma^k_1, \gamma^k_2, \ldots, \gamma^k_{m+1}) \) defined by (27) are nonnegative

\[
\pi^k B = \gamma^k \geq 0 \quad (\gamma^k_i \geq 0)
\]

Observe that \( \pi^k = \gamma^k B^{-1} \), and in particular, that

\[
\pi^k_0 = \pi^k U_0 = \gamma^k (B^{-1}U_0) = \gamma^k \lambda^0 = \gamma^k_1 \lambda^0_1 + \gamma^k_2 \lambda^0_2 + \ldots + \gamma^k_{m+1} \lambda^0_{m+1} - z^0
\]

Hence, noting that \( \pi^k_0 = -z^k \leq -\phi(\bar{x}^k) \leq - \min \phi_0(x) \), we have

\[
z^k - \min \phi_0(x) \geq (\gamma^k_1 \lambda^0_1 + \gamma^k_2 \lambda^0_2 + \ldots + \gamma^k_{m+1} \lambda^0_{m+1}) \quad (\lambda^0_i > 0)
\]

It is now easy to see, because \( \gamma^k_i \geq 0 \), and \( \lambda^0_i > 0 \), that by reducing the right-hand side of (28) by dropping all products except the \( i \)th,

\[
0 \leq \gamma^k_i \leq [z^k - \min \phi_0(x)]/\lambda^0_i
\]

Therefore the components of \( \gamma^k \) have finite upper and lower bounds and Theorem 4 follows from the exercises below.

**Exercise:** If the components of \( \gamma^k \) have finite upper and lower bounds, then the same is true for any linear transform, in particular, the components of \( \pi^k \), where \( \pi^k = \gamma^k B^{-1} \).

**Exercise:** If the components of \( \pi^k \) have finite upper and lower bounds, there exists an infinite subset, \( K \), of values \( k \) such that \( \lim \pi^k \) exists for \( k \in K \) as \( k \to \infty \).

**Theorem 5:** For \( x \) satisfying the conditions of Problem B,

\[
\lim_{k \to \infty} \phi_0(\bar{x}^k) = \min \phi_0(x)
\]

**Proof:** Either the process is finite and an optimum solution is obtained or for all \( k \) we have

\[
\min \Delta(x|\pi^k) = \pi^k P_{k+1} < 0
\]

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and, since the master program for any cycle \( l > k \) contains the column \( P_{k+1} \), we have also for all \( k \) and all \( l > k \),

\[(31)\quad \pi^i P_{k+1} \geq 0 \quad (l > k)\]

For \( k \in K \) and \( l \in K \), the difference, \( (\pi^k - \pi^l) \to 0 \) as \( k \to \infty \) and \( l > k \), by Theorem 4. Since \( R \) is bounded and \( \phi_i(x) \) is continuous in \( R \), \( \phi_i(x) \) is bounded in \( R \) and so is the \( i \)th component, \( \phi_i(x_j) \), of \( P_j \) over all \( j \). Because the components of \( P_{k+1} \) are bounded from above and below, the difference \( (\pi^k - \pi^l) P_{k+1} \) must also tend to zero. But, if the difference between the left sides of (30) and (31) goes to zero and \( \pi^k P_{k+1} \) is negative and \( \pi^l P_{k+1} \) is nonnegative, then \( \pi^k P_{k+1} \) must come arbitrarily close to zero; that is, for any \( \varepsilon > 0 \), there exists a \( k_\varepsilon \) such that for any \( k \in K \) and greater than \( k_\varepsilon \),

\[(32)\quad -\varepsilon < \min_{x \in R} \Delta(x|\pi^k) < 0 \quad (k \geq k_\varepsilon, \ k \in K)\]

From Theorem 3 and (32), the convergence of \( z_k \) to \( \min \phi_0(x) \) now follows on the set \( k \in K \). But the \( z_k \) are monotonically decreasing for all \( k \). We conclude \( z_k \) tends to \( \min \phi_0(x) \) for any set \( k \to \infty \) (not just for \( k \in K \)). Since \( z_k \) is an upper bound for \( \phi_0(\hat{x}) \), the latter also must converge to this limit. This establishes Theorem 5.

**Theorem 6:** Let \( \hat{x} = \lim_{k \to \infty} \pi^k \) for \( k \in K \) and let \( \hat{x} \) be any optimum solution to Problem B, then

\[(33)\quad F(\hat{x}) = \min_{x \in R} F(x) = \min_{x \in R} \left[ \phi_0(x) + \sum_{i=1}^{m} \hat{\phi}_i(x) \right]\]

where \( \hat{x} \) has nonnegative components for \( i = r + 1, \ldots, m \).

**Proof:** From (32), for \( k > k_\varepsilon \) and \( k \in K \)

\[(34)\quad -\varepsilon \leq \Delta(x|\pi^k) \leq \phi_0(x) + \pi_0^k\]

where the inequality on the right is from (13). In the limit, letting \( k \to \infty \), \( \varepsilon \to 0 \), \( \lim \pi^k = \hat{x} \) and

\[(35)\quad 0 \leq \Delta(x|\hat{x}) = F(x) + \hat{\sigma}_0 \leq \phi_0(x) + \hat{\sigma}_0\]

where \( \Delta(x|\hat{x}) \) is defined by (10).

On the other hand, by (20)

\[(36)\quad \hat{\sigma}_0 = \lim_{x \to R} \pi^k_\sigma = \lim_{x \to R} (-z_k) = -\min_{x \in R} \phi_0(x) = -\phi_0(\hat{x})\]

Hence, substituting \( x = \hat{x} \) into (35) and noting the above, we have

\[(37)\quad 0 = F(\hat{x}) + \hat{\sigma}_0 \leq F(x) + \hat{\sigma}_0\]

thus establishing Theorem 6 and, as a special case, Theorem 1.
24-2. HOMOGENEOUS OBJECTIVES, CHEMICAL EQUILIBRIUM PROBLEM

24-2. HOMOGENEOUS OBJECTIVES AND THE CHEMICAL EQUILIBRIUM PROBLEM

Homogeneous Objective Functions of the First Degree.

In some applications, such as the chemical problem to be discussed later, we have to minimize a convex function

\[ G(x) = \bar{x} \bar{G} \left( \frac{x_1}{\bar{x}}, \frac{x_2}{\bar{x}}, \ldots, \frac{x_n}{\bar{x}} \right) \]

where

\[ \bar{x} = x_1 + x_2 + \ldots + x_n \]

subject to a system of linear equations in nonnegative variables,

\[ \sum_{j=1}^{n} a_{ij} x_j = b_i, \quad x_j \geq 0 \quad (i = 1, 2, \ldots, m) \]

Note that if each component of \( x \) is multiplied by \( t \), the value of \( G(x) \) is multiplied by \( t \):

\[ G(tx) = tG(x) \]

That is to say, \( G \) is a homogeneous function of first degree.

We will assume that \( G(u) > 0 \) is a continuous convex function on the set of possible \( u \) satisfying

\[ u_1 + u_2 + \ldots + u_n = 1 \quad (u_j \geq 0) \]

During the iterative process, we shall generate solutions \( \bar{x}^1, \bar{x}^2, \ldots \) satisfying (3), such that \( G(\bar{x}) \) is monotonically decreasing. Letting \( u_0 \) be an upper bound for \( G(x) \), for \( x = \bar{x}^k \) we have for such \( x \)

\[ G(x) = \bar{x} \bar{G}(u) < u_0 \quad (x = \bar{x}^2) \]

\[ 0 \leq \bar{x} < u_0 / \text{Min} \bar{G}(u) \]

It follows that the components of such \( x \) are bounded from above and below.

Consider the equivalent single-variable generalized program

\[ \bar{x} \left[ \sum_{j=1}^{n} a_{1j} u_j \right] = b_1 \quad (\bar{x} \geq 0, u_j \geq 0, \sum u_j = 1) \]

\[ \bar{x} \left[ \sum_{j=1}^{n} a_{2j} u_j \right] = b_2 \]

\[ \ldots \ldots \ldots \ldots \]

\[ \bar{x} \left[ \sum_{j=1}^{n} a_{mj} u_j \right] = b_m \]

\[ \bar{x} \bar{G}(u) = z \text{ (Min)} \]

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where \( \bar{x} \geq 0 \) is the variable whose coefficients are linear in \( u_j \) subject to (5). This gives rise to a master program that forms a general solution out of a nonnegative linear combination of columns of coefficients generated by various solutions \( u^k \) to the subprograms. This is in contradistinction to the usual case where convex combinations are required. This greater flexibility is possible, because the set of coefficients are homogeneous functions in \( u \).

To be explicit, we start with some set of \( m \) vectors \( u = u^p \) satisfying (5) and, setting \( \{u_i\} = A \), generate

\[
S_p = Au^p \quad (p = 1, 2, \ldots, m) \\
c_p = G(u^p)
\]

Assuming that the \( m \) columns form a feasible basis the first restricted master becomes

\[
\sum_{p=1}^{m} S_p \lambda_p^1 = b \\
(\lambda_p^1 \geq 0) \\
\sum_{p=1}^{m} c_p \lambda_p^1 = z^1 (\text{Min})
\]

This determines the simplex multipliers \( \pi^1 \) which satisfy

\[
\pi^1 S_p + c_p = 0 \quad (p = 1, 2, \ldots, m)
\]

To test optimality, the expression

\[
\Delta(u|\pi^1) = G(u) + (\pi^1 A) u
\]

is minimized over all \( u \) satisfying (5). If \( \min \Delta \geq 0 \), the solution

\[
\bar{x} = \sum_{p=1}^{m} \lambda_p^1 u^p
\]

is optimal. If not, choose \( u^{m+1} \) such that

\[
G(u^{m+1}) + (\pi^1 A) u^{m+1} = \min \Delta(u|\pi^1)
\]

Augment the master system (9) by \( S_{m+1} = Au^{m+1} \) and \( c_{m+1} = G(u^{m+1}) \), optimize the new restricted master with \( \lambda = \lambda^1 \), and repeat the cycle with new multipliers \( \pi = \pi^1 \), etc.

A slight variation in our earlier proof given in § 24-1 (to take account of the fact that we no longer have the \( \sum \lambda_i = 1 \) constraint or its multiplier \( s \)) yields the following

**Theorem 1:** If there exists at least one nondegenerate basic feasible solution to a master program, then the modified algorithm converges to an optimal solution.

**Exercise:** Show that, if \( G(x) \) is a linear objective form, then it is also
24.2. HOMOGENEOUS OBJECTIVES, CHEMICAL EQUILIBRIUM PROBLEM

convex and homogeneous of the first degree, and that the procedure just developed reduces to the standard simplex method.

Exercise: Prove Theorem 1. What role does (6) play in the proof?

The Chemical Equilibrium Problem.

For an application of the preceding theory, let us consider the problem of determining the molecular composition of the equilibrium state of a gaseous mixture containing $m$ different types of atoms [White, Johnson, and Dantzig, 1958-1]. While in theory these will combine into all chemically possible molecular species, in practice only the standard types which occur in measurable amounts are considered.

Let
\[ b_i = \text{the number of atomic weights of atom type } i \text{ present in the mixture}, \]
\[ x_j = \text{the number of moles of molecular species } j \text{ present in the mixture}, \]

where
\[ x_j \geq 0 \quad (j = 1, 2, \ldots, n) \]
\[ \bar{x} = \text{the total number of moles of gas in the mixture, i.e.,} \]
\[ \bar{x} = \sum x_j \]
\[ a_{ij} = \text{the number of atoms of type } i \text{ in a molecule of species } j. \]

Then the mass-balance equations are
\[ \sum_{j=1}^{n} a_{ij}x_j = b_i \quad \text{for } i = 1, 2, \ldots, m \]

The determination of the equilibrium composition of a gaseous mixture is equivalent to the determination of the values of the mole numbers $x_j$ that obey constraints (16) and minimize the total free energy of the mixture given by

\[ G(x_1, \ldots, x_n) = \sum_{i=1}^{n} c_i x_i + \sum_{i=1}^{n} x_i \log \left(\frac{x_i}{\bar{x}}\right) \]
\[ = \bar{x} \left[ \sum_{i=1}^{n} c_i(x_i/\bar{x}) + \sum_{i=1}^{n} (x_i/\bar{x}) \log \left(\frac{x_i}{\bar{x}}\right) \right] \]
\[ = \bar{x} \sum_{i=1}^{n} (c_i u_j + u_j \log u_j) \quad (u_j = x_i/\bar{x} \geq 0) \]

which can be shown to be a convex function. The $c_i$ are the values of Gibbs free energy functions $F_j/RT$ of the atomic species at a given temperature plus the natural logarithm of the pressure in atmospheres.

Our problem is to minimize (17), a first degree homogeneous form, subject

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to the linear equality and inequality constraints (14), (15), and (16). The function

\[ G(u) = \sum (c_j u_j + u_j \log u_j) \quad (u_j \geq 0) \]

is clearly convex.

For this application, then,

\[ \Delta = G(u) + \sum \pi_i^k \sum a_{ij} u_j \]

\[ = \sum (u_j \log u_j + c_j^k u_j) \]

where \( \pi_i^k \) are the simplex multipliers of some iteration defined by relations analogous to (10). Let

\[ c_j^k = c_j + \sum_{i=1}^n \pi_i^k a_{ij} \]

To find the Min \( \Delta \) subject to

\[ \sum u_j = 1 \quad (u_j \geq 0) \]

we ignore the relations \( u_j \geq 0 \) and find the unconditional minimum of the function

\[ \hat{\Delta} = \sum \left( u_j \log u_j + c_j^k u_j \right) - \theta \left( \sum u_j - 1 \right) \]

where \( \theta \) is a Lagrange multiplier (see § 6-5). We set the partial derivatives of \( \hat{\Delta} \) with respect to \( u_j \) to zero; thus

\[ \frac{\partial \hat{\Delta}}{\partial u_j} = 1 + \log u_j + c_j^k - \theta = 0 \]

whence \( u_j \) may be written in the form

\[ u_j = A e^{-c_j^k} \]

where \( A = e^{\theta - 1} > 0 \). Substituting into (21) determines \( A \) and

\[ u_j = e^{-c_j^k} \left/ \sum_{i=1}^n e^{-c_i^k} \right. \]

so that the conditions \( u_j \geq 0 \) hold at the minimum. These, then, are the values \( u_j = u_j^{k+1} \) with which to initiate the next iteration.

24-3. SEPARABLE CONVEX OBJECTIVES

**Definition**: If the objective function to be minimized, instead of being linear, is of the form

\[ \sum_{j=1}^n \phi_j(x_j) = z \quad (\text{Min}) \quad (0 \leq x_j \leq h_j) \]

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where \( \phi_j(x_j) \) is a convex function, it is called convex-separable, a term used by Charnes to describe this class of objective forms [Charnes and Lemke, 1954-1; Dantzig, 1956-2]. We shall assume that \( h_j \) is a given finite upper bound for \( x_j \) and the \( x_j \) are subject to

\[
\sum_{i=1}^{n} a_{ij}x_j = b_i \quad (i = 1, 2, \ldots, m)
\]

To illustrate, if the first 100 units of an activity can be performed at $1 per unit, the next 50 units at $1.25 per unit and the next 50 units at $1.50 per unit, then the total cost \( \phi(x) \) is convex in the range \( 0 \leq x \leq 200 \). In general, if the first \( x_1 \) units cost \( s_1 \) per unit, the second \( x_2 \) units cost \( s_2 \) per unit, \ldots, the last \( x_n \) units cost \( s_n \) per unit, then the total cost \( \phi(x) \) is convex if \( s_1 \leq s_2 \leq \ldots \leq s_n \), but is not convex if, for any \( r, s_r > s_{r+1} \).

**Exercise:** The definition of a convex function is given in § 7-1. Show that it is equivalent to the definition: a function \( \phi(x) \) is convex if

\[
\phi \left( \sum \lambda_i x_i \right) \leq \sum \lambda_i \phi(x_i)
\]

for any \( \lambda_i \geq 0 \), such that \( \sum \lambda_i = 1 \).

**Exercise:** Show that, if the cost of the \( j^{th} \) activity is proportional to the square of the \( j^{th} \) activity, \( \phi_j(x_j) = c_j x_j^2 \), then \( \phi(x_j) \) is convex for \( c_j \geq 0 \) but is not convex for \( c_j < 0 \).

As a third example, if the total cost \( \phi(x) \) consists of a fixed charge \( f \) and the remaining cost is proportional to the activity level, then \( \phi(x) \) is convex. On the other hand, if there is a fixed charge \( f \) only if \( x > 0 \), then we can write

\[
\phi(x) = \begin{cases} f + hx, & \text{if } x > 0 \\ 0, & \text{if } x = 0 \end{cases}
\]

In this case \( \phi(x) \) is not convex, if \( f > 0 \).

**Exercise:** Show that if \( f \leq 0 \), \( \phi(x) \), above, is convex.

To replace equations (1) and (2) by a standard linear programming problem, we assume that \( \phi_j(x_j) \) is a broken-line function. Later we shall remove this restriction. (In the event that \( \phi_j(x_j) \) has a continuous derivative, one can select \( k + 1 \) points on the curve such that the broken line fit through these points is a sufficiently close approximation.)

The Equivalent Linear Program.

For \( r = 0, 1, 2, \ldots, k \), let \( (f_{rj}, g_{rj}) \) be the coordinates of the break points \( (x_j, \phi_j(x_j)) \) of the function \( \phi_j(x) \) (see Fig. 24.3-I). Any \( x_j \) in the range \( f_{oj} \leq x_j \leq f_{kj} \) may be represented by

\[
x_j = \lambda_{oj}f_{oj} + \lambda_{ij}f_{ij} + \ldots + \lambda_{kj}f_{kj} \quad (\lambda_{rj} \geq 0)
\]

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where

\[ 1 = \lambda_0 + \lambda_1 + \ldots + \lambda_k \]  

\[ \phi_j(x^0) = \min_{\lambda} \sum \lambda_j g_j \] given \[ \sum \lambda_j f_j = 0. \]

Figure 24.3.1. Converting a convex function into a linear programming format.

Since \( \phi_j \) is a convex function, we then have, by (3),

\[ \phi_j(x_j) \leq \lambda_0 g_{j0} + \lambda_1 g_{j1} + \ldots + \lambda_k g_{jk} \]

To solve (1) and (2), determine \( \lambda_j \geq 0 \), and Min \( z' \) satisfying

\[ \sum_{j=1}^{n} a_{ij}[\lambda_0 g_{0j} + \lambda_1 g_{1j} + \ldots + \lambda_k g_{kj}] = b_i \quad (i = 1, 2, \ldots, m) \]

\[ \lambda_j + \lambda_{j1} + \ldots + \lambda_{jk} = 1 \quad (j = 1, 2, \ldots, n) \]

and substitute the resulting \( \lambda \) into (5) to determine \( x_j \). To prove that solving (8)–(10) is equivalent to solving (1) and (2), we have only to show that Min \( z \geq \text{Min } z' \). From (7), Min \( z \leq \text{Min } z' \). To show that Min \( z \geq \text{Min } z' \), take the \( x_j \) yielding the minimum to (1) and (2) and represent them as combinations of the abscissas of the two breakpoints immediately to the left and right. The resulting \( \lambda \) satisfy (8) and (9) and satisfy (7) with equality, so that the \( z' \) resulting in (10) equals Min \( z \). Hence, Min \( z \geq \text{Min } z' \), as we were to show.

**Bounded-Variable Method.**

It will be noted that the above procedure increases the number of variables and increases the number of equations by one for each \( \phi_j(x_j) \). By use of the upper bounding method, it is possible to maintain the original number of equations. The original variables will be replaced by sets of new bounded variables which (except in the cost row) will all have their several columns of coefficients identical (so that a number of short cuts are possible;
see Chapter 18). In Fig. 24-3-II the slopes of the broken line are denoted by $s_i$ and the width of the intervals by $a_i$.

![Figure 24-3-II. Converting a convex function into a linear programming format using bounded variables.](image)

From the convexity of $\phi(x)$ follow the relations

$$s_1 \leq s_2 \leq \ldots \leq s_k .$$

We now assert that

$$\phi(x) = g_0 + \text{Min} \left[ s_1 \Delta_1 + s_2 \Delta_2 + \ldots + s_k \Delta_k \right]$$

where

$$x = \Delta_1 + \Delta_2 + \ldots + \Delta_k$$

and

$$0 \leq \Delta_i \leq a_i$$

Indeed, since $s_1 \leq s_2 \leq \ldots \leq s_k$, it is obvious that the way to find the minimum is to choose $\Delta_i$ as large as possible until it hits its upper bound $a_i$, then take $\Delta_2$ in turn, etc., until a $\Delta_i$ is reached, such that setting $\Delta_i = x_i$, the value of $x$ is exceeded, in which case the value of $\Delta_i$ is reduced so that (13) holds. It is clear that this process is simply generating the curve $\phi(x)$ from 0 up to the value $x$.

**Equivalent Linear Program.**

To solve (1) and (2), determine $\Delta_{ij} \geq 0$ and Min $z'$ satisfying

$$\sum_{j=1}^{n} a_{ij} \Delta_{ij} + \Delta_{ij} + \ldots + \Delta_{kj} = b_i \quad (i = 1, 2, \ldots, m)$$

$$\sum_{j=1}^{n} [s_{ij} \Delta_{ij} + s_{ij} \Delta_{ij} + \ldots + s_{kj} \Delta_{kj}] = z' \quad (\text{Min})$$

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where

\[ 0 \leq \Delta_{ij} \leq \alpha_{ij} \]

and determine \( x_j \) by

\[ x_j = \Delta_{1j} + \Delta_{2j} + \ldots + \Delta_{kj} \]

**The Variable-Coefficient Approach.**

This method has the advantage that it uses the original convex functions instead of a broken line fit. While the procedure appears to be the continuous analogue of our earlier procedure, we do require the convergence proof of § 24-1 to justify it. Referring to equations (5), (6), and (7), we may write in a purely formal way

\[ x_j = \lambda_j f_j, \]

\[ 1 = \lambda_i, \]

\[ \phi_i(x_i) \leq \lambda_i g_i, \]

where \((f_j, g_j)\) is a pair of variable coefficients. The set, \( C_j \), of possible values for these coefficients consists of those points \((f_j, g_j)\) for which \( g_j \geq \phi_j(f_j) \). Since the function \( \phi_j \) is convex, this set is convex by definition; it is therefore appropriate to use the variable coefficient method given in Chapter 22. In that chapter, however, we assumed that the \( C_j \) were defined by a finite number of linear equations. In that case the iterative process is finite. The process is an infinite one if the derivative of \( \phi_j \) is continuous and non-constant. (See § 24-1 for convergence proof.)

Formally, the full system with variable coefficients takes the form:

Find \( x_j \geq 0, f_j, g_j \geq \phi_j(f_j) \), and Min \( z \) satisfying

\[ \begin{array}{c}
\begin{align*}
a_{11} x_1 + a_{12} x_2 + \ldots + a_{1n} x_n &= b_1 \\
a_{21} x_1 + a_{22} x_2 + \ldots + a_{2n} x_n &= b_2 \\
\cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \\
a_{m1} x_1 + a_{m2} x_2 + \ldots + a_{mn} x_n &= b_m \\
x_1 - \lambda_1 f_1 &= 0 \\
\lambda_1 &= 1 \\
x_2 - \lambda_2 f_2 &= 0 \\
\lambda_2 &= 1 \\
\cdots \\
x_n - \lambda_n f_n &= 0 \\
\lambda_n &= 1 \\
\lambda_1 g_1 + \lambda_2 g_2 + \ldots + \lambda_n g_n &= z \text{ (Min)}
\end{align*}
\end{array} \]

\[ \begin{array}{c}
\begin{align*}
&\text{Multipliers} \\
&\pi_1 \\
&\pi_2 \\
&\cdots \\
&\pi_m \\
&s_1 \\
&i_1 \\
&s_2 \\
&i_2 \\
&\cdots \\
&s_n \\
&i_n
\end{align*}
\end{array} \]

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where the multipliers associated with the system are shown on the right. In all, there are $2n + m$ constraints.

**Exercise:** Show that the set of possible coefficients $(f_1, g_1)$ in (19) is a convex set.

According to the variable coefficient theory (Chapter 22), a basis is formed using particular values for $f_j$ and $g_j$ where one is allowed to form columns using more than one set of $(f_j, g_j)$ values for a given $j$. Certain of the $j$ will have associated with them just one column of values $(f_{j1}, g_{j1})$ in the basis, and others will have two associated values $(f_{j1}, g_{j1})$ and $(f_{j2}, g_{j2})$.

**Exercise:** Show that it is not possible to have zero or more than two different $(f_{ji}, g_{ji})$, $i = 1, 2, 3, \ldots$ in a basis.

We will use $\lambda_j$ for the variable associated with $(f_{ji}, g_{ji})$. It can be arranged that all the $x_j$ are in the basic set. For example, we could initiate Phase I with $x_j$, $\lambda_j$, and a set of $m$ artificial variables as a basic set. Since $x_j$ can be assumed unrestricted in sign, they will remain in all subsequent basic sets. Assuming no artificial variables remain at the end of Phase I, it follows, because there are $2n + m$ basic variables, that $n$ are $x_j$; $n - m$ are singles, $\lambda_{j1}$; and $m$ are pairs, $\lambda_{j1}$ and $\lambda_{j2}$.

Interpreted another way, $m$ of the $x_j$, say $x_{j_1}, x_{j_2}, \ldots, x_{j_m}$, satisfy a relation

$$f_{j1} \leq x_j \leq f_{j2} \quad (j = j_i)$$

while the remaining $x_j$ satisfy

$$x_j = f_{j2} \quad (j \neq j_i)$$

**Exercise:** Discuss the case where there may be artificial variables in Phase II.

**Theorem 1:** The simplex multipliers are determined by

$$s_j = (g_{j2} - g_{j1})/(f_{j2} - f_{j1}) \quad (j = j_1, j_2, \ldots, j_m)$$

(22)

$$\sum_{i=1}^{m} a_{ij} \pi_i = s_j \quad (j = j_1, j_2, \ldots, j_m)$$

(23)

$$s_j = \sum_{i=1}^{m} a_{ij} \pi_i \quad \text{for } j \neq j_i$$

(24)

$$t_j = g_{j1} - s_jf_{j1} \quad \text{all } j$$

(25)

**Proof:** From (19) we have that

$$s_jf_{j1} + t_j = g_{j1} \quad (j = j_1, j_2, \ldots, j_m)$$

(26)

$$s_jf_{j2} + t_j = g_{j2}$$

Subtracting the first from the second and solving for $s_j$ give (22). Equations
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(23)–(25) follow directly from (19). Note that in (23) the \( s_i \) are known and
the \( \pi_i \) are to be determined, while in (24) the \( \pi_i \) are known and the \( s_i \) are
determined. In (25), only \( t_j \) is unknown.

For optimality of a solution \( x_j = x_j^0 \), we require that

\[
g_j - (s_j f_j + t_j) \geq 0 \quad (j = 1, 2, \ldots, n)
\]

for all possible choices of \( (f_j, g_j) \).

**Exercise:** Why is this sufficient?

Since \( s_j \) and \( t_j \) are fixed, we solve the subproblem of minimizing
\( z_j = \phi_j(f_j) - s_j f_j \). If \( \phi_j \) has a continuous slope, \( \phi_j'(f_j) \), we seek \( f_j \geq 0 \) such that

\[
\phi_j'(f_j) = s_j
\]

In Fig. 24.3.11, we graph the function \( g_j = \phi_j(f_j) \), and for each point \((f_j^*, g_j^*)\) on
the curve we consider the line passing through it, \( g_j - s_j f_j = g_j^* - s_j f_j^* \). We then seek that line with minimum \( g_j \) intercept, denoted by \( z_j \). By (28) this
occurs at the point of tangency if such a point exists.

![Figure 24.3.11. Solving a separable objective problem using a generalized
programming approach.](image)

It may not be possible to find such a tangency point \((f_j, g_j)\), for it may be
that the slope at \( f_j = 0 \) is greater than \( s_j \); then the best choice is \( f_j = 0 \),
\( g_j = \phi_j(0) \), since convexity of \( \phi_j(x) \) implies a monotone increasing slope. If
\( \phi_j'(f_j) \leq s_j \) for all \( f_j > 0 \), then the best choice is \( f_j = h_j. \) If \( j \) corresponds
to a variable having two associated \( \lambda \)'s in the basis, then the slope of the
line joining \((f_{j1}, g_{j1})\) to \((f_{j2}, g_{j2})\) is \( s_j \), by (22); in this case there is always
somewhere between these two points, a point satisfying (28), provided the
slope is a continuous function of \( f_j \). We conclude
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Theorem 2: A solution \( (x^*_1, x^*_2, \ldots, x^*_m) \) is optimal if for each \( j \) the simplex multipliers \( s_j \) determined by Theorem 1 satisfy

\[
\begin{align*}
    s_j &= \phi_j(x^*_j) & \text{if } 0 < x^*_j < h_j \\
    s_j &\geq \phi_j(0) & \text{if } 0 = x^*_j \\
    s_j &\geq \phi_j(h_j) & \text{if } x^*_j = h_j
\end{align*}
\]

or, more generally, \( \phi^L_j(x^*_j) \leq s_j \leq \phi^R_j(x^*_j) \) where \( \phi^L \) and \( \phi^R \), the left or right derivatives, are omitted for \( \phi^L_j(0) \) or \( \phi^R_j(h_j) \).

Algorithm.

The foregoing analysis suggests a variant of the simplex method in which \( m \) variables \( x_j \) are considered basic, with bounds \( f_{iL} \leq x_j \leq f_{iH} \) and \( n - m \) variables are non-basic at fixed values \( f_{iL} \). It is assumed a basic feasible solution \( x_j = x^*_j \) of this type is at hand to initiate the algorithm whose steps are as follows:

Step 1. Compute slopes \( s_j = \phi_j(x^*_j) \); for basic variables \( x_j \), either decrease upper bound, \( f_{iH} \), or increase lower bound, \( f_{iL} \), so that the adjusted bounds are closer together and satisfy

\[
(29) \quad s_j = \phi'_j(x^*_j) = \frac{g^L_j - g^R_j}{f^H_j - f^L_j} \quad (x_j \text{ basic})
\]

(In case \( \phi'_j(x_j) \) is discontinuous, replace \( \phi'_j(x_j) \) by the left derivative \( \phi^L_j(x_j) \) in the above discussion.)

Step 2. Compute the simplex multipliers \( \pi_j \) by (23).

Step 3. Compute the \( s_j \) and \( t_j \) for non-basic variables by (24) and (25).

Step 4. For non-basic \( j \), determine \( f_j^* \) such that

\[
\begin{align*}
    (a) \quad f_j^* &= 0 & \text{if } s_j < \phi^L_j(0) \\
    (b) \quad f_j^* &= h_j & \text{if } s_j \geq \phi^R_j(h_j) \\
    (c) \quad \phi^L_j(f_j^*) \leq s_j \leq \phi^R_j(f_j^*) & \text{otherwise}
\end{align*}
\]

Step 5. Compute \( g_j^* = \phi_j(f_j^*) \) and \( z_j^* = g_j^* - s_j f_j^* \).

Step 6. Determine \( p \), non-basic, such that

\[
(z_p^* - t_p) = \min_{j \text{ non-basic}} (z_j^* - t_j) \leq 0
\]

If \( \min (z_j - t_j) = 0 \), terminate. The basic solution is optimal.

Step 7. Keeping all other non-basic variables at their values \( f_{iL} \), adjust the value of \( x_p \) and the basic variables as follows:

Decrease or increase \( x_p \) from its fixed value \( f_{pL} \) according to whether \( f_p^* \) is less than or greater than \( f_{pL} \). Drop the basic variable which hits its upper or lower bound first or stop if \( x_p \) hits the value \( f_{pL} \) first. In the latter case, \( f_p^* \) is the new fixed value of \( x_p \) which is still non-basic. In the
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former case, $x_p$ becomes a new basic variable with $f^*_p$ and $f_{p+}$ as its new bounds; the basic variable which hits its bound is then dropped from the basis and fixed at the value of this bound.

Convergence: It is not known whether or not the algorithm as given above converges to Min $z$. In order that the proof of convergence given in § 24-1 apply, some provision must also be made in the algorithm for first re-introducing into the basis any previously generated column such that $g_i - s_i f_i - t_i < 0$.

EXERCISE: Expand the algorithm to allow the re-introduction of previously generated columna. Review the proof of convergence and show why it breaks down if the latter is not done.

EXERCISE: Develop a simpler form of the algorithm by replacing the upper and lower bounds $f_{i1}$ and $f_{i2}$, as defined above, by $f_{i1} = 0$ and $f_{i2} = h_i$ and setting $s_i = \phi_i(x^*_i)$ for basic $x_i$.

24-4. QUADRATIC PROGRAMMING

Although a convex quadratic objective can be treated by the methods of § 24-1 and can be reduced to the convex separable case discussed in § 24-3, the linear nature of its partial derivatives has given rise to an elegant theory important in its own right. It is doubtful at this writing that the full potentiality of this theory has been realized.

Quadratic programs can arise in several ways; four listed by Wolfe in his [1959-1] paper are as follows:

Regression: To find the best least-square fit to given data, where certain parameters are known a priori to satisfy linear inequalities constraints.

Efficient Production: Maximization of profit, assuming linear production functions and linearly varying marginal costs [Dorfman, 1951-1].

Minimum Variance: To find the solution of a linear program with variable cost coefficients which will have given expected costs and minimum variance [Markowitz, 1956-1, 1959-1].

Convex Programming: To find the minimum of a general convex function under linear constraints and quadratic approximation [White, Johnson, and Dantzig, 1958-1].

Historically, it was Barankin and Dorfman [1958-1] who first pointed out that, if the linear Lagrangian conditions of optimality were combined with those of the original system, the optimum solution was a basic solution in the enlarged system with the property that only one of certain pairs of variables were in the basic set. Markowitz [1956-1, 1959-1], on the other hand, showed that it was possible to modify the enlarged system and then parametrically generate a class of basic solutions with the above special property which converged to the optimum in a finite number of iterations. Finally, Wolfe [1959-1] proved that an easy way to do this is by slightly modifying the simplex algorithm so as not to allow a variable to enter the
24.4. QUADRATIC PROGRAMMING

basic set if its "complementary" variable is already in the basic set. Thus, by modifying a few instructions in a simplex code for linear programs, it was possible to solve a convex quadratic program! We shall present here a variant of Wolfe's elegant procedure. The chief difference is that ours is more nearly a strict analogue of the simplex method; it has a tighter selection rule and a monotonically decreasing objective.

Preliminaries.

Before stating the problem, let us note that every quadratic form can be conveniently expressed in terms of a symmetric matrix associated with its coefficients. For example, for \( n = 3 \) variables,

\[
Q(x) = c_{11}x_1^2 + c_{22}x_2^2 + c_{33}x_3^2 + 2c_{12}x_1x_2 + 2c_{23}x_2x_3 + 2c_{13}x_1x_3
\]

\[
= [x_1, x_2, x_3] \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{12} & c_{22} & c_{23} \\ c_{13} & c_{23} & c_{33} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = x^TCx
\]

where \( T \) stands for transpose.

Definition: A quadratic form is called positive definite if \( x^TCx \geq 0 \) for all \( x \neq 0 \); it is called positive semi-definite if \( x^TCx \geq 0 \) for all \( x \).

Problem: Find \( x = (x_1, x_2, \ldots, x_n) \geq 0 \) and \( \min Q(x) \) satisfying

\[
Ax = b \quad A = [a_{ij}] \quad (i = 1, 2, \ldots, m)
\]

\[
x^TCx = Q(x) \quad C = [c_{kl}]
\]

where \( Q(x) \) is a convex quadratic function.

Lemma 1: \( x^TCx \) is convex if and only if it is positive semi-definite.

Proof: Assume \( x^TCx \) is a convex function. To prove \( x^TCx \geq 0 \), suppose on the contrary, \( (x^*)^TCx^* < 0 \) for some \( x = x^* \). Then, for \( x' = -x^* \), it is also true \( (x')^TCx' < 0 \) and for any convex combination, \( x^* \) of \( x^* \) and \( x' \), we also have \( (x^*)^TCx^* < 0 \) because \( x^TCx \) is convex. In particular, for \( x^* = \frac{1}{2}x^* + \frac{1}{2}x' \), we have \( (\frac{1}{2}x^* + \frac{1}{2}x')^TC(\frac{1}{2}x^* + \frac{1}{2}x') < 0 \) or \( (0)^TC(0) < 0 \), a contradiction, since \( \frac{1}{2}x^* + \frac{1}{2}x' = 0 \).

The convexity of a positive semi-definite form follows from Lemma 2 below because a linear transform, \( \tilde{z} \), of the variables \( x \) reduces \( Q(x) \) to a sum of convex functions in \( \tilde{z} \).

Lemma 2: If \( x^TCx \) is positive semi-definite, there exists a non-singular matrix \( E \) such that a change of variables \( x = E\tilde{z} \) yields

\[
x^TCx = \sum_{i=1}^{n} \lambda_i x_i^2 \quad (\lambda_i \geq 0)
\]

where \( \lambda_i \geq 0 \) is the \( j^{th} \) diagonal element of a diagonal matrix \( E^TCE \).
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Proof: Select any variable, say $x_1$, with $c_{11} > 0$. (See first exercise below.) Express $Q(x)$ as a quadratic polynomial in $x_1$ and “complete the square”; thus

$$x^TCx = c_{11}x_1^2 + 2x_1 \sum_{j=2}^{n} c_{1j}x_j + \sum_{i=2}^{n} \sum_{j=2}^{n} c_{ij}x_ix_j,$$

$$= \frac{1}{c_{11}} \left[ \sum_{j=2}^{n} c_{1j}x_j \right] - \frac{1}{c_{11}} \left[ \sum_{j=2}^{n} c_{1j}x_j \right]^2 + \sum_{i=2}^{n} \sum_{j=2}^{n} c_{ij}x_ix_j$$

$$= \frac{1}{c_{11}} \tilde{x}_1^2 + \sum_{i=2}^{n} \sum_{j=2}^{n} c_{ij}x_ix_j$$

where $\tilde{x}_1 = \sum_{j=2}^{n} c_{1j}x_j$ and $c''_{ij} = (c_{11}c_{ij} - c_{1i}c_{1j})/c_{11}$. The process may now be repeated using the quadratic expression in $(x_2, \ldots, x_n)$ on the right. The process terminates in $k \leq n$ steps. Set $\tilde{x}_j = x_j$ and $\lambda_j = 0$ for $j = k + 1, \ldots, n$.

Exercise: Show that either $c_{11} > 0$ or all $c_{11} = c_{12} = \ldots = c_{1n} = 0$ in a positive semi-definite quadratic form.

Exercise: Show that the determinants of all the principal minors of $C$ are positive if $Q(x)$ is positive definite, in particular $c_{11} > 0$.

Exercise: Show that if $k = n$, $Q(x)$ is positive definite; and that if $k < n$, it is semi-definite.

Exercise: Apply Lemma 2 to show that, if $x^TCx$ is positive semi-definite and if $(x^e)^TCx^e = 0$, for $x = x^e$, then $Cx^e = 0$.

Exercise: Complete the proof of Lemma 1.

Optimality Conditions.

Let $A_i, C_i$ denote the $j$th columns of $A$ and $C$, respectively, and let

$$y_j = C_i^Tx - \pi A_i,$$ \hspace{1cm} $(\pi = \pi_1, \pi_2, \ldots, \pi_m)$

Theorem 1: A solution $x = x^e$ is minimal if there exist $\pi = \pi^e$ and $y = y^e$ such that

$$Ax^e = b,$$

$$y_j^e = C_i^Tx^e - \pi^e A_i \geq 0 \hspace{1cm} (j = 1, 2, \ldots, n)$$

$$y_j^e = 0 \text{ if } x_j^e > 0.$$

Proof: Rewrite $Q(x)$ in the form

$$Q(x) - Q(x^e) = 2 \sum_{j=1}^{n} \left[ \sum_{i=1}^{m} c_{ij}x_j^e \right] (x_j - x_j^e) + \sum_{j=1}^{n} \sum_{i=1}^{m} c_{ij}(x_i - x_i^e)(x_j - x_j^e)$$

$$= 2 \sum_{j=1}^{n} \left( C_i^T x^e \right) (x_j - x_j^e) + (x - x^e)^T C (x - x^e)$$
Let \( x \geq 0 \) be any solution satisfying \( Ax = b \), then

\[
\begin{align*}
A(x - x^0) &= \sum_{j=1}^{n} A_j(x_j - x^0_j) = 0
\end{align*}
\]

Multiplying on the left by \( 2\pi^2 \) and subtracting from (9) yield

\[
\begin{align*}
Q(x) - Q(x^0) &= 2 \sum_{j=1}^{n} (C_j^T x^0 - \pi^2 A_j)(x_j - x^0_j) + (x - x^0)^T C(x - x^0) \\
&= 2 \sum_{j=1}^{n} y_j^0(x_j - x^0_j) + (x - x^0)^T C(x - x^0)
\end{align*}
\]

For the class of solutions with the property \( y_j^0 = 0 \) for \( x_j^0 > 0 \), (11) simplifies to

\[
\begin{align*}
Q(x) - Q(x^0) &= 2 \sum_{j \neq 0} y_j^0 x_j + (x - x^0)^T C(x - x^0)
\end{align*}
\]

Note that (12) holds by (8) and \( y_j^0 \geq 0 \) holds by (7), thus all terms in (12) are nonnegative, therefore \( Q(x) \geq Q(x^0) \).

Improving a Non-optimal Solution.

Consider the system

\[
\begin{align*}
Ax &= b \\
Cy &= A^T \pi^2 - I_n y = 0
\end{align*}
\]

where \( x^T Cx \) is assumed to be positive semi-definite. Let \( x^0, \pi^0, y^0 \) be a basic feasible solution associated with a basic set with the complementarity property, namely, for each \( j \) either \( x_j \) or \( y_j \), but not both, is in the basic set. We shall assume further that the right-hand side has been perturbed to insure that all basic solutions are nondegenerate. Note that neither \( \pi \) nor \( y \) is sign restricted; only \( x \geq 0 \) is required for a feasible solution to (13); an optimal solution will have been obtained if \( y_j \geq 0 \) and \( x_j y_j = 0 \) for all \( j \).

**Theorem 2:** If a basis is complementary and \( y_j^s < 0 \), then any increase of the non-basic variable \( x_j \), with adjustment of only the basic variables, generates a class of solutions \( x', \pi', y' \), such that \( x'^T Qx \) decreases as long as \( y_j' < 0 \).

**Proof:** Let \( x \) be any solution in the class above, i.e., generated by increasing \( x_j \); in particular, let \( x' \) be generated by \( x_j = x_j' \). Analogous to (11), \( Q(x) - Q(x') = 2y_j^s(x_j - x_j') + (x - x')^T C(x - x') \) since for all \( j \neq s \) either \( x_j = x_j' = 0 \) if \( x_j \) is non-basic or if \( x_j \) is basic \( y_j = y_j' = 0 \) by the complementarity assumption. The adjusted values of the basic variables are linear functions of \( x_j \), hence it follows that \( (x - x') = (x_j - x_j')v \) where \( v \) is a constant vector. Hence, \( Q(x) - Q(x') = (x_j - x_j')(2y_j^s + (x_j - x_j')(v^T C v)] \) and it is clear that, if \( y_j < 0 \), the right-hand side is negative for sufficiently small \( (x_j - x_j') > 0 \).
Moreover for \( Q(x) \) to decrease with an increase of \( x_i \geq 0 \) from, say, \( x'_i \) to \( x''_i \), it must be accompanied by \( y'_i < y''_i \) because
\[
Q(x'') - Q(x') = 2(x''_i - x'_i)y'_i + (x''_i - x'_i)^2 v^T C v
\]

and, by interchanging the roles of \( x' \) and \( x'' \),
\[
Q(x') - Q(x'') = 2(x'_i - x''_i)y''_i + (x'_i - x''_i)^2 v^T C v
\]

whence \( 2(y'_i - y''_i) = 2(x'_i - x''_i)v^T C v \geq 0 \). But \( v^T C v \neq 0 \) because \( v^T C v = 0 \) implies \( C v = 0 \) for positive semi-definite forms (see last exercise following proof of Lemma 2) and if \( C v = 0 \), then from (9), \( Q(x'') - Q(x') = 2(x''_i - x'_i) (x'^T C + (x''_i - x'_i) v^T C v = 0 \) which contradicts \( Q(x') - Q(x') < 0 \); we conclude \( y''_i > y'_i \).

As in the simplex method, we require that all solutions generated by increasing \( x_i \) and adjusting the basic variables remain feasible, i.e., \( x_i \geq 0 \) for all \( i \). In this process, either \( y_i \) attains the value zero first, and thus can be dropped from the basic set, or the value of some basic \( x_i \) attains the zero value first and is dropped.

**Theorem 3:** If \( x_i \) drops as basic variable, introduction of \( y_i \) either causes \( x^T C x \) to decrease (and some \( x_i \) or \( y_i \) to be dropped) or causes \( x^T C x \) to stay fixed and \( y_i \) to be dropped; if \( x_i \) is dropped, this theorem may be reapplied; if \( y_i \) is dropped either initially or upon increase of \( y_i \), Theorem 2 may be reapplied.

**Proof:** Our proof is completely general; however, for convenience we will illustrate it on system (14)

\[
\begin{array}{cccccccccc}
& x_1 & x_2 & x_3 & x_4 & x_5 & -\pi_1 & -\pi_2 & y_1 & y_2 & y_3 & y_4 & y_5 & \text{Constants} \\
\hline
a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & & b_1 \\
a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & & b_2 \\
\hline
b_{11} & b_{12} & c_{13} & c_{14} & c_{15} & a_{11} & a_{12} & -1 & 0 & 0 & 0 & 0 \\
b_{21} & b_{22} & c_{23} & c_{24} & c_{25} & a_{21} & a_{22} & -1 & 0 & 0 & 0 & 0 \\
b_{31} & b_{32} & c_{33} & c_{34} & c_{35} & a_{31} & a_{32} & -1 & 0 & 0 & 0 & 0 \\
b_{41} & b_{42} & c_{43} & c_{44} & c_{45} & a_{41} & a_{42} & -1 & 0 & 0 & 0 & 0 \\
b_{51} & b_{52} & c_{53} & c_{54} & c_{55} & a_{51} & a_{52} & -1 & 0 & 0 & 0 & 0 \\
\hline
B: & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
B': & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet
\end{array}
\]

Let system (14) in vector form be
\[
(15) \quad P_1 x_1 + P_2 x_2 + P_3 x_3 + P_4 x_4 + P_5 x_5 + (P_6 \pi_1 + P_7 \pi_2) + P_8 y_1 + P_9 y_2 + P_{10} y_3 + P_{11} y_4 + P_{12} y_5 = P_0
\]

We suppose that we have on some cycle a basis \( B \) and a basic feasible complementary solution \((x', \pi', y')\) with basic variables \( x_1, x_2, x_3, x_4, \pi_1, \pi_2, y_5 \).
and the value of \( y_5 = y_6^2 \leq 0 \). In this case, \( x_5 \) will be the new basic variable and we assume that \( x_4 \) will drop. This yields a new basis \( B' \). In (14), the heavy dots (●) indicate that the column is in the basis \( B \), and the star indicates that the column \( P_5 \) associated with \( x_5 \) is replacing a vector \( P_4 \) of the basis \( B \) to form basis \( B' \); see second row of dots. The dropping of \( x_4 \) automatically requires that \( y_4 \) become the new basic variable for the basis following \( B' \); see * in the \( B' \) row of (14).

Let the representation of both \( P_5 \) and \( P_4 \) in terms of the basis \( B \) be:

\[
\begin{align*}
\mathbf{P}_5 &= P_1 x_1 + P_2 x_2 + P_3 x_3 + P_4 x_4 + (P_5 x_4 + P_6 x_7) + P_5 \tilde{x}_6 \\
\mathbf{P}_4 &= P_1 \lambda_1 + P_2 \lambda_2 + P_3 \lambda_3 + P_4 \lambda_4 + (P_5 \lambda_4 + P_6 \lambda_7) + P_5 \tilde{\lambda}_6
\end{align*}
\]

We first show that \( \lambda_4 \leq 0 \) in (17). Setting \( \lambda = (\lambda_1, \lambda_2, \lambda_3, \lambda_4) \), the first six rows of representation (17) yield (18) and (19):

\[
\begin{align*}
\begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \end{bmatrix} \lambda^T &= 0 \\
\begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} \\ c_{21} & c_{22} & c_{23} & c_{24} \\ c_{31} & c_{32} & c_{33} & c_{34} \\ c_{41} & c_{42} & c_{43} & c_{44} \end{bmatrix} \lambda^T + \begin{bmatrix} a_{11} \\ a_{12} \\ a_{13} \\ a_{14} \end{bmatrix} \lambda_4 + \begin{bmatrix} a_{21} \\ a_{22} \\ a_{23} \\ a_{24} \end{bmatrix} \lambda_7 &= \begin{bmatrix} 0 \\ 0 \\ 0 \\ -1 \end{bmatrix}
\end{align*}
\]

Multiplying (19) by \( \lambda \) on the left and denoting the square matrix by \( C_4 \), yield, by (18), \( \lambda C_4 \lambda^T = -\lambda_4 \). Since \( \lambda C_4 \lambda^T \) is positive semi-definite (\( C_4 \) is a principal minor of \( C \)), \( \lambda C_4 \lambda^T \geq 0 \) and \( \lambda_4 \leq 0 \).

Case \( \lambda_4 < 0 \): Our objective is to show that, if \( x_4 \) drops out of the basis set upon introduction of \( x_5 \) into the basic set and if the non-basic complementary variable to \( x_4 \), namely \( y_4 \), is subsequently increased (with adjustment of the values of the new basic variables), then \( x_5 \) and \( y_5 \) will continue to increase and \( x^T C x \) to decrease as long as \( y_6 \) remains negative. This assumes \( \lambda_4 < 0 \). (Later, for the case \( \lambda_4 = 0 \), we shall show that \( x_5 \) and \( x^T C x \) will remain unchanged but \( y_5 \) will decrease to zero when \( y_4 \) is increased in value.) Let the representation of \( P_4 \) in terms of the basis \( B' \) be

\[
\mathbf{P}_4 = P_1 \lambda_1' + P_2 \lambda_2' + P_3 \lambda_3' + P_4 \lambda_4' + (P_5 \lambda_4' + P_6 \lambda_5') + P_5 \tilde{\lambda}_6
\]

and let the basic solution associated with \( B' \) be

\[
\begin{align*}
\mathbf{P}_5 &= P_1 x_1' + P_2 x_2' + P_3 x_3' + P_4 x_4' + (P_5 x_4' + P_6 x_5') + P_5 y_6' \\
\mathbf{P}_4 &= P_1 \lambda_1' + P_2 \lambda_2' + P_3 \lambda_3' + P_4 \lambda_4' + (P_5 \lambda_4' + P_6 \lambda_5') + P_5 \tilde{\lambda}_6
\end{align*}
\]

We observe that in the representation (16) of \( P_5 \) in terms of \( B \), the weight \( a_4 \) on \( P_4 \) is positive (since \( x_4 \) decreased when \( x_5 \) increased). Since (20) is obtained by eliminating \( P_4 \) from (16) and (17) and since \( \lambda_4 < 0 \) and \( a_4 > 0 \), it follows that \( \lambda_4' < 0 \). If \( y_4 = \theta > 0 \) units of \( P_4 \) are introduced into
the solution and the values of the basic variables are adjusted, we obtain from (20) and (21),

(22) \[ P_0 = P_1(x'_1 - \theta \lambda'_1) + \ldots + P_3(x'_3 - \theta \lambda'_3) + \ldots \]

Thus \( x_4 = x'_4 - \theta \lambda'_4 \) will increase when \( y_4 = \theta > 0 \) is increased since \( \lambda'_4 < 0 \).

Moreover, we may adopt the point of view for the purpose of the proof, that it is the increase in \( x_4 \) that is "causing" the increase in \( y_4 \) (instead of the other way around), so that we are, in fact, repeating the situation just considered of increasing \( x_4 \) and adjusting the other "basic" variables, except here \( y_4 \) is in the basic set instead of \( x_4 \). It follows, therefore, as before, that an increase in \( x_4 \) decreases \( x^T C x \) as long as \( y_4 \) remains negative in value in the adjustment of the basic solution by the increase of \( x_4 \).

**Case \( \lambda_4 = 0 \):** On the other hand, if \( \lambda_4 = 0 \) in (17), then we must set \( \lambda_4 = \lambda'_4 \) in (20) because the representation of \( P_4 \) is the same, whether in terms of \( B \) or \( B' \); hence, \( \lambda'_4 = 0 \). In this case \( \lambda C \lambda^T = -\lambda_4 = 0 \) and therefore, because \( C \) is positive semi-definite, \( C \lambda = 0 \). In addition, \( \lambda = 0 \) must hold because \( \lambda \neq 0 \) implies a dependence of the first four columns of (18) and (19) which is impossible because then the square array of coefficients of (18) and (19), and in turn \( B \), would be singular. Setting \( \lambda'_1, \ldots, \lambda'_4 = 0 \) in (20) and (21), we observe (and this holds in general) that \( P_4 \) is independent only on the columns of \( \pi_4 \) and of \( y_4 \), and therefore the values of \( x'_i - \theta \lambda'_i \) remain unchanged in (21) with increasing values of \( y_4 = \theta \).

Because the \( y_4 \) are not sign restricted, \( y_4 \) can be increased until \( y_4 \) is dropped out of the basic set at value zero (since all \( x_i \) values are unaffected). Hence, in this shift of basis there is no change in the value of \( x^T C x \); however, the introduction of \( y_4 \) into the basic set and the dropping of \( y_4 \) give rise to a new basic set that satisfies the complementarity property. We may thus reapply Theorem 2 to reduce \( x^T C x \).

The Quadratic Algorithm.

**Step I.** Initiate: Let \( x^0 \) be a basic feasible solution for \( Ax = b, x \geq 0 \), with basic variables \( x_i, x_{i'}, \ldots, x_m \); choose for the initial set of basic variables \( x_i \), the enlarged problem these \( x_i \), the complements \( y_i \) of the non-basic \( x_i \), and the set of \( \pi_i \).

**Step II.** For the values of \( y_i^0 \) of the basic solution, determine Min \( y_i^0 = y_i^* \). If \( y_i^* \geq 0 \), terminate; the solution is optimal. If \( y_i^* < 0 \) introduce into the basic set \( x_i \); if \( y_i^* \) drops from the basic set, repeat Step II. Go to Step III if \( x_i^* \) drops.

**Step III.** Introduce \( y_i \) into basic set. If \( y_i \) drops, return to Step II; otherwise, if some \( x_i^* \) drops, repeat Step III with \( r_i \) playing the role of \( r \).

**Theorem 4.** The iterative process is finite.

**Exercise:** Prove Theorem 4.

**Exercise:** Extend the results of this section to cover the case of a convex objective form consisting of mixed quadratic and linear terms.
24-5. PROBLEMS

1. Show that the bounded variable problem of § 24-3-(12), (13), (14) is equivalent to the original convex-separable problem.
2. Show for § 24-3-(15), (16), (17) that, if $\Delta_{pt}$ is in the basis, $\Delta_{qt}$ is not, where $t \neq p$. Show under the simplex criterion that $\Delta_{qt}$ is not a candidate to enter the basic set if $\Delta_{pt}$ is in the basic set.
3. Solve the distribution problem below by both methods of § 24-3. Which is easier?

### Distribution Problem

<table>
<thead>
<tr>
<th>$x_{11}$</th>
<th>$x_{12}$</th>
<th>$x_{13}$</th>
<th>$x_{14}$</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>10</td>
<td>4</td>
<td>8</td>
<td>40</td>
</tr>
</tbody>
</table>

[407]
where the cost per unit shipped from \((i)\) to \((j)\) has incrementally increasing costs per total amount shipped as follows:

<table>
<thead>
<tr>
<th>1st unit</th>
<th>2nd unit</th>
<th>3rd unit</th>
<th>4th unit</th>
<th>5th unit</th>
<th>6th unit</th>
<th>7th unit</th>
<th>8th unit</th>
<th>9th unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
</tr>
</tbody>
</table>

4. Show that the total cost \(\phi(x)\) of shipping \(x = x_{ij}\) units from \(i\) to \(j\) in Problem 3 is \(\phi(x) = x(x + 1)/2\) if \(x\) is an integer. Show that, if we set 
\(\phi(x) = x(x + 1)/2\) for fractional values of \(x\), the optimal solution has 
fractional values for \(x_{ij}\).

5. Show how to get a solution to a distribution problem with integer-valued variables when the objective form is convex-separable. To be precise, find integers \(x_{ij} \geq 0\), \(\text{Min} \ z\) satisfying

\[
\sum_{j=1}^{m} x_{ij} = a_i \quad (i = 1, 2, \ldots, m)
\]

\[
\sum_{i=1}^{n} x_{ij} = b_j \quad (j = 1, 2, \ldots, n)
\]

\[
\sum_{i=1}^{n} \sum_{j=1}^{m} \phi_{ij}(x_{ij}) = z \quad (\text{Min})
\]

where \(a_i\) and \(b_j\) are integers, and \(\phi_{ij}(x_{ij})\) are convex functions (for example, 
\(\phi_{ij}(x_{ij}) = x_{ij}^2\) or \(x_{ij}(x_{ij} + 1)/2\)).

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CHAPTER 25

UNCERTAINTY

In the final analysis, most applied programming problems involve uncertainty in either the technology matrix or the constant terms. The techniques discussed so far, however, do not take into account the uncertain nature of the coefficients of the program. In the period 1955-60, various individuals have tried to extend linear programming methods to deal with the problem of optimizing in some sense an objective function, subject to constraints whose constants are subject to random variation [Dantzig, 1955-1; Ferguson and Dantzig, 1956-1]. One of the basic difficulties is that the problem is capable of many formulations, with only fragmentary results for each of the formulations [Madansky, 1959-1]. In this chapter we shall examine some of the solved problems in this area, cautioning the reader that the treatment is incomplete and that much research remains to be done.

For the concepts of probability and statistical theory used in this chapter, the reader is referred to [Feller, 1957-1].

25-1. SCHEDULING TO MEET VARIABLE COST

By way of background let us recall that there are in common use two essentially different types of scheduling applications—one designed for the short run and one for the long run. For the latter the effect of probabilistic or chance events is reduced to a minimum by the usual technique of providing plenty of fat in the system. For example, consumption rates, attrition rates, and wear-out rates are all planned on the high side; times to ship, times to travel, and times to produce are always made well above actual needs. Indeed, the entire system is put together with plenty of fat with the hope that it will be a shock absorber, which will permit the general objective and timing of the plan to be executed in spite of unforeseen events. More precisely, the fat is introduced into the system so that, whatever be the random unforeseen event, the activities chosen will still be feasible. Activities which satisfy this proviso are called permanently feasible. The effect of chance events is also reduced to a minimum by the technique of providing plenty of slack in the system. By this we mean that scarce exogenous inputs to the system are estimated on the low side, so that it is highly unlikely for the set of chosen activities to be infeasible because of shortages.

In the general course of things, long-range plans are revised frequently
UNCERTAINTY

because the stochastic elements of the problem have a nasty way of intruding. For this reason the chief contribution, if any, of the long-range plan, is to effect an immediate decision—such as the appropriation of funds or the initiation of an important development contract.

For short-run scheduling, many of the slack and fat techniques of its long-range brother are employed. The principal differences are attention to detail and the short time-horizon. As long as capabilities are well above requirements (or demands) or if the demands can be shifted in time, this approach presents no problems, since it is feasible to implement the schedule in detail. However, where there are shortages, the projected plan based on such techniques may lead to actions far from optimal, whereas these new methods, where applicable, may result in considerable savings.

Minimum Expected Costs.

A nutrition expert wishes to advise his followers on a minimum-cost diet without prior knowledge of the prices [Stigler, 1945-1]. Because prices of food (except for general inflationary trends) are likely to show variability due to weather conditions, supply, etc., he wants to assume a distribution of possible prices rather than a fixed price for each food, and determine a diet that meets specified nutritional requirements and minimizes the expected total cost. Let $x_j$ be the quantity in pounds of $j$th food purchased, $p_j$ its price; let $a_{ij}$ be the quantity of the $i$th nutrient (e.g., Vitamin A) contained in a unit quantity of the $j$th food; and let $b_i$ be the minimum quantity required by an individual for good health. Then the $x_j$ must be chosen so that

$$
\sum_{j=1}^{n} a_{ij} x_j \geq b_i, \quad x_j \geq 0 \quad (i = 1, 2, \ldots, m)
$$

(1)

The cost of the diet will be

$$
C = \sum_{j=1}^{n} p_j x_j
$$

(2)

However, the $x_j$ are chosen before the prices are known, so that for the fixed selected values of $x_j$ the total cost $C$ becomes a random variable that is a weighted sum of random variables $p_j$. We shall denote the expected value of any variable, say $u$, by $\mathbb{E}(u)$ or $\mathbb{E}(u)$. Accordingly, the expected cost $E$ of such a diet is clearly

$$
E = \mathbb{E}(C) = \sum_{j} \hat{p}_j x_j
$$

(3)

where $\hat{p}_j$ is the expected price of food $j$. Since the $\hat{p}_j$ are assumed known in advance, the best choices of $x_j$ are those which satisfy (1), and minimize $E$. We have, therefore, in general

[ 500 ]
THEOREM 1: If the unit costs \( p_i \) in (2) are randomly distributed independently of the \( x_j \), then the minimum expected total cost solution is obtained by finding \( x_j \geq 0 \) satisfying (1) and minimizing \( C \) with \( p_i \) replaced by \( \bar{p}_i = \mathbb{E}(p_i) \).

On the other hand if each \( p_i \) depends on \( x_j \), we write \( p_i x_j = \phi(x_j, p_i) \); remembering the expectation of a sum is equal to the sum of the expectations:

\[
E = \mathbb{E}C = \sum_{j=1}^{n} \mathbb{E}\phi(x_j, p_i) = \sum_{j=1}^{n} \phi(x_j)
\]

where \( \phi(x_j) \) is some (not necessarily linear) function of \( x_j \). Special methods for minimizing \( E \) for the case where \( \phi(x_j, p_i) \) is convex in the \( x_j \) were given in § 24-3.

The following example illustrates a case where the expected cost is not linear in the \( x_j \). Let \( x_j \) be the quantity of the \( j^{th} \) good manufactured and let the constraints be manufacturing capacity restraints. Assume that costs are threefold: there are a non-random manufacturing cost \( c_{m} \), a non-random stockage cost \( c_{s} \), and for those items not bought by a random demand, and a non-random shortage cost \( c_{u} \), if the random demand exceeds the supply; then

\[
E = \sum_{j} c_{m}x_j + \sum_{j} c_{s}(x_j - d_j|x_j > d_j) + \sum_{j} c_{u}(d_j - x_j|x_j < d_j)
\]

where the symbol \( \mathbb{E}(A|B) \) is read the expected value of \( A \) given that \( B \) is true.

This problem, though set up as a one-stage problem with the uncertainty appearing only in the objective function, could be set up as a two-stage problem with the uncertainty in the constraints instead. As such, it becomes a problem of the type described in § 25-2 and treated more fully in § 25-3 and in Elmaghraby's paper [1960-1].

Minimum Variance for Fixed Expected Costs.

Referring again to our nutrition problem, it may be desirable to control the variance \( V \) of the expected costs. Thus, a solution to (1) and (3) that results in a low expected cost, but one that has great variability, may not be as desirable as one which shows greater cost stability. This certainly was the case considered by H. Markowitz in his analysis of "portfolio" selections [Markowitz, 1952-1]. Stockbrokers often advise their customers to buy a variety of stocks, some of which they regard as very safe, low-yield stocks, while others (like oil exploration stocks) may have a high average yield but show great variation (depending, say, on whether or not oil is discovered). The objective of such an analysis is to produce for each of a variety of expected profit levels \(-E\), portfolio selections that minimize variance (Fig. 25-1-1).

It is then left to the customer to decide what combination of "yield level" and "risk level" (Min \( V \)) he wants.
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Let us now assume that the price is independent of \( x_i \) and that we know the variance (or standard error squared) \( \sigma^2 \) of \( p_i \), the price of an individual item, and the covariance \( \sigma_{jk} \) between two prices \( p_j \) and \( p_k \). Let \( \sigma_{jk} = \sigma_{j}\sigma_{k}\rho_{jk} \) where the correlation coefficient between the two prices \( \rho_{jk} \) satisfies \(-1 \leq \rho_{jk} \leq +1\). Since all \( x_i \) units are purchased at the same cost \( p_i \), the variance of \( x_i p_i \) is given by \( x_i^2 \sigma^2 \) and the covariance between \( x_i p_j \) and \( x_i p_k \) is given by \( x_j x_k \sigma_{jk} \). From this it follows that the variance \( V \) of \( E \) is given by the quadratic expression

\[
V = \mathcal{A}(C - E)^2 = \sum_{j=1}^{n} \sum_{k=1}^{n} x_j x_k \sigma_{jk} \quad (\sigma_{jj} = \sigma^2)
\]

(5)

If, in particular, food prices are highly correlated so that for all practical purposes \( \rho_{jk} = 1 \) and \( \sigma_{jk} = \sigma_j \sigma_k \), then in this case it would be advisable to replace \( V^1 \) by the linear expression bounding it given in (6),

\[
V^1 \leq x_1 \sigma_1 + x_2 \sigma_2 + \ldots + x_n \sigma_n
\]

(6)

where equality holds if all correlation coefficients \( \rho_{jk} = 1 \). On the other hand, if the prices are independent so that \( \rho_{jk} = 0 \), then

\[
V = x_1^2 \sigma_1^2 + x_2^2 \sigma_2^2 + \ldots + x_n^2 \sigma_n^2 \quad (\rho_{jk} = 0)
\]

(7)

We now address ourselves to the general problem of determining the solution to (1), (3), and (5) that minimizes \( V \) for fixed \( E \).

Case I: \( V^1 \) is Linear. If (6) holds, then we solve the problem of determining \( \text{Min} V^1 \) subject to \( E \leq E^* \), where \( E^* \) is an upper bound which we wish to impose on expected costs. Since the restriction is linear, we may study the effect on \( V \) of varying \( E^* \) as a parameter. In this case we have a standard parametric programming problem (see §11-3).

Case II: \( V \) is a Sum of Squares. If (7) holds, then \( V \) is convex-separable and the convex functions \( x_i^2 \) may be approximated by broken-line functions. This reduces the problem again to a standard parametric programming problem (combined with an upper-bounding technique, if desired). Here
we are varying one of the constant terms. See § 11-3 and § 24-3. However, the following alternative is recommended. Replace $V$ by

$$V = x_1^2 s_1^2 + x_2^2 s_2^2 + \ldots + x_n^2 s_n^2 + E^* (E \leq E^*)$$

(8)

Again using a broken-line fit for $x_j^2$, the problem is first solved using $k = 0$; it is easy to see that this corresponds to setting $E^* = +\infty$. If now $k$ is allowed to increase gradually, a critical value $k = k_1$ would be determined for which the solution would no longer be optimal. This will result in one or more basis changes until the solution is again optimal. After this, $k$ can again be increased until a new critical value $k = k_2$ is obtained, etc.

**Exercise:** Prove the latter procedure is the first parametric linear programming method in disguise. Develop other alternatives based on § 24-3. Why is $E^*$ instead of $E$ used above?

It is probably worth while, however, instead of choosing to increase $k$ gradually, to choose a number of discrete values in advance. The solution will generate a number of different pairs of $E^*$ and $V$ values that can be used to spot points on the curve. A plot of $E^*$ against $k$ can be used to determine what new $k$ values to use if a better spacing of $E^*$ values is desired.

**Case III:** $V$ Is General. Since $V$ is positive (semi-) definite, it can, by a suitable linear transformation, be reduced to Case II; hence this procedure can be used in general to effect a solution to the problem. Alternatively, a general quadratic programming procedure such as that developed by Markowitz [1956-1] or by Wolfe [1959-1] may be used, combined with a parametric programming method for the right-hand side (see § 11-3). However, an analogue of (8) using an $E^*$ term weighted by a parameter $k$ is recommended.

**Exercise:** Combine methods for solving quadratic programs and parametric programs as given in § 24-4 and § 11-3 to solve the minimum-variance problem.

---

**25-2. SCHEDULING TO MEET AN UNCERTAIN DEMAND**

Let us consider a simple case: A factory has 100 items on hand which may be shipped to an outlet at the cost of $1$ apiece to meet an uncertain demand $d$. In the event that the demand should exceed the supply, it is necessary to meet the unsatisfied demand by purchases on the local market at $2$ apiece. The equations that the system must satisfy are

$$100 = x + y \quad (x, y, v, s \geq 0)$$

$$d = x + v - s$$

$$C = x + 2v$$

[ 503 ]
where \( x = \) number shipped from the factory,
\( y = \) number stored at factory;
\( v = \) number purchased on open market,
\( s = \) excess of supply over demand;
\( d = \) unknown demand uniformly distributed between 70 and 80;
\( C = \) total costs.

We view the shipping and purchasing as part of a two-stage process. In the first stage a decision is made consistent with the initial inventory of amounts to ship. In the second stage, the unknown demands occur.

The simple example above belongs to a general class of two-stage problems that have the following structure. In the first stage, \( x_i \geq 0, u_k \geq 0 \) are determined such that

\[
\sum_{j=1}^{n} a_{ij} x_j = b_i \quad (i = 1, 2, \ldots , m)
\]

\[
\sum_{j=1}^{n} \bar{a}_k x_j = u_k \quad (k = 1, 2, \ldots , p)
\]

where the initial inventories \( b_i \) for \( i = 1, 2, \ldots , m \) are known; the \( x_i \geq 0 \) represent decisions in the first stage resulting in specified quantities \( u_k \) being made available for the second stage. For the second stage, the quantities \( v_k \) and \( s_k \) are determined such that

\[
d_k = u_k + v_k - s_k \quad (k = 1, 2, \ldots , p)
\]

where \( d_k \) is the unknown demand whose probability distribution is known, \( v_k \) is the shortage of supply, and \( s_k \) is the excess of supply over demand. Assuming for convenience no purchases on the open market in case of shortage, the total cost is of the form

\[
C = \sum_{j=1}^{n} c_j x_j - \sum_{k=1}^{p} f_k (d_k - v_k) \quad \text{where } v_k = 0 \text{ if } u_k \geq d_k
\]

where \( c_j \) is the cost of performing the \( j^{th} \) activity and \( f_k \geq 0 \) is the revenue from satisfying one unit of demand. Thus, it always pays to sell as much of the amount, \( u_k \), supplied as possible so that \((d_k - v_k) = \text{Min} (u_k, d_k)\) and

\[
C = \sum_{j=1}^{n} c_j x_j - \sum_{k=1}^{p} f_k \text{Min} (u_k, d_k)
\]

It is clear that, for any particular choice of \( x_j \) and \( u_k \) consistent with the first-stage equations, the value of \( C \) depends on this choice and on the
unknown demand. Hence, for fixed choice of \( x_i \) and \( u_i \), the expected value of \( C \) is given by

\[ \mathcal{E}C = \sum_{j=1}^{n} c_j x_j - \sum_{k=1}^{p} f_k \mathcal{E} \text{Min}(u_k, d_k) \]  

(6)

Since the expected value of \( \text{Min}(u_k, d_k) \) depends on \( u_k \), let us denote this function (of \( u_k \)) by

\[ \phi_k(u_k) = \mathcal{E} \text{Min}(u_k, d_k) \]  

(7)

Given the demand distribution of \( d_k \), the function \( \phi_k(u_k) \) is easily calculated. Suppose \( d_k = 1, 2 \) with probability \( \frac{1}{4}, \frac{1}{2} \), respectively, then \( \phi_k(u_k) \) is easily determined.

<table>
<thead>
<tr>
<th>Amount Supplied ((u_k))</th>
<th>Amount Sold (d_k - v_k = \text{Min}(u_k, d_k))</th>
<th>Expected Value (^1) (revenue) (\phi_k(u_k))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>where ( d_k = 1 )</td>
<td>where ( d_k = 2 )</td>
</tr>
<tr>
<td>( u_k = 0 )</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( 0 &lt; u_k &lt; 1 )</td>
<td>( u_k )</td>
<td>( u_k )</td>
</tr>
<tr>
<td>( u_k = 1 )</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>( 1 &lt; u_k &lt; 2 )</td>
<td>1</td>
<td>( u_k )</td>
</tr>
<tr>
<td>( u_k = 2 )</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>( 2 &lt; u_k )</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

\(^1\) Entries in column (3) are formed by multiplying the entries in column (1) by \( p_1 = \frac{1}{4} \), those in column (2) by \( p_2 = \frac{1}{2} \), and summing.

In general, to compute \( \phi(u) = \mathcal{E} \text{Min}(u, d) \) where \( d \) can take on successive values \( e_1 \leq e_2 \ldots \leq e_r \) with probability \( p_1, p_2, \ldots, p_r \) and \( \sum p_i = 1 \), we note

\[ \text{Min}(u, d) = u \quad \text{if } d > u \]
\[ \text{Min}(u, d) = d \quad \text{if } d \leq u \]  

(9)

Suppose \( e_{r-1} \leq u < e_r \), then

\[ \phi(u) = u \text{ Prob}(d > u) + \text{Prob}(d \leq u)\mathcal{E}(d|d \leq u) \]

[ 505 ]
whence

\begin{equation}
\phi(u) = u(p_r + p_{r+1} + \ldots + p_l) + (e_1 p_1 + e_2 p_2 + \ldots + e_{r-1} p_{r-1}) \\
= u(1 - p_1 - p_2 - \ldots - p_{r-1}) + (e_1 p_1 + e_2 p_2 + \ldots + e_{r-1} p_{r-1})
\end{equation}

where we define, for \( r = 1 \) in (10), \( e_0 = 0 \) and \( p_0 = 0 \). Thus, \( \phi(u) \) is a broken-line function starting at the origin with initial slope \( s_1 = 1 \); at \( u = e_1 \), the slope decreases to \( s_2 = 1 - p_1 \), etc. (see Fig. 25.2-I).

![Figure 25.2-I. Maximum expected revenue is a concave function of the amount supplied.](image)

Referring to our section on convex separable functions, § 24-3, it should be noted that \(-\phi(u)\) is convex because of the decreasing slopes in Fig. 25.2-I. Indeed, \( s_i - s_{i+1} = p_i > 0 \). We have therefore shown a result of H. Scarf (informal demonstration to the author).

**Theorem 1:** The total expected costs under uncertain demand is a convex separable function

\begin{equation}
\mathcal{C} = \sum_{j=1}^{n} c_j x_j - \sum_{k=1}^{m} f_k \phi_k(u_k)
\end{equation}

where \( \phi_k(u_k) \) is a broken-line function whose slope between two successive demands \( d_k = e_{r,k} \), and \( e_{r+1,k} \) is equal to the probability of exceeding the demand \( e_{r,k} \).

**Theorem 2:** To minimize expected costs, determine \( x_j \geq 0, u_k \geq 0 \), satisfying (2), such that the convex separable function (11) is minimized.

**Continuous Demand Distribution.**

To illustrate an example involving a continuous distribution, consider the small two-stage case described earlier in (1). The costs are given by

\begin{equation}
C = x_1 + 2 \text{Max} (0, d - x_1)
\end{equation}

where \( d \) is uniformly distributed between 70 and 80. The determination of
expected costs requires the evaluation of $\mathcal{E} \text{Max} [0, d - x_1]$ as a function of $x_1$:

$$
\mathcal{E} \text{Max} (0, d - x_1) = \begin{cases} 
75 - x_1 & \text{if } 0 \leq x_1 \leq 70 \\
\int_{x_1}^{80} (t - x_1) dt & \text{if } 70 \leq x_1 \leq 80 \\
0 & \text{if } 80 \leq x_1 
\end{cases}
$$

whence from (12)

$$
\mathcal{E}C = \begin{cases} 
150 - x_1 & \text{if } 0 \leq x_1 \leq 70 \\
x_1 + (80 - x_1)^3/10 & \text{if } 70 \leq x_1 \leq 80 \\
x_1 & \text{if } 80 \leq x_1 
\end{cases}
$$

It then follows that Min$_{x_1} \mathcal{E}C = 77.5$ occurs at $x_1 = 75$, i.e., it is best to ship the expected demand in this case.

**Exercise:** Modify the above problem to show that it is not always best to ship the expected demand.

*When is it best to ship the expected demand?* The following result, due to Madansky [1960-1] (see also Reiter, [1957-1]), is a generalization of earlier results [Theil, 1957-1; Simon, 1956-1], and gives a sufficient condition for the solution of the linear program when the demand is replaced by its expected value also to solve the problem of scheduling to meet uncertain demand. If $C$ can be expressed as $C_1(d, x) + C_2(d)$ where $C_1(d, x)$ is a linear function of $d$ for each $x$ and $C_2(d)$ involves only $d$ and not $x$, then the $x$ which solves the linear program with $d$ replaced by $\mathcal{E}(d)$ also solves the uncertainty problem.

**Exercise:** Prove this result. Does the example above satisfy the sufficiency condition?

**25-3. ON MULTI-STAGE PROBLEMS**

The Two-stage Problem with General Linear Structure.

We shall prove a general theorem on convexity for the two-stage problem that forms the inductive step for the multi-stage problem. We shall say a few words about the significance of this convexity later on. The assumed structure of the general two-stage model (of which § 25-2-(3) is a special case) is

$$
\begin{align*}
\mathbf{b}_1 &= A_{11} \mathbf{X}_1 \\
\mathbf{b}_2 &= A_{21} \mathbf{X}_1 + A_{22} \mathbf{X}_2 \\
\mathbf{C} &= \phi(\mathbf{X}_1, \mathbf{X}_2 | \mathbf{E}_2)
\end{align*}
$$

where $A_{ij}$ are known matrices; $\mathbf{b}_1$, a known vector of initial inventories; $\mathbf{b}_2$, an unknown vector whose components depend on a set of parameters $\mathbf{E}_2$; and $\mathbf{C}$, the cost, depends on $\mathbf{X}_1$, $\mathbf{X}_2$, and $\mathbf{E}_2$.

\footnote{The material for this section is based on [Dantzig, 1955-1].}
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We assume the following sequence of events:

1. \( X_1 \geq 0 \) is chosen to satisfy \( b_1 = A_{11}X_1 \). We denote by \( \Omega_1 \) the set of possible vectors \( X_1 \). It is assumed that \( \Omega_1 \) is nonempty.

2. \( E_1 \) is drawn randomly as a point from a multidimensional sample space \( S \) with known probability distribution. \( E_1 \) determines \( b_2 \).

3. \( X_2 \geq 0 \) is chosen to satisfy \( b_2 = A_{21}X_1 + A_{22}X_2 \). We denote by \( \Omega_2 = \Omega_2(X_1|E_1) \) the set of possible vectors \( X_2 \). It is assumed that \( \Omega_2 \) is nonempty, that is to say, there exists at least one such vector whatever be the values of \( X_1 \) and \( E_1 \) chosen above.

The problem is to select \( X_1 \) and later \( X_2 \) so that the expected value of \( C \) is minimum.

Observing that the nonnegative weighted sum of convex functions is convex and that an expected value is such a sum (or more generally a Stieltjes integral), the following useful lemma results:

**Lemma 1:** If \( \phi(X|E) \) is convex in \( X \in \Omega \) whatever \( E \) be chosen from a sample space \( S \) with known probability distribution, then the function \( \phi(X) = E \phi(X|E) \) is convex.

**Theorem 1:** If \( \phi(X_1, X_2|E_2) \) is a convex function in \( X_1 \in \Omega_1, X_2 \in \Omega_2(X_1|E_2) \), then the function

\[
\phi(X_1) = \inf_{E_1, X_1} [\phi(X_1, X_2|E_2)]
\]

is convex and has the property that \( X_1 = X_1^* \) solves the uncertainty problem if

\[
\phi(X_1^*) = \min \phi(X_1)
\]

The expectation (\( \mathcal{E} \)) is taken with respect to the distribution of \( E_2 \) and the greatest lower bound (\( \inf \)) is taken with respect to all \( X_2 \in \Omega_2(X_1|E_2) \).

**Proof:** In order to minimize \( \mathcal{E}\phi(X_1, X_2|E_2) \), it is clear that, once \( X_1 \) has been selected and \( E_2 \) determined by chance, \( X_2 \) must be selected so that \( \phi(X_1, X_2|E_2) \) is minimized for fixed \( X_1 \) and \( E_2 \). Thus, the cost for given \( X_1 \) and \( E_2 \) is given by

\[
\phi(X_1|E_2) = \inf_{X_2 \in \Omega_2} \phi(X_1, X_2|E_2)
\]

The expected cost for a given \( X_1 \) is then simply the expected value of \( \phi(X_1|E_2) \) and this we denote by \( \phi_0(X_1) \). The optimal choice of \( X_1 \) to minimize expected cost is thus reduced to choosing \( X_1 \) so as to minimize \( \phi_0(X_1) \).

---

1. This assumption can be interpreted as assuring either that there is enough *fat* in the system or that there are enough *slack* variables in the system so that the set of permanently feasible \((X_1, X_2)\) is not null.

2. The greatest lower bound instead of minimum is used to avoid the possibility that the minimum value is not attained for any admissible point \( X_1 \in \Omega_1 \) or \( X_2 \in \Omega_2 \). In the case where the latter occurs, it should be understood that while there exists no \( X_2 \) where the minimum is attained, there exists \( X_1 \) for which values as close to minimum as desired are attained.

3. This proof is along lines suggested by I. Glicksberg.
25.3. ON MULTI-STAGE PROBLEMS

There remains only to establish the convexity property. We shall show first that \( \phi(X_t|E_2) \) for bounded \( \phi \) is convex for \( X_t \) in \( \Omega_t \). If true, then applying the lemma, the result that \( \phi_0(X) \) is convex readily follows. Let us suppose that \( \phi_1(X_1|E_2) \) is not convex; then there exist three points \( X'_1, X'_2, X''_1 \) in \( \Omega_t \), \( X''_1 = \lambda X'_1 + \mu X'_2, (\lambda + \mu = 1, 0 \leq \lambda \leq 1) \) that violate the condition for convexity, i.e.,

\[
(4) \quad \lambda \phi_1(X'_1|E_2) + \mu \phi_1(X'_2|E_2) < \phi_1(X''_1|E_2)
\]
or

\[
(5) \quad \lambda \phi_1(X'_1|E_2) + \mu \phi_1(X'_2|E_2) = \phi_1(X''_1|E_2) - \epsilon_0 \quad (\epsilon_0 > 0)
\]

For any \( \epsilon_0 > 0 \), however, there exist \( X'_1 \) and \( X'_2 \) such that

\[
(6) \quad \phi_1(X'_1|E_2) = \phi(X'_1, X'_2|E_2) - \epsilon_1 \quad (0 \leq \epsilon_1 < \epsilon_0)
\]

\[
(7) \quad \phi_1(X'_2|E_2) = \phi(X'_1, X'_2|E_2) - \epsilon_2 \quad (0 \leq \epsilon_2 < \epsilon_0)
\]

Setting \( X''_1 = \lambda X'_1 + \mu X'_2 \) we note because of the assumed linearity of the model (1) that \( (\lambda X'_1 + \mu X'_2) \in \Omega_t(X''_1|E_2) \) and hence by convexity of \( \phi \)

\[
(7) \quad \lambda \phi(X'_1, X'_2|E_2) + \mu \phi(X'_1, X'_2|E_2) \geq \phi(X''_1, X''_2|E_2)
\]

whence by (6)

\[
(8) \quad \lambda \phi_1(X'_1|E_2) + \mu \phi_1(X'_2|E_2) \geq \phi(X''_1, X''_2|E_2) - \lambda \epsilon_1 - \mu \epsilon_2
\]

and by (5)

\[
(9) \quad \phi_1(X''_1|E_2) > \phi(X''_1, X''_2|E_2) - \lambda \epsilon_1 - \mu \epsilon_2 + \epsilon_0
\]

where \( 0 < \lambda \epsilon_1 + \mu \epsilon_2 < \epsilon_0 \), which contradicts the assumption that

\[
\phi_1(X''_1|E_2) = \inf_{X'_2 \in \Omega_t} \phi(X''_1, X'_2|E_2)
\]

The proof for unbounded \( \phi \) is omitted; see [Dantzig, 1955-1]. For an illustration of the use of this theorem in solving a linear program under uncertainty, see Chapter 28.

The Multi-stage Problem with General Linear Structure.

The structure assumed is

\[
\begin{align*}
b_1 &= A_{11}X_1 \\
b_2 &= A_{21}X_1 + A_{22}X_2 \\
b_3 &= A_{31}X_1 + A_{32}X_2 + A_{33}X_3 \\
b_4 &= A_{41}X_1 + A_{42}X_2 + A_{43}X_3 + A_{44}X_4 \\
&\vdots \\
b_m &= A_{m1}X_1 + A_{m2}X_2 + A_{m3}X_3 + \ldots + A_{mm}X_m \\
C &= \phi(X_1, X_2, \ldots, X_m|E_2, E_3, \ldots, E_m)
\end{align*}
\]

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where $b_1$ is a known vector; $b_i$ is a chance vector ($i = 2, \ldots, m$) whose components are functions of a point $E_i$ drawn from a known multidimensional distribution; $A_{ij}$ are known matrices. The sequence of decisions is as follows: $X_1$, the vector of nonnegative activity levels in the first stage, is chosen so as to satisfy the first-stage restrictions $b_1 = A_{11}X_1$; the values of components of $b_2$ are chosen by chance by determining $E_2$; $X_2$ is chosen to satisfy the second-stage restrictions $b_2 = A_{21}X_1 + A_{22}X_2$, etc., iteratively for the third and higher stages. It is further assumed that:

(a) The components of $X_i$ are nonnegative.
(b) There exists at least one $X_i$ satisfying the $j$th-stage restraints, whatever be the choice of $X_1, X_2, \ldots, X_{j-1}$ satisfying the earlier restraints or the outcomes $b_1, b_2, \ldots, b_m$.
(c) The total cost $C$ is a convex function in $X_1, \ldots, X_m$ which depends on the values of the sample points $E_2, E_3, \ldots, E_m$.

THEOREM 2: An equivalent $(m - 1)$-stage programming problem with a convex payoff function can be obtained by dropping the $m$th-stage restrictions and replacing the convex cost function $\phi$ by

\[
\phi_{m-1}(X_1, X_2, \ldots, X_{m-1}|E_2, \ldots, E_{m-1}) = \mathcal{E} \inf_{E_m} \phi(X_1, X_2, \ldots, X_m|E_2, \ldots, E_m)
\]

where $\Omega_m$ is the set of possible $X_m$ that satisfy the $m$th-stage restrictions.

Since the proof of the above theorem is identical to the two-stage case, no details will be given. The fact that a cost function for the $(m - 1)$st stage can be obtained from the $m$th stage is simply a consequence of the fact that optimal behavior for the $m$th stage is well defined, that is, given any state, $(X_1, X_2, \ldots, X_{m-1})$ at the beginning of this stage, the best possible actions can be determined and the minimum expected cost evaluated. This is a standard technique in "dynamic programming." The reader interested in methods built around this approach is referred to R. Bellman’s book on dynamic programming [1957-1].

While the existence of convex functions has been demonstrated that permit reduction of an $m$-stage problem to equivalent $m - 1, m - 2, \ldots$, one-stage problems, it appears unlikely that such functions can be computed except in very simple cases. The convexity theorem was demonstrated not as a solution to an $m$-stage problem but only in the hope that it will spur the development of an efficient computational theory for such models. It should be remembered that any procedure that yields a local optimum will be a true (global) optimum if the function is convex. This is important because multidimensional problems in which non-convex functions are defined over non-convex domains lead, as a rule, to local optima and an
almost hopeless task, in general, of exploring other parts of the domain for the other extremes [Dantzig and Madansky, 1960-1]. See § 26-3.

The General Two-stage Case.

When the set of possibilities for the chance vector \( b_2 \) is \( b_2^{(1)}, b_2^{(2)}, \ldots, b_2^{(k)} \) with probabilities \( p_1, p_2, \ldots, p_k \), \( (\sum p_i = 1) \), it is not difficult to obtain a direct linear programming solution for small \( k \), say \( k = 3 \). Since this type of structure is very special, it appears likely that techniques can be developed to handle large \( k \), which could be used to approximate the solution when \( b_2 \) has a general distribution. For \( k = 3 \), the problem is equivalent to determining vectors \( x_1 \) and vectors \( x_2^{(1)}, x_2^{(2)}, x_2^{(3)} \) such that

\[
\begin{align*}
b_1 &= A_{11}x_1 \\
b_2^{(1)} &= A_{21}x_1 + A_{22}x_2^{(1)} \\
b_2^{(2)} &= A_{21}x_1 + A_{22}x_2^{(2)} \\
b_2^{(3)} &= A_{21}x_1 + A_{22}x_2^{(3)} \\
\xi C &= \gamma_1 x_1 + p_1 \gamma_2 x_2^{(1)} + p_2 \gamma_2 x_2^{(2)} + p_3 \gamma_2 x_2^{(3)} = z \text{ (Min)}
\end{align*}
\]

where for simplicity we have assumed a linear objective function. Thus a general two-stage linear program with an uncertain constant vector for the second stage reduces to a linear program of a special structure like (12).

**Exercise:** Develop an algorithm for solving systems like (12) for large \( k \), by dualizing and then using the Decomposition Principle (Chapter 23). Take advantage of the repetitive appearance of \( A_{22} \) and \( \gamma_2 \).

### 25-4. PROBLEMS

1. Prove that the quadratic expression given in § 25-1-(5) is positive semi-definite, i.e., \( V \succeq 0 \).
2. Prove that any quadratic expression \( Q \) can by linear transformation be reduced to sum and difference of squares of the new variables. Show that \( Q \) cannot be positive definite if it involves differences of squares. (Review.)
3. Show that if \( Q \) is positive (semi-) definite, \( Q \) is a convex function. (Review.)
4. Show for \( V \) and \( x \) satisfying § 25-1-(1, 3, 5) and \( E \leq E^* \), where \( E^* \) is a parameter, that \( \text{Min } V \) is a monotonically decreasing function of \( E^* \) if we allow \( E^* \) to take on increasing values.
5. Show above that if \( Q \) is any convex function of \( x \), then \( \text{Min } Q \) is a convex function of \( E \) (where \( E \) and \( x \) satisfy § 25-1-(1, 3).
6. Solve the same problem as § 25-2-(1) using the discrete distribution \( d = 70, 71, 72, \ldots, 80 \) with probability 1/11 each.
7. (a) Solve the transportation problem

<table>
<thead>
<tr>
<th></th>
<th>$x_{11}$</th>
<th>$x_{12}$</th>
<th>$x_{13}$</th>
<th>$x_{14}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Available:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$x_{11}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>$x_{21}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>2</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>$x_{31}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>2</td>
</tr>
</tbody>
</table>

Required: $d_1$, $d_2$, $d_3$, $d_4$

where the demands are

$d_1 = 3$ with probability 1
$d_2 = 3$ "  "  
$d_3 = 2$ "  "  
$d_4 = 2$ "  "  

(b) Solve, if

$d_1 = 2, 3, 4$ with probability $\frac{1}{3}$ each
$d_2 = 2, 3, 4$ "  "  
$d_3 = 1, 2, 3$ "  "  
$d_4 = 1, 2, 3$ "  "  

Compare this solution with that of 7(a) which uses expected demands in place of the variable demands 7(b).

8. Consider a linear program where all coefficients are subject to uncertainty. Suppose (for $i = 1, 2, \ldots, m$) that

$$
\varepsilon_i(x) = \sum_{j=1}^{n} a_{ij}x_j + a_0 \leq 0 \quad (x_j \geq 0)
$$

$$
\varepsilon_0(x) = \sum_{j=1}^{n} a_{0j}x_j = z \quad (\text{Min})
$$

is desired but, unfortunately, all $x_j$ must be selected prior to a random choice of the coefficients $a_{ij}$ whose distributions are, however, known. Denote by $\sigma_i(x)$ the standard error of $\varepsilon_i(x)$. Show that

$$
\sigma_i(x) = \left( \sum_{j=1}^{n} \sum_{k=1}^{n} x_j x_k \mathbb{E}(a_{ij} - \bar{a}_{ij})(a_{ik} - \bar{a}_{ik}) \right)^{\frac{1}{2}}
$$
REFERENCES

Suppose we solve the program (for $i = 1, 2, \ldots, m$)

$$
\begin{align*}
\bar{\varepsilon}_i(x) + t_i \sigma_i(x) & \leq 0 \\
\bar{\varepsilon}_i(x) + t_i \sigma_i(x) & = z \text{ (Min)}
\end{align*}
$$

where $t_i = 3$, say, means that we have built in a safety factor so that $\varepsilon_i(x)$, the expected value of $\varepsilon_i(x)$, is three standard errors below zero. Prove that this is a convex program. Apply § 24-1 to solve such a problem. Show by Tchebycheff's inequality that

$$
\text{Prob} \left[ \varepsilon_i(x) > 0 \right] < \frac{1}{t_i^2}
$$

What is the above probability if $\varepsilon_i(x)$ is approximately normally distributed? Show that if the $a_{ij}$ are independent and normally distributed, then $\varepsilon_i(x)$ is normally distributed.

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Wolfe, 1959-1
CHAPTER 26

DISCRETE-VARIABLE EXTREMUM PROBLEMS

Our purpose now is to solve programs involving variables that have integer values. This first section is confined to a general survey; the second section describes Gomory’s Method of Integer Forms, which has now replaced the earlier incomplete work in the field; and the third section gives an appreciation of these results by describing a large class of difficult mathematical problems which are reducible to integer programs. In § 26.3-(14) a simple device is given for transforming a discrete-valued variable to an integer-valued variable.

26-1. SURVEY OF METHODS

A number of important scheduling problems, such as the assignment of flights for an airline or the arrangement of stations on an assembly line, require the study of an astronomical number of arrangements to determine which one is “best.” The mathematical problem is to find some short-cut way of getting this best assignment without going through all the combinations. By allowing the unknown assignments to vary continuously over some range, one can obtain pseudo-solutions in which one or more assignments turn out to be fractions instead of whole numbers. It is common practice to adjust such values to whole numbers. Because mathematical models are often imperfect mirrors of reality, this approach is recommended for most practical problems. But since such procedures can occasionally give far from the best answer, mathematicians have been working on improved techniques.

The purpose of the present section is to review some recent successes using linear programming methods in this difficult area. We shall also say a few words about the functional-equation approach of dynamic programming; one example is presented in which this method provides an efficient algorithm.

To be more explicit, certain classes of problems are combinatorial in nature and easy to formulate, but mathematicians have had only partial success in solving them. These arise often in the form of discrete-variable programming problems, such as:

1. The empty-containers problem. A transport company has a large
26.1. SURVEY OF METHODS

number of objects for shipment that it places in empty containers of fixed size. What is the least number of containers required?

2. The multi-stage machine-scheduling problem. A machine shop has a large number of different types of tasks to be performed. Each task must be processed first on machine A, then B, then C, . . . ; the time required depends on the task. In what order should the processing be done to complete all the tasks in the least time? [Johnson, 1958-1]

3. The flight-scheduling problem. Given a number of sources that must ship specified quantities to a number of destinations, arrange an efficient flight schedule [Markowitz and Manne, 1957-1].

4. The trim problem. Newsprint comes in rolls of varying widths that are cut from rolls many times these widths. How are these to be cut to minimize trim? [Paull and Walter, 1955-1; Eisemann, 1957-1; Land and Doig, 1957-1; Doig and Belz, 1956-1.]

5. The fixed-charge problem. See § 26.3.


Examples of problems that have yielded to analysis, as we have seen in earlier chapters, are the following:


8. The problem of the shortest route in a network. See Chapter 17.

The mind seems to have a remarkable facility for scanning many combinations and arriving at what appears to be either a best one or a very good one. The number of possible combinations can be extremely large, however, making it difficult to verify that the choice is, indeed, a good one. Any ideas, therefore, that help verify that a conjectured solution is optimal are of interest. We shall consider the following class of problems:

Find \( x_i \), satisfying

\[
\sum_{j=1}^{n} a_{ij}x_j = b_i \quad (i = 1, 2, \ldots, m)
\]

and

\[
x_i = 0 \text{ or } 1
\]

that minimize the linear form

\[
\sum_{j=1}^{n} c_jx_j = z
\]

For a programming problem to be discrete, it is not necessary that the variables be 0 or 1. In flight-scheduling problems, for example, the variables that represent the number of flights are required to be nonnegative integers. There exists, however, a very simple device by which such problems can be reduced to the "0 or 1" form if the variables have known upper bounds. Indeed, let \( z \) be a variable that can take on only nonnegative integral values
and let the integer \( k \) be an upper bound for \( x \), so that \( x \leq k \); then \( x \) can be replaced by the sum
\[
x = y_1 + y_2 + \ldots + y_k \quad (y_j = 0 \text{ or } 1)
\]
For this reason the representation (1), (2), and (3) of a discrete programming problem is often referred to as the \textit{standard discrete form}.

An important property of any set of points whose coordinates satisfy equation (2) is that the points are vertices of a convex polyhedral set in \( n \)-dimensional space. This is perhaps intuitively obvious since a point such as \((0, 1, 0, \ldots, 1)\) is one of the vertices of the unit \( n \)-cube (which of course is convex). As we know in a linear programming problem, if an optimal solution exists, there is one that is an extreme point of feasible solutions. This suggests that, in seeking a solution to the standard discrete problem, we first weaken the hypothesis as follows:

\[
\text{(4)} \quad \text{Replace } \begin{cases} x_j = 0 \text{ or } x_j = 1 \\ \text{a discontinuous range} \end{cases} \text{ by } \begin{cases} 0 \leq x_j \leq 1 \\ \text{a continuous range} \end{cases}
\]

Because the replacement given in (4) is less restrictive than the condition (2), it follows that the set of feasible solutions to the linear programming problem (1) and (4) forms a convex polyhedral set \( C^* \) that contains the convex polyhedral set \( C^* \), which is the convex hull of the solution points of (1) and (2). It is easy to see, however, that every extreme point (vertex) of \( C^* \) is an extreme point of \( C \) (see open dots in Fig. 26-1-I); but there may be extreme points of \( C \) that are outside of \( C^* \) (see closed dots in Fig. 26-1-I). The

![Figure 26-1-I. Schematic representation (two-dimensional case) of the polyhedral set \( C^* \) whose vertices are the solutions for a discrete program and of the convex polyhedral set \( C \) of solutions for the corresponding continuous problem.](image)
parallel lines in Fig. 26-1-I represent different positions of the hyperplane

\[ c_1x_1 + c_2x_2 + \ldots + c_nx_n = z = \text{constant} \]

and it is clear that, depending on the values of the \( c_i \), an extreme point corresponding to minimum \( z \) may belong to \( C^* \) (as in Fig. 26-1-I) or may belong to \( C \) and not to \( C^* \) [Hoffman and Kruskal, 1956-1].

A remarkable property of the "assignment" problem, and the same holds true for the "shortest-route" problem, is that

(5)

\[ C^* = C \]

Indeed, this result holds true for a general class of "transportation" problems of which these are special cases. Thus, in the marriage problem (Chapter 13), when we replace the condition \( x_{ij} = 0 \) or 1 by \( 0 \leq x_{ij} \leq 1 \), we are, in effect, allowing the class of solutions to be extended from the monogamous to the polygamous situation in which sharing mates is possible. The fact that \( C^* = C \) states that monogamy will turn out to be the best after all!

The Knapsack Problem.

In certain types of problems, we can get extreme-point solutions for which not all the values of the \( x_i \) are either zero or one. When any of the \( x_i \) have fractional values, the corresponding extreme points are referred to as fractional extreme points. An example of this occurs in the knapsack problem: A person is planning a hike and has decided not to carry more than 70 pounds of various items, such as bed roll, geiger counters (these days), cans of food, etc.

We try to formulate this in mathematical terms. Let \( a_j \) be the weight of the \( j^{th} \) object and let \( b_j \) be its relative value determined by the hiker in comparison with the values of the other objects he would like to have on his trip. Let \( x_j = 1 \) mean that the \( j^{th} \) item is selected, and \( x_j = 0 \) mean that it is not selected. We express the weight limitation by

(6)

\[ \sum_{j=1}^{n} a_jx_j \leq 70 \]

(7)

\[ x_j = 0 \text{ or } 1 \]

and wish to choose the \( x_j \), so that the total value

(8)

\[ \sum_{j=1}^{n} b_jx_j = z \]

is a maximum.

Now we can show this pictorially in the plane (Fig. 26-1-II) if one coordinate axis measures weight, \( a_i \), and the other measures value, \( b_j \). Each object then is represented by a point having coordinates \((a_i, b_j)\). The problem,
graphically, is to select a subset of these points that represents the set of items that he carries with him on his hike; the others he rejects. Let us see what type of graphical solution is obtained if the condition \( x_j = 0 \) or 1 is replaced by the condition that the variables can lie anywhere in the interval from 0 to 1. The latter problem can be solved by regular linear programming methods; indeed, because of its very simple form, it admits an immediate solution: Rotate clockwise a ray with the origin as pivot point and \( b \) axis as starting position. Items corresponding to points swept out by the ray are selected in turn until the sum of their weights exceeds the weight limitation. If upon selection of item \( j \) the weight limitation is exceeded, the value \( x_j \) is chosen as that fractional part of its weight \( a_j \) that would make the sum come exactly to 70 lbs. With the exception of this one item, all the items swept out by the ray have the value \( x_j = 1 \), while those not swept out have the value \( x_j = 0 \). It will be noted that this is very close to the kind of
solution desired; all the $x_j$'s are either 0 or 1 with the exception of the one that has a fractional value.

Now at this point the natural question is, "What happens if the solution is rounded?" The effect of rounding up or down is of course to change the total weight carried to a number different from 70 lbs. If the model is imperfect (in other words, if the hiker really has a limitation of roughly 70 lbs) this may be a satisfactory way of getting rid of the fractional solution; this is particularly true if the weight of individual items is small relative to 70 lbs. For most practical problems, this is probably all that is needed. Our object here, however, is to explore ways of getting an exact mathematical solution.

The functional-equation approach of dynamic programming (see § 1-4) is the best technique so far devised for the case where there are only a few items and only one kind of limitation. Extensions to two or more limitations—say one on total weight and another on total volume—can be done, but there would be a considerable increase in the amount of computational work. The method consists in ordering the items in any arbitrary way and determining what items would be carried if (a) the selections were restricted to only the first $k$ items, and (b) the weight limitations were $w = 1, 2, \ldots, 70$. For example, if $k = 1$ and $w < a_1$ (where $a_1$ is the weight of the first item), then the item would not be selected; but if $w \geq a_1$, it would be. From this it is easy to decide what the selections would be for the first two items ($k = 2$) for every total weight $w = 1, 2, \ldots, 70$, and then, inductively, for $k = 3, 4, \ldots, n$. To see this, suppose we wish to determine whether we select the $(k + 1)^{st}$ item if our weight limitation is $w$ when we know how to make the selections for the first $k$ items for any weight $w = 1, 2, \ldots, 70$.

Let $F_k(w)$ be the highest total value that can be obtained with the first $k$ objects under weight limitation $w$. Then, under the same weight limitation $w$, the highest total value that can be obtained with first $k + 1$ objects is $F_k(w)$ if the $(k + 1)^{st}$ object is not selected, but is $b_{k+1} + F_k(w - a_{k+1})$ if the $(k + 1)^{st}$ object is selected. Hence, the $(k + 1)^{st}$ object is or is not selected depending on which of these is higher. Thus, not only is the selection for the first $k + 1$ objects determined, but it also is clear that $F_{k+1}(w)$ is given by

$$F_{k+1}(w) = \begin{cases} \max \{F_k(w), \ b_{k+1} + F_k(w - a_{k+1})\} & \text{for } w \geq a_{k+1} \\ F_k(w) & \text{for } w < a_{k+1} \end{cases}$$

The procedure is iterated for each $w$ and repeated for $k = 1, 2, \ldots, n$. Although for the functional-equation approach the terms were ordered in an arbitrary way, it is recommended that in a practical application they be ordered initially in sequence corresponding to decreasing $b_j/a_j$ (see Fig. 26-1-II).
The linear programming approach consists in adding new linear-inequality constraints to the system, so that the fractional extreme points of C in the neighborhood of Max z will be excluded, but the set of extreme points of the convex hull C* of admissible solutions will be in the new C. The procedure would be complete except that the rules for systematically generating additional constraints require the use of methods discussed in the next section.

Definition: A cutting plane is the hyperplane boundary of an added linear inequality constraint. It is thought of as "cutting off" part of the convex of feasible solutions to form a new convex.

Let us suppose, as in Fig. 26-1-II, that the ray swept out items 5, 3, 12, 11, 8, and 9 before the weight limitation was exceeded, but included item 6 just after it was exceeded; then

\[ a_5 + a_3 + a_{12} + a_{11} + a_8 + a_9 < 70 \]
\[ a_5 + a_3 + a_{12} + a_{11} + a_8 + a_9 > 70 \]

We wish to exclude the fractional extreme-point solution

(10) \[ x_5 = x_3 = x_{12} = x_{11} = x_8 = x_9 = 1, \quad x_6 = f \quad (0 < f < 1) \]

and \[ x_j = 0 \] for all other \( j \).

It is clear that for an admissible solution not all \( x_j = 1 \) for the seven points \( j = 5, 3, 12, 11, 8, 9, 6 \), because the weight limitation would be violated. This means that the sum of these variables cannot exceed 6, or

(11) \[ x_5 + x_3 + x_{12} + x_{11} + x_8 + x_9 + x_6 \leq 6 \]

Since the fractional extreme-point solution (10) does not satisfy this constraint, it is clear that the effect of adding the particular inequality (11) is to exclude this fractional extreme point. Form (8) is maximized under conditions (6) and \( 0 \leq x_j \leq 1 \), but with the constraint (11) added. Again a new fractional extreme point may turn up for the new convex C, and it will be necessary again to seek a condition that will exclude it. For the most part the conditions added will be other partial sums of the \( x_j \) similar to (11). However, at times more subtle relations will be required until at last an extreme point is obtained that is admissible. The method discussed in the next section provides a straightforward way to determine these constraints.

Many experiments by the author and others indicate that very often a practical problem can be solved using only such obvious supplementary conditions as (11). In an experiment with a number of randomly chosen traveling-salesman problems involving nine cities, simple upper bounds and so-called simple "loop conditions" on the variables were often sufficient to yield the desired discrete solution [Dantzig, Fulkerson, and Johnson, 1954-1, 1959-1]. To appreciate the power of this procedure it should be noted that, for each nine-city case solved, the tour that minimized the total distance covered was one from among 362,880 ways of touring nine cities and was selected in about two hours of hand-computation time.
26-2. GOMORY'S METHOD OF INTEGER FORMS

In this section we shall present a method due to R. Gomory [1958-1, 2] of automatically generating cutting planes or integer forms which gives promise of providing an efficient solution to linear programs in integers in a finite number of steps. This approach has been generalized to the case where some variables are continuous and some are constrained to be integers. This was first done by E. M. L. Beale [1958-1], and by Gomory [1958-3] in a different way, which we follow here.

We begin by giving the method in a precise form and then discuss various ways that it may be relaxed in practice. Our concern is with linear-programming-type problems where, however, some of the variables must have integer values and the others may have fractional values. The former we shall call integer variables and the latter fractional variables.

Problem: Determine $\text{Min } v$ and $y_j \geq 0$ for $j = 1, 2, \ldots, n$ such that $v$ and $y_j$ are integers for a subset $J$ of the indices $j$ and such that

\begin{align*}
(a) & \quad a_{11}y_1 + a_{12}y_2 + \ldots + a_{1n}y_n = b_1 \\
& \quad a_{21}y_1 + a_{22}y_2 + \ldots + a_{2n}y_n = b_2 \\
& \quad \ldots \ldots \ldots \ldots \\
& \quad a_{m1}y_1 + a_{m2}y_2 + \ldots + a_{mn}y_n = b_m \\
& \quad c_1y_1 + c_2y_2 + \ldots + c_ny_n = v \ (\text{Min})
\end{align*}

(y \geq 0)

Note that $v$ as well as $y_j$ for $j \in J$ are required to be integers while the remaining variables are allowed to take on fractional values.

The Initial Primal and Dual Systems.

To initiate the algorithm, the problem is first solved ignoring the integer restrictions. Suppose the canonical form obtained on the final iteration is

\begin{align*}
(b) & \quad \bar{a}_{11}y_1 + \bar{a}_{12}y_2 + \ldots + \bar{a}_{1,n-m}y_{n-m} + y_{n-m+1} = \bar{b}_1 \\
& \quad \bar{a}_{21}y_1 + \bar{a}_{22}y_2 + \ldots + \bar{a}_{2,n-m}y_{n-m} + y_{n-m+2} = \bar{b}_2 \\
& \quad \ldots \ldots \ldots \ldots \\
& \quad \bar{a}_{m1}y_1 + \bar{a}_{m2}y_2 + \ldots + \bar{a}_{m,n-m}y_{n-m} + y_n = \bar{b}_m \\
& \quad \bar{c}_1y_1 + \bar{c}_2y_2 + \ldots + \bar{c}_{n-m}y_{n-m} = v - \bar{c}_0
\end{align*}

where we have assumed, for convenience, $y_{n-m+1}, \ldots, y_n$ as basic variables. Because our solution is optimal, we have for $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$,

\begin{align*}
\bar{b}_i & \geq 0, \quad \bar{c}_i \geq 0
\end{align*}
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If we now set

$$y_i = \pi_i \quad (i = 1, 2, \ldots, n - m)$$

for all the non-basic variables and solve for basic variables in terms of $\pi_i$,

$$y_{n-m+k} = b_k - \sum_{i=1}^{n-m} a_{ki} \pi_i \quad (k = 1, \ldots, m)$$

$$v = \delta_0 + \sum_{k=1}^{n-m} c_k \pi_k$$

then all the variables $y_1, y_2, \ldots, y_n$ are expressed parametrically in terms of $\pi_i$.

In the expression for $y_i$, let us now denote by $+a_{ij}$ the coefficient of $\pi_i$, by $\alpha_{i0}$ the constant terms, and by $\alpha_{ij}$ the coefficients of $v$. Setting

$$m = n - m$$

then the original problem can be cast in the following form:

Find Min $v, y_i \geq 0, \pi_i$ where $v$ and $y_i$ are integers for $j \in J$, such that

$$y_1 = \alpha_{01} + \alpha_{11} \pi_1 + \ldots + \alpha_{m1} \pi_m$$

$$y_2 = \alpha_{02} + \alpha_{12} \pi_1 + \ldots + \alpha_{m2} \pi_m$$

$$\vdots \quad \vdots \quad \vdots$$

$$y_n = \alpha_{0n} + \alpha_{1n} \pi_1 + \ldots + \alpha_{mn} \pi_m$$

$$v = \alpha_{00} + \alpha_{10} \pi_1 + \ldots + \alpha_{m0} \pi_m$$

If we set aside the integer restrictions, we can replace (7) by

$$\alpha_{i0} + \sum \alpha_{ij} \pi_i \geq 0 \quad (j = 1, 2, \ldots, n)$$

$$\alpha_{00} + \sum \alpha_{i0} \pi_i = v \text{ (Min)}$$

and it is clear that the dual problem for (7) becomes

**Dual:** Find Max $x_0$ and $x_j \geq 0$ for $j \neq 0$ satisfying

$$x_0 + x_{a1} x_1 + x_{a2} x_2 + \ldots + x_{a0} x_n = \alpha_{00}$$

$$\alpha_{11} x_1 + \alpha_{12} x_2 + \ldots + \alpha_{1n} x_n = \alpha_{10}$$

$$\vdots \quad \vdots \quad \vdots$$

$$\alpha_{m1} x_1 + \alpha_{m2} x_2 + \ldots + \alpha_{mn} x_n = \alpha_{m0}$$

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Because system (7) is by definition the same as (4), (5), system (8) is the same as (9) below

\[
\begin{align*}
  x_0 & + b_1 x_{m+1} + \ldots + b_n x_n = c_0 \\
  x_1 & - a_{11} x_{m+1} - \ldots - a_{1n} x_n = c_1 \\
  & \quad \vdots \\
  x_m & - a_{m1} x_{m+1} - \ldots - a_{mn} x_n = c_m \\
\end{align*}
\]

which is in canonical form and the basic solution is feasible and optimal \((b_i \geq 0, c_i \geq 0)\). The actual order of the variables \(x_i\) can be the same as in the primal, and the order of the equations can correspond to the order of the non-basic variables in the primal. We shall assume that this is the case. Moreover, we assume that the variables of the primal have been previously arranged so that all the integer variables are ahead of the others. This assumption is not made merely for convenience of exposition; indeed, the finiteness of Gomory’s algorithm depends on its being satisfied.

To illustrate, consider the problem of finding Min \(v\), \(y_i \geq 0\), where \(v, y_1, y_2\) are integers satisfying

\[
\begin{align*}
  2y_1 + y_2 + \frac{2}{3}y_3 & = \frac{1}{3} \\
  \frac{1}{2}y_1 + \frac{2}{3}y_2 + y_4 & = \frac{2}{3} \\
  \frac{1}{3}y_1 + \frac{5}{3}y_3 & = v + \frac{1}{3} \\
\end{align*}
\]

If we set \(y_1 = \pi_1\), \(y_3 = \pi_2\), then

\[
\begin{align*}
  y_1 & = \pi_1 \\
  y_2 & = \frac{1}{2} \pi_1 - 2 \pi_3 - \frac{2}{3} \pi_2 \\
  y_3 & = \pi_3 \\
  y_4 & = \frac{1}{3} - \frac{1}{2} \pi_1 - \frac{5}{6} \pi_2 \\
  v & = -\pi_2 + \frac{1}{3} \pi_1 + \frac{2}{3} \pi_3 \\
\end{align*}
\]

where the parameter \(\pi_1\) is an integer. Ignoring the integer restriction, the dual of (11), is

\[
\begin{align*}
  x_0 & + \frac{1}{3} x_2 + \frac{2}{3} x_4 = -\pi_2 \\
  x_1 & - 2x_2 - \frac{1}{3} x_4 = \frac{1}{2} \\
  & - \frac{2}{3} x_2 + x_3 - \frac{1}{3} x_4 = \frac{1}{3} \\
\end{align*}
\]

Generating New Restrictions.

If the minimizing solution to the primal problem happens to satisfy the integer conditions, this solves the original problem. Thus, if the values of \(v = a_{00}\) and \(y_i = a_{0i}\) are integers for the integer variables, the basic solution is integral and optimal. If not, then the constant term is fractional for at
least one expression for an integer variable or for the expression for \( v \) as given in (7). In our example, we have two such:

\[
\begin{align*}
v &= -\frac{1}{2} + \frac{1}{3} \pi_1 + \frac{1}{3} \pi_3 \\
y_2 &= \frac{1}{3} \pi_1 - 2 \pi_2 - \frac{1}{3} \pi_3
\end{align*}
\]

Any such expression can be used to generate a linear inequality (indeed a class of inequalities) which is not satisfied by the current basic solution formed by setting \( \pi_i = 0 \).

It will be convenient to introduce\(^1\) the symbol \([\alpha_j]*\) which represents here the greatest integer \( \leq \alpha_j \); we define

\[
f_j = \alpha_j - [\alpha_j]* \geq 0
\]

to be the positive proper fractional part of \( \alpha_j \). For example, if \( \alpha_j = \frac{3}{4} \), then \([\alpha_j]* = 1 \) and \( f_j = \frac{1}{4} \); if \( \alpha_j = -\frac{5}{4} \), then \([\alpha_j]* = -2 \) and \( f_j = -\frac{1}{4} \). We also define the complement, \( f_j' \), of the positive fractional part of \( \alpha_j \), as the positive proper fractional part of \(-\alpha_j \). It is easy to see that

\[
f_j' = \begin{cases} 1 - f_j & \text{if } f_j > 0 \\ 0 & \text{if } f_j = 0 \end{cases}
\]

**Theorem 1**: If \( y \) is an integer variable and \( \pi_i \geq 0 \) are parameters related by

\[
y = \alpha_0 + \alpha_1 \pi_1 + \ldots + \alpha_m \pi_m \quad ([\alpha_0]* < \alpha_0)
\]

where \( \alpha_i \geq 0 \), for \( i \neq 0 \), then the linear inequality

\[
y \leq f_0 + \alpha_1 \pi_1 + \ldots + \alpha_m \pi_m
\]

holds for all \( \pi_i \), generating integral \( y \) but is not satisfied by the basic solution generated by \( \pi_i = 0 \) for \( i = 1, \ldots, m \).

**Proof**: Since \( \alpha_i \geq 0 \), and \( \pi_i \geq 0 \), Min \( y \geq \alpha_0 \); but the possible values of \( y \) are integers, so

\[
y \geq [\alpha_0]* + 1
\]

Subtracting from (16) yields (17). Moreover, writing \( y - y* = [\alpha_0]* + 1 \) where \( y* \geq 0 \) is an integer and subtracting from (16) yield

\[
y* = -f_0 + \alpha_1 \pi_1 + \ldots + \alpha_m \pi_m \quad (y* \geq 0)
\]

This is a stronger form of (17) because the new slack variable, \( y* \), is required to be a nonnegative integer.

In our illustrative example

\[
v = -\frac{1}{2} + \frac{1}{3} \pi_1 + \frac{1}{3} \pi_3
\]

\(^1\) The customary symbol for the largest integer part of a number is a bracket without a star; however, with a star there is less possibility of confusion with ordinary brackets.
where \( v \) is an integer variable unrestricted in sign and \( \pi_1 \geq 0, \pi_3 \geq 0 \). (Actually \( \pi_1 \geq 0 \) is required to be an integer also.) Applying our theorem we have, setting \( y^* = y_v \), say

\[
y_v = -\frac{\pi_1}{2} + \frac{\pi_3}{3} \quad (y_v \geq 0)
\]

where \( y_v \geq 0 \) is a new integer variable.

System (11) may now be augmented by the expression for this new (basic) variable in terms of \( \pi_1, \pi_3 \). It will be noted that the basic solution generated by setting \( \pi_1 = \pi_3 = 0 \) is no longer feasible, because \( y_v = -\frac{\pi_1}{2} \).

It will be also noted that the dual of the augmented system is formed by adding a new variable, say \( z_v \), with coefficients \((-\frac{\pi_1}{2}, \frac{1}{3}, \frac{1}{3}\)) (see (57)). The dual is still in canonical form, and its basic solution is feasible but no longer optimal. It will be shown later that the sequence of basic changes required to make it optimal, correspond to a change of the parameters \( \pi_i \) used to represent the \( y_i \).

We may also generate other inequalities by multiplying expression (20) by any integer \( k \); since, if \( v \) is an integer, so is \( kv \); thus

\[
kv = -\frac{7}{12}k + \frac{k}{4}\pi_1 + \frac{4k}{3}\pi_3 \quad (k \geq 0)
\]

\[
y^* = \left[\frac{7}{12}k\right]^* - \frac{7}{12}k + \frac{k}{4}\pi_1 + \frac{4k}{3}\pi_3 \quad (y^* \geq 0)
\]

where \( y^* \) is an integer.

The knowledge that one or more of the \( \pi_i \) are integers can be used, however, to generate in general new, even stronger inequalities.

**Theorem 2**: If \( y \) is an integer variable and the \( \pi_i \geq 0 \) are integer-valued variables related by

\[
y = \pi_0 + \pi_1 + \ldots + \pi_m \pi_m \quad ([\pi_0]^* < \pi_0)
\]

Then the linear inequality,

\[
1 \leq f_0 + f_1\pi_1 + \ldots + f_m\pi_m
\]

holds for all \( \pi_i \) generating integral \( y \) but is not satisfied by the basic solution generated by setting all \( \pi_i = 0 \).

**Proof**: Note that in this theorem the \( \pi_i \) may have either sign, and the \( \pi_i \) are nonnegative integers. Substituting \( \pi_i = f_i + [\pi_i]^* \) in (23) yields

\[
y - \left[\pi_0\right]^* - \sum [\pi_i]^*\pi_i = f_0 + f_1\pi_1 + \ldots + f_m\pi_m
\]

The left member is an integer and \( f_i \geq 0 \); hence, Theorem 1 may be applied to yield (24) or the stronger form

\[
y^{**} = -f_0 + f_1\pi_1 + f_2\pi_2 + \ldots + f_m\pi_m \quad (y^{**} \geq 0)
\]

where \( y^{**} \) is an integer-valued variable.

\footnote{In (57) we have used a stronger condition than (21) by applying Theorem 2.}
EXERCISE: Interpret (24) if $f_1 = f_2 = \ldots = f_m = 0$.
For example, suppose $y \geq 0$ and the $\pi_i \geq 0$ are integer variables related by
\[ y = \frac{1}{3} + (7/4)\pi_1 - (8/3)\pi_2 + (1/2)\pi_3 \]
then a new condition is
\[ y^* = -\frac{1}{3} + (3/4)\pi_1 + (1/3)\pi_2 + (1/2)\pi_3 \quad (y^* \geq 0 \text{ integer}) \]
Another new condition can be generated using $2y$, thus
\[ 2y = \frac{1}{3} + (14/4)\pi_1 - (16/3)\pi_2 + (2/2)\pi_3 \]
implies
\[ y^{**} = -\frac{1}{3} + (1/2)\pi_1 + (2/3)\pi_2 \quad (y^{**} \geq 0 \text{ integer}) \]

A simple extension of these two theorems occurs in the case where some $\alpha_i$ refer to integer parameters $\pi_i$, for $i = 1, 2, \ldots, k$, and the remaining parameters may take a fractional value with the property all $\alpha_i \geq 0$ (or all $\alpha_i \leq 0$) for $i > k$; then the mixed expression
\[ y^* = -f_0 + f_1\pi_1 + \ldots + f_k\pi_k + (\alpha_{k+1}\pi_{k+1} + \ldots + \alpha_m\pi_m) \]
holds for the case $\alpha_i \geq 0$, for all $i > k$, and
\[ y^* = -f_0 + f_1\pi_1 + \ldots + f_k\pi_k - (\alpha_{k+1}\pi_{k+1} + \ldots + \alpha_m\pi_m) \]
holds for the case $\alpha_i \leq 0$ for all $i > k$, for any $\pi_i$ generating integral $y$ where $y^* \geq 0$, an integer. (This $y^*$ is not the same $y^*$ used earlier.)

In our illustrative example
\[ y_2 = \frac{1}{3} - 2\pi_1 - \frac{1}{3}\pi_3 \]
where $y_2 \geq 0$, $\pi_1 \geq 0$ are integers and $\pi_3 \geq 0$. Applying the second case, setting $y^* = y_2$, then
\[ y_2 = -\frac{1}{3} + \frac{1}{3}\pi_3 \]
where $y_2 \geq 0$ is a new integer variable whose expression in terms of the $\pi_i$ may also be used to augment the system (11) and (21).

If all parameters $\pi_i$ are integers, then it is interesting to observe that a particularly simple relation exists consisting of a partial sum of $\pi_i$. This condition is not as strong as earlier ones, since it can be found by combining two known inequalities. Thus for $k = m$, (27) implies both
\[ y^* = -f_0 + f_1\pi_1 + \ldots + f_m\pi_m \quad (y^* \geq 0) \]
\[ y^{**} = -f_0 + f_1\pi_1 + \ldots + f_m\pi_m \quad (y^{**} \geq 0) \]
where $y^*$ and $y^{**}$ are integers, and we have by adding and setting $y' = y^* + y^{**}$
\[ y' = -1 + \delta_1\pi_1 + \ldots + \delta_m\pi_m \quad (y' \geq 0) \]

[ 526 ]
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where $\delta_j = 1$, if $f_j > 0$, and $\delta_j = 0$, if $f_j = 0$. For example, if $\pi_1$ and $\pi_3$ were both integer variables in (28), then a new relation would be

$$y' = -1 + \pi_3$$

It is also interesting to observe that a strong condition can sometimes be generated from an integer variable $y$, which has an integer value in a solution when all $\pi_i = 0$. For example, suppose

$$y = 2 + \frac{3}{2} \pi_1 - \frac{1}{2} \pi_3$$

where $\pi_1$ and $\pi_3$ constitute all the parameters. Writing

$$y - 2 - \pi_1 + \pi_2 = \frac{1}{2} \pi_1 + \frac{1}{2} \pi_2$$

we note that the left member is integral. Because the right member is nonnegative, we conclude

$$y^* = \frac{1}{2} \pi_1 + \frac{1}{2} \pi_2$$

where $y^* \geq 0$ is an integer. However $y^* = 0$ is not possible, because then $\pi_1 = \pi_2 = 0$ and the other integral $y_j$ would have to take on the fractional values of the current basic solution. Hence $y^* = y^{**} + 1 \geq 1$ and

$$y^{**} = -1 + \frac{1}{2} \pi_1 + \frac{1}{2} \pi_2$$

becomes the new restriction. In general, if for some $j$, $x_{ji} = [x_{ji}]^*$ and $f_i = x_{ji} - [x_{ji}]^* > 0$ for all $i \neq 0$, then a new restriction is

$$y^{**} = -1 + \sum f_i \pi_i$$

(37) \hspace{1cm} (f_i \neq 0)

Generating New Conditions for the General Mixed Integer Case.

For problems involving mixed integer and “fractional” variables (variables which may assume fractional values), we must however, in general, be able to generate new inequalities when the coefficients of the fractional variables have either sign. Let

$$y = \alpha_0 + \sum_{i=1}^m \alpha_i \pi_i = \alpha_0 + P - N$$

(38) \hspace{1cm} ([x_0]^* < \alpha_0)

where $P$ and $-N$ are the partial sums of the positive and negative terms, $\alpha_0$ is not an integer and $y$ is an integer variable.

If for certain values of $\pi_i$, $P - N \geq 0$, then, since $y = \alpha_0 + P - N$ must be an integer so must $f_0 + P - N$; but the latter is strictly positive (for we are assuming that $\alpha_0$ is non-integral). Hence we must have

$$1 \leq f_0 + P - N$$
$$f_0 \leq P - N$$

$$1 \leq \frac{1}{f_0} P - \frac{1}{f_0} N \leq \frac{1}{f_0} P + \frac{1}{f_0} N$$

(39) \hspace{1cm} \left[ 527 \right]
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If for other values of \( \pi_1, N - P \geq 0 \), then \(-y = -\alpha_0 + N - P\) is an integer; therefore

\[
1 \leq f_0 + N - P \\
f_0 \leq N - P \\
1 \leq \frac{1}{f_0} N - \frac{1}{f_0} P \leq \frac{1}{f_0} N + \frac{1}{f_0} P
\]

Hence for any set of \( \pi_1 \) values,

\[
1 \leq \frac{1}{f_0} P + \frac{1}{f_0} N
\]

**Theorem 3:** If \( y \) is an integer variable, and \( \pi_1 \geq 0 \) satisfy

\[
y = \alpha_0 + \sum_{i=1}^{m} \alpha_i \pi_i \quad \text{where} \quad \alpha_0 = [\alpha_0]^*
\]

then

\[
1 \leq \frac{1}{f_0} \left( \sum_{i \in I_1} f_i \pi_i + \sum_{i \in I_2} \alpha_i \pi_i \right) + \frac{1}{f_0} \left( \sum_{i \in I_3} f_i \pi_i - \sum_{i \in I_4} \alpha_i \pi_i \right)
\]

holds for all \( \pi_1 \) generating integer \( y \) but is not satisfied by the basic solution generated by \( \pi_1 = 0 \). Here

\[
i \in I_1 \text{ if } f_i \leq f_0 \text{ and } \pi_i \text{ integral} \\
i \in I_2 \text{ if } \alpha_i > 0 \text{ and } \pi_i \text{ fractional} \\
i \in I_3 \text{ if } f_i < f_0 \text{ and } \pi_i \text{ integral} \\
i \in I_4 \text{ if } \alpha_i < 0 \text{ and } \pi_i \text{ fractional}
\]

**Proof:** If \( \pi_1 \) is an integer, set in (42) \( \alpha_i = [\alpha_i]^* + f_i \) or \( \alpha_i = [\alpha_i]^* + 1 - f_i \) according to whether \( f_i < f_0 \) or \( f_i > f_0 \). Moving all integer terms to the left and calling the left member \( y' \), we have

\[
y' = \alpha_0 + \left( \sum_{i \in I_1} f_i \pi_i + \sum_{i \in I_2} \alpha_i \pi_i \right) - \left( \sum_{i \in I_3} f_i \pi_i - \sum_{i \in I_4} \alpha_i \pi_i \right)
\]

where \( y' \) is an integer variable. Identifying (45) with (38), relation (43) corresponds to (41) and the theorem follows.

If we let \( y^* \geq 0 \) represent the slack in the inequality (43), then the new relation may be written

\[
y^* = -1 + \frac{1}{f_0} \left( \sum_{i \in I_1} f_i \pi_i + \sum_{i \in I_2} \alpha_i \pi_i \right) + \frac{1}{f_0} \left( \sum_{i \in I_3} f_i \pi_i - \sum_{i \in I_4} \alpha_i \pi_i \right)
\]

However, it no longer follows that the added new variable is an integer as was the case with all previous relations that have been developed. (This is too bad because, as we have seen, when \( y^* \) is an integer this fact can be
used to advantage to develop, at a later stage, new stronger inequalities.) To illustrate, suppose

\[ y = \frac{1}{3} + \frac{2}{5} \pi_1 + \frac{2}{5} \pi_2 - \frac{2}{5} \pi_3 - \frac{2}{5} \pi_4 \quad (\pi_i \geq 0) \]  

where \( y, \pi_1, \) and \( \pi_3 \) are integers. We may rewrite this

\[ (y - 1 + \pi_3) = \frac{1}{3} + \frac{2}{5} \pi_1 + \frac{2}{5} \pi_2 - \frac{2}{5} \pi_3 - \frac{2}{5} \pi_4 \]

which, if we simply group positive and negative terms, leads to the inequality

\[ 1 \leq \frac{1}{3} \left( \frac{2}{5} \pi_1 + \frac{2}{5} \pi_2 \right) + \frac{1}{3} \left( \frac{2}{5} \pi_3 + \frac{2}{5} \pi_4 \right) \]  

We may alternatively in (48) set \( \frac{2}{5} \pi_1 = \pi_1 - \frac{2}{5} \pi_1. \) Then grouping integer terms

\[ y - 1 + \pi_3 - \pi_1 = \frac{1}{3} + \left( \frac{2}{5} \pi_2 \right) - \left( \frac{2}{5} \pi_1 + \frac{2}{5} \pi_3 + \frac{2}{5} \pi_4 \right) \]

leads to the inequality

\[ 1 \leq \frac{1}{3} \left( \frac{2}{5} \pi_2 \right) + \frac{1}{3} \left( \frac{2}{5} \pi_3 + \frac{2}{5} \pi_4 \right) \]

This is a stronger inequality than (49), because it has a smaller coefficient of \( \pi_1. \)

Indeed, we may arrange matters, in general, so that the coefficients of all the integer variables never exceed unity when the constant terms on the new constraints are unity. To see this, suppose \( \pi_i \geq 0 \) is an integer; replace \( \pi_i \) by either \( [\pi_i]_0 + \pi_i \) or \( [\pi_i]_0 + 1 - \pi_i \), according to whether \( f_i \leq f_0 \) or \( f_i < f_0 \). In the first case the coefficient of \( \pi_i \) becomes \( f_i / f_0 \) and in the second case \( f_i / f_0 \leq 1 \).

It is also possible to develop a second type of inequality for the general case that introduces a \textit{sharper inequality} but increases the size of the system. Let \( i = 1, \ldots, k \) refer to integer variables and \( i > k \) to fractional variables. Set

\[ \tilde{y} = \sum_{i > k} \alpha_i \pi_i - \pi^* \quad (0 \leq \pi^* \leq 1) \]

where \( \tilde{y} \) is a new integer variable unrestricted in sign and \( \pi^* \) is the positive \textit{proper fractional part} of the sum of fractional variable terms; then the new restriction becomes

\[ y^* = -f_0 + \sum_{i = 1}^{k} f_i \pi_i + \pi^* \quad (0 \leq \pi^* \leq 1) \]

where \( y^* \) is an integer. Since the new restrictions now involve a \textit{bounded} variable \( \pi^* \), it is probably better to stay in the primal system rather than pass to the dual system.
Iterative Procedure.

Any new restriction
\[
y_t = \alpha_{0t} + \alpha_{1t} \pi_1 + \cdots + \alpha_{mt} \pi_m
\]
used to augment the initial system will result in a new variable \( x_t \) for the dual system with coefficients \( \alpha_{it} \). The dual system is still of course in canonical form but the basic solution is no longer optimal (since \( \alpha_{0t} < 0 \)). Hence, \( x_t \) will be introduced into the basis by pivoting on some element \( \alpha_{it} \) in the dual system. This transforms the dual matrix \( [\alpha_{it}] \) into \( [\alpha'_{it}] \).

On the other hand, if we go back to the primal system and introduce a new parameter \( y_t \) in place of \( \pi_t \), by solving equation (54) for \( \pi_t \) in terms of the other \( \pi_t \), and substitute in the expressions for \( y_t \) and \( v_t \), then it is easy to see that the matrix \( [\alpha_{it}] \) will also be transformed into \( [\alpha'_{it}] \).

Thus the new dual corresponds to the primal being represented by a set of parameters such that the slack variable of the new restriction becomes a new parameter in place of one of the old parameters. In general, each subsequent dual cycle corresponds to using one of the variables \( y_t \) as a new parameter in place of a previous one.

If, after a pivot operation, the dual is still not optimal because some \( \alpha_{0t} < 0 \), the simplex algorithm is applied until it is. Formally, this corresponds to successively using as “new” restrictions for the primal any existing relation (54) with \( \alpha_{0t} < 0 \).

**Example:** Find integers Min \( v, y_t \geq 0 \) satisfying
\[
\begin{align*}
2y_1 + y_2 + 5y_3 &= 3^3 \\
\frac{1}{2}y_1 + \frac{2}{3}y_2 + y_4 &= \frac{2}{5} \\
\frac{1}{3}y_1 + \frac{1}{3}y_2 &= v + 2
\end{align*}
\]
Fortunately, the system is in optimal canonical form if the integer constraints are set aside. Next, set non-basic variables \( y_t \), equal to \( \pi_t \), and represent all variables in terms of \( \pi_t \). (In the steps below, each \( y_t \) used as a parameter is, for convenience, identified by setting \( \pi_t = y_t \).)

**Primal Cycle 0:**
\[
\begin{align*}
y_1 &= \pi_1 \\
y_2 &= \frac{1}{3} - 2\pi_1 - \frac{5}{3}\pi_3 \\
y_3 &= \pi_3 \\
y_4 &= \frac{2}{5} - \frac{1}{3}\pi_1 - \frac{2}{5}\pi_3 \\
v &= -\frac{1}{2} + \frac{1}{3}\pi_1 + \frac{5}{3}\pi_2 \\
y_5 &= -\frac{1}{2} + \frac{1}{3}\pi_1 + \frac{1}{3}\pi_3
\end{align*}
\]
where the new restriction \( y_5 \) is derived from \( v \). We now dualize and optimize:
26.2. Gomory's Method of Integer Forms

\textbf{Dual Cycle 0}:

\begin{align*}
(57) \quad x_0 + \frac{1}{3}x_2 + \frac{1}{3}x_4 - \frac{1}{3}x_5 &= -\frac{1}{3} \\
x_1 - \frac{2}{3}x_2 - \frac{1}{3}x_4 + \frac{1}{3}x_5 &= \frac{1}{3} \\
- \frac{1}{3}x_2 + x_3 - \frac{1}{3}x_4 + \frac{1}{3}x_5 &= \frac{1}{3}
\end{align*}

\textbf{Dual Cycle 1}:

\begin{align*}
(58) \quad x_0 + \frac{1}{3}x_1 - \frac{1}{3}x_2 + \frac{1}{6}x_4 &= 0 \\
4x_1 - 8x_2 - 2x_4 + x_5 &= 1 \\
- \frac{1}{3}x_1 + \frac{1}{3}x_2 + x_3 - \frac{1}{3}x_4 &= 1
\end{align*}

This corresponds to eliminating \( \pi_1 \) from the primal, using

\[ \pi_2 = y_5 = -\frac{7}{12} + \frac{\pi_1}{4} + \frac{\pi_3}{3} \]

where we have let \( y_5 = \pi_3 \) be a new parameter; operationally, this is accomplished by pivoting on the \( \frac{1}{3} \pi_1 \) term in (56) after first moving the \( \pi_1 \) term to the right-hand side, next to the \( \pi_1 \) term. After pivoting, the pivot equation is dropped. The \( \pi_1 \) terms after elimination are all zero and do not appear. Thus

\textbf{Primal Cycle 1}:

\begin{align*}
(59) \quad y_1 &= \frac{1}{3} + 4\pi_0 - \frac{1}{3}\pi_3 \\
y_2 &= -\frac{1}{3} - 8\pi_0 + \frac{1}{3}\pi_3 \\
y_3 &= \pi_3 \\
y_4 &= \frac{1}{6} - 2\pi_0 - \frac{1}{3}\pi_3 \\
y_5 &= \pi_5 \\
v &= \pi_5 + \pi_3
\end{align*}

Returning to (58), since the basic solution is not optimal, we perform the indicated pivot step. This yields (except for the boxed column):

\textbf{Dual Cycle 2}:

\begin{align*}
(60) \quad x_0 + 2x_1 + \frac{1}{3}x_2 + \frac{1}{3}x_4 - \frac{2}{3}x_5 &= \frac{1}{3} \\
- 4x_1 + 6x_2 - \frac{2}{3}x_4 + x_5 &= 7 \\
- x_1 + x_2 + \frac{1}{3}x_3 - \frac{1}{3}x_4 + \frac{2}{3}x_5 &= \frac{1}{3}
\end{align*}

This corresponds to eliminating \( \pi_3 \) from the primal by formally adjoining one of the existing relations, namely,

\[ \pi_2 = y_2 = -\frac{1}{3} - 8\pi_0 + \frac{1}{3}\pi_3 \]

and letting \( y_2 = \pi_3 \) be a new parameter; we can accomplish this by pivoting
on the $\$\pi_3$ term above with respect to (59) (after first moving $\pi_2 = y_2$ to the right). This will eliminate $\pi_3$ from the other equations, yielding

**Primal Cycle 2:**

$$
\begin{align*}
  y_1 &= 2 - 4\pi_5 - \pi_2 \\
  y_2 &= \pi_2 \\
  y_3 &= \frac{1}{3} + 6\pi_5 + \frac{1}{2}\pi_2 \\
  y_4 &= \frac{1}{3} - \frac{1}{2}\pi_5 - \frac{1}{5}\pi_2 \\
  y_5 &= \pi_5 \\
  v &= \frac{1}{3} + 7\pi_5 + \frac{1}{2}\pi_2 \\
  y_6 &= -\frac{1}{4} + \frac{1}{3}\pi_2
\end{align*}
$$

The new column for (60) is derived from the coefficients of $x_3$ which correspond to $y_3 = \frac{1}{3} + 6\pi_5 + \frac{1}{2}\pi_2$; namely, the new column corresponds to the new restriction $y_6 = -\frac{1}{4} + \frac{1}{3}\pi_2 \geq 0$ shown in (61). Iterating

**Dual Cycle 3:** (Optimal Integral Solution)

$$
\begin{align*}
  x_0 + x_1 + x_2 + x_3 + x_4 + x_5 &= 1 \\
  -4x_1 + 6x_2 - \frac{1}{2}x_4 + x_5 &= 7 \\
  -\frac{1}{3}x_1 + \frac{1}{3}x_2 + x_3 - \frac{1}{5}x_4 + x_6 &= 1
\end{align*}
$$

**Primal Cycle 3:**

$$
\begin{align*}
  y_1 &= 1 - 4\pi_5 - \frac{1}{3}\pi_2 \\
  y_2 &= 1 + \frac{1}{3}\pi_2 \\
  y_3 &= 1 + 6\pi_5 + \pi_6 \\
  y_4 &= 1 - \frac{1}{2}\pi_5 - \frac{1}{5}\pi_6 \\
  v &= 1 + 7\pi_5 + \pi_6 \\
  y_6 &= -\frac{1}{4} + \frac{1}{3}\pi_2
\end{align*}
$$

where the optimal solution is found by setting $\pi_5 = \pi_6 = 0$.

**Proof of Finiteness of Algorithm.** [Gomory, 1958-2, 3.]

For this purpose we regard the initial dual's right-hand side (8) as perturbed by the columns appearing on the left for $j \neq 0$. (See Chapter 10.)

$$
\begin{align*}
  x_0 + \sum_{i=1}^{n} x_{0i} x_i &= \sum_{i=0}^{n} x_{0i} e_i = x_0(e) \\
  \sum_{i=1}^{n} x_{0i} x_i &= \sum_{i=0}^{n} x_{0i} e_i = \alpha_0(e) \\
  \sum_{i=1}^{n} x_{ij} x_i &= \sum_{i=0}^{n} x_{ij} e_i = \alpha_i(e) \quad (i = 1, \ldots, m)
\end{align*}
$$

[532]
Thus the values of the basic variables become polynomials in \( \epsilon \). It will be assumed that the leading term (i.e., the lowest-power non-zero term) of each \( \alpha_i(\epsilon) \) is positive except possibly \( i = 0 \).

If the basic variables can be arranged ahead of the non-basic variables as in (9), this assumption is initially satisfied. However, as noted in the paragraph following (9), we require for the convergence proof that \( x_j \) corresponding to integer variables \( y_j \) precede the fractional variables.

**Exercise:** Use artificial variables and the simplex algorithm with perturbation to obtain in the latter case an initial canonical system with the requisite properties, provided one exists. What happens if none exists?

After each augmentation with a supplementary variable (corresponding to a new restriction) we require that the simplex method with perturbation be applied to (64) until it is rendered optimal. We shall refer to this as an *optimal stage*; at such a stage, the coefficients of \( \alpha_d(\epsilon) \) are just the values of \( v \) and \( y_f \) of a feasible solution to the primal, i.e., \( \alpha_{dj} \geq 0 \) for \( j = 1, 2, \ldots, n \). Because we assume that the convex set of feasible solutions to the primal is bounded, the values of the \( \alpha_{dj} \) will have, at each such optimal stage, a finite upper bound.

If the \( k + 1 \) leading coefficients \( \alpha_{d0}, \alpha_{d1}, \ldots, \alpha_{dk} \) of \( \alpha_d(\epsilon) \) are all integers then the nonnegative coefficients solve the primal and the process terminates. However, if any among the first \( k + 1 \) are fractional, let \( j = j_0 \) be the first such. Let \( j = n + 1 \) be the index of the new column generated from \( j = j_0 \); then since \( \alpha_{d,n+1} < 0 \), the new pivot \((r, s)\) is chosen in column \( s = n + 1 \) and row \( r = i \) where \( \alpha_{i,n+1} > 0 \) and

\[
0 < \frac{\alpha_i(\epsilon)}{\alpha_{r,n+1}} = \min_{s \neq 0} \frac{\alpha_s(\epsilon)}{\alpha_{r,n+1}} \tag{65}
\]

Because (64) is in canonical form it is not difficult to show that the choice of pivot is unique (see Chapter 10). As a result of the pivot the new value of \( \alpha_d(\epsilon) \) is

\[
\alpha_{d*}(\epsilon) = \alpha_d(\epsilon) - \alpha_s(\epsilon)(\alpha_{d,n+1}/\alpha_{r,n+1}) > \alpha_d(\epsilon) \tag{66}
\]

For clarity we give again the definition of \( j = j_0 \) and also define \( j = j^* \):

(a) Let \( j = j_0 \) be the subscript of the first term of \( \alpha_d(\epsilon) \) with non-integral coefficient.

(b) Let \( j = j^* \) be the subscript of the first term of \( \alpha_{d*}(\epsilon) - \alpha_d(\epsilon) \) with non-zero coefficient.

**Theorem 4:** Either \( j^* < j_0 \) or \( j^* = j_0 \) and \( \alpha_{d*} = [\alpha_{d*}]^* + 1 \).

**Proof:** The \( j_0 \) coefficient of \( \alpha_{d*}(\epsilon) \) is

\[
\alpha_{d*} = \alpha_{d0} - \alpha_{rj_0}(\alpha_{d,n+1}/\alpha_{r,n+1}) \tag{67}
\]

The first non-zero term of \( \alpha_{d*}(\epsilon) - \alpha_d(\epsilon) \) is positive by (66). If it does not occur before \( j^* = j_0 \), then \( \alpha_{rj_0} \geq 0 \) (since \( \alpha_{d,n+1} < 0 \) and the pivot \( \alpha_{r,n+1} > 0 \).
it follows that $\alpha_{r,i} < 0$ would contradict the inequality in (66)). The remainder of the theorem follows from the relation between

$$y_{i_0} = \alpha_{0,i_0} + \sum_i \alpha_{i,i_i} \pi_i$$

and the new restriction on $y^*$. If all $\pi_i$ are integer parameters, then

$$y^* = -f_0 + \sum_i f_i \pi_i$$

where $\alpha_{i,i_0} = [\alpha_{i,i_0}]^* + f_i$, so that

$$\alpha_{r,i}^* = \alpha_{r,i} - ([\alpha_{r,i}]^* + f_i)(-f_0/f_r) \geq (\alpha_{0,i} + f_0) = [\alpha_{0,i}]^* + 1$$

which establishes the theorem for this case. If some $\pi_i$ are fractional parameters, we have (46) as the new relation for $y^*$. In this case $\alpha_{0,n+1} = -1$. If $\pi_r$ is integral, then

$$\alpha_{r,n+1} = \text{Min} \left[ \frac{f_r}{f_0}, \frac{f_r}{f_0} \right] < 1$$

where the latter relation was established in the discussion following (51). The remainder of the proof parallels (70) if $\alpha_{r,n+1} = f_r/f_0$. On the other hand, if $0 < \alpha_{r,n+1} = f_r/f_0 < 1$, then

$$\alpha_{r,n+1} = \text{Min} \left[ \frac{f_r}{f_0}, \frac{f_r}{f_0} \right] < 1$$

Finally, if $\pi_r$ is a fractional parameter, then (since $\alpha_{r,i} \geq 0$)

$$\alpha_{r,n+1} = \alpha_{r,i}/f_0 > 0$$

so that (67) reduces simply to

$$\alpha_{0,i}^* = \alpha_{0,i} + f_0 = [\alpha_{0,i}]^* + 1$$

**Theorem 5**: If the convex of fractional solutions is bounded, then the algorithm is finite.

**Proof**: Suppose, on the contrary, the algorithm is infinite; then $\alpha_0(e)$ forms a monotonically increasing sequence. However, the first term must assume some finite integer value after a finite number of iterations and remain unchanged thereafter. Otherwise (because of the assumption of a bounded convex) for some infinite sequence of optimal stages it would take on a set of values increasing toward or attaining some upper bound, and hence, an infinite sequence of non-decreasing fractional values, whose difference tends to zero. By the preceding theorem, at each optimum stage a solution is obtained such that the first term of $\alpha_0(e)$ which takes on a fractional value, must on the next cycle be at least equal to the next higher integer value. Here $j_0 = j^* = 0$. Hence, the fractional value of one optimal stage and that of the one after the one which follows are separated by at least unity—a contradiction.
26-3. SOLVING L.P. PROBLEMS WITH SOME INTEGER VARIABLES

Having established that the first term has a constant integer value after
$p_1$ iterations, the second must also after $p_1 + p_2$ iterations. The argument
is the same: Since $z_0(\epsilon)$ is monotonically increasing for sufficiently small $\epsilon$, it
means that after $p_1$ iterations the second term must be non-decreasing.
Because of boundedness of the convex, the values at the end of successive optimum stages must approach or attain a finite upper bound. It cannot take
on an infinite set of fractional values because by the preceding theorem it would (because the first component is fixed) on each subsequent stage assume
values at least equal to the next higher integer values, etc. The argument may
thus be repeated until the first $k$ components which correspond to integer
variables are all integers.

Variations.

In practice the selection of the new restriction is not always made by
the lowest-index rule; i.e., generated by the integer variable $y_j$ with the
lowest index whose value is fractional in a basic solution. Instead, $j$ is often
selected so that $-f_{ej}$ is minimal. This has sometimes cut down the number
of iterations in a number of test runs. If this rule is periodically mixed with
the lowest index rule, convergence is still guaranteed. Another device is to
impose not one but many new constraints simultaneously. If this is done
for our example, the simultaneous imposing of all constraints generated by
the integer variables and their multiples yields the required integral solution.
If it did not, new simultaneous sets of conditions would have to be imposed
and the process repeated. Using perturbation and noting that $z_0(\epsilon)$ is at least
as large as before, this variation will converge to a solution in a finite number
of steps.

Another weakness of the lowest-index rule is that it requires that $v$ be
an integer corresponding to the lowest index. It would be much more satis-
factory if $v$ could also be a fractional variable. Gomory has devised special
rules to guarantee convergence where $v$ is a fractional variable and all other
variables are integers. The proof, however, breaks down in the mixed case
if conditions (46) are used. It is not known what happens if (53) are used
instead. In practice, of course, the above variants are often used even when
$v$ is not an integer.

Exercise: If $v$ is a fractional variable and all other variables are
integer variables, show for rational coefficients that another form can replace
the $v$ form which can be maximized instead and whose value is an integer.

26-3. ON THE SIGNIFICANCE OF SOLVING LINEAR
PROGRAMMING PROBLEMS WITH SOME INTEGER
VARIABLES

Our purpose is systematically to review and classify problems that can
be reduced to linear programs, some or all of whose variables are integer
valued [Dantzig, 1960-2]. We shall show that a host of difficult, indeed seemingly impossible, problems of a nonlinear, nonconvex, and combinatorial character are now open for direct attack. The outline for this section is as follows:

I. General Principles.
   (a) Discussion.
   (b) Dichotomies.
   (c) k-fold Alternatives.
   (d) Selection from Many Pairs of Regions.
   (e) Discrete-variable Problems.
   (f) Nonlinear-objective Problems.
   (g) Conditional Constraints.
   (h) Finding a Global Minimum of a Concave Function.
II. The Fixed-charge Problem.
III. The Traveling-salesman Problem.
IV. The Orthogonal Latin-Square Problem.
V. Four-Coloring a Map (if possible).

I. General Principles

(a) Discussion. Let us now turn to the main subject, types of problems that are reducible to linear programs some or all of whose variables are integer-valued.

Quite often in the literature, papers appear which formulate a problem in linear programming format except for certain side conditions such as $x_1 \cdot x_2 = 0$, or the sum of products of this type, such as $x_1 \cdot x_2 + x_3 \cdot x_4 = 0$, which imply for nonnegative variables that at least one variable of each pair must be zero. Superficially this seems to place the problem in the area of quadratic programming. However, the presence of such conditions can change entirely the character of the problem (as we shall see in a moment) and should serve a warning to those who would apply willy-nilly a general nonlinear programming method. If we graph the conditions $x_1 \cdot x_2 = 0$, $x_1 \geq 0, x_2 \geq 0, x_1 + x_2 \geq 1$, the double lines depict the domain of feasible solutions (see Fig. 26-3-I). It will be noted that this domain has two disconnected parts. If there are many such dichotomies in a larger problem, the result can be a domain of feasible solutions with many disconnected parts or connected non-convex regions. For example, $k$ pairs of variables whose products are zero might lead to $2^k$ disconnected parts. Usual mathematical approaches can guarantee at best a local optimum solution to such problems, i.e., a solution which is optimum only over some connected convex part.

It is well known that in many cases, local optimum solutions could be avoided by the introduction of integer-valued variables, but this fact has been of only passing interest until the recent developments rendered this approach practical. Our purpose here will be to systematize this knowledge.
(b) Dichotomies. Let us begin with the important class of problems that have "either-or" conditions. For such a problem to be computationally difficult, there must be many sets of such conditions. Let us focus our attention on one of them; say

(1) \[ \text{either: } G(x_1, x_2, \ldots, x_n) \geq 0 \]

(2) \[ \text{or: } H(x_1, x_2, \ldots, x_n) \geq 0 \]

must hold for vectors \((x_1, x_2, \ldots, x_n)\) chosen from some set \(S\). We do not exclude the case of both holding if this is possible. For example, a contractor in a bid might stipulate either \(x_1 \geq 10,000\) or \(x_1 = 0\). If all bids are nonnegative so that \(x_1 \geq 0\), then we can write

(3) \[ \text{either: } x_1 - 10,000 \geq 0 \]
\[ \text{or: } -x_1 \geq 0 \]

From other considerations it may be known that no bid can exceed \(1,000,000\), so that the set \(S\) of interest is \(0 \leq x_1 \leq 1,000,000\).

We now assume that lower bounds for the functions \(G\) and \(H\) are known for all vectors \((x_1, x_2, \ldots, x_n)\) in \(S\). If \(L_G\) is a lower bound for \(G\) and \(L_H\) for \(H\), then for \(\delta = 1\) the condition

\[ G(x_1, x_2, \ldots, x_n) - \delta L_G \geq 0 \]

holds for all \((x_1, x_2, \ldots, x_n)\) in \(S\). Similarly for \(\delta = 0\) the condition

\[ H(x_1, x_2, \ldots, x_n) - (1 - \delta)L_H \geq 0 \]

holds for all \((x_1, x_2, \ldots, x_n)\) in \(S\). For our example we would have

(4) \[ x_1 - 10,000 - \delta(-10,000) \geq 0 \]
\[ -x_1 - (1 - \delta)(-1,000,000) \geq 0 \]

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The either-or condition (1), (2) can now be replaced by

\[ G(x_1, x_2, \ldots, x_n) - \delta L_G \geq 0 \] \hspace{1cm} (5) \hspace{1cm} (\delta = 0, 1)

\[ H(x_1, x_2, \ldots, x_n) - (1 - \delta) L_H \geq 0 \] \hspace{1cm} (6)

\[ 0 \leq \delta \leq 1 \] \hspace{1cm} (7)

where \( \delta \) is an integer variable. The effect of \( \delta = 1 \) is to relax the \( G \) condition when \( H \) holds and that of \( \delta = 0 \) is to relax \( H \) when \( G \) holds. If \( G \) and \( H \) are linear functions, we have reduced the either-or condition to three simultaneous linear inequalities in which the variable \( \delta \) must be 0 or 1.

A dichotomy can be used to describe an \( L \)-shaped region (non-convex): for example, \( x_1 \geq 0, x_2 \geq 0, x_1 \leq 2, x_2 \leq 2 \), and either \( x_1 \leq 1 \) or \( x_2 \leq 1 \). We replace this by

\[ 0 \leq x_1 \leq 1 + \delta \]
\[ 0 \leq x_2 \leq 2 - \delta \]
\[ 0 \leq 8 \leq 1 \]

\[ (8 + 0, 1) \]

If now a problem contains not one but several such pairs of dichotomies (1) and (2), each one would be replaced by a simultaneous set (5), (6), (7) in integer variables \( \delta_i \).

(c) \( k \)-fold Alternatives. More generally suppose that we have a set of conditions

\[ G_1(x_1, x_2, \ldots, x_n) \geq 0 \]
\[ G_2(x_1, x_2, \ldots, x_n) \geq 0 \]
\[ \vdots \]
\[ G_p(x_1, x_2, \ldots, x_n) \geq 0 \]

Suppose a solution is required in which at least \( k \) of the conditions must hold simultaneously. We replace (9) by

\[ G_1(x) - \delta_1 L_1 \geq 0 \]
\[ G_2(x) - \delta_2 L_2 \geq 0 \]
\[ \vdots \]
\[ G_p(x) - \delta_p L_p \geq 0 \]

where \( L_i \) is the lower bound for \( G_i(x) \) for \( x = (x_1, x_2, \ldots, x_n) \) in \( S \), and \( \delta_i \) are integer-valued variables satisfying

\[ \delta_1 + \delta_2 + \ldots + \delta_p \leq p - k \]

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and

\[ 0 \leq \delta_i \leq 1 \quad (\delta_i = 0 \text{ or } 1) \]

An example of this type of problem might occur if one wishes to find the minimum over the shaded regions described by \( G_1 \geq 0, G_2 \geq 0, G_3 \geq 0 \), and at least two of the conditions \( G_4 \geq 0, G_5 \geq 0, G_6 \geq 0 \) as in Fig. 26-3-II.

(d) Selection from Many Pairs of Regions. The six-pointed "Star of David" region shown in Fig. 26-3-II (lower part) can best be described as a dichotomy in which a point must be taken from one of two triangles. It is only when there are many such pairs to be chosen at the same time that the problem becomes significant. In general we might have several pairs of regions \((R_i, R_i')\), \((R_2, R_2')\), \ldots, \((R_n, R_n')\), and the solution point \(z\) must lie in either \(R_i\) or \(R_i'\) for each \(i\). For each pair \(R\) and \(R'\) we proceed as follows. Let region \(R\) be described by a set of inequalities \(G_1(x) \geq 0, G_2(x) \geq 0, \ldots, G_m(x) \geq 0\),
... $G_m(x) \geq 0$, and $R'$ by $H_3(x) \geq 0$, $H_4(x) \geq 0$, ..., $H_n(x) \geq 0$. The condition that the point must be selected from either the first or the second region can be written

\begin{align*}
G_1(x) - \delta L_1 &\geq 0, & H_3(x) - (1 - \delta)L'_1 &\geq 0, \\
G_2(x) - \delta L_2 &\geq 0, & H_4(x) - (1 - \delta)L'_2 &\geq 0, \\
& \vdots & & \vdots \\
G_m(x) - \delta L_m &\geq 0, & H_n(x) - (1 - \delta)L'_n &\geq 0,
\end{align*}

where $L_i$, $L'_i$ are lower bounds for $G_i$ and $H_i$. The more general case of selection from several regions can be done by introducing several $\delta_i$ as in (11) and (12).

(c) **Discrete-variable Problems.** Suppose that a variable is constrained to take one of several values: $x_1 = a_1$ or $x_2 = a_2$, ..., or $x_k = a_k$ and at the same time several other variables are also constrained the same way. It would be a formidable task to test all the combinations. Instead we replace each $k$-fold dichotomy by

\begin{align*}
x_1 &= a_1\delta_1 + a_2\delta_2 + \cdots + a_k\delta_k \\
1 &= \delta_1 + \delta_2 + \cdots + \delta_k
\end{align*}

Similarly let $x = (x_1, x_2, \ldots, x_n)$ represent a vector which may only take on specified vector values $x = a^1$ or $x = a^2$ or $x = a^3$ ... . This may be replaced by

\begin{align*}
x &= a^1\delta_1 + a^2\delta_2 + \cdots + a^k\delta_k \\
1 &= \delta_1 + \delta_2 + \cdots + \delta_k
\end{align*}

This device permits the replacement of a nonlinear function $F_i(x_j) = F_{ij}(x_j)$, in a system $\sum_{j=1}^{k} F_{ij}(x_j) = 0$ for $i = 1, 2, \ldots, m$, by the values of the function corresponding to a sprinkling of representatative values of $x_j$, say $x_i = x'_i$ where $r = 1, 2, \ldots, k$. In this case the vector takes on the set of values $F_{i1}, F_{i2}, \ldots, F_{im}$ for each value $x_i = x'_i$.

(f) **Nonlinear-objective Problems.** Referring to Fig. 26-3-III, suppose the objective form can be written

\begin{equation}
\sum_{j=1}^{n} \phi_j(x_j) = z \text{ (Min)}
\end{equation}

where $\phi_j$ is nonlinear and non-convex. Let each $\phi(x)$ be approximated by a broken line function. These define a set of intervals $i = 1, 2, \ldots, k$ of
width $h_i$ and slopes $s_i$ for the approximating chords. We now define $y_i$ as the amount of overlap of the interval from 0 to $x$ with interval $i$. Then

$$x = y_1 + y_2 + \ldots + y_k$$

and $\phi(x)$ is given approximately by

$$\phi(x) = b_0 + s_1y_1 + s_2y_2 + \ldots + s_ky_k$$

where

$$0 \leq y_i \leq h_i \quad (i = 1, 2, \ldots, k)$$

In the case of convex $\phi$, the procedure is to replace $x$ and $\phi(x)$ by (19) and (20) and conditions (21). Here the slopes are monotonically increasing so that

$$s_1 \leq s_2 \leq \ldots \leq s_k$$

For a fixed $x$, $\phi(x)$ would be minimum if $y_1$ is chosen maximum and if for $y_i$ maximum, $y_i$ is chosen maximum, etc. In other words, for the minimizing solution the $y_i$'s are the overlap of the $i^{th}$ interval with the interval 0 to $x$, and all is well. See § 24-3.

However, if $\phi(x)$ is not convex as in Fig. 26-3-III, then simple replacement of $x$ and $\phi(x)$ would result, for fixed $x$, in those $y_i$ with smaller slopes being maximized first. In this case the segments that comprise $x$ would be disconnected and our approximation for $\phi(x)$ would no longer be valid. In order to avoid this, we impose the condition that

$$\text{either } h_i - y_i = 0 \quad \text{or } y_{i+1} = 0$$

which implies that unless $y_i$ is maximum, $y_{i+1} = 0$, and if $y_i$ is maximum, then $y_{i+1} \geq 0$ is possible. We rewrite this condition

$$\text{either } y_i - h_i \geq 0 \quad \text{or } -y_{i+1} \geq 0$$
and then replace it formally by

\[
\begin{aligned}
-y_1 + λ_1 &\geq 0 \\
y_i - h_i - (-h_i)δ_i &\geq 0 & (i = 1, 2, \ldots, k - 1) \\
y_{i+1} - (-h_{i+1})(1 - δ_i) &\geq 0 \\
0 &\leq δ_i &\leq 1
\end{aligned}
\]

(25)

Upon substitution of \(δ'_i = 1 - δ_i\), (25) simplifies to

\[
\begin{aligned}
y_1 &\leq h_1 \\
y_i &\geq h_i δ'_i & (i = 1, 2, \ldots, k - 1) \\
y_{i+1} &\leq h_{i+1} δ'_i \\
0 &\leq δ'_i &\leq 1
\end{aligned}
\]

(26)

which together with (19) and (20) formulates the problem (note that (21) is not required). The above procedure for the non-convex case was discussed in the paper of Markowitz and Manne [1957-1]. The convex case will be found in [Dantzig, 1956-2] and [Charnes and Lemke, 1954-1].

A second method based on (16) is worth noting. Any point on the curve \(φ(x)\) can be represented as a weighted average of two successive breakpoints. Hence we may replace \(x\) and \(φ(x)\) by

\[
\begin{aligned}
x &= λ_0 a_0 + λ_1 a_1 + \ldots + λ_k a_k & (0 \leq λ_i) \\
φ(x) &= λ_0 δ_0 + λ_1 δ_1 + \ldots + λ_k δ_k \\
1 &= λ_0 + λ_1 + \ldots + λ_k
\end{aligned}
\]

(27)

(28)

and then impose the conditions that all \(λ_i = 0\) except for one pair \(λ_i\) and \(λ_{i+1}\). For \(k = 4\) this may be expressed by

\[
\begin{aligned}
λ_0 &\leq δ_0 \\
λ_1 &\leq δ_0 + δ_1 \\
λ_2 &\leq δ_1 + δ_2 \\
λ_3 &\leq δ_2 + δ_3 \\
λ_4 &\leq δ_3 + δ_4
\end{aligned}
\]

(29)

where the \(δ_i\) are integer-valued variables satisfying

\[
δ_0 + δ_1 + δ_2 + δ_3 + δ_4 + δ_5 = 1 \quad (δ_i = 0, 1)
\]

(30)

Indeed it will be noted, when \(δ_i = 1\) for some \(i = i_0\), the inequalities involving \(λ_{i_0}\) and \(λ_{i_0+1}\) are relaxed but the remainder satisfy \(λ_i \leq 0\) since their \(δ_i = 0\) by (30).

(g) Conditional Constraints. Suppose \(x\) and \(y\) are functions of several variables. We assume that an upper bound \(U_x\) is known for \(x\), and lower
bounds \( L_x \) and \( L_y \) are known for \( x \) and \( y \). We wish to impose conditions such as

\[
(31) \quad z > 0 = y \geq 0
\]

We can write (31) as

\[
(32) \quad \text{either } z > 0, y \geq 0 \text{ or } z \leq 0
\]

which we rewrite as

\[
(33) \quad \begin{cases} 
  x \geq \delta L_x \\
  y \geq \delta L_y \\
  z \leq (1 - \delta)U_x 
\end{cases} \quad (\delta = 0, 1)
\]

where the first inequality is written \((\geq)\) instead of \((>)\) because the condition \( y \geq 0 \) is automatically relaxed for \( x = 0 \) by selecting \( \delta = 1 \).

We can now elaborate this method to impose conditions such as

\[
(34) \quad x > 0 \Rightarrow u \geq 0 \\
  x < 0 \Rightarrow w \geq 0
\]

which may be written as

\[
(35) \quad \begin{cases} 
  x \geq (1 - \delta_1)L_x \\
  x \leq (1 - \delta_2)U_x \\
  x \geq \delta_1 L_x \\
  u \geq \delta_1 L_u \\
  x \leq \delta_2 U_x \\
  w \geq \delta_2 L_w \\
  \delta_1 + \delta_2 = 1 + \delta_3 
\end{cases} \quad (\delta_i = 0, 1)
\]

For example, suppose in a \( T \)-period program we wish to complete a specified work load by the earliest period possible. Let \( x_t \) be the cumulative sum of activity levels from the \( t \)th period through the last period \( T \), then we wish to arrange matters so that \( x_t = 0 \) for the smallest \( t \). Note in this case \( x_t > 0 \) implies \( x_s > 0 \) for \( s < k \). In this case we can define for \( t = 1, 2, \ldots, T \),

\[
(36) \quad \delta_t = 0 \Rightarrow x_t = 0
\]

We may rewrite (36)

\[
(37) \quad 0 \leq x_t \leq \delta_t U_t \quad (\delta_t = 0, 1)
\]

where \( U_t \) is an upper bound for \( x_t \), and then determine Min \( z \) where

\[
(38) \quad z = \delta_1 + \delta_2 + \ldots + \delta_T
\]

(h) Finding a Global Minimum of a Concave Function.\(^3\) Suppose the

\(^3\) This application was developed jointly with P. Wolfe.
conceave function $Z = Z(x_1, x_2, \ldots, x_n)$ is to be minimized over a region $R$. If $R$ is convex, this is intrinsically a difficult problem because the concave function could have local minima at many, indeed at all, the extreme points of $R$. We shall in fact assume $R$ convex, for we note that the devices discussed earlier allow us to use a convex domain coupled with integer-valued variables to solve a wide class of problems expressible by either-or conditions. We suppose $R$ to be given, after suitable change in variables, in standard linear programming form

$$Ex = e, \quad x \geq 0$$

where $E$ is a given $m \times n$ matrix and $e$ a given $m$-component vector.

The concave function $Z$ may be given explicitly or be given implicitly. As an example of the latter, suppose vector $y$ and quantity $Z$ for fixed $x$ is given by

$$Fy = f + \hat{E}x, \quad y \geq 0$$

$$\max_{\beta y = Z} \text{(Min)}$$

where $\hat{E}$ and $F$ are given matrices and $f$ and $\beta$ are given vectors.

Exercise: Prove $\max_{\beta y} \beta y$ is a concave function of $x$. Prove that $\phi(x) = \min(\phi_1(x), \phi_2(x), \ldots)$ is a concave function if $\phi_i(x)$ is concave for all $i$.

An illustration having a striking parallel in the real world can be given: Consider a two-move game in which the first player, $A$, by choosing his activity levels $x$ consistent with (39) modifies the inventory $f$ of his opponent by an amount $\hat{E}x$. The second player, $B$, by choosing his activity levels $y$ consistent with (40) obtains a payoff $\beta y$. $A$'s problem is to choose $x$ so as to minimize the maximum payoff to $B$.

We shall suppose that $Z$ can reasonably be approximated at all points $x$ in $R$ by the minimum $Z$ of a finite set of $k$ tangent hyperplanes,

$$Z = a_{i1}x_1 + a_{i2}x_2 + \ldots + a_{in}x_n - b_i \quad (i = 1, 2, \ldots, k)$$

to the surface $Z = Z(x)$. The problem reduces to choosing $x$, $\min Z$ satisfying (39) such that $(x, Z)$ satisfies at least one of the conditions

$$Z - [a_{i1}x_1 + a_{i2}x_2 + \ldots + a_{in}x_n - b_i] \geq 0$$

$$Z - [a_{i1}x_1 + a_{i2}x_2 + \ldots + a_{in}x_n - b_i] \geq 0$$

$$\cdots$$

$$Z - [a_{i1}x_1 + a_{i2}x_2 + \ldots + a_{in}x_n - b_i] \geq 0$$

We may rewrite (42) as

$$Z - [a_{i1}x_1 + a_{i2}x_2 + \ldots + a_{in}x_n] \geq M(1 - \delta_i) \quad (i = 1, 2, \ldots, k)$$

$$\delta_1 + \delta_2 + \ldots + \delta_k = 1$$

($\delta_i = 0, 1$)

where $M$ is some assumed lower bound for the differences. This solution
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depends on the approximation of the function $Z = Z(x)$ by $k$ hyperplanes. The solution, given in [Dantzig, 1958-2], for the case where $Z$ is given implicitly by (40), requires finding $x, y, \text{Min} z$, and auxiliary variables $\pi = (\pi_1, \pi_2, \ldots, \pi_m)$ and $\eta \geq 0$, for $j = 1, 2, \ldots, n'$, satisfying

$$Ex = e, \quad Fy = f + E\bar{x}, \quad z = \beta y$$

$$\pi F + \eta - \beta = 0$$

either $\eta_j \geq 0$ or $y_j \geq 0$

where $\pi = (\pi_1, \pi_2, \ldots, \pi_m)$ is a row vector, $y_j$ is the $j$th component of $y$, and $\eta_j$ the $j$th component of $\eta$.

EXERCISE: Verify (44).

II. The Fixed-charge Problem.

Earlier we described a problem where a bidder required that the size of the bid satisfies either $x = 0$ or $x \geq a$. In this and many other problems there is an underlying notion of a fixed charge that is independent of the size of the order. In this case $x = a$ represents the break-even point to the bidder. In general, the cost $C$ is characterized by

$$C = \begin{cases} \frac{kx + b}{0} & \text{if } x > 0 \\ 0 & \text{if } x = 0 \end{cases}$$

where $b$ is the fixed charge. We may write this in the form

$$C = kx + \delta b$$

where $x = 0$ if $\delta = 0$, which we impose by

$$x \leq \delta U$$

and

$$0 \leq \delta \leq 1$$

where $U$ is some upper bound for $x$. A discussion of the fixed-charge problem including this device will be found in the paper by W. Hirsch and the author [1954-1].

III. The Traveling-salesman Problem.

The Problem. In what order should a traveling salesman visit $n$ cities to minimize the total distance covered in a complete circuit? We shall give three formulations of this well-known problem. Let $x_{ijt} = 1$ or $0$ according to whether the $t$th directed arc on the route is from node $i$ to node $j$ or not. Letting $x_{i(n+1)} \equiv x_{ijt}$, the conditions

$$\sum_i x_{ijt} = \sum_k x_{i,k,t+1} \quad (j, t = 1, \ldots, n)$$

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(50) \[ \sum_{i, t} x_{it} = 1 \quad (i = 1, \ldots, n) \]

(51) \[ \sum_{i, j, t} d_{ij} x_{ijt} = z \text{ (Min)} \]

express (a) that if one arrives at city \( j \) on step \( t \), one leaves city \( j \) on step \( t + 1 \), (b) that there is only one directed arc leaving node \( i \), and (c) the length of the tour is minimum. It is not difficult to see that an integer solution to this system is a tour [Flood, 1956-1].

In two papers by Dantzig, Fulkerson, and Johnson [1954-1, 1959-1] the case of a symmetric distance \( d_{ij} = d_{ji} \) was formulated with only two indices. Here \( x_{ij} = x_{ji} = 1 \) or 0 according to whether the route from \( i \) to \( j \) or from \( j \) to \( i \) was traversed at some time on a route or not. In this case

(52) \[ \sum_{i} x_{ij} = 2 \quad (j = 1, 2, \ldots, n) \]

and

(53) \[ \sum_{i, j} d_{ij} x_{ij} = z \text{ (Min)} \]

express the condition that the sum of the number of entries and departures for each node is two. Note in this case that no distinction is made between the two possible directions that one could traverse an arc between two cities. These conditions are not enough to characterize a tour even though the \( x_{ij} \) are restricted to be integers in the interval

(54) \[ 0 \leq x_{ij} \leq 1 \]

since sub-tours like those in Fig. 26.3-IV also satisfy the conditions. However,

![Figure 26.3-IV](image)

Figure 26.3-IV. Loop conditions are added to rule out sub-tours in the traveling-salesman problem.

if so-called loop conditions like

(55) \[ x_{12} + x_{33} + x_{31} \leq 2 \]

are imposed as added constraints as required, these will rule out integer solutions which are not admissible.
EXERCISE: Construct a fractional solution to (49), (50), (51) that is extremal. Show that any integer solution without sub-tours is a full tour.

A third way to reduce a traveling-salesman problem to an integer program is due to A. W. Tucker [1960-1]. It has less constraints and variables than those above. Let \( x_{ij} = 1 \) or \( 0 \), depending on whether the salesman travels from city \( i \) to \( j \) or not, where \( i = 0, 1, 2, \ldots, n \). Then an optimal solution can be found by finding integers \( x_{ij} \), arbitrary real numbers \( u_i \), and \( \text{Min } z \) satisfying

\[
\sum_{i=0}^{n} x_{ij} = 1 \quad (j = 1, 2, \ldots, n)
\]

\[
\sum_{j=0}^{n} x_{ij} = 1 \quad (i = 1, 2, \ldots, n)
\]

\[
u_i - u_j + nx_{ij} \leq n - 1 \quad (1 \leq i \neq j \leq n)
\]

\[
\sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij}x_{ij} = z \text{ (Min)}
\]

The third group of conditions is violated whenever we have an integer solution to the first two groups that is not a tour, for in this case it contains two or more loops with \( k < n \) arcs. In fact, if we add all inequalities corresponding to \( x_{ij} = 1 \) around such a loop not passing through city 0, we will cancel the differences \( u_i - u_j \) and obtain \( nk \leq (n - 1)k \), a contradiction. We have only to show for any tour starting from \( i = 0 \) that we can find \( u_i \) that satisfies the third group of conditions. Choose \( u_i = t \) if city \( i \) is visited on the \( t \)th step where \( t = 1, 2, \ldots, n \). It is clear that the difference \( u_i - u_j \leq n - 1 \) for all \((i, j)\). Hence the conditions are satisfied for all \( x_{ij} = 0 \); for \( x_{ij} = 1 \) we obtain \( u_i - u_j + nx_{ij} = (t - (t + 1) + n = n - 1 \).

IV. The Orthogonal Latin-Square Problem.

A latin square consists of \( n \) sets of \( n \) objects \((1), (2), \ldots, (n)\) assigned to an \( n \times n \) square array so that no object is repeated in any row or column. Two latin squares are orthogonal if the \( n^2 \) ordered pairs of corresponding entries are all different; for example

\[
\begin{array}{ccc}
(1) & (2) & (3) \\
(2) & (3) & (1) \\
(3) & (1) & (2)
\end{array}
\]

\[
\begin{array}{ccc}
(1) & (2) & (3) \\
(2) & (3) & (1) \\
(3) & (1) & (2)
\end{array}
\]

It was conjectured by Euler that there are no orthogonal latin squares for certain \( n \). After a great deal of research, the case for \( n = 10 \), for example,
DISCRETE VARIABLE EXTREMUM PROBLEMS

was settled in 1959. It has been suggested informally by David Gale that integer programming be tried in this area.

The formulation is straightforward and well known. Let \( x_{ijkl} = 0 \) or 1 according to whether or not the pair \((i, j)\) is assigned to row \(k\), column \(l\). The condition that each pair \((i, j)\) is assigned to only one location is given by

\[
\sum_{k,l} x_{ijkl} = 1 \quad (i, j = 1, 2, \ldots, n)
\]

The condition that one pair \((i, j)\) is assigned to each location \(k, l\) is:

\[
\sum_{i,j} x_{ijkl} = 1 \quad (k, l = 1, 2, \ldots, n)
\]

The condition that \(i\) appears only once in the first latin square in column \(l\) is given by (60). The condition that \(j\) appears only once in the second latin square in column \(k\) is given by (61).

\[
\sum_{j,k} x_{ijkl} = 1 \quad (i, l = 1, 2, \ldots, n)
\]

\[
\sum_{i,k} x_{ijkl} = 1 \quad (j, l = 1, 2, \ldots, n)
\]

Similarly the condition that \(i\) and \(j\) appear only once in the first and second latin square respectively in row \(k\) is given by

\[
\sum_{i,k} x_{ijkl} = 1 \quad (i, k = 1, 2 \ldots, n)
\]

\[
\sum_{j,k} x_{ijkl} = 1 \quad (j, k = 1, 2 \ldots, n)
\]

It is interesting to note that all pairs of subscripts possible out of four are summed to form the six sets of \(n^2\) equations. For \(n = 10\) there are 600 equations which are too many for any integer programming code devised up to 1962 to handle. However, with some short-cuts introduced, it might become tractable.

V. Four-Coloring a Map (If Possible).

A famous unsolved problem is to prove or disprove that any map in the plane can be colored using at most four colors; regions with a boundary in common (other than a point) must have different colors. We shall give two ways to color constructively a particular map, if possible. While this does not

\* R. C. Bose and S. S. Shukhade proved that Euler's famous conjecture about the non-existence of orthogonal latin squares of certain even orders was false. E. T. Parker has constructed a pair of orthogonal latin squares of order 10. For further information the reader is referred to Abstract 558-27 of the August 1959 Notices of the American Mathematical Society. A non-technical report of their results has appeared in the Scientific American, Vol. 201, No. 5, November 1959, pp. 181-188.
26.3. SOLVING L.P. PROBLEMS WITH SOME INTEGER VARIABLES

contribute to a proof of the truth or falsity of this conjecture, nevertheless an efficient way for solving particular examples on an electronic computer may serve as an aid in finding a counter example.

Without difficulty it can be arranged (as below) so that three regions

have at most one point in common which will be called a node. There will be, accordingly, three arcs leading from any node \( i \) to other nodes \( j \). It is well known that if it is possible to four-color a map, then (and this will be true conversely) it is possible (treating the nodes as cities and the arcs as routes between cities) either to tour all the nodes or to make a group of mutually exclusive sub-tours of the cities in several even (sub-cycle) loops as in Fig. 26.3-V.

![Diagram showing four-color problem](image)

**Figure 26.3-V.** The four-color problem is equivalent to finding a set of even-order sub-tours.

**Exercise:** Show that the number of arcs is a multiple of 3 and the number of nodes is even.

We may associate with each such even-cycle sub-tour, directed arcs that reverse their direction as we pass from node to node. This means the nodes \( i \) can be divided into two classes: those which have two arcs pointing away from them and those which have two arcs pointing toward them. Let us set \( x_{ij} = 1 \), if the directed arc \( (i \rightarrow j) \) is part of such a sub-tour; otherwise \( x_{ij} = 0 \). Hence

\[
0 \leq x_{ij} \leq 1
\]  

(63)

It is understood that only arcs \( (i, j) \) and variables \( x_{ij} \) are considered corresponding to regions that have a boundary in common. All arcs \( (i, j) \) that do not correspond to boundaries are omitted in the constraints.

The conditions

\[
\sum_j x_{ij} = 2\delta_i \quad (\delta_i = 0, 1)
\]

(64)

[549]
express the fact there must be two arcs on some sub-tour leading away from node $i$ if $\delta_i = 1$; otherwise there are none. The conditions

$$\sum_i x_{ij} = 2 - 2\delta_i$$

state there must be two arcs on some sub-tour leading into node $i$ if $\delta_i = 0$, and otherwise none. The three sets of conditions (63), (64), and (65) are those of a bounded transportation problem and will be integers (at an extreme point) if the $\delta_i$ are integers. This would seem to imply that it is only necessary to assume that the $\delta_i$ are integers and the $x_{ij}$ will come out automatically integral in an extremizing solution without further assumptions. However, the wrong choice of integral $\delta_i$ could lead to an empty solution set. As an alternative to using an integer programming method to solve this problem, it might be practical to allow the $\delta_i$ to vary $0 \leq \delta_i \leq 1$ but to randomly choose various objective forms (since these are open to choice) until an optimal extreme-point solution with integral $x_{ij}$ is obtained.

A second formulation suggested informally by Gomory is straightforward. Let the regions be $r = 1, 2, \ldots, R$, and let $t_r$ be an integer-valued variable such that

$$0 \leq t_r \leq 3$$

where the four values $t_r = 0, 1, 2, 3$ correspond to the four colors. If regions $r$ and $s$ have a boundary in common, their colors must be different. Hence for each such pair

$$t_r - t_s \neq 0$$

This may be written in either-or form:

$$t_r - t_s \geq 1 \text{ or } t_s - t_r \geq 1$$

which we may rewrite as

$$t_r - t_s \geq 1 - 4\delta_{rs} \quad (\delta_{rs} = 0, 1)$$

$$t_s - t_r \geq -3 + 4\delta_{rs}$$

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CHAPTER 27

STIGLER’S NUTRITION MODEL:
AN EXAMPLE OF FORMULATION AND SOLUTION

One of the first applications of the simplex algorithm was to the determination of an adequate diet that was of least cost.\(^1\) In the fall of 1947, J. Laderman of the Mathematical Tables Project of the National Bureau of Standards undertook, as a test of the newly proposed simplex method, the first large-scale computation in this field. It was a system with nine equations in seventy-seven unknowns. Using hand-operated desk calculators, approximately 120 man-days were required to obtain a solution.

The particular problem solved was one which had been studied earlier by G. J. Stigler [1945-1], who had proposed a solution based on the substitution of certain foods by others which gave more nutrition per dollar. He then examined a “handful” of the possible 510 ways to combine the selected foods. He did not claim the solution to be the cheapest but gave good reasons for believing that the annual cost could not be reduced by more than a few dollars. Indeed, we shall see that Stigler’s solution, when converted from a cost-per-day to a cost-per-year, was only 24 cents higher than the true minimum for the year, which was $39.69 (10.9 cents per day).

27-1. PROBLEMS IN FORMULATING A MODEL

Before launching into the mathematical characteristics of the nutrition problem, it is worthwhile to see just how to develop a “mathematical model.” It will be seen to be far from a precise operation, and it is only natural to question the validity of refined techniques for solving what is clearly an approximate model. This situation is typical almost everywhere programming techniques are applied. One should remember, however, that one reason why only the approximate models exist today has been the historic inability of the investigator to solve any large-scale complex model. As the tools for handling these systems increase, so does the desire of the investigator increase to refine his models to take advantage of these new techniques. The next few years will probably see the end of this vicious

\(^1\) J. Cornfield of the U.S. Government formulated such a mathematical problem as early as 1940.
circle of the past, in which poor model building justified rapid rough "solutions" and, conversely, the non-existence of methods of accurate solution justified poor model building. It is likely that both model building and solution techniques will begin to reinforce each other in a positive manner.

Stigler’s paper [1945-1] provides a very frank discussion of the background of the nutrition model; the greater part of what follows is based upon this source and follows it very closely. In the years since his paper was published, many improvements in the model have been made. However, it is interesting to study some of the typical situations that confront a model builder in the early stages. Stigler began with some findings of nutrition studies:

(1) After certain minimum values of the nutrients are secured, additional quantities yield decreasing (and, in some cases, eventually negative) returns to health.

(2) The optimum quantity of any nutrient depends on the quantities of the other nutrients available.

Diminishing returns are illustrated by the fact that the amount of calcium in the body increases much more slowly than the input of calcium, and that increases of longevity are not proportional to calcium inputs. It appears possible in some cases to substitute one type of nutrition for another type. Stigler cites an example in which it was recommended that 30 micrograms of thiamine be substituted for 100 calories derived from sources other than fats. Another example cited is that a loss of riboflavin accompanies a deficiency of thiamine.

Stigler then turned to another question: How much of various nutrients are required? How do the requirements differ from one individual to another? In resolving this difficulty, he noted that the optimum quantity of calories is known fairly accurately, but that the requirements of other nutrients are known only roughly or not at all. Many minima (to which 50 per cent is usually added as a safety factor) are found by determining the lowest level of input compatible with a stable rate of loss of the nutrient through excreta. The interrelationships among various nutrients are even more obscure, and they are virtually ignored in dietary recommendations. Even the statement of what substances are necessary for health is very complex. Thus, in addition to calcium, the body requires about 13 minerals (some in minute quantities), many kinds of vitamins, a dozen or so types of amino acids, and perhaps many more nutrients yet to be discovered.

The diets developed by Stigler were considerably lower in cost than those developed by others. One of the reasons given is that the other diets included a greater variety of foods as a kind of “insurance” against omitting any of the unknown dietary elements. Another reason is that diet experts do give some weight to social and institutional pressures, particularly where they are not on firm grounds to support alternatives. On the other hand,
Stigler justifies his diet in this regard by citing the National Research Council's belief that these other minerals and vitamins are supplied in adequate amounts automatically when a certain group of common nutrients are obtained from natural foods. Based on considerations of this kind, the first step in setting up a mathematical model was to accept the Council's statement of daily nutritional requirements (given in Table 27-1-I). Note that only nine of the more common nutrients were used, and the others were assumed to be automatically satisfied. It should also be noted that the requirements (discussed earlier) are rough, and, possibly with the exception of calories, almost any number in a very broad range probably could equally well be justified.

In considering the nutritive values of foods, again we see a similar situation, for the nutritive values of common foods are known only approximately, and that is all that can be known about them. A large margin of uncertainty arises on several scores. For example, the milligrams of ascorbic acid per 100 grams of apples vary with the type of apple:

<table>
<thead>
<tr>
<th>Apple</th>
<th>Milligrams of Ascorbic Acid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jonathan</td>
<td>4.4</td>
</tr>
<tr>
<td>McIntosh</td>
<td>2.0</td>
</tr>
<tr>
<td>Northern Spy</td>
<td>11.0</td>
</tr>
<tr>
<td>Ontario</td>
<td>20.8</td>
</tr>
<tr>
<td>Winesap</td>
<td>5.8</td>
</tr>
<tr>
<td>Winter Banana</td>
<td>6.6.</td>
</tr>
</tbody>
</table>

The ascorbic acid in milk varies with season. Conditions of storage, such as temperature and length of time in storage, are important factors. The more corn matures, the greater is the amount of vitamin A, but the ascorbic acid content decreases. Long cooking decreases the nutritive value; well-done roasts of beef have roughly 70 per cent of the thiamine, riboflavin, and niacin of raw cuts. Not only is there a considerable variability in foods,
which conceivably could be taken into account in programming, by introducing probabilistic considerations (as is done in Chapter 25 on uncertainty), but there is also the fact, according to Stigler, that the nutritive values that had been established in 1944 for many foods had been determined by obsolete and inaccurate techniques, or may be just plain wrong for other reasons.

Ignoring these difficulties, a model was set up in which some kind of average nutritive per unit quantity for each food as purchased was developed. If $x_j$ units of the $j$th food were purchased and each food contained, per unit quantity, $a_{ij}$ units of the $i$th nutrient, then it was assumed that the individual would receive

$$\sum_{j=1}^{n} a_{ij} x_j$$

units of the $i$th nutrient, assuming there are no losses due to preparation of the foods. There is also a tacit assumption that there is no interaction between various foods; i.e., the total number of units of a nutrient available in a food is unaffected by the presence of some other food in the diet.

Finally, a list of potential foods was selected for which retail prices were reported by the Bureau of Labor Statistics. The list was not complete since it excluded almost all fresh fruits, many cheap vegetables rich in nutrients, and fresh fish. If these could have been included, it would seem that the minimum cost diet could be reduced by a substantial amount. However, other investigators have found that the optimal choice is quite insensitive to these particular prices due to the presence of certain staples in the optimum diet.

In Table 27-1-II, the coefficients $a_{ij}$ per dollar expenditure are given for an abbreviated list of some 77 types of foods considered by Stigler. He recommended, however, where prices are subject to change because of local and seasonal conditions, and if it is desired to compute not one but several such problems, that the units for measuring the quantity of foods be physical units such as weight, or possibly volume in case of liquids. If this is done, the price data and the nutritive data can be developed independently.

Mathematical Formulation.

The nutrition model may now be set up in linear programming terms. Let the set of possible activities ($j$) and activity levels $x_j$ be:

<table>
<thead>
<tr>
<th>Activities</th>
<th>Activity Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Buying the 1st type food (wheat flour)</td>
<td>$x_1$</td>
</tr>
<tr>
<td>2. Buying the 2nd type food (macaroni)</td>
<td>$x_2$</td>
</tr>
<tr>
<td>........................................</td>
<td>...</td>
</tr>
<tr>
<td>$n$. Buying the $n = 77$th type food (strawberry preserves)</td>
<td>$x_{77}$</td>
</tr>
</tbody>
</table>

[ 554 ]
TABLE 27-1-II
NUTRITIVE VALUES OF COMMON FOODS PER DOLLAR OF EXPENDITURE
August 15, 1939
(Abbreviated List of 20 of the 77 Foods)

<table>
<thead>
<tr>
<th>Nutritive Items (i)</th>
<th>Calories (1,000)</th>
<th>Protein (grams)</th>
<th>Calcium (grams)</th>
<th>Iron (mg.)</th>
<th>Vitamin A (1,000 I.U.)</th>
<th>Thiamine (mg.)</th>
<th>Riboflavin (mg.)</th>
<th>Niacin (mg.)</th>
<th>Ascorbic Acid (mg.)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1. Wheat flour (enriched)</strong></td>
<td>44.7</td>
<td>1,411</td>
<td>2.0</td>
<td>365</td>
<td>—</td>
<td>55.4</td>
<td>33.3</td>
<td>441</td>
<td></td>
</tr>
<tr>
<td><strong>5. Corn meal</strong></td>
<td>36.0</td>
<td>897</td>
<td>1.7</td>
<td>99</td>
<td>—</td>
<td>30.9</td>
<td>17.4</td>
<td>7.9</td>
<td>106</td>
</tr>
<tr>
<td><strong>15. Evaporated milk (can)</strong></td>
<td>8.4</td>
<td>422</td>
<td>15.1</td>
<td>9</td>
<td>26.0</td>
<td>3.0</td>
<td>23.5</td>
<td>11</td>
<td>60</td>
</tr>
<tr>
<td><strong>17. Oleomargarine</strong></td>
<td>20.6</td>
<td>17</td>
<td>6</td>
<td>6</td>
<td>55.8</td>
<td>2</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td><strong>19. Cheese (Cheddar)</strong></td>
<td>7.4</td>
<td>448</td>
<td>16.4</td>
<td>19</td>
<td>28.1</td>
<td>.6</td>
<td>10.3</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td><strong>21. Peanut butter</strong></td>
<td>15.7</td>
<td>661</td>
<td>1.0</td>
<td>48</td>
<td>—</td>
<td>9.6</td>
<td>8.1</td>
<td>471</td>
<td></td>
</tr>
<tr>
<td><strong>24. Lard</strong></td>
<td>41.7</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>.2</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td><strong>30. Liver (beef)</strong></td>
<td>2.2</td>
<td>333</td>
<td>7.2</td>
<td>66.2</td>
<td>5.4</td>
<td>3.6</td>
<td>79</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>34. Pork loin roast</strong></td>
<td>4.4</td>
<td>249</td>
<td>.3</td>
<td>37</td>
<td>18.2</td>
<td>3.6</td>
<td>79</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>40. Salmon, pink (can)</strong></td>
<td>5.8</td>
<td>705</td>
<td>6.8</td>
<td>45</td>
<td>3.5</td>
<td>1.0</td>
<td>4.9</td>
<td>209</td>
<td></td>
</tr>
<tr>
<td><strong>45. Green beans</strong></td>
<td>2.4</td>
<td>138</td>
<td>3.7</td>
<td>80</td>
<td>66.0</td>
<td>4.3</td>
<td>5.8</td>
<td>37</td>
<td>862</td>
</tr>
<tr>
<td><strong>46. Cabbage</strong></td>
<td>2.6</td>
<td>125</td>
<td>4.0</td>
<td>3.6</td>
<td>7.2</td>
<td>9.0</td>
<td>4.5</td>
<td>26</td>
<td>5,369</td>
</tr>
<tr>
<td><strong>50. Onions</strong></td>
<td>5.8</td>
<td>166</td>
<td>3.8</td>
<td>59</td>
<td>16.6</td>
<td>4.7</td>
<td>5.9</td>
<td>21</td>
<td>1,184</td>
</tr>
<tr>
<td><strong>51. Potatoes</strong></td>
<td>14.3</td>
<td>336</td>
<td>1.8</td>
<td>118</td>
<td>6.7</td>
<td>7.1</td>
<td>52</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>52. Spinach</strong></td>
<td>1.1</td>
<td>106</td>
<td>—</td>
<td>138</td>
<td>918.4</td>
<td>5.7</td>
<td>13.8</td>
<td>33</td>
<td>2,755</td>
</tr>
<tr>
<td><strong>53. Sweet potatoes</strong></td>
<td>9.6</td>
<td>138</td>
<td>2.7</td>
<td>54</td>
<td>290.7</td>
<td>8.4</td>
<td>5.4</td>
<td>83</td>
<td>1,912</td>
</tr>
<tr>
<td><strong>84. Peaches, dried</strong></td>
<td>8.5</td>
<td>87</td>
<td>1.7</td>
<td>173</td>
<td>86.8</td>
<td>1.2</td>
<td>4.3</td>
<td>55</td>
<td>57</td>
</tr>
<tr>
<td><strong>85. Prunes, dried</strong></td>
<td>12.8</td>
<td>99</td>
<td>2.5</td>
<td>164</td>
<td>85.7</td>
<td>3.9</td>
<td>4.3</td>
<td>65</td>
<td>267</td>
</tr>
<tr>
<td><strong>68. Lima beans, dried</strong></td>
<td>17.4</td>
<td>1,055</td>
<td>3.7</td>
<td>459</td>
<td>5.1</td>
<td>26.9</td>
<td>38.2</td>
<td>93</td>
<td></td>
</tr>
<tr>
<td><strong>69. Navy beans, dried</strong></td>
<td>26.0</td>
<td>1,091</td>
<td>11.4</td>
<td>792</td>
<td>—</td>
<td>38.4</td>
<td>24.6</td>
<td>217</td>
<td></td>
</tr>
</tbody>
</table>

---

1 Commodity numbers refer to Stigler's original list. Starred lines refer to a reduced list explained in § 27.2.
Let the set of items (i) be, in this case, the nine different types of nutrients given in Table 27-1-I. Then the only question remaining with regard to formulation of the mathematical model is whether we want to specify that the requirements are met exactly or can be exceeded. In the first case we are considering a problem of the type

\[(1) \quad \sum_{j=1}^{n} a_{ij}x_j = b_i \quad (x_j \geq 0)\]

and in the second case, we are considering a problem of the type

\[(2) \quad \sum_{j=1}^{n} a_{ij}x_j \geq b_i \quad (x_j \geq 0)\]

where we wish to choose \(x_j\) to minimize the total cost

\[(3) \quad z = \sum_{j=1}^{n} x_j\]

It might seem that asking for exact requirements is better than allowing the possibility of exceeding requirements, since getting more than one really needs should be more costly. This reasoning is fallacious, however, since any set of \(x_j\) which satisfies (1) automatically satisfies (2) and hence the minimal value of \(z\) attained in (2) is certainly no greater than that in (1). In other words, it is always cheaper (or at least no more costly) to permit an excess over requirements than to insist that requirements be met exactly.

Often people criticize a plan because they observe what they believe are "wastes." They note that not everybody is busy all the time, or an installation or machine is idle part of the time. They believe a good plan would find some way to put all these people and machines to work constructively. However, one of the first things one learns in programming is that it is not always efficient to try to remove these "defects." For example, putting idle people to work may require that they have tools and materials at their disposal that are badly needed elsewhere. Referring to the footnote of Table 27-2-I, it is seen for the nutrition problem that insistence on no surplus in nutritives would increase the minimum cost per day from 10.9 cents to 13.8 cents, an increase of over 25 per cent.

We shall formulate the nutrition problem allowing surpluses of all nutrients. There is one risk we take in such a procedure; namely, the solution may be a diet which contains an excess of calories or some other nutrient known to be harmful to health.

First, augment the system by introducing slack variables \(x_{n+1}, \ldots, x_{n+m}\), yielding

\[(4) \quad \sum_{j=1}^{n} a_{ij}x_j - x_{n+i} = b_i \quad (i = 1, 2, \ldots, m)\]

\[(5) \quad \sum_{i=1}^{m} x_i = z \quad (\text{Min})\]
27-2. NUMERICAL SOLUTION OF THE NUTRITION PROBLEM

We now further augment the system by introducing artificial variables \(x_{n+m+1}, \ldots, x_{n+2m+1}\), so that now for \(i = 1, 2, \ldots, m\)

\[
\sum_{j=1}^{n} a_{ij}x_j - x_{n+i} + x_{n+m+i} = b_i
\]

27-2. NUMERICAL SOLUTION OF THE NUTRITION PROBLEM

Solution by Electronic Computer.

The nutrition problem that took 120 man-days to compute in 1948 (using desk computers) can be run in a few minutes on a modern electronic computer. The exact time depends on just how much information one wants to print regarding the problem. In 1953, using an IBM 701 machine, the RAND Simplex Code, and printing out each iteration, the total time was 12 minutes; without printing, the time would have been cut to about one-fourth. If run on a post-1960 computer, the time would be a fraction of a minute.

Since it was desired to compare the minimum cost solutions when exact requirements must be satisfied, § 27-1-(1), and when excesses of requirements are permitted, § 27-1-(2), the instruction code did not allow any slack variable to enter the basic set initially. In 12 iterations Phase I was completed and a basic feasible solution was obtained. On the 18th iteration, Phase II was completed and an optimal feasible solution was obtained for § 27-1-(1). At this point, excess variables were allowed to enter the basic set and an additional 8 iterations were required to obtain an optimal solution for § 27-1-(2). In order to see whether the number of iterations for the latter could be reduced, a second problem was run in which the excess variables were allowed to enter the basic set at any time. By some odd coincidence the same set of 24 iterations took place. See Problem 15 for a possible explanation. The results of these computations are summarized in Table 27-2-I and Fig. 27-2-I.

![Graph](image)

Figure 27-2-I. Decrease in the value of the feasibility and objective forms as a function of iteration in the nutrition problem.

[557]
<table>
<thead>
<tr>
<th>Iteration</th>
<th>Basic Activities</th>
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<th>Objective Form ( z ) (cents)</th>
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Minimized cost \( z \), the best cost solution, without excess nutrients. Minimized cost \( z \), the best cost solution, with excess nutrients.
27.2. NUMERICAL SOLUTION OF THE NUTRITION PROBLEM

Solution by Hand Techniques.

Stigler reduced the list of 77 foods to a list of 15 foods (starred lines in Table 27.1-II) by dropping from the list any food which had, per dollar, no more of each nutrient than did some other food. He effected a further reduction to a list of 9 foods (double starred lines) by dropping any food which had, per dollar, no more of each nutrient than did a mixture of other foods costing a dollar. However, this method can only be used if the nutritional requirements may be exceeded. Where nutritional requirements must be met exactly, this short cut is no longer valid. In Problems 1–5, proofs of these statements are suggested as exercises.

In the final solution for the case where excess nutrients are allowed, nutrients protein, iron, thiamine, and niacin exceeded requirements. With this foreknowledge, it is possible to present here a complete short cut numerical solution of the nutrition problem. To do this, we shall follow Stigler and use the reduced set of 9 foods in place of the 77, and use only 5 of the 9 equations of § 27.1-(2). Equations \( i = 2, 4, 6, 8 \) (corresponding to the excess slack variables for niacin, thiamine, protein, and iron) have been ignored. The complete computations are given in Table 27.2-II.

It is natural to question any procedure which ignores certain of the restrictions in the problem and solves a smaller problem with fewer than the total number of restraints. In certain cases, however, this approach can be made the basis of a very efficient algorithm. Let us suppose that \( k \) equations, each having a slack variable, are ignored in solving a linear programming problem. After solution, the values of the variables of the reduced system may be substituted into these \( k \) equations and the values of the omitted slack variables determined. If, by good luck, the values of these slack variables are positive or zero, then it is easy to see that the solution for the restricted system, together with the solution for the slack variables, constitutes an optimal solution for the entire system.

The nutrition problem requires a slight modification in the setup if the simplex multipliers \( \pi_i \) are to be interpreted as the implicit costs of a calorie, a gram of calcium, etc. The \( c_j \) represent costs in the model but the \( a_{ij} > 0 \) are outputs of the \( i^{th} \) type of nutrient in a unit quantity of the \( j^{th} \) food. It is inconvenient in this instance to follow our sign convention that inputs should be positive and outputs negative. In this case, the prices \( \pi_i \) described in Chapters 9 and 12 will turn out to have the wrong sign.
AN EXAMPLE OF FORMULATION AND SOLUTION

### TABLE

**SIMPLEX SOLUTION TO AN ABBREVIATED CIRCLE**

<table>
<thead>
<tr>
<th>Item</th>
<th>Basic Solution</th>
<th>Wheat Flour (Enriched)</th>
<th>Evaporated Milk</th>
<th>Cheddar Cheese</th>
<th>Beef Liver</th>
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[ 560 ]
### 27.2. NUMERICAL SOLUTION OF THE NUTRITION PROBLEM

#### 27.2-II

**FORM OF STIGLER’S NUTRITION PROBLEM**

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[ 561 ]
AN EXAMPLE OF FORMULATION AND SOLUTION

TABLE 2
SIMPLEX SOLUTION TO AN ABBREVIATION

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<th>Item</th>
<th>Basic Solution</th>
<th>Wheat Flour (Enriched)</th>
<th>Evaporated Milk</th>
<th>Cheddar Cheese</th>
<th>Beef Liver</th>
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### 27.2. NUMERICAL SOLUTION OF THE NUTRITION PROBLEM

#### 2.2-III (contd.)

**Form of Stigler’s Nutrition Problem**

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### AN EXAMPLE OF FORMULATION AND SOLUTION

#### TABLE I

**SIMPLEX SOLUTION TO AN ABBREVIATED PROBLEM**

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[564]
### 27.2. Numerical Solution of the Nutrition Problem

#### Form of Stigler's Nutrition Problem

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[585]
27-3. PROBLEMS

1. Solve the nutrition problem using the revised simplex algorithm.
2. What are the implicit prices of the nutrients? Comment on the sign of the \( \pi_i \).
3. What must the price of evaporated milk drop to before it will affect the solution? What food will drop out of the basis?
4. Assuming all other food costs stable, what must be the relationship between the cost of evaporated milk and the cost of the food being dropped out of the basic set for one or the other to be in the solution.
5. Prove that in a nutrition-type problem where all requirements may be exceeded, that the quantity of any food, \( s \), in an optimal solution can be replaced by purchase of an equal number of dollars of another food \( j \), provided \( a_{ij} \geq a_{is} \) for all \( i \).
6. Prove, more generally, that the purchase of any food, \( s \), in an optimal solution can be replaced, per dollar of expenditure, by the purchase of \( \lambda_1 \) dollars of food 1, \( \lambda_2 \) dollars of food 2, \ldots, \( \lambda_r \) dollars of food \( r \), provided

\[
\begin{align*}
\lambda_1 a_{11} + \lambda_2 a_{12} + \ldots + \lambda_r a_{1r} & \geq a_{is} \quad (i = 1, 2, \ldots, m) \\
\lambda_1 + \lambda_2 + \ldots + \lambda_r & = 1 \\
\lambda_1 & \geq 0, \lambda_2 \geq 0, \ldots, \lambda_r \geq 0
\end{align*}
\]

7. Prove for a general linear programming problem:

\[
\begin{align*}
\sum a_{ij}x_j & \geq b_i \quad (x_j \geq 0; i = 1, 2, \ldots, m) \\
\sum c_jx_j & = z \text{ (Min)}
\end{align*}
\]

that if, by relabeling, for \( k = 1, 2, \ldots, r \) and \( i = 1, 2, \ldots, m \)

\[
\begin{align*}
\lambda_1 a_{k1} + \lambda_2 a_{k2} + \ldots + \lambda_r a_{kr} & \geq a_{is} \\
\lambda_1 c_1 + \lambda_2 c_2 + \ldots + \lambda_r c_r & \leq c_i
\end{align*}
\]

then an optimal feasible solution exists with \( x_s = 0 \).

8. Prove that in a nutrition problem where requirements may be exceeded, at least one requirement must be satisfied exactly in an optimal solution.

9. Prove, as a Corollary to Problem 8, that no \( x_s > 0 \) can occur in an optimal solution if there exists a \( j \) satisfying \( a_{ij} > a_{is} \) for all \( i \) or, more generally, a set \( j = 1, 2, \ldots, r \) (by relabeling) satisfying the relations of Problem 6 with strict inequality.

10. Prove for the general linear programming system § 27-1.(2) with a general linear objective that strict inequalities cannot hold for all \( i \) in an optimal feasible solution when \( \text{Min } z \neq 0 \). Show, by a counter-example, that this theorem need not be true if \( \text{Min } z = 0 \).

11. Construct an example to show that, if requirements are to be met exactly, then it is possible that there exists an optimal solution with
REFERENCES

$x_j > 0$ in spite of the existence of a $j$ satisfying conditions of Problems 5 or 6 above.

12. In solving the nutrition problem, suppose a guess is made as to which slack variables are positive. Suppose the corresponding equations are omitted and an optimal solution is obtained for the resulting system. Suppose finally that substitutions of this optimal solution into the omitted equations yield positive values for their slack variables. Show, by eliminating the basic variables of the restricted system from the omitted equations, that (a) the entire system is reduced to canonical form, (b) the proposed solution to the entire system is a basic solution, and (c) it is an optimal solution.

13. Suppose in Problem 12 that, upon substitution into the omitted equations, one of the corresponding slack variables is negative. Show that one way to eliminate infeasibility is to introduce an artificial variable whose coefficients are the negative of the slack variable, and then proceed to minimize this variable. Generalize this procedure.

14. Show that, by increasing sufficiently the quantity of evaporated milk ($j = 15$), an immediate feasible solution can be obtained for the abbreviated nutrition problems of § 27.2 (see Table 27.2-II).

15. Show by altering the units of a variable that the rule to choose Max $z_j > 0$ will choose any $j$ such that $z_j > 0$. Illustrate in Table 27.2-II how a change in the units of some variable would have altered the course of calculation. Use this to explain why the introduction of slack variables from the start of the computations could give the same sequence of iterations as their introduction after a minimum was reached without allowing slacks.

REFERENCES

Fisher and Schruben, 1963-1
Newman, 1955-1
Smith, V. E., 1959-1
Stigler, 1945-1
Swanson, 1955-2
Waugh, 1951-1
CHAPTER 28

THE ALLOCATION OF AIRCRAFT TO ROUTES UNDER UNCERTAIN DEMAND

28-1. STATEMENT AND FORMULATION

The purpose of this chapter is to illustrate an application of linear programming to the problem of allocating aircraft to routes to maximize expected profits when there is uncertain customer demand. The computational procedure is similar to the fixed demand case with only slightly more computational effort required. After solution of a numerical case we shall compare the allocations with those obtained under the common practice of assuming a fixed demand equal to the expected value. The material for this chapter has been taken, with only minor changes, from the joint papers by Alan Ferguson and the author [Ferguson and Dantzig, 1954-1, 1956-1].

Many business, economic, and military problems have the following characteristics in common: a limited quantity of capital equipment or final product must be allocated among a number of final-use activities, where the level of demand for each of these activities, and hence the payoff, is uncertain; further, once the allocation is made, it is not economically feasible to reallocate because of geographical separation of the activities, or because of differences in form of the final products, or because of a minimum lead time between the decision and its implementation. Examples of such problems are (1) scheduling transport vehicles over a number of routes to meet a demand in some future period and (2) allocating quantities of a commodity at discrete time intervals among several storage or distribution points while the future demand for the commodity is unknown. It is assumed, however, that demand can be forecast or estimated as a distribution of values, each with a specified probability of being the actual value.

The general area where the techniques of this chapter apply may be schematized broadly as problems where

(a) alternative sets of activity levels can be chosen consistent with given resources;
(b) each set of chosen activity levels provides the facilities or stocks to meet an unknown demand whose distribution is assumed known;
(c) profits depend on the costs of the facilities, stocks, and on the revenues from the demand,

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and where the general objective is to determine that set of activity levels that maximizes profits.

Chapter 25, which is based on the paper entitled "Linear Programming under Uncertainty" [Dantzig, 1955-1], forms the theoretical basis for the present chapter. Here we shall illustrate the procedural steps on an example [Ferguson and Dantzig, 1956-1] which, in fact, originally inspired the theoretical work in this area. Thus, little in the way of rigorous theory will be attempted, although each step will be justified intuitively.

The method is explained by the use of a model for routing aircraft. Several types of aircraft are allocated over a number of routes; the monthly demand for service over each route is assumed to be known only as a distribution of probable values. The aircraft are so allocated as to minimize the sum of the cost of performing the transportation, plus the expected value of the revenue lost through the failure to serve all the traffic that actually developed.

For purposes of month-to-month scheduling, an air-transport operator would probably be more willing to make an estimate of the range and general distribution of future travel (or shipment) over his routes than to commit himself to a single expected value. Indeed, he might feel that the optimal assignment should be insensitive to a wide range of demand distribution, and that an assignment based on expected values (as these were known fixed demands) would be misleading. It is suggested that the reader make sensitivity tests by modifying the demand distributions given in the illustrative example to develop this point. Sensitivity analysis is discussed in §12-4.

Passenger demand, of course, occurs on a day-by-day or, in fact, on a flight-by-flight basis. The assumed number of passengers per type aircraft per given type flight may be thought of as an ideal number which can be increased slightly by decreasing the amount of air freight and by "smoothing" the demand by encouraging the customers to take open reservations on alternative flights as opposed to less certain reservations on the desired flight. In spite of these possible adjustments, traveler preferences and the inevitable last-minute cancellations do cause loss of seat-carrying capacity. However, the best way to reflect these effects of the daily variations in demand is beyond the scope of this chapter. For our purpose here, either the aircraft passenger capability or the demand may be thought of as adjusted downward to reflect the loss due to daily variations of demand. Our concern will be in over-all monthly variability.

The method employed is simple, and the example used can be solved by hand in an hour or two. Larger problems can be solved with computing machines.

After we formulate the problem, we will (a) briefly indicate the nature of the solution based on fixed demand [Ferguson and Dantzig, 1954-1], (b) show the method of solving the problem using stochastic values for
demand, and (c) compare the two solutions. Note that the example has been so constructed that the fixed demand is the same as the expected value of the uncertain demand.

A Fixed-demand Example.

The fixed-demand example, used to illustrate the method, assumes a fleet of four types of aircraft, as shown in Table 28-1-I. These aircraft have differences in speeds, ranges, payload capacities, and cost characteristics. The assumed routes and expected traffic loads (the distribution of demand will be discussed later) are shown in Table 28-1-II.

### Table 28-1-I
**Assumed Aircraft Fleet**

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
<th>Number Available</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Postwar 4-engine</td>
<td>10</td>
</tr>
<tr>
<td>B</td>
<td>Postwar 2-engine</td>
<td>19</td>
</tr>
<tr>
<td>C</td>
<td>Prewar 2-engine</td>
<td>25</td>
</tr>
<tr>
<td>D</td>
<td>Prewar 4-engine</td>
<td>15</td>
</tr>
</tbody>
</table>

### Table 28-1-II
**Traffic Load by Route**

<table>
<thead>
<tr>
<th>Route</th>
<th>Route Miles(^1)</th>
<th>Expected Number of Passengers(^1)</th>
<th>Price One-way Ticket ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) N.Y. to L.A. (1-stop)</td>
<td>2,475</td>
<td>25,000</td>
<td>130</td>
</tr>
<tr>
<td>(2) N.Y. to L.A. (2-stop)</td>
<td>2,475</td>
<td>12,000</td>
<td>130</td>
</tr>
<tr>
<td>(3) N.Y. to Dallas (0-stop)</td>
<td>1,381</td>
<td>18,000</td>
<td>70</td>
</tr>
<tr>
<td>(4) N.Y. to Dallas (1-stop)</td>
<td>1,439</td>
<td>9,000</td>
<td>70</td>
</tr>
<tr>
<td>(5) N.Y. to Boston (0-stop)</td>
<td>185</td>
<td>60,000</td>
<td>10</td>
</tr>
</tbody>
</table>

\(^1\) Official Airline Guide, July, 1954, p. 276. The New York-Los Angeles routes are via Chicago and via Chicago-Denver; the stop on route between New York and Dallas is at Memphis.

This is the expected number of full one-way fares per month to be carried on each route. If a passenger gets off on route and is replaced by another passenger, it is counted as one full fare.

Since this chapter proposes to illustrate the applicability of a method of solving problems in which several realistic elements are considered, it is assumed that not all aircraft can carry their full loads on all routes and that the obtainable utilization varies from route to route. Specifically, Type B is assumed to be able to operate at only 75 per cent payload on Route 3, and Type D at 80 per cent on Route 1; Type C cannot fly either Route 1 or Route 3, and Type B cannot fly Route 1. Utilization is defined as the
average number of hours of useful work performed per month by each aircraft assigned to a particular route. Utilization of 300 hours per month is assumed on Routes 1 and 2; 285 on Routes 3 and 4; and 240 on Route 5.

The assumed dollar costs per 100 passenger-miles are shown in Table 28-1-III. These do not include any capital costs such as those of the aircraft.

| Type of Aircraft | Route | Dollar Costs Per 100 Passenger-miles | Dollar Costs Per Passenger Turned Away
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) N.Y.</td>
<td>(2) N.Y.</td>
<td>(3) N.Y.</td>
</tr>
<tr>
<td>1—A</td>
<td>0.45</td>
<td>0.57</td>
<td>0.45</td>
</tr>
<tr>
<td>2—B</td>
<td>—</td>
<td>0.64</td>
<td>0.83</td>
</tr>
<tr>
<td>3—C</td>
<td>—</td>
<td>0.92</td>
<td>—</td>
</tr>
<tr>
<td>4—D</td>
<td>0.74</td>
<td>0.61</td>
<td>0.59</td>
</tr>
</tbody>
</table>

1 Figures shown in parentheses are thousands of dollars lost per 100 passengers turned away. (Throughout this discussion, passengers are measured in units of hundreds.)

and ground facilities; they represent variable costs such as the cost of gasoline, salaries of the crew, and costs of servicing the aircraft.

There is, however, a second kind of "cost." It is the loss of revenue when not enough aircraft are assigned to the route to meet the passenger demand. We shall assume that this loss of revenue is the same as the price of a one-way ticket shown in the E row of Table 28-1-III.

Based on the speeds, ranges, payload capacities, and turn-around times, passenger-carrying capabilities were determined. The resultant potential number \( p_{ij} \) (in hundreds) of passengers that can be flown per month per aircraft of type \( i \) on route \( j \) is shown in Table 28-1-IV, as the upper right figure in each box. By multiplying these numbers by the corresponding costs per 100 passenger-miles given in Table 28-1-III and by the number of miles given in Table 28-1-II, the monthly cost per aircraft can also be obtained. This is given in the lower left figure \( c_{ij} \) in each box; explicitly, \( c_{ij} \) is the cost in thousands of dollars per month per aircraft of type \( i \) assigned to the route \( j \). The revenue losses \( c_{ij} \), in thousands of dollars per 100 passengers not carried, are given in the E row of Table 28-1-IV; finally, we define \( p_{xji} = 1 \). The staggered layout of the table was chosen so as to

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**TABLE 28-1-IV**

**Passenger-Carrying Capabilities and Costs**

<table>
<thead>
<tr>
<th>Type of Aircraft</th>
<th>Route</th>
<th>Per Aircraft Per Month</th>
<th>Per 100 Passengers Not Carried (Losses)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) N.Y. to L.A. 1-stop</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) N.Y. to L.A. 2-stop</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3) N.Y. to Dallas 0-stop</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4) N.Y. to Dallas 1-stop</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5) N.Y. to Boston 0-stop</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1—A</td>
<td></td>
<td>$p_{11} = 16$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>$c_{11} = 18$</td>
<td></td>
</tr>
<tr>
<td>2—B</td>
<td></td>
<td>$p_{22} = 10$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>$c_{22} = 15$</td>
<td></td>
</tr>
<tr>
<td>3—C</td>
<td></td>
<td>$p_{33} = 14$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>$c_{33} = 16$</td>
<td></td>
</tr>
<tr>
<td>4—D</td>
<td></td>
<td>$p_{44} = 22$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>$c_{44} = 17$</td>
<td></td>
</tr>
<tr>
<td>5—E</td>
<td></td>
<td>$p_{55} = 1$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>$c_{55} = 13$</td>
<td></td>
</tr>
</tbody>
</table>

Identify the corresponding data found in Table 28-2-II; the latter is the work sheet upon which the entire problem is solved.

The basic problem is that of determining the number of aircraft of each type to assign to each route consistent with aircraft availabilities, and of determining how much revenue will be lost due to failure of allocated aircraft to meet passenger demand on various routes. Since many alternative allocations are possible, our specific objective will be to find that allocation that minimizes total costs, where costs are defined as operating costs plus lost revenues based on the cost factors given in Table 28-1-III.

This may be formulated mathematically as a linear programming problem. Let $x_{ij}$ denote the unknown quantity of the $i$th type aircraft assigned to $j$th route, where $i = 1, 2, \ldots, m - 1$ and $j = 1, 2, \ldots, n - 1$. If $x_{ia}$ denotes the surplus or unallocated aircraft, then (1) states that the sum of allocated and unallocated aircraft of each type accounts for the total available aircraft $a_i$. If $x_{aj}$ denotes the number of passengers in hundreds turned away, then equation (2) states that the sum of passenger carrying capability of each type aircraft allocated to the $j$th route, $p_{ij}x_{ij}$, plus the unsatisfied demand accounts for the total demand, $d_j$. Relation (3) states
that all unknown quantities $x_{ij}$ must be either positive or zero. Finally, if $z$
 is total cost, it is the sum of all the individual operating costs of each
allocation, $c_{ij}x_{ij}$, plus the revenues lost by unsatisfied demands $c_{mj}x_{mj}$ (see
equation (4)).

<table>
<thead>
<tr>
<th>Fixed-demand Model</th>
</tr>
</thead>
</table>
| Find numbers $x_{ij}$, and the minimum value of $z$ such that for $i = 1, 2,$
| \ldots , m; $j = 1, 2, \ldots , n$: |
| (1) Row Sums: $x_{i1} + x_{i2} + \ldots + x_{in} = a_i$ ($i \ne m$) |
| (2) Col. Sums: $p_{1i}x_{1i} + p_{2i}x_{2i} + \ldots + p_{mi}x_{mi} = d_i$ |
| (3) $x_{ij} \ge 0$ |
| (4) $\sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij}x_{ij} = z$ |

The optimal assignment of aircraft to routes based on fixed demand is
a \textit{weighted distribution problem}. The numerical solution shown in Table
28-2-II was obtained using the methods of Chapter 21. The values assigned
to the unknowns $x_{ij}$ appear boldfaced in the upper left of each box unless
$x_{ij} = 0$ in which case it is omitted; the entire layout takes the form:

$\begin{array}{c}
x_{ij} \\
p_{ij} \\
c_{ij}
\end{array}$

The sums by rows of $x_{ij}$ entries in Table 28-2-II equated to availabilities
yield equations (1). The sums by columns of $x_{ij}$ weighted by corresponding
values of $p_{ij}$ equated to demands yield equations (2); the $x_{ij}$ weighted by
corresponding $c_{ij}$ and summed over the entire table yields (4). As noted
earlier, Table 28-2-II is actually the work sheet upon which the entire
problem is solved. Later we shall discuss a revision of this work sheet for
solving problems with variable demand. All figures in the table, except for
the upper left entries, $x_{ij}$ and values of the so-called "implicit prices" $u_i$ and
$v_j$, shown in the margins, are constants which do not change during the
course of computation. The values of the variables $x_{ij}$, $u_i$, and $v_j$, however,
will change during the course of successive iterations of the simplex method
as adapted for this problem. For this reason it is customary to cover the
work sheet with clear acetate and to enter the variable information with a
grease pencil which can be easily erased; alternatively, a blackboard or
semi-transparent tissue paper overlays can be used. The detailed rules for
obtaining the optimal solution shown are given in Chapter 21 and will not
ALLOCATION OF AIRCRAFT UNDER UNCERTAIN DEMAND

be repeated here. Instead a more general set of rules for the uncertain demand case will be given which, of course, could be used for the expected demand case.

In Table 28-1-V we have a convenient summary serving to identify and define the numerical data entered in Table 28-2-II and to give the test for optimality.

TABLE 28-1-V
SUMMARY OF NOTATION AND RULES FOR FIXED-DEMAND CASE
(as displayed in Table 28-2-II)

Indices:

- \( i = 1, 2, \ldots, m - 1 \) refers to type of aircraft to which passengers are assigned
- \( i = m \) if passengers are unassigned
- \( j = 1, 2, \ldots, n - 1 \) refers to type of route to which an aircraft is assigned
- \( j = n \) if aircraft is unassigned (surplus)

Constants:

- \( a_i \) = number of available aircraft of type \( i \)
- \( d_j \) = expected passenger demand in 100's per month, on route \( j \)
- \( p_{ij} \) = passenger-carrying capability in 100's per month per aircraft of type \( i \) assigned to route \( j \) (Definition)
- \( c_{ij} \) = costs in 1000's of dollars per month per aircraft of type \( i \) assigned to route \( j \) (\( c_{mj} \) is cost per 100 passengers turned away)

\( x_{ij} \) Entries:

- \( x_{ij} \) = number of aircraft of type \( i \) assigned to route \( j \)
- \( x_{mj} \) is 100's of passengers turned away

Omitted \( x_{ij} \) Entries: \( x_{ij} = 0 \) if upper left entry in box is missing

Implicit Prices:

- \( u_i \) and \( v_j \) are determined such that \( u_i + p_{ij}v_j = c_{ij} \) for \( (i, j) \) boxes corresponding to \( x_{ij} > 0 \), i.e., non-omitted \( x_{ij} \) entries \( (u_m = v_n = 0 \) by definition)

Test for Optimality: Solution is optimal if, for all \( (i, j) \), the relation \( u_i + p_{ij}v_j \leq c_{ij} \) holds

Extension of the Example to Uncertain Demand.

To introduce the element of uncertain demand, we assume not a known fixed demand on each route but a known frequency distribution of demand. The assumed frequency distributions are shown in Table 28-1-V1. Thus on Route 2 (N.Y. to L.A., 2-stop) either 5,000 or 15,000 passengers will want transportation during the month, with probabilities 30 or 70 per cent respectively. The assumed traffic distributions are, of course, hypothetical to illustrate our method. The demand distributions on the five routes vary over wide ranges and have different characteristics; Route 1 is flat, Route 2 is U-shaped, Routes 3, 4, and 5 are unimodular but have differing degrees of concentration about the mode. Route 4 has a distribution with a very long tail that may reflect a realistic traffic situation.
28.1. **STATEMENT AND FORMULATION**

To illustrate the essential character of the linear programming problem for the case of uncertain demand, let us focus our attention on a single route—say, Route 1—with probability distribution of demand as given in Table 28.1-VI. Let us suppose that aircraft assigned to Route 1 are capable

<table>
<thead>
<tr>
<th>Route</th>
<th>Passenger Demand (in hundreds)</th>
<th>Approx. Mean (in hundreds)</th>
<th>Probability of Passenger Demand</th>
<th>Probability of Equaling or Exceeding Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>200 = d_{11}</td>
<td>250</td>
<td>0.2 = \lambda_{11}</td>
<td>1.0 = \gamma_{11}</td>
</tr>
<tr>
<td></td>
<td>220 = d_{12}</td>
<td></td>
<td>0.05 = \lambda_{12}</td>
<td>0.8 = \gamma_{12}</td>
</tr>
<tr>
<td></td>
<td>250 = d_{13}</td>
<td></td>
<td>0.35 = \lambda_{13}</td>
<td>0.75 = \gamma_{13}</td>
</tr>
<tr>
<td></td>
<td>270 = d_{14}</td>
<td></td>
<td>0.2 = \lambda_{14}</td>
<td>0.4 = \gamma_{14}</td>
</tr>
<tr>
<td></td>
<td>300 = d_{15}</td>
<td></td>
<td>0.2 = \lambda_{15}</td>
<td>0.2 = \gamma_{15}</td>
</tr>
<tr>
<td>(2)</td>
<td>50 = d_{21}</td>
<td>120</td>
<td>0.3 = \lambda_{21}</td>
<td>1.0 = \gamma_{21}</td>
</tr>
<tr>
<td></td>
<td>150 = d_{22}</td>
<td></td>
<td>0.7 = \lambda_{22}</td>
<td>0.7 = \gamma_{22}</td>
</tr>
<tr>
<td>(3)</td>
<td>140 = d_{31}</td>
<td>180</td>
<td>0.1 = \lambda_{31}</td>
<td>1.0 = \gamma_{31}</td>
</tr>
<tr>
<td></td>
<td>160 = d_{32}</td>
<td></td>
<td>0.2 = \lambda_{32}</td>
<td>0.9 = \gamma_{32}</td>
</tr>
<tr>
<td></td>
<td>180 = d_{33}</td>
<td></td>
<td>0.4 = \lambda_{33}</td>
<td>0.7 = \gamma_{33}</td>
</tr>
<tr>
<td></td>
<td>200 = d_{34}</td>
<td></td>
<td>0.2 = \lambda_{34}</td>
<td>0.3 = \gamma_{34}</td>
</tr>
<tr>
<td></td>
<td>220 = d_{35}</td>
<td></td>
<td>0.1 = \lambda_{35}</td>
<td>0.1 = \gamma_{35}</td>
</tr>
<tr>
<td>(4)</td>
<td>10 = d_{41}</td>
<td>90</td>
<td>0.2 = \lambda_{41}</td>
<td>1.0 = \gamma_{41}</td>
</tr>
<tr>
<td></td>
<td>50 = d_{42}</td>
<td></td>
<td>0.2 = \lambda_{42}</td>
<td>0.8 = \gamma_{42}</td>
</tr>
<tr>
<td></td>
<td>80 = d_{43}</td>
<td></td>
<td>0.3 = \lambda_{43}</td>
<td>0.6 = \gamma_{43}</td>
</tr>
<tr>
<td></td>
<td>100 = d_{44}</td>
<td></td>
<td>0.2 = \lambda_{44}</td>
<td>0.3 = \gamma_{44}</td>
</tr>
<tr>
<td></td>
<td>540 = d_{45}</td>
<td></td>
<td>0.1 = \lambda_{45}</td>
<td>0.1 = \gamma_{45}</td>
</tr>
<tr>
<td>(5)</td>
<td>580 = d_{51}</td>
<td>600</td>
<td>0.1 = \lambda_{51}</td>
<td>1.0 = \gamma_{51}</td>
</tr>
<tr>
<td></td>
<td>600 = d_{52}</td>
<td></td>
<td>0.8 = \lambda_{52}</td>
<td>0.9 = \gamma_{52}</td>
</tr>
<tr>
<td></td>
<td>620 = d_{53}</td>
<td></td>
<td>0.1 = \lambda_{53}</td>
<td>0.1 = \gamma_{53}</td>
</tr>
</tbody>
</table>

of taking 100\textit{X}_i passengers where \textit{X}_i is to be determined. Up to 200 units (in hundreds of passengers) of this capability are certain to be used, and revenues from this source (negative costs) will be 13 = k_1 units (in thousands of dollars) per unit of capability. If 100\textit{X}_1 \geq 200, up to an additional 20 units of this capability will be used with probability \gamma_{21} = 0.8. Indeed, 80 per cent of the time the demand will be 220 units or greater, while 20 per cent of the time it will be 200 units; hence, the expected revenue per unit from this increment of capability is 0.8 \times 13 = 10.4, or 10.4 = k_1\gamma_{21} units. On the third increment of 30 units (22,001 to 25,000 seats), the expected revenue is 0.75 \times 13 = 9.8 or k_1\gamma_{31}, units per unit of capability since there is a 25 per cent chance that none of these units of capability will be used and 75 per cent that all will be used. For the fourth increment of 20 units (25,001 to 27,000 seats) of capability, the expected revenue is 0.4 \times 13 = 5.2 or k_1\gamma_{41} units per unit of capability, while for the fifth increment of 30
units (27,001 to 30,000 seats) it is \(0.2 \times 13 = 2.6\) or \(k_1y_{31}\) units per unit. For the sixth increment, which is the number of units assigned above the 30,000 seat mark, the expected revenue is \(0.0 \times 13 = 0\) per unit, since it is certain that none of these units of capability can be used. It is clear that no assignments above 30,000 seats are worthwhile, and hence the last increment can be omitted. The index \(k = 1, 2, 3, 4, 5\) will be used to denote the \(1^{st}, 2^{nd}, \ldots, 5^{th}\) increment of demand.

The number of assigned units in each increment, however, can be viewed as an unknown that depends on the total (passenger-carrying) capability assigned to route \(j = 1\). Thus, if the total assigned is \(Y_1 = 210\) units of capability, then the part of this total belonging to the first increment, denoted by \(y_{11}\), is \(y_{11} = 200\) and the part belonging to the second increment, denoted by \(y_{21}\), is \(y_{21} = 10\). The amounts in the higher increments are \(y_{3i} = 0\) for \(i = 3, 4, 5\). To review, the passenger-carrying capability \(Y_j\) is determined by the number of aircraft assigned to route \(j\), so that

\[
Y_j = p_{1j}x_{1j} + p_{2j}x_{2j} + p_{3j}x_{3j} + p_{4j}x_{4j} + p_{5j}x_{5j}
\]

On the other hand, \(Y_j\) itself breaks down into five increments

\[
Y_j = y_{1j} + y_{2j} + y_{3j} + y_{4j} + y_{5j}
\]

for routes \(j = 1, 3, 4\), and correspondingly fewer for \(j = 2, 5\). Regardless of the total \(Y_j\), the amount \(y_{3j}\) belonging to each increment is bounded by the total size \(b_{3j}\) of that increment; the latter, however, is simply the change in demand level, so that

\[
0 \leq y_{1j} \leq d_{1j} = b_{1j}
\]

\[
0 \leq y_{2j} \leq d_{2j} - d_{1j} = b_{2j}
\]

\[
0 \leq y_{3j} \leq d_{3j} - d_{2j} = b_{3j}
\]

\[
0 \leq y_{4j} \leq d_{4j} - d_{3j} = b_{4j}
\]

\[
0 \leq y_{5j} \leq d_{5j} - d_{4j} = b_{5j}
\]

Letting

\[
\lambda_{3j} = \text{probability of demand } d_{3j},
\]

the total expected revenue from route \(j\) is, therefore,

\[
k_j(y_{3j}y_{3j} + y_{3j}y_{3j} + \cdots + y_{3j}y_{3j})
\]

where \(k_j\) is revenue (in thousands) per 100 passengers carried on route \(j\) and, as seen in Table 28-1.VI, the probability, \(\gamma_{3j}\), of exceeding or equaling demand \(d_{3j}\) is related to \(\lambda_{3j}\), the probability of demand \(d_{3j}\), by

\[
1 = \gamma_{3j} = \lambda_{3j} + \lambda_{3j} + \lambda_{3j} + \lambda_{3j} + \lambda_{3j}
\]

\[
\gamma_{3j} = \lambda_{3j} + \lambda_{3j} + \lambda_{3j}
\]

\[
\gamma_{4j} = \lambda_{3j} + \lambda_{3j}
\]

\[
\gamma_{5j} = \lambda_{3j}
\]
28.1. STATEMENT AND FORMULATION

The numerical values of \( \lambda_{ik} \) and \( \gamma_{ik} \) are given in Table 28-1-VI. Applying (9), the total expected revenues for Route 1 are

\[
13(1.0y_{11} + .8y_{21} + .75y_{31} + .4y_{41} + .2y_{51})
\]

The most important fact to note about this linear form is the decrease in the successive values of the coefficients \( \gamma_{ik} \). Moreover, this will always be the case whatever the distribution of demand, since the probability of equating or exceeding a given demand level \( d_{ik} \) decreases with increasing values of demand.

Suppose now that \( y_{11}, y_{21}, \ldots \), are treated as unknown variables in a linear programming problem subject only to (6) and (7) where the objective is to maximize revenues. Let us suppose further that \( Y_1 \) is fixed. It is clear, since the coefficient of \( y_{11} \) is largest in the maximizing form (9), \( y_{11} \) will be chosen first and made as large as possible consistent with (6) and (7); for the chosen value \( y_{11} \), the next increment \( y_{21} \) will be chosen as large as possible consistent with (6) and (7), etc.; as a result, when the maximum is reached, the values of the variables \( y_{11}, y_{21}, \ldots \), are precisely the incremental values associated with \( Y_1 \), which we discussed earlier, (6). Even if passenger capability \( Y_1 \) is not fixed, as in the case about to be considered, it should be noted that whatever the value of \( Y_1 \), the values of \( y_{11}, y_{21}, \ldots \), which minimize an over-all cost form such as in (14) below, must maximize (9) for \( j = 1 \) and hence the incremental values of \( Y_1 \) will be generated by \( y_{11}, y_{21}, \ldots \).

The linear programming problem in the case of uncertain demand is shown by (11), (12), (13), and (14).

<table>
<thead>
<tr>
<th>Uncertain Demand Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Find numbers ( x_{ij} ) and ( y_{ij} ) and the minimum value of ( z ) such that for ( i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; h = 1, 2, \ldots, r ):</td>
</tr>
<tr>
<td>(11) Row Sums: ( x_{1i} + x_{2i} + \ldots + x_{ni} = a_i ) ( (i \neq m) )</td>
</tr>
<tr>
<td>(12) Column Sums: ( p_{1j}x_{1j} + p_{2j}x_{2j} + \ldots + p_{nj}x_{nj} = y_{1j} + y_{2j} + \ldots + y_{rj} ) ( (j \neq n) )</td>
</tr>
<tr>
<td>(13) Expected Costs: ( z = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij}x_{ij} + R_0 - \sum_{j=1}^{n} \sum_{h=1}^{r} \gamma_{ih}y_{ij} )</td>
</tr>
<tr>
<td>(14) Expected Costs: ( 0 \leq y_{ij} \leq b_{ij} )</td>
</tr>
</tbody>
</table>

Thus expected costs are defined as the total outlays (first term) plus the expected loss of revenue due to shortage of seats (last two terms), where \( R_0 \), a constant, is the expected revenue if sufficient seats were supplied for all customers.

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**Allocation of Aircraft Under Uncertain Demand**

For the problem at hand, the bounds, $b_{hi}$, and the expected revenues, $k_{ij}y_{hi}$, per unit for the "incremental variables" $y_{hi}$ can be computed from probability distributions Table 28-1-VI via (7) and (10).

The numerical values of the constants for the stochastic case are tabulated in Table 28-1-VII.

**Table 28-1-VII**

<table>
<thead>
<tr>
<th>Increment</th>
<th>Route 1</th>
<th>Route 2</th>
<th>Route 3</th>
<th>Route 4</th>
<th>Route 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h$</td>
<td>$b_{h1}$</td>
<td>$k_{i'y_{h1}}$</td>
<td>$b_{i'3}$</td>
<td>$k_{i'y_{h3}}$</td>
<td>$b_{i'4}$</td>
</tr>
<tr>
<td>1</td>
<td>200</td>
<td>$k_1 = 13$</td>
<td>50</td>
<td>$k_2 = 13$</td>
<td>140</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>$0.8k_1 = 10.4$</td>
<td>100</td>
<td>$0.7k_2 = 9.1$</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>30</td>
<td>$0.75k_1 = 9.8$</td>
<td>**</td>
<td>**</td>
<td>20</td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>$0.5k_1 = 15.2$</td>
<td>**</td>
<td>**</td>
<td>20</td>
</tr>
<tr>
<td>5</td>
<td>30</td>
<td>$0.2k_1 = 2.6$</td>
<td>**</td>
<td>**</td>
<td>20</td>
</tr>
</tbody>
</table>

**Rules for Computation.**

The worksheet for determining the optimal assignment under uncertain demand is shown in Table 28-2-III.

The entries in the $x_{ij}$ boxes and $y_{hi}$ boxes take the form:

\[
\begin{array}{ccc}
    x_{ij} & p_{ij} & y_{hi} \\
    c_{ij} & -1 & -k_{ij}y_{hi}
\end{array}
\]

To form the new row equations (11), the $x_{ij}$ entries are summed to yield the $a_i$ values given in the aircraft-available column. To form the column equations (12), the $x_{ij}$ entries are multiplied by $p_{ij}$, the $y_{hi}$ by $-1$, and summed down to yield zero.

**Step 1.** To initiate the computation any set of nonnegative values may be assigned to the unknown $x_{ij}$ and $y_{hi}$, provided they satisfy the equations and thereby constitute a feasible solution.

**Step 2.** Put a box around any $(m + n - 2)$ of $x_{ij}$ and $y_{hi}$ entries where $m + n$ is the number of row plus column equations. These boxed entries can be arbitrarily selected except that they must have the property that if the fixed values assigned to the other non-boxed variables and the constant
terms were arbitrarily changed to other values, then the boxed variables would be determined uniquely in terms of the latter. Such a boxed set of variables constitutes, of course, a basic set of variables; the array of coefficients associated with this set in the equations (11) and (12) forms a basis (Chapter 8).

Note: One simple way of selecting a basic set is shown in Table 28-2-IV. One $x_{ij}$ entry is arbitrarily selected and boxed in each row corresponding to a row equation (it is suggested that entries be boxed that appear to have a chance of having a positive value in an optimum solution). Next, each $y_{hj}$, in turn, $h = 1, 2, \ldots$, in a column is assigned its upper bound value $b_j$ until for some $h = h_0$ the column “net” goes negative, in which case a value $y_{hj} < b_j$ for $h = h_0$ is assigned so that the net is zero; the $(h_0,j)$ entry is then boxed.

Step 3. For $(i, j)$ and $(h, j)$ combinations corresponding to basic entries, compute implicit prices $u_i$ and $v_j$ associated with equations by determining values of $u_i$ and $v_j$ satisfying the equations

\begin{align}
(15) \quad & u_i + p_{ij}v_j = c_{ij} \quad \text{ (for } x_{ij} \text{ basic)} \\
(16) \quad & 0 + (-1)v_j = -k_i\gamma_{hj} \quad \text{ (for } y_{hj} \text{ basic)}
\end{align}

There are always $m + n - 2$ equations (15) and (16) in $m + n - 2$ unknowns $u_i$ and $v_j$ that can be shown easily to have a unique solution (see § 21-1). They can be solved by inspection, for it can be shown that the system is either completely triangular or, at worst, contains subsystems, some triangular and some triangular if one unknown is specified.\(^5\)

Step 4. Compute for all $(i, j)$ and $(h, j)$

\begin{align}
(17) \quad & \xi_{ij} = +c_{ij} - (u_i + p_{ij}v_j) \\
(18) \quad & \xi'_{hj} = +(-k_i\gamma_{hj}) - (0 - v_j)
\end{align}

It has been shown in § 5-2 that, if the $x_{ij}$ or $y_{hj}$ value associated with some non-basic entry is changed to

\begin{align}
(19) \quad & x_{ij} \pm \theta \quad \text{ or } y_{hj} \pm \theta \quad (\theta \geq 0)
\end{align}

the other non-basic variables remaining fixed, and the basic variables adjusted, then the expected costs $z$ will change to $z'$ where

\begin{align}
(20) \quad & z' = z \pm \theta \xi_{ij} \quad \text{ or } z' = z \pm \theta \xi'_{hj}
\end{align}

Assuming, for generality, that $x_{ij}$ may also be a bounded variable, it pays to increase $x_{ij}$ or $y_{hj}$ if $\xi_{ij}$ or $\xi'_{hj} < 0$, if either is at its upper bound, in which case no increase is allowed; also it pays to decrease $x_{ij}$ or $y_{hj}$ if $\xi_{ij}$ or $\xi'_{hj} > 0$, unless $x_{ij} = 0$ or $y_{hj} = 0$, in which case no decrease is allowed.

\(^5\) This is the analogue for the weighted distribution problem (11), (12), (13), (14) of the well-known theorem for the standard transportation problem that all bases are triangular. Its proof is similar. See Chapters 14 and 21.
ALLOCATION OF AIRCRAFT UNDER UNCERTAIN DEMAND

Test for Optimality.

According to the theory of the simplex method with bounded variables (see Chapter 18), if the non-basic variables satisfy the following conditions:

(a) they are all at either their upper or lower bounds,
(b) their corresponding \( \ell_{ij} \) and \( \ell'_{ij} \geq 0 \), if they are at their lower bound, and
(c) their corresponding \( \ell_{ij} \) and \( \ell'_{ij} \leq 0 \) if they are at their upper bound,

then the solution is optimal and the algorithm terminates. Otherwise there are \( \ell_{ij} \) or \( \ell'_{ij} \) for which (b) or (c) does not hold. In which case an increase or decrease (depending on whether the sign is negative or positive) in the corresponding variable is allowed; we will call these \( (i, j) \) or \( (h, j) \) combinations out-of-kilter; let the largest \( \ell_{ij} \) or \( \ell'_{ij} \) among them in absolute value be denoted by \( \ell_{rs} \) or \( \ell'_{rs} \).

Step 5. Leaving all non-basic entries fixed except for the value of the variable corresponding to the \((r, s)\) determined in Step 4, modify the value of \( x_{rs} \) (or \( y_{rs} \)), if not at its upper bound, to

\[
(21) \quad x_{rs} + \theta \text{ (or } y_{rs} + \theta) \text{ if } \ell_{rs} < 0 \text{ (or } \ell'_{rs} < 0)
\]

or, if not at its lower bound, to

\[
(22) \quad x_{rs} - \theta \text{ (or } y_{rs} - \theta) \text{ if } \ell_{rs} > 0 \text{ (or } \ell'_{rs} > 0)
\]

where \( \theta \geq 0 \) is unknown for the moment, and recompute the values of the basic variables as linear functions of \( \theta \). Choose the value of \( \theta = \theta^* \) at the largest value possible consistent with keeping all basic variables (whose values now depend on \( \theta \)) between their upper and lower bounds; in the next cycle correct the values of the basic variables on the assumption \( \theta = \theta^* \).

Also, if at the value \( \theta = \theta^* \) one (or more) of the basic variables attains its upper or lower bound, in the next cycle drop any one of these variables (never drop more than one) from the basic set and box the variable \( x_{rs} \) instead. Should it happen that \( x_{rs} \) or \( y_{rs} \) attains its upper or lower bound at \( \theta = \theta^* \), the set of basic variables is the same as before; their values, however, are changed to allow \( x_{rs} \) or \( y_{rs} \) to be fixed at its new bound.

Start the next cycle of the iterative procedure by returning to Step 3.

28-2. NUMERICAL SOLUTION OF THE ROUTING PROBLEM

For our starting solution in Table 28-2-IV, cycle 0, we used for values of \( x_{ij} \) the best solution assuming fixed demands equal to the expected values of the distribution\(^3\) shown in Table 28-2-II. These \( x_{ij} \) will meet the expected
28.2. NUMERICAL SOLUTION OF THE ROUTING PROBLEM

demands so that \( Y_j = d_j \), except for Route 5 where there is a deficit of 100
and \( Y_5 = 500 \) (see § 28-1-25)). These \( Y_j \) are broken down into the incremental
values shown below the double line in Table 28-2-IV, cycle 0.

Next, one of the variables in each row is boxed. The selected variables
are \( x_{11}, x_{22}, x_{33}, x_{44} \); each appears likely to be in an optimal solution; however,
\( x_{43} \) has been boxed rather than \( x_{41} \), which may be a better choice. Next, the
last positive entry in each column is boxed, i.e., the variables \( y_{31}, y_{22}, y_{33},
y_{44}, y_{15} \). In all there are \( m + n - 2 = 9 \) boxed variables. The implicit values,
\( u_i \) and \( v_j \), shown in the table are determined by solving the nine equations:

\[
\begin{align*}
& u_1 + p_{11} v_1 = c_{11} & (p_{11} = 16; c_{11} = 18) \\
& u_2 + p_{22} v_2 = c_{22} & (p_{22} = 10; c_{22} = 15) \\
& u_3 + p_{33} v_3 = c_{33} & (p_{33} = 29; c_{33} = 6) \\
& u_4 + p_{44} v_4 = c_{44} & (p_{44} = 22; c_{44} = 17) \\
& 0 + (-1)v_1 = -k_1 y_{31} & (k_1 y_{31} = 9.8) \\
& 0 + (-1)v_2 = -k_2 y_{22} & (k_2 y_{22} = 9.1) \\
& 0 + (-1)v_3 = -k_3 y_{33} & (k_3 y_{33} = 4.9) \\
& 0 + (-1)v_4 = -k_4 y_{44} & (k_4 y_{44} = 2.1) \\
& 0 + (-1)v_5 = -k_5 y_{15} & (k_5 y_{15} = 1.0)
\end{align*}
\]

This permits the computation of \( \xi_{ij} \) and \( \xi^*_i \) (see § 28-1-25). As a check,
\( \xi_{ij} = 0 \) and \( \xi^*_i = 0 \) for \((i, j)\) corresponding to basic variables. The
\( \xi_{ij} \) or \( \xi^*_i \) of largest absolute value for those \((i, j)\) or \((h, j)\) that are out-of-kilter is

\[ \xi_{44} = 14 - [-76 + 15(2.1)] = +58.5 \]

Hence a decrease in the variable \( x_{44} \) with adjustments of the basic variables
will result in a decrease in the expected costs by an amount of 58.5 units
per unit decrease in \( x_{44} \). If \( x_{44} = 6 \) is changed to \( x_{44} = 6 - \theta \), then, in order
to satisfy the column 4 equation, the basic variable \( y_{44} = 10 \) must be
modified to \( y_{44} = 10 - 16\theta \) (all other variables in column 4 are fixed).
Also, to satisfy the row equation 2, \( x_{22} = 8 \) must be modified to
\( x_{22} = 8 + \theta \); this in turn causes \( y_{22} = 70 \) to be changed to \( y_{22} = 70 + 10\theta \n\)
in order to satisfy column equation 2. The largest value of \( \theta \) is \( \theta^* = \frac{18}{5} \)
at which value \( y_{44} = 0 \).

The numerical values of the variables appearing in Table 28-2-IV, cycle
1, are obtained from those of Table 28-2-IV, cycle 0, by setting \( \theta = \theta^* = \frac{18}{5} \).
The variable \( x_{44} \) becomes a new basic variable in place of \( y_{44} \) which hits its
lower bound, zero. Computing the new set of implicit prices the largest \( \xi_{ij} \)
in absolute value which can increase or decrease according to sign of \( \xi_{ij} \), is
\[ \xi_{23} = -23.4 \]. Changing \( x_{23} \) to \( 5 - \theta \) requires that the variables \( x_{23}, y_{23}, y_{33} \)
be modified as shown, Table 28-2-IV, cycle 1. The maximum value of \( \theta \) is
\( \theta = \theta^* = \frac{18}{5} \) at which value \( y_{33} = 0 \). The new solution in which \( x_{23} \) replaces
\( y_{33} \) as a basic variable is given in Table 28-2-IV, cycle 2. In Table 28-2-IV,
ALLOCATION OF AIRCRAFT UNDER UNCERTAIN DEMAND

cycle 2, the decrease in non-boxed variable \( x_{41} \) causes changes in the variables \( x_{43}, x_{52}, x_{53}, y_{51}, y_{22} \). The largest value of \( \theta = \frac{1}{10^5} \), at which value \( y_{22} \) hits its upper bound \( \delta_{22} = 100 \).

In the passage from Table 28.2-IV, cycle 3, to Table 28.2-IV, cycle 4, we have become a little fancy and have taken a "double" step. The maximum increase is \( \theta = \frac{1}{10^5} \) at which point \( y_{13} \) hits its upper bound \( b_{13} = 580 \). It is easy to see that if next the incremental variable \( y_{33} \) is increased, \( \epsilon_{32} \) associated with \( x_{21} \) should be changed to \( \epsilon_{32} = 29(y_{15} - y_{33})/\epsilon_4 = +4.5 - 29(1.0 - .9) = +1.6 \); therefore, it is economical to increase \( y_{33} \) as well as \( y_{15} \). However, it can be shown that signs of \( \epsilon_{32} \) would become negative if the next increment, \( y_{35} \), were considered. The maximum value of \( \theta = \theta^* = \frac{1}{10^5} \).

It will be noted that in the passage from cycle 4 to cycle 5 of Table 28.2-IV, the variable \( y_{33} \) is again brought into solution after having been dropped earlier. The maximum value of \( \theta \) is \( \frac{1}{10^5} \) at which value \( y_{33} \) reaches its upper bound, so that the solution, Table 28.2-IV, cycle 5, has the same set of basic variables and hence the same implicit values as Table 28.2-IV, cycle 4. Moreover, the solution is optimal since all non-basic variables are either at their upper or lower bounds; those at upper bounds have corresponding \( \epsilon_{ij} \leq 0 \) and those at lower bounds have \( \epsilon_{ij} \geq 0 \).

In comparing this solution (Table 28.2-IV, cycle 5) with the optimal solution for the fixed-demand case (Table 28.2-II), it is interesting to note that the chief difference appears to be a general tendency to shift the total seats made available on a route to the mode of the distribution rather than to the mean of the distribution for those distributions with sharp peaks. The total seats made available to routes with flat distributions of demand appear to be at highest level attainable with the residual passenger-carrying potential.

### TABLE 28.2-I

<table>
<thead>
<tr>
<th>(Refer to Table 28.2-IV)</th>
<th>Expected Revenues for Seats Supplied (1)</th>
<th>Expected Lost Revenues¹ (2)</th>
<th>Operating Costs (3)</th>
<th>Net Expected Cost (Thousands) (2) + (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cycle 0</td>
<td>-6,534</td>
<td>786</td>
<td>900</td>
<td>1,866</td>
</tr>
<tr>
<td>Cycle 1</td>
<td>-6,574</td>
<td>726</td>
<td>901</td>
<td>1,627</td>
</tr>
<tr>
<td>Cycle 2</td>
<td>-6,607</td>
<td>693</td>
<td>901</td>
<td>1,594</td>
</tr>
<tr>
<td>Cycle 3</td>
<td>-6,633</td>
<td>662</td>
<td>899</td>
<td>1,661</td>
</tr>
<tr>
<td>Cycle 4</td>
<td>-6,641</td>
<td>659</td>
<td>883</td>
<td>1,542</td>
</tr>
<tr>
<td>Cycle 5</td>
<td>-6,659</td>
<td>641</td>
<td>883</td>
<td>1,524</td>
</tr>
</tbody>
</table>

¹ Data in column (2) are obtained by subtracting the expected revenues for seats supplied, column (1), from \( R_e = 7,300 \), the expected revenues if an unlimited number of seats were supplied.
28-2. NUMERICAL SOLUTION OF THE ROUTING PROBLEM

To compute the expected costs of the various solutions the first step (see § 28-1-(14)), is to determine what the expected revenues $R_0$ would be if sufficient seating capacity were furnished at all times to supply all passengers that show up. Referring to Table 28-1-II, it is easy to see that $R_0 = 13(250 + 13(150) + 13(120) + 7(180) + 7(90) + 1(600)) = 7,300$ or $7,300,000$.

It is seen that the solution presented in Table 28-2-II (the same as the starting solution, Table 28-2-IV, cycle 0, which assumes demands to be exactly equal to the expected values of demand) has a net expected cost of $1,666,000$. (It is interesting to note that if the demands were not variable, but were fixed and equal to expected demands, the costs would only be $1,000,000$ (see Table 28-2-II). The 67 per cent increase in net cost for the variable demand case is due to 13,400 additional passengers (on the average) being turned away because of the distributions of demand assumed.\(^4\)

### TABLE 28-2-II

**Optimal Assignment for Fixed Demand**

Operating Costs and Lost Revenues = $1,000,000

<table>
<thead>
<tr>
<th>Type of Aircraft</th>
<th>Route</th>
<th>Aircraft Available</th>
<th>Implicit Prices $u_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) N.Y. to L.A. 1-stop</td>
<td>(2) N.Y. to L.A. 2-stop</td>
<td>(3) N.Y. to Dallas 0-stop</td>
</tr>
<tr>
<td></td>
<td>(1) A</td>
<td>(2) B</td>
<td>(3) C</td>
</tr>
<tr>
<td>(10) 16</td>
<td>18 15</td>
<td>28 16</td>
<td>23 10</td>
</tr>
<tr>
<td>(10) 19</td>
<td>15 16</td>
<td>14 9</td>
<td>57</td>
</tr>
<tr>
<td>(25) 17</td>
<td>15 16</td>
<td>14 9</td>
<td>57</td>
</tr>
<tr>
<td>(15) 16</td>
<td>17 15</td>
<td>17 10</td>
<td>55</td>
</tr>
<tr>
<td>(10) 13</td>
<td>1 7 100</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Demand $d_i$,
Implicit Prices $v_i$

| 250 | 120 | 180 | 90 | 600 | *** |
| 11.8 | 6.6 | 4.8 | 4.33 | 1 | 0 |

\(^*\) Box not used; aircraft cannot fly range.  \(^***\) Row or column has no equation.

\(^4\) For concluding remarks, turn to page 591.

[583]
# Allocation of Aircraft Under Uncertain Demand

## Table 28-2.11

**Worksheet for Determining Optimal Assignment Under Uncertain Demand**

<table>
<thead>
<tr>
<th>Type of Aircraft</th>
<th>Route</th>
<th>Aircraft Available</th>
<th>Implicit Prices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) N.Y. to L.A. 1-stop</td>
<td>(2) N.Y. to L.A. 2-stop</td>
<td>(3) N.Y. to Dallas 0-stop</td>
</tr>
<tr>
<td>(1) A</td>
<td>( x_{11} = 16 )</td>
<td>( x_{12} )</td>
<td>( x_{13} )</td>
</tr>
<tr>
<td>( \rho_{11} = 18 )</td>
<td>21</td>
<td>15</td>
<td>28</td>
</tr>
<tr>
<td>(2) B</td>
<td>( x_{22} )</td>
<td>( x_{23} )</td>
<td>( x_{24} )</td>
</tr>
<tr>
<td>( \rho_{22} = 18 )</td>
<td>10</td>
<td>15</td>
<td>14</td>
</tr>
<tr>
<td>(3) C</td>
<td>( x_{33} )</td>
<td>( x_{34} )</td>
<td>( x_{35} )</td>
</tr>
<tr>
<td>( \rho_{33} = 18 )</td>
<td>5</td>
<td>9</td>
<td>7</td>
</tr>
<tr>
<td>(4) D</td>
<td>( x_{44} )</td>
<td>( x_{45} )</td>
<td>( x_{46} )</td>
</tr>
<tr>
<td>( \rho_{44} = 18 )</td>
<td>0</td>
<td>11</td>
<td>22</td>
</tr>
</tbody>
</table>

| Increment (1) | \( y_{11} \leq 200 \) | \( y_{12} \leq 50 \) | \( y_{13} \leq 140 \) | \( y_{14} \leq 10 \) | \( y_{15} \leq 580 \) |
|---------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| \( y_{22} \leq 20 \) | \( y_{23} \leq 100 \) | \( y_{24} \leq 20 \) | \( y_{25} \leq 40 \) | \( y_{26} \leq 20 \) |
| \( y_{33} \leq 30 \) | \( y_{34} \leq 20 \) | \( y_{35} \leq 30 \) | \( y_{36} \leq 20 \) |
| \( y_{44} \leq 20 \) | \( y_{45} \leq 20 \) | \( y_{46} \leq 240 \) |

| Net Implicit Prices | \( v_1 \) | \( v_2 \) | \( v_3 \) | \( v_4 \) | \( v_5 \) | 0 |

**Box not used because aircraft type cannot fly required range, or fewer increments are needed to describe the distribution of demand on the route.**

**Corresponding row or column has no equation.**

[584]
### Table 28.2-IV

**Cycle 0**

**Work Sheet for Determining Optimal Assignment Under Uncertain Demand**

\( c_{ij} = +58.4, \theta^* = \frac{1}{4}, \) Expected Cost = $1,866,000

<table>
<thead>
<tr>
<th>Type of Aircraft</th>
<th>Route</th>
<th>Aircraft Available</th>
<th>Implicit Prices ( v_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) N.Y. to L.A. 1-stop</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2) N.Y. to L.A. 2-stop</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3) N.Y. to Dallas 0-stop</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4) N.Y. to Dallas 1-stop</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5) N.Y. to Boston 0-stop</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6) Surplus Aircraft</td>
<td></td>
<td></td>
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<td>10</td>
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<td>16</td>
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<td>15</td>
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<td>28</td>
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<td>23</td>
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<td></td>
<td>81</td>
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<td>5</td>
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<td></td>
<td>17.3</td>
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<td></td>
<td>17</td>
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<td>55</td>
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<td>0</td>
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<tr>
<td></td>
<td>9.8</td>
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<tr>
<td></td>
<td>9.1</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>4.9</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>2.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

[585]
### Allocation of Aircraft Under Uncertain Demand

**Table 28.2-IV**

*Cycle 1*

**Work Sheet for Determining Optimal Assignment Under Uncertain Demand**

\[ \delta = +23.4, \theta = +4, \text{ Expected Cost} = \$1,627,000 \]

<table>
<thead>
<tr>
<th>Type of Aircraft</th>
<th>Route</th>
<th>Aircraft Available</th>
<th>Implicit Prices ( \nu_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) A</td>
<td>10</td>
<td>18 16 21 15 28 23 81 0</td>
<td>10 -139</td>
</tr>
<tr>
<td>(2) B</td>
<td>**</td>
<td>8.7 + 6 16 14 5 - 9* 5.3 15 9 10</td>
<td>19 -76</td>
</tr>
<tr>
<td>(3) C</td>
<td>**</td>
<td>5 16 14 7 9 6 29 0</td>
<td>25 -23</td>
</tr>
<tr>
<td>(4) D</td>
<td>10</td>
<td>10 18 11 11 22 17 55 0</td>
<td>15 -91</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Increment</th>
<th>(1)</th>
<th>200 -1 50 -1 140 -1 10 -1</th>
<th>500 -1 ** *** 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>(2)</td>
<td>20</td>
<td>77 +106 -1 20 -1 40 -1 -1 ** *** 0</td>
<td></td>
</tr>
<tr>
<td>(3)</td>
<td>30</td>
<td>9.8 ** 20 -140 30 -1 -1 ** *** 0</td>
<td></td>
</tr>
<tr>
<td>(4)</td>
<td>10</td>
<td>-5.2 ** -2.1 -2.1 ** ** *** 0</td>
<td></td>
</tr>
<tr>
<td>(5)</td>
<td>-1</td>
<td>-2.6 ** -1 -1 ** ** *** 0</td>
<td></td>
</tr>
</tbody>
</table>

| Net Implicit Prices \( \nu_i \) | 9.8 9.1 4.9 6 1 0 *** | [586] |
28.2. NUMERICAL SOLUTION OF THE ROUTING PROBLEM

| Type of Aircraft | Route | Aircraft Available
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) A</td>
<td>N.Y. to L.A. 1-stop</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>N.Y. to L.A. 2-stop</td>
<td>18</td>
</tr>
<tr>
<td>(2) B</td>
<td>N.Y. to Dallas 2-stop</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>3.0 + 1.50</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>N.Y. to Dallas 0-stop</td>
<td>3.0</td>
</tr>
<tr>
<td></td>
<td>5.3</td>
<td>14</td>
</tr>
<tr>
<td>(3) C</td>
<td>N.Y. to Boston 0-stop</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>17.2</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>9</td>
</tr>
<tr>
<td>(4) D</td>
<td>10 - 6*</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>5 + 2</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>22</td>
<td>10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Increment</th>
<th>200</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>140</td>
</tr>
<tr>
<td></td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>(500)</td>
</tr>
<tr>
<td>(2)</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>-7</td>
</tr>
<tr>
<td></td>
<td>-7</td>
</tr>
<tr>
<td></td>
<td>-1</td>
</tr>
</tbody>
</table>

| (3)              | 20  |
|                  | 91 + 160 |
|                  | -10.4 |
|                  | -9.1  |
|                  | -6.3  |
|                  | -5.6  |
|                  | -9    |

| (4)              | 30  |
|                  | -99 |
|                  | -1  |
|                  | -4.9 |
|                  | -4.2 |
|                  | -1   |

| (5)              | 30  |
|                  | -5.2 |
|                  | -2.1 |
|                  | -2.1 |

| Net Implicit Prices \(v_i\) | 9.8 | 9.1 | 6.6 | 6 | 1 | 0 |

\[ 587 \]
**ALLOCATION OF AIRCRAFT UNDER UNCERTAIN DEMAND**

**TABLE 28-24V**

Cycle 3

**Work Sheet for Determining Optimal Assignment Under Uncertain Demand**

\( \alpha = +5.5, \theta = 14^\circ \), Expected Cost = $1,561,000

<table>
<thead>
<tr>
<th>Type of Aircraft</th>
<th>Route</th>
<th>Aircraft Available</th>
<th>Implicit Prices ( u_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) N.Y. to L.A. 1-stop</td>
<td>(2) N.Y. to L.A. 2-stop</td>
<td>(3) N.Y. to Dallas 0-stop</td>
</tr>
<tr>
<td>(1) A</td>
<td>10</td>
<td>16</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td>18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) B</td>
<td>**</td>
<td>11 + 5^\circ</td>
<td>2.7 - 5^\circ</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>14</td>
<td></td>
</tr>
<tr>
<td>(3) C</td>
<td>**</td>
<td>7.8 - 6^\circ</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>(4) D</td>
<td>9.4 - 3^\circ</td>
<td>9.4 + 3^\circ</td>
<td>3.8 + 3^\circ</td>
</tr>
<tr>
<td></td>
<td>17</td>
<td>16</td>
<td>17</td>
</tr>
<tr>
<td>Increment (1)</td>
<td>-1</td>
<td>50</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>-13</td>
<td>-13</td>
<td>-7</td>
</tr>
<tr>
<td>(2)</td>
<td>50</td>
<td>-1</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>-10.4</td>
<td>-9.1</td>
<td>-8.3</td>
</tr>
<tr>
<td>(3)</td>
<td>25 - 2.70</td>
<td>30</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>-9.8</td>
<td>**</td>
<td>-4.9</td>
</tr>
<tr>
<td>(4)</td>
<td>**</td>
<td>1</td>
<td>-3</td>
</tr>
<tr>
<td></td>
<td>-5.2</td>
<td>-2.1</td>
<td>-2.1</td>
</tr>
<tr>
<td>(5)</td>
<td>-1</td>
<td>**</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>-2.6</td>
<td>-1</td>
<td></td>
</tr>
<tr>
<td>Net Implicit Prices ( v_i )</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**[588]**
### 28.2. NUMERICAL SOLUTION OF THE ROUTING PROBLEM

#### TABLE 28.2-IV

**Cycle 4**

**Worksheet for Determining Optimal Assignment Under Uncertain Demand**

\[ \bar{c}_{ik} = -0.9, \bar{d} = \bar{d}, \text{ Expected Cost} = \$1,542,000 \]

<table>
<thead>
<tr>
<th>Type of Aircraft</th>
<th>Route</th>
<th>Aircraft Available</th>
<th>Implicit Prices ( u_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) N.Y. to L.A. 1-stop</td>
<td>(2) N.Y. to L.A. 2-stop</td>
<td>(3) N.Y. to Dallas 0-stop</td>
</tr>
<tr>
<td>(1) A</td>
<td>10</td>
<td>15</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>18</td>
<td>21</td>
<td>16</td>
</tr>
<tr>
<td>(2) B</td>
<td>**</td>
<td>12.8</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>16</td>
<td>14</td>
</tr>
<tr>
<td>(3) C</td>
<td>**</td>
<td>4.3</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>5</td>
<td>14</td>
</tr>
<tr>
<td>(4) D</td>
<td>[8.3 - 9]</td>
<td>11</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>17</td>
<td>16</td>
<td>15</td>
</tr>
</tbody>
</table>

| Increment | (1) | 200 | -1 | -1 | 140 | -4 | -1 | 580 | -1 | ** | *** |
|           |     |     | -13| 15 | -7 | 7 | -1 |    |    | 0 |    |
| (2)      | 20  | 100 | -1 | -1 | 20  | 40 | -1 | 20  | -1 | ** | *** |
|          | 10.4| -9.1| 6.3| -5.6| -9 | 0 |    |    |    | 0 |    |
| (3)      | \[15 - 69\] | 220 | 30 | -1 | -4.9 | -4.2 | -1 | ** | *** |
|          | -9.8| 226 | -4.1 | -4.2 | -1 |    |    |    | 0 |    |
| (4)      | -1  | ** | -1 | -1 | ** | ** | ** | ** | ** | *** |
|          | -5.2| -2.1 | -2.1 | -2.1 | ** | ** | ** | ** | 0 |    |
| (5)      | -1  | ** | -1 | -1 | ** | ** | ** | ** | 0 |    |

| Net Implicit Prices \( u_i \) | 0 | 0 | 0 | 0 | 0 | *** |

[ 589 ]
# Allocation of Aircraft Under Uncertain Demand

**Table 28.2.14**

*Cycle 5 (Optimal)*

**Work Sheet for Determining Optimal Assignment Under Uncertain Demand**

Minimum Expected Cost $1,524,000

<table>
<thead>
<tr>
<th>Type of Aircraft</th>
<th>Route</th>
<th>Aircraft Available</th>
<th>Implicit Prices υ_i</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>N.Y.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>to</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>L.A.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1-stop</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>N.Y.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>to</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>L.A.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2-stop</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>N.Y.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>to</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dallas</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0-stop</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>N.Y.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>to</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dallas</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1-stop</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>N.Y.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>to</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Boston</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0-stop</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Surplus</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Aircraft</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1) A</td>
<td>10</td>
<td>16</td>
<td>15</td>
</tr>
<tr>
<td></td>
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The successive improvements in the solution, Table 28-2-IV, cycles 0-5, reduced the net expected costs from $1,866,000 to $1,524,000 for the optimal solution.

Thus, the best solution obtained by pretending that demands are fixed at their expected values has a 9 per cent higher expected cost than that for the best solution obtained by using the assumed distributions of demand. It is also seen that very little additional computational effort was required to take account of this uncertainty of demand.

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