1973

Integer Programming by Cutting Planes Methods

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INTEGER PROGRAMMING BY CUTTING PLANES METHODS

by

Sung-Yen Wu

A report submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

in

Applied Statistics

Plan B

Approved:

UTAH STATE UNIVERSITY
Logan, Utah

1973
ACKNOWLEDGMENTS

I wish to express my sincere thanks to Dr. Bartell C. Jensen for his valuable suggestions and guidance in the preparation of this report. I would also like to thank Professor Ronald V. Canfield and Dr. Grace Y. Chen for their time spent and support given in this effort.

A great deal of appreciation and thanks go to my parents for their support in my graduate studies at Utah State University.

Sung-Yen Wu
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACKNOWLEDGMENTS</td>
<td>ii</td>
</tr>
<tr>
<td>LIST OF TABLES</td>
<td>iv</td>
</tr>
<tr>
<td>LIST OF FIGURES</td>
<td>v</td>
</tr>
<tr>
<td>INTRODUCTION</td>
<td>1</td>
</tr>
<tr>
<td>BASIC CONCEPT OF LINEAR PROGRAMMING</td>
<td>5</td>
</tr>
<tr>
<td>Description</td>
<td>5</td>
</tr>
<tr>
<td>Slack, surplus and artificial variables</td>
<td>6</td>
</tr>
<tr>
<td>The simplex method</td>
<td>7</td>
</tr>
<tr>
<td>The dual simplex algorithm</td>
<td>13</td>
</tr>
<tr>
<td>INTEGER PROGRAMMING BY CUTTING PLANES METHODS</td>
<td>14</td>
</tr>
<tr>
<td>Description</td>
<td>14</td>
</tr>
<tr>
<td>Formulation methods and solutions</td>
<td>15</td>
</tr>
<tr>
<td>NUMERICAL EXAMPLES</td>
<td>23</td>
</tr>
<tr>
<td>COMPARISON OF THE EFFICIENCY, USAGE, AND RELATIONSHIP OF DIFFERENT CUTTING PLANES METHODS</td>
<td>34</td>
</tr>
<tr>
<td>Summary</td>
<td>35</td>
</tr>
<tr>
<td>REFERENCES</td>
<td>37</td>
</tr>
<tr>
<td>APPENDIX</td>
<td>38</td>
</tr>
<tr>
<td>Computer Programs</td>
<td>39</td>
</tr>
</tbody>
</table>
# LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>The initial primal feasible tableau</td>
<td>23</td>
</tr>
<tr>
<td>2.</td>
<td>The optimal linear programming tableau with no cut</td>
<td>24</td>
</tr>
<tr>
<td>3.</td>
<td>The optimal tableau after the first Gomory's cut</td>
<td>25</td>
</tr>
<tr>
<td>4.</td>
<td>Computation of $D_5^5$</td>
<td>27</td>
</tr>
<tr>
<td>5.</td>
<td>Computation of $D_5^3$</td>
<td>28</td>
</tr>
<tr>
<td>6.</td>
<td>Computation of $D_5^1$</td>
<td>28</td>
</tr>
<tr>
<td>7.</td>
<td>The optimal tableau after the first Kianfar's cut</td>
<td>29</td>
</tr>
<tr>
<td>8a.</td>
<td>Gomory's algorithm</td>
<td>36</td>
</tr>
<tr>
<td>8b.</td>
<td>Kianfar's algorithm</td>
<td>36</td>
</tr>
</tbody>
</table>
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Cutting Planes Methods on two dimensions</td>
<td>4</td>
</tr>
</tbody>
</table>

INTRODUCTION

Linear programming is a relatively new, very important branch of modern mathematics and is about twenty five years old.

In this day and age, most planners and decision makers will acknowledge that some linear optimization problems are worth the expense and trouble to solve. Using linear programming technique as a tool to make decision planners are able to greatly reduce cost or increase profit for any project under consideration.

Since Dr. George B. Dantzig published his first paper on the simplex method in 1947, progress in that field has been rapid. Although the first applications were military in nature, it was not long before it became apparent that there were important economic and industrial applications as well.

Typical areas of application in linear programming are inventory control, quality control, production scheduling, forecasting, maintenance and repairs, process design, accounting procedures, capital budgeting, the diet problem, machine-loading problem, and the transportation problem.

Integer linear programming was first introduced by Dantzig, Fulkerson, and Johnson in 1954 in their work on solving the traveling salesman problem and subsequently by Markowitz and Manne in
their work on the solution of discrete programming problems. In 1958 Gomory developed a systematic procedure for obtaining cuts which can be shown to lead to an optimal solution in a finite number of steps, when all of the variables are constrained to be integers. Later, in 1960, the algorithm for solving the mixed-integer case was also developed.

In many practical problems, some or all the variables are restricted to integer values. Integer programming was introduced to solve such kind of problems. Integer programming can be used to solve such problems as the fixed-charge problem, discrete programming problems, project planning, manpower scheduling, and the traveling salesman type problems as well as capital budgeting problems. The most interesting integer programming problems are those with variables taking only one of the values 0 or 1.

At present, many algorithms are available for solving linear programs of the type discussed here. Four of the most famous methods are:

1. Cutting-plane algorithms (Gomory, Balas, Kianfar)
2. Group theory for the all integer problem (Gomory, Shapiro)
3. Decomposition (Benders)
4. Enumerative
   a. Implicit enumeration for the pure integer problem (Balas)
The intention of this study is to review some of the cutting plane methods and to compare one with another in terms of the number of iterations required and the computation time which results from each method.

There are two methods that will be considered. The first is Gomory's method which adds a new constraint, one at a time, to the original constraint system to yield a sequence of new linear programming problems until the optimal solution has satisfied the integerality requirement (Hadley, 1964).

The second method is Kianfar's stronger inequalities for 0, 1 integer programming using Knapsack Functions (Kianfar, 1971).

In Gomory's method, the integer points outside the 0, 1 space can limit the parallel movement of the hyperplane of the cut toward the solution set, furthermore it does not allow this hyperplane to rotate for a deeper cut. This method removes these two limitations to form a stronger cut in solving 0, 1 integer programming problem. The cut means to add a new constraint to the original linear programming problem such that some areas in the convex set are cut off. (See Figure 1)

This report surveys the literature on basic linear programming, the simplex method and dual simplex algorithm used in integer
Figure 1. Cutting Planes Methods on two dimensions

programming. It also illustrates two methods of finding solutions to 0,1 integer linear programming problem by cutting planes methods.

Finally, computer programs will be written for the two methods to compare their efficiency one with the other. Efficiency as defined here is the time required on an electronic computer or the number of iterations and arithmetic operations. Moreover, an efficient algorithm may be one which requires relatively little computer core storage.
BASIC CONCEPT OF LINEAR PROGRAMMING

Description

The goal in solving a linear programming problem is to identify an optimal solution and its associated value of the objective function.

Mathematically speaking, we have m inequalities or equations in r variables (m and r are independent) of the form:

\[
\text{max. or min. } Z = c_1 x_1 + c_2 x_2 + \ldots + c_r x_r \quad (1)
\]

subject to the constraints

\[
a_{i1} x_1 + a_{i2} x_2 + \ldots + a_{ir} x_r \begin{cases} \leq & b_i \text{, } i = 1, \ldots, m \end{cases} \quad (2)
\]

where the \(a_{ij}, c, \text{ and } b_i\) are assumed known constants, and (1) is called the objective function. Usually, some or all of the variables are restricted to be non-negative. Sometimes, it may be required that some or all of the variables are allowed to take only integral values.

When (1) and (2) are used as a model for a decision problem, the variables \((x_i, i = 1, \ldots, r)\) represent the decision maker's possible policy choices, the relations (2) express the constraints, and the objective function is the measure of effectiveness.
Any set of \( x_j \) which satisfies the set of constraints (2) is called a solution. Any solution which satisfies the non-negativity restrictions is called a feasible solution. Any feasible solution which maximizes the \( z \) of (2) is called an optimal feasible solution.

The problem itself may be infeasible, if no solution can satisfy every constraint. Another possibility is that the problem has no finite maximum value of objective function \( Z \). Such a problem is unbounded or has an unbounded optimal solution (Hadley, 1962).

**Slack, surplus and artificial variables**

We note that an inequality of the type

\[
\sum_{j=1}^{r} a_{hj} x_j \leq b_h
\]  

(3)

can be converted into an equation by adding a slack variable \( x_{r+h} \)

where \( x_{r+h} \geq 0 \).

\[
\sum_{j=1}^{r} a_{hj} x_j + x_{r+h} = b_h
\]

(4)

Next consider inequalities having a \( \geq \) sign

\[
\sum_{j=1}^{r} a_{kj} x_j \geq b_k
\]

(5)

Equation (5) can be rearranged to
by adding a surplus variable $x_{r+k}$, where $x_{r+k} \geq 0$.

The effect of this change is that the inequality constraints with $\leq$ or $\geq$ signs have been converted into equations, so that a system of simultaneous linear equations is obtained. The adjusted problem has the same set of optimal solutions as the original one (Hadley, 1962).

Usually it starts in initial basic solution by setting the basis matrix $B = I$.

If some constraints do not require the addition of a slack variable, the initial basic feasible solution may not be easy to find.

In such cases, artificial variables and vectors are added to the set of constraints to ensure an initial basic feasible solution to a linear programming problem can be found.

The simplex method

In solving an integer linear programming problem by the use of cutting plans, the simplex method seems more suitable and common than the revised simplex method. The reason is in the simplex method, it transforms all the $y_j$, $x_j$, $z_j - c_j$ and $z$ at each iteration.

Where $y_j = B^{-1} a_j$, $j = 1, \ldots, n$, $x_B = B^{-1} b$, $c_B = (c_{B1}, \ldots, c_B m)$, $z = c_B x_B$, $z_j = c_B y_j$, the basis matrix $B = (b_1, \ldots, b_m)$. All such
information in the simplex method tableau is needed to form a cut in integer programming.

Although the revised simplex method has the advantage of speed and storage saving over the standard simplex method, it does not yield all the information to form a cut. This is due to the fact that only the basis inverse is transformed at each iteration.

The simplex method is a scheme which systematically evaluates the extreme points of the convex set in terms of the objective function until a terminal status is reached.

Three types of terminal status can be identified.

(a) a finite optimal solution; that is an optimal basic feasible solution.

(b) an infinite optimal solution; that is an unbounded solution.

(c) the problem has no feasible solution; that is the constraints can not simultaneously be satisfied.

The simplex method starts with a basis that yields a basic feasible solution. It then moves on to a new basis associated with a better basic feasible solution which increases the value of the maximizing function (or vis vasa) by means of replacing one of the current basis vectors with a non-basis vector. The non-basic vector to enter the basis will yield the greatest contribution to the improvement of the objective function if it is a maximizing function. On the other hand, the current basis vector to be removed is selected according to a rule which insures the continued feasibility of the new solution.
After the vectors to enter and leave the basis have been found, we start to form a new basis by using transformation formulas. Once the new basis is established, it forms the new starting point for repeating the same evaluative process to determine a still better basic feasible solution. This continues until the final stage is reached.

Computational procedure for the simplex method (Hadley, 1962).

Step 1. One wishes to solve the linear programming problem

\[
\begin{align*}
\sum_{j=1}^{r} a_{ij} x_j \leq & \quad b_i, \quad i=1, \ldots, m \\
\end{align*}
\]

(7)

\[
\sum_{j=1}^{r} c_j x_j
\]

(8)

with the non-negativity restrictions

\[
x_j \geq 0, \quad (j=1, \ldots, r)
\]

For the convenience of computation, at the beginning check to see that all the \(b_i\) are non-negative. If any of the \(b_i\) are negative multiply it by \(-1\) to obtain \(b_i \geq 0\). Next add slack or surplus variables to the inequality constraints

Then

\[
\sum_{j=1}^{r} a_{ij} x_j \leq b_i
\]

will become
\[ \sum_{j=1}^{r} a_{ij} x_j + x_{r+i} = b_i, \quad x_{r+i} \geq 0 \quad (9) \]

and

\[ \sum_{j=1}^{r} a_{ij} x_j = b_i \quad (10) \]

will become

\[ \sum_{j=1}^{r} a_{ij} x_j - x_{r+i} = b_i, \quad x_{r+i} \geq 0 \]

every slack or surplus variable is given a price zero. After the conversion the problem will become

\[ Ax = b, \quad x \geq 0, \quad \max z = cx \]

where

\[ A = (a_1, \ldots, a_n) \].

Step 2. Check to see whether the matrix A contains an m x m identity matrix, assumes \( r(A) = m \). If the identity matrix does not exist, add the necessary number of artificial variables and artificial vectors to obtain an identity matrix. The two phase method is used to treat artificial vectors. The phase I drive all artificial variables to zero and the phase II maximize the actual objective function z.

In phase I, assign prices of zero to the legitimate variables
and of $-1$ to the artificial variables. Now maximize the function

$$z = \sum_{i=1}^{s} (-1)x_{ai} = -1X_a$$

where $X_a$ is an $s$-component column vector containing the artificial variables. Notice, that $z^* \leq 0$ is always true, and the maximum value of $z^*$ is zero.

At the end of phase I, we may have $\max z^* < 0$. This means the problem has no feasible solution. If we have $\max z^* = 0$ at the end of phase I, we have a basic feasible solution to the original problem, and all the artificial variables have been driven to zero.

In phase II, we assign its actual price $c_j$ to each legitimate variable and a price of zero to any artificial variables which may appear in the basis at a zero level. The function to be optimized is the actual objective function $z$.

Step 3. Construct an initial tableau, and compute $z_j - c_j$ from

$$z = c_B b_j, \quad z_j - c_j = c_j a_j - c_j$$

Step 4. If all $z_j - c_j \geq 0$, there are two possibilities. If some of the $x_{Bj}$ in the basis do not satisfy the non-negativity restrictions we have an infeasible solution, otherwise an optimal basic feasible solution is obtained.
If one or more \((z_j - c_j) < 0\), proceed by determining the vector \(a_k\) in A but not in B to enter the basis from

\[
z_k - c_k = \min_j (z_j - c_j), \quad z_k - c_k < 0 \tag{13}\]

After \(a_k\) is selected, check \(y_{ik}\). If \(y_{ik} < 0\) for all \(i\), there have an unbounded solution.

Step 5. If \(y_{ik} > 0\) for at least one \(i\), proceed by determining the vector to be removed from the basis. The criteria that insures feasibility is

\[
\frac{x_{Br}}{y_{rk}} = \min_i \left\{ \frac{x_{Bi}}{y_{ik}}, \quad y_{ik} > 0 \right\} \tag{14}
\]

where the subscript \(y\) identifies the vector to leave the basis.

Step 6. Use the vector transformation formuli to find the new basic feasible solution. The "ring around the rosy" method is

\[
y_{ij} = y_{ij} - \frac{y_{ik}}{y_{rk}} y_{rj}; \quad \text{all } j, \ i=1, \ldots, m+1, \ i \neq j \tag{15}
\]

\[
y_{rj} = \frac{y_{rj}}{y_{rk}}, \quad \text{all } j
\]

\[
x_B = y_0, \quad z = y_{m+1}, 0, \quad z_j - c_j = y_{m+1}, j = 1, \ldots, n
\]

Step 7. Go to step 4, for another iteration. There will be a finite iterative process to find an optimal solution.
The dual simplex algorithm

Every linear programming problem (primal) has associated with it a companion problem which is called the dual.

The solution to the dual is simultaneously determined when solving the primal problem. In many cases, the duality can be of considerable help in solving linear programming problems.

Because the dual simplex algorithm will be used to determine the vectors to enter and leave basis in integer linear programming, a short discussion of this algorithm will be presented here.

When the simplex tableau have one or more $x_{Bi} < 0$, but with $z_j - c_j > 0$ for all $j$, the criteria for the change of basis is;

1. Vector to be removed from basis: Choose

$$x_{Br} = \min x_{Bi}, \ x_{Bi} < 0$$

(16)

Column $Br$ is removed from the basis and $x_{Br}$ is therefore driven to zero.

2. Vector to enter basis: The vector $a_k$ to enter the basis is determined from

$$\theta = \frac{z_k - c_k}{y_{rk}} = \max_{j} \frac{z_j - c_j}{y_{rj}}, \ y_{rj} < 0$$

(17)

Note that in the dual simplex algorithm one first determines the vector to leave the basis and then the vector to enter. This is the reverse of that done in the simplex method.
INTEGER PROGRAMMING BY CUTTING PLANES METHODS

Description

An integer programming problem is a linear programming problem with the additional feature that some or all of the variables are required to take on integer values only.

The most general problem of this type of problem can be written as

\[ \text{max } z = cx \]

\[ \text{subject to } Ax = b; \ x \geq 0; \ x_j \text{ an integer, } j \in J_1 \]

If \( J_1 \) contains all \( j \), we have an all integer problem. If \( J_1 \) is empty, (18) is a linear programming problem and if \( J_1 \) contains part of \( j \), we have an mix-integer problem. In an all integer problem if \( x_j \) can take only the value of 0 or 1, we consider it a 0,1 integer programming problem.

In theory, every integer linear programming problem can be solved. However, in practice, due to the difficulties of too much time involved to obtain the solution (even with today's computer) and the effect of round-off error and machine storage size, more research work in this area is still needed.
Formulation methods and solutions

A basic technique for solving the integer programming problems is (Hadley, 1964).

Step 1. Solve the problem ignoring the integrality restriction.

Step 2. If an optimal solution is not feasible due to the violation of the integrality restrictions, a new constraint is added to the original constraint equations, then proceed to step 1. Otherwise, the optimal solution with the required integer variables has been obtained.

The first method discussed here is Gomory's Algorithm. The essential nature of this algorithm is that it provides the proof of finiteness.

Gomory's algorithm for the all integer programming problem

Step 1. Solve LP (18) and let the optimal solution so obtained by \( x_B = y_0 \), where

\[
 y_0 = x_B + \sum_{j \in R} y_j x_j
\]  

(19)

where \( R \) is the set of \( j \) corresponding to the nonbasic variables.

Step 2. If all components of \( y_0 \) are integers, we have an optimal solution; otherwise let

\[
 x_{Bu} = y_{u0} - \sum_{j \in R} y_j x_j
\]  

(20)

where \( y_{u0} \) is not integral.
Now write

\[ y_{uj} = \sigma_{uj} + f_{uj}, \quad \text{for } j \in R; \quad y_{u0} = \sigma_{u0} + f_{u0}, \]

where \( \sigma_{uj} \) is the largest integer \( \leq y_{uj} \),

\( j \in R \) and \( j = 0 \); and \( 0 < f_{uj} < 1 \).

If more than a single component of \( y_0 \) is nonintegral, we adopt the equation for which \( f_{u0} \) is largest, where \( 0 < f_{u0} < 1 \).

Step 3. Add constraint (22) to the constraints of LP (16)

\[ f_{u0} - \sum_{j \in R} f_{uj} x_j \leq 0 \]  \hfill (22)

where

\[ f_{u0} > 0, \quad 1 > f_{uj} > 0. \]

Step 4. Use the dual simplex algorithm to obtain an optimal solution to the augmented problem and let \( x_B = y_0 \) then return to step 2.

Gomory's algorithm for the mixed-integer programming problem.

Step 1. Same as all integer case.

Step 2. Same as all integer case.

Step 3. Use formula (23) and (24) to obtain the cut.

\[ \sum_{j \in R} (-d_{uj}) x_j \leq -f_{u0} \]  \hfill (23)
\[
\begin{align*}
  d_{uj} &= \begin{cases} 
    y_{uj}, & j \in \mathbb{R}^*_+, \text{ for the variables not required to be integer.} \\
    \frac{f_{u0}}{1-f_{u0}} y_{uj}, & j \in \mathbb{R}^*_-, \text{ for the variables require to take integer value.} \\
    f_{u0} (1-f_{uj}), & j \in \mathbb{R} \setminus J, f_{uj} < f_{u0} \\
  \end{cases} 
\end{align*}
\]

where \( \mathbb{R}^* \) is the subset of \( \mathbb{R} \) not in \( \mathbb{R} \setminus J \), \( \mathbb{R}^*_+ \) and \( \mathbb{R}^*_- \) are the subsets of \( \mathbb{R}^* \) for which \( y_{uj} \geq 0 \) and \( y_{uj} < 0 \) respectively.

Step 4. Same as all integer cases.

Another method for solving the \( 0,1 \) all integer programming problem is suggested by Ferydoon Kianfar. This method uses Gomory's cutting-plane method to obtain the first cut and then allows the hyperplane of that cut to be rotated in any direction until the final hyperplane passes through as many integer points not in convex set \( S \) (defined below) as possible (Kianfar, 1971).

Let the sets of points be

\[
S = \{ X = (x_1, \ldots, x_n) \mid x_j = 0,1, \text{ for } j=1, \ldots, n \} 
\]  

(25)

and
\[ A = \{ x = (x_1, \ldots, x_n) \mid x \in S; \sum_{j=1}^{n} a_j x_j \leq L \} \]  

where \( a_j \) for all \( j \), and \( L \) are positive integer constants.

The problem is to find the largest integer \( a^r \), \( r \leq n \), denoted by \( a^r \), such that \( a^r > a^r \) and \( A = A^r \), where

\[
A = \{ x \mid x \in S; \sum_{j=1}^{n} a_j x_j + a^r x < L \}
\]

if we assume that \( a^r > a^r \), then the inequality

\[
\sum_{j=1}^{n} a_j x_j + a^r x \leq L
\]

is stronger than the original inequality

\[
\sum_{j=1}^{n} a_j x_j \leq L
\]

where \( a^r \) should be selected such that

\[
A_1 = \{ x \mid x \in A; x^r = 1 \}, \quad A_1 \leq A \quad \text{and} \quad A^r = A \quad \text{for} \quad a^r = a^r
\]

this is equivalent to selecting \( a^r \) as

\[
a^r = L - \max_{X \in A} \sum_{j=1}^{n} a_j x_j
\]

but in fact \( a^r \) is equal to \( a^r + S^r (L - a^r) \) by theorem 1

where
\[ S_n^r(L-a_r) = L-a_r - F_n^r(L-a_r) \] (31)

and

\[ F_n^r(L-a_r) = \max_{X \in A} \sum_{j=1, j \neq r}^n a_j x_j \] (32)

is a special case of the Knapsack Function (Kianfar, 1971).

Using the Knapsack Function we have

Theorem 1. Let

\[ M = \{ X = (x_1, \ldots, x_n) \mid \sum_{j=1}^n a_j x_j < L; x_j = 0, 1, 2, \ldots, \text{all } j \} \] (33)

\[ N = \{ X = (x_1, \ldots, x_n) \mid \sum_{j=1}^n a_j x_j + (a_r + k)x_r < L; \]
\[ x_j = 0, 1, 2, \ldots, \text{all } j \} \] (34)

where

\[ 0 \leq k < \min_{n=1, 2, \ldots} \left\lfloor \frac{L}{a_r} \right\rfloor \frac{(S_n^r(L-ha_r)/h)}{r} \]

Then \( M = N \). (The notation \( \lfloor y \rfloor \) means the largest integer

less than or equal to \( y \).)

Proposition 1.

\[ S_1(k) = \infty, k < 0; S_1(k) = k, 0 \leq k \leq a_1; \]

\[ S_1(k) = k - a_1, a_1 \leq k \leq L; \] (35)

\[ S_j(k) = \min \{ S_{j-1}(k), S_{j-1}(k-a_j) \} \} (j=2, \ldots, n) \]
Proposition 2.

$S_j(k)$ is either zero or is equal to $S_j(k - 1) + 1$.

Where $S_j(k) = k - k'$ and $k'$ is the largest integer $p \leq k$ such that $S_j(p) = 0$.

Now let

$$D_j = \left\{ k \mid S_j(k) = 0, \ 0 \leq k \leq L \right\}; \ (j=1, \ldots, n),$$

then proceed to find $D_n$. From (35) we obtain

$$D_1 = \left\{ 0, a_1 \right\}, \ a_1 \leq L,$$

$$D_j = D_{j-1} + \left\{ k+a_j \mid k \in D_{j-1}, k+a_j \leq L \right\}, \ (j=2, \ldots, n)$$

each $D_j, j=2, \ldots, n$ is computed from $D_{j-1}$ by $\min \left\{ N(D_{j-1}), L-a_j \right\}$

where $N(D_{j-1})$ denotes the number of elements (Kianfar, 1971).

The $S^r_n(k)$ of the Knapsack Function is that

$$S^r_n(k) = k - F^r_n(k), \text{ where } F^r_n(k) = \max \sum_{j=1, j \neq r}^n a_j x_j$$

subject to $\sum_{j=1, j \neq r}^n a_j x_j = k, \ x_j = 0, 1, \text{ all } j$,

then

$$a_r' = a_r + S^r_n(L-a_r) \ (37)$$

and
\[ S_{n}^{r}(k) = k - k', \quad (k=0, 1, \ldots, L) \]  

(38)

Using (37) and (38) we compute \( \alpha_{n} \). Next, we set \( r = n - 1 \)

and compute \( D_{n}^{n-1} \) but \( D_{j}^{n} \), \( j=1, \ldots, n-2 \) and hence

\[ D_{n}^{n-1} = D_{n}^{n-2} + \left\{ \frac{k+a}{n} \bigg| k \epsilon D_{n}^{n-2}, \frac{k+a}{n} \leq L \right\} \]  

(39)

From Proposition 1 it follows that

\[ D_{r+1}^{r} = D_{r-1}^{n} + \left\{ \frac{k+a}{r+1} \bigg| k \epsilon D_{r-1}^{n}, \frac{k+a}{r+1} \leq L \right\} \]  

(40)

\[ D_{j}^{r} = D_{j-1}^{r} + \left\{ \frac{k+a}{j} \bigg| k \epsilon D_{j-1}^{r}, \frac{k+a}{j} \leq L \right\}, \quad (j=r+2, \ldots, n) \]  

(41)

The steps used to get a stronger cut is (Kianfar, 1971)

**Step 1.** Apply Gomory's algorithm to obtain original cut. The cut at this stage is

\[ F_{k}^{T}k \leq 0 \]  

(42)

where

\[ F_{k} = (f_{0}, -f_{1}, -f_{2}, \ldots, -f_{n}) \]

is the vector of the constants of this cut. \( T_{k}^{T} \) has 1 as its first component and the nonbasic variables of the kth tableau as the rest of its components.

Also we define
Step 2. Find $D^n_j = D_j$, $j = 1, \ldots, n-1$ using (36), and $D^n_n = D^n_{n-1}$.

Compute $\hat{a}_r$ using (37) and (38) and set $r = n-1$, where $r$ is a variable that is to run over the coordinate currently being considered for an increase in its coefficient (Kianfar, 1971).

Step 3. If $r = 1$ go to step 4; also check whether $(L - a_r) \epsilon D^n_r - 1$. If yes, set $\hat{a}_r = a_r$; otherwise, using (40) and (41) to compute $D^n_r$, and use (37) and (38) to find $\hat{a}_r$. In either case, set $r = r - 1$ and go to step 3.

Step 4. Set $D^1_2 = \{0, a_2\}$. Use (41) to compute $D^1_n$, and use (37) and (38) to compute $a_1$, and we arrived at strongest inequality, the coefficient is denoted by $\overline{a}_j$ for all $j$.

$$\sum_{j=1}^{n} a_j x_j \leq L$$

(45)
NUMERICAL EXAMPLES

In the previous chapter, two methods to solve 0, 1 integer linear programming problem by cutting planes methods have been discussed. It will be helpful to illustrate the two methods by considering some simple numerical examples. As the first example, assume the following 0, 1 integer linear programming problem:

Example 1.

Max. $7x_1 - 8x_2 - 9x_3 + 4x_4 + 5x_5$

subject to

\[
\begin{align*}
2x_1 + 4x_2 - 4x_3 + 2x_4 + 4x_5 & \leq 7 \\
x_1 + 3x_2 + 2x_3 + x_4 - x_5 & \leq 4 \\
2x_2 - 2x_3 - x_4 + x_5 & \leq 3
\end{align*}
\]

\[x_j = 0 \text{ or } 1, \quad j = 1, \ldots, 5\]

Table 1. The initial primal feasible tableau.

<table>
<thead>
<tr>
<th>$x$</th>
<th>B</th>
<th>1</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_1$</td>
<td>0</td>
<td>-7</td>
<td>8</td>
<td>9</td>
<td>-4</td>
<td>-5</td>
<td></td>
</tr>
<tr>
<td>$x_6$</td>
<td>7</td>
<td>2</td>
<td>4</td>
<td>-4</td>
<td>2</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>$x_7$</td>
<td>4</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>-1</td>
<td></td>
</tr>
<tr>
<td>$x_8$</td>
<td>3</td>
<td>0</td>
<td>2</td>
<td>-2</td>
<td>-1</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>
First, to solve this problem by the regular simplex method without considering its integer requirement.

The solution is given in Table 2. Notice the optimal solution does not meet the integrality restriction.

To obtain the first cut, using the \((x_{B}$ = $x_7)\) row in Table 1. Note that \(y_{20} = 2.75, y_{22} = 4.00, y_{23} = 1.00, y_{26} = 0.25, y_{29} = -1.50,\)
We see that $f_{20} = 0.75$, $f_{22} = 0$, $f_{23} = 0$, $f_{26} = 0.25$, $f_{29} = 0.5$, $f_{212} = 0.5$

Thus by (22), the cut is

$$0.75 - 0.25x_6 - 0.5x_9 - 0.5x_{12} \leq 0 \quad (47)$$

Annex (47) to the original problem and apply the dual simplex algorithm to solve it.

One obtains an optimal solution in two iterations. For this solution given in Table 3, all $x$ are integers. Thus, one has obtained the optimal solution to (46). It is $x_1 = x_5 = 1, x_2 = x_3 = x_4 = 0, z = 12.$

<table>
<thead>
<tr>
<th>$x_B$</th>
<th>$1$</th>
<th>$x_2$</th>
<th>$x_3$</th>
<th>$x_4$</th>
<th>$x_9$</th>
<th>$x_{s1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Z$</td>
<td>12.00</td>
<td>13.00</td>
<td>4.00</td>
<td>1.00</td>
<td>2.00</td>
<td>5.00</td>
</tr>
<tr>
<td>$x_6$</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>-2.00</td>
<td>2.00</td>
<td>-4.00</td>
</tr>
<tr>
<td>$x_7$</td>
<td>4.00</td>
<td>4.00</td>
<td>1.00</td>
<td>2.00</td>
<td>-2.00</td>
<td>1.00</td>
</tr>
<tr>
<td>$x_1$</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>$x_{10}$</td>
<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>$x_{13}$</td>
<td>0.00</td>
<td>-1.00</td>
<td>1.00</td>
<td>-1.00</td>
<td>1.00</td>
<td>-1.00</td>
</tr>
<tr>
<td>$x_5$</td>
<td>1.00</td>
<td>1.00</td>
<td>-1.00</td>
<td>1.00</td>
<td>-1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>$x_{12}$</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Next one considers to use Kianfer's stronger cut, which modify the Gomory's cut. From (47) one has

\[ 0.75 - 0.25x_6 - 0.5x_9 - 0.5x_{12} \leq 0 \]

or

\[ FT = (0.75, 0, 0, -0.25, -0.5, -0.5), \quad [1, x_2, x_3, x_6, x_9, x_{12}] \leq 0 \]

to convert this cut to a cut that contains only 0,1 variables, one first finds

\[
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
7 & -2 & -4 & 4 & -2 & -4 \\
1 & -1 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & -1 & 0
\end{bmatrix}
\]

Then \( F^o = FP = (-2, 1, 1, -1, 1, 1) \)

The equivalent cut with 0,1 variables

\[ F^o T^o = (-2, 1, 1, -1, 1, 1) \cdot [1, x_2, x_3, x_6, x_9, x_{11}] = 0 \]

or

\[ x_2 + x_3 - x_6 + x_9 + x_{11} \leq 2, \quad (48) \]
We make this inequality stronger by the method of replacing inequalities:

Let \( a_1 = 1, a_2 = 1, a_3 = -1, a_4 = 1, a_5 = 1, L = 2. \)

To compute \( A_5 \) we compute \( D_5^5 \) (See Table 4),

From (37), (38), it follows that \( S_5^5(L - a_5) = S_5^5(1) = 1 - 1 = 0, \)
and \( a_5 = 1+0 = 1. \) To find \( A_4 \) we first check to see whether \( (L - a_4) \)
\( \in D_3^5, \) and \( L - a_4 = 2 - 1 = 1 \) \( \in D_3^5, \) thus \( A_4 = a_4 = 1. \) To find \( a_3, \) we
check \( L - a_3 = 2 - (-1) = 3 \notin D_2^5; \) hence we compute \( D_3^5 \) using (40),
(41) (See Table 5), from (37), (38) we have \( S_5^3(L - a_3) = S_5^3(3) = 3 - 2 = 1, \)
\( A_3 = -1 + 1 = 0. \) Next we compute \( A_2. \) First we check \( L - a_2 = 2 - 1 = 1 \)
\( \in D_2^5, \) hence \( A_2 = a_2 = 1. \) One now computes \( D_5^1 \) as shown in Table 6,
using (38), we have \( S_5^1(L - a_1) = S_5^1(1) = 1 - 1 = 0, \) Hence, from (37)

<table>
<thead>
<tr>
<th>( D_1^5 )</th>
<th>( D_2^5 )</th>
<th>( D_3^5 )</th>
<th>( D_4^5 = D_5^5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 4. Computation of \( D_5^5 \)
Table 5. Computation of $D_5^3$

<table>
<thead>
<tr>
<th>$D_2^3 = D_3^3 = D_4^3$</th>
<th>$D_4^3$</th>
<th>$D_5^3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 6. Computation of $D_5^1$

<table>
<thead>
<tr>
<th>$D_2^1$</th>
<th>$D_3^1$</th>
<th>$D_4^1$</th>
<th>$D_5^1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

$A_{a_1} = a_1 = 1$

The modified cut now is $\overline{F}_0 = (-2, 1, 1, 0, 1, 1)$ or

$$x_2 + x_3 + x_9 + x_{11} \leq 2 \quad (49)$$

To compute $\overline{F}$ we need $p^{-1}$, which can be obtained from Table 2.

$$p^{-1} = \begin{bmatrix}
1.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
1.00 & 0.00 & 0.00 & 0.00 & -1.00 & 0.00 \\
0.00 & 1.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
0.00 & 0.00 & 1.00 & 0.00 & 0.00 & 0.00 \\
1.00 & 0.00 & 0.00 & 0.00 & 0.00 & -1.00 \\
0.75 & -1.00 & 1.00 & -0.25 & 0.50 & 0.50
\end{bmatrix}$$
The vector $\overline{F}$ is

$$\overline{F} = \overline{F}_0 P^{-1} = (0.75, 0, 1, -0.25, -0.50, -0.50)$$

and the stronger inequality in terms of nonbasic variables of the tableau of Table 2 is

$$0.75 + x_3 - 0.25x_6 - 0.5x_9 - 0.5x_{11} \leq 0$$

This row is annexed to Table 2 and the resulting tableau is made optimal by the dual simplex method.

Table 7 shows the optimal tableau. For this solution, the integer requirements are satisfied. Thus one has obtained the optimal solution to (46). It is

$$x_1 = x_5 = 1, \quad x_2 = x_3 = x_4 = 0, \quad z = 12.$$
In addition to the above example, three more examples are provided below.

Example 2.

Max. \[ 5x_1 - 7x_2 - 10x_3 + 3x_4 - x_5 \]

subject to

\[
\begin{align*}
  x_1 + 3x_2 - 5x_3 + x_4 + 4x_5 & \leq 1 \\
  2x_1 + 6x_2 + 3x_3 + 2x_4 + 2x_5 & \leq 4 \\
  2x_2 - 2x_3 - x_4 + x_5 & \leq 2 \\
  x_j & = 0 \text{ or } 1, \ j = 1, \ldots, 5
\end{align*}
\]

Using Gomory's algorithm, one has the following results.

<table>
<thead>
<tr>
<th>Solution</th>
<th>( Z )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial</td>
<td>5.77</td>
</tr>
<tr>
<td>1st cut</td>
<td>5.42</td>
</tr>
<tr>
<td>2nd cut</td>
<td>5.00</td>
</tr>
</tbody>
</table>

After two cuts one obtains the integer solution with

\[ x_1 = 1, \ x_2 = x_3 = x_4 = x_5 = 0, \ Z = 5. \]

Using Kianfar's algorithm, one has the following results.

<table>
<thead>
<tr>
<th>Solution</th>
<th>( Z )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial</td>
<td>5.77</td>
</tr>
<tr>
<td>1st cut</td>
<td>5.00</td>
</tr>
</tbody>
</table>

The solution is the same as in the Gomory's algorithm, except this method only needs one cut to obtain an integer solution.

The third problem is from Kianfar's example.
Example 3.

Max. $15x_1 - 2x_2 + 16x_3 + 6x_4$

subject to

$$36x_1 - 46x_2 + 18x_3 - 34x_4 \leq 28$$
$$75x_1 - 20x_2 + 30x_3 + 27x_4 \leq 93$$
$$78x_1 + 91x_2 + 69x_3 - 16x_4 \leq 122$$

$x_j = 0 \text{ or } 1, j=1, \ldots, 4$

Using Gomory's algorithm the results are

Initial solution $Z = 20.69$
1st cut $Z = 20.68$
2nd cut $Z = 20.66$
3rd cut $Z = 20.64$
4th cut $Z = 20.62$
5th cut $Z = 20.61$
6th cut $Z = 20.59$
7th cut $Z = 20.50$
8th cut $Z = 20.38$
9th cut $Z = 20.37$
10th cut $Z = 20.35$
11th cut $Z = 20.34$
12th cut $Z = 20.28$
13th cut $Z = 20.26$
14th cut $Z = 20.22$
15th cut $Z = 20.21$
16th cut $Z = 20.21$
17th cut $Z = 20.20$
18th cut $Z = 20.19$
19th cut \quad Z = 20.15
20th cut \quad Z = 19.95
21st cut \quad Z = 19.87
22nd cut \quad Z = 19.85
23rd cut \quad Z = 19.86
24th cut \quad Z = 19.85
25th cut \quad Z = 16.00

After 25 cuts the solution is \( x_1 = x_2 = x_4 = 0, \quad x_3 = 1, \quad z = 16 \)
and is all integers. The above tells us that in this problem Gomory's
algorithm needs 25 cuts to obtain the solution.

Now, by using Kianfar's algorithm the results are:

<table>
<thead>
<tr>
<th>Initial solution</th>
<th>Z = 20.69</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st cut</td>
<td>Z = 19.48</td>
</tr>
<tr>
<td>2nd cut</td>
<td>Z = 16.00</td>
</tr>
</tbody>
</table>

Here the Kianfar's algorithm uses only two cuts to reach the solution.

The last and the largest example is presented below:

Example 4.

\[
10x_1 - 7x_2 + x_3 - 12x_4 + 2x_5 + 8x_6 - 3x_7 - x_8 + 5x_9 + 3x_{10} = \text{Max}
\]

\[
-3x_1 - 12x_2 + 8x_3 + x_4 + 7x_9 - 2x_{10} \leq 8
\]

\[
x_2 + 10x_3 + x_5 - x_6 + 7x_7 + x_8 \leq 13
\]

\[
5x_1 + 3x_2 - x_3 + 2x_8 + x_{10} \leq 6
\]

\[
4x_3 - 2x_4 + 5x_6 + x_7 - 9x_8 + 2x_9 \leq 8
\]
\[9x_2 - 12x_4 + 7x_5 - 6x_6 + 2x_8 + 12x_9 + 3x_{10} \leq 12\]

\[8x_1 + 5x_2 - 2x_3 - 7x_4 + x_5 - 5x_7 + 10x_9 \leq 16\]

\[x_j = 0 \text{ or } 1, \quad (j = 1, \ldots, 10)\]

In this example, Gomory’s algorithm used 88 cuts and still did not obtain the solution \(Z = 24.12\) while Kianfar’s algorithm used only 13 cuts to get the solution.

The solution is

\[x_1 = x_5 = x_6 = x_{10} = 1\]

\[x_2 = x_3 = x_4 = x_7 = x_8 = x_9 = 0\]

\[z = 23.\]
COMPARISON OF THE EFFICIENCY, USAGE, AND RELATIONSHIP OF DIFFERENT CUTTING PLANES METHODS

All the four numerical examples cited in the previous chapter have been tested by computer codes generated by the author using Fortran IV language on B 6700.

From the four examples discussed, it can be seen that the number of cuts needed to obtain the solution by Gomory's method are greater than or equal to Kianfar's method in 0, 1 integer programming problem. Kianfar's method may be viewed as the modification of Gomory's method in actual practice. The only difference between these two methods is that after the cut the Gomory's method has been obtained, Kianfar's method changes that cut so as to make it stronger.

It is believed that the larger the problem the more efficiency the Kianfar's method can be seen. The results from Kianfar's method are very encouraging but of course this experience is insufficient for a firm judgement of the efficiency of the algorithm. However, Gomory's algorithm imposes a heavy burden on the storage system and processing time on a computer, if the problem is large. Kianfar's method tends to have the ability of lessening this burden.

Due to the fact that the computer programs and the numerical
examples given are problem specific, the comment made here can only be viewed as a suggestion or reference. In addition, the efficiency of each method is partly dependent on the nature and characters of the problem being solved.

Summary

In summary the advantage and disadvantage of the two methods will be discussed.

The Gomory's method: This method has the ability to solve all kinds of all integer and mix-integer programming problems. It is easier to learn and perform, and more suitable for small problems. Less arithmetic operations are needed to form a cut. However, if the problem turns large, the number of cuts needed to solve the problem increases rapidly.

The Kianfar's method: This method can be used to solve 0,1 integer programming problem only. It is hard to learn and not efficient on small problems. Usually more arithmetic operations are needed to form a cut, however if the problem turns large the number of cuts needed to solve the problem increases gently.

Another point that is worth mentioning is that the Kianfar's approach can also be applied to the original constraints. In order to maintain the finiteness property of the Kianfar's algorithm, Gomory's cut should be added to it every 50 or 100 iterations.
### Table 8a. Gomory’s algorithm

<table>
<thead>
<tr>
<th>Problem No.</th>
<th>No. of variables</th>
<th>No. of constrnts</th>
<th>Virtual memory</th>
<th>Processor time</th>
<th>No. of cuts</th>
<th>No. of Ite.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>4</td>
<td>1.17</td>
<td>0.12</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>4</td>
<td>1.34</td>
<td>0.14</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>4</td>
<td>1.64</td>
<td>0.22</td>
<td>25</td>
<td>48</td>
</tr>
<tr>
<td>4 **</td>
<td>10</td>
<td>7</td>
<td>41.22</td>
<td>3.11</td>
<td>88</td>
<td>299</td>
</tr>
</tbody>
</table>

### Table 8b. Kianfar’s algorithm

<table>
<thead>
<tr>
<th>Problem No.</th>
<th>No. of variables</th>
<th>No. of constrnts</th>
<th>Virtual memory</th>
<th>Processor time</th>
<th>No. of cuts</th>
<th>No. of Ite.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>4</td>
<td>2.69</td>
<td>0.25</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>4</td>
<td>2.79</td>
<td>0.24</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>4</td>
<td>2.58</td>
<td>0.25</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>4</td>
<td>10</td>
<td>7</td>
<td>3.59</td>
<td>0.42</td>
<td>13</td>
<td>50</td>
</tr>
</tbody>
</table>

* The unit of virtual memory is kiloword-minutes.

* The unit of processor time is minutes.

* Both compilation time and execution time are all included in memory and time calculation.

**Problem No. 4 by Gomory’s algorithm after 88 cuts still does not obtain the answer.**
REFERENCES


C THIS PROGRAM USE GOMORY'S ALGORITHM TO SOLVE ALL INTEGER LINEAR PROGRAMMING PROBLEM. WHERE II = TOTAL NUMBER OF ROWS.
C LD(I)=VARIABLES NOT IN THE BASIS.
C B(I)=THE PIVOT ROW.
C L(I)=VARIABLES IN THE BASIS.
C JJ=TOTAL NUMBER OF COLUMNS. S(I, J)=TABLEAU FOR SIMPLEX METHOD.
C
DIMENSION S(80, 180), L(80), DUJ(80), LD(80), B(80)
READ(5, 4) II, JJ
4 FORMAT(1814)
III = II + 1
C READ IN THE MATRIX
DO 10 I=1, III
10 READ(5, 12) (S(I, J), J=1, JJ)
12 FORMAT(7F10.4)
C READ IN THE SUBSCRIPT FOR THE SLACK VARIABLE
READ(5, 4) (L(I), I=2, II)
III = II - 1
REGA = 0.
21 KKK = 0
REGB = 0.
C CALCULATE NEW LAST ROW
22 DO 23 I=2, II
23 IF(L(I), NE. 0) GO TO 23
DO 27 J=1, JJ
27 CONTINUE
23 CONTINUE
C SEARCHING FOR THE MOST NEGATIVE ENTRY
K=III
44 JJJ=JJ-1
IF(REGA, EQ. 1.) GO TO 500
B(K) = 0.
L(K) = 0
DO 42 J=1, JJJ
42 IF(S(K, J). GE. 0.) GO TO 42
IF(B(K), LE. S(K, J)) GO TO 42
B(K)=S(K, J)
L(K)=J
42 CONTINUE
C TEST FOR L(K).
REG B=1.
45 IF(L(K)) 46, 62, 46
C FIND OUT THE PIVOT COLUMN
46 KJ=L(K)
DO 120 I=2, II
IF(S(I, KJ)) 120, 120, 121
120 CONTINUE
WRITE(6, 130)
130 FORMAT(1X, 'UNBOUNDED')
GO TO 1
C COMPUTING THE RATIO
121 JK=0
DO 50 I=Z, II
IF(S(I, KJ), LE, 0.) GO TO 50
X=S(I, JJ)/S(I, KJ)
IF(JK, EQ, 0) GO TO 53
IF(X, GE, XMIN) GO TO 50
53 XMIN=X
JK=I
50 CONTINUE
56 X=S(JK, KJ)
L(JK)=KJ
C CALCULATING THE NEW ROWS ABOVE THE PIVOT ROW
DO 57 I=1, III
57 B(I)=S(I, KJ)
IJ=JK-I
DO 59 I=1, IJ
DO 59 J=1, JJ
IF (S(JK, J)) 58, 59, 58
58 IF (B(I)) 580, 59, 580
580 S(I, J) = S(I, J) - B(I)*S(JK, J)/X
59 CONTINUE
C CALCULATING THE NEW ROWS BELOW THE PIVOT ROW
IJ=JK+1
DO 61 I=IJ, III
DO 61 J=1, JJ
IF (S(JK, J)) 60, 61, 60
60 IF(B(I))600, 61, 600
600 S(I, J)=S(I, J)-B(I)*S(JK, J)/X
61 CONTINUE
C NORMALIZATION
DO 205 J=1, JJ
205 S(JK, J)=S(JK, J)/X
KKK=KKK+1
WRITE(6, 105) KKK, S(K, JJ), L(JK)
105 FORMAT (1X, I4, 6X, F15.2, 10X, I4)
GO TO 44
62 IF (K-1) 70, 70, 63
63 JJ=JJ-1
C TEST TO SEE WHETHER ALL THE ELEMENTS ON THE
C LAST ROW ARE CLOSE TO ZERO.
DO 65 J=1, JJ
IF(S(K, J)< 0.0001) 65, 65, 66
65 CONTINUE
WRITE (6, 103)
103 FORMAT (1X, 'FEASIBLE')
WRITE(6, 101)
101 FORMAT(1X, 'ITERATION OBJ. FUNCTION NEW BASIC VAR.')
C TEST TO SEE WHETHER ALL THE ELEMENTS ON THE LAST
C ROW
DO 140 J=1, JJ
140 S(III), J)=0.
K=1
KKK=0
IF(REGB.EQ.0) GO TO 31
GO TO 44
31 REGB=1.
GO TO 500
66 WRITE(6, 6)
6 FORMAT(1X, 'INFEASIBLE')
GO TO 1
70 WRITE(6, 8) S(I, JJ)
8 FORMAT(/// /1X, 'OBJ. FUNCTION,', F20.8/, 1X)
C FIND THE LARGEST S(I, JJ)
199 FUO=0.
DO 202 I=2, II
REMAN=S(I, JJ)-AINT(S(I, JJ))
IF(REMAN.GE.0.9999995) GO TO 201
IF(REMAN.LE.0.0000005) S(I, JJ)=AINT(S(I, JJ))
IF(REDMAN.LE. FUO) GO TO 202
FUO=REMAN
LL=I
GO TO 202
201 S(I, JJ)=S(I, JJ)+0.0000005
S(I, JJ)+AINT(S(I, JJ))
202 CONTINUE
IF(FUO.LE.0.5E-5) GO TO 1
C
300  INTS=JJ-II
  DO 216 I=1, INTS
216  DUJ(I)=0.
   JC=1
   DO 218 I=1, JJ
   DO 220 J=2, II
220  IF(I.EQ.L(J)) GO TO 218
   LD(JC)=I
   JC=JC+1
218  CONTINUE
   JC=JC-1
   DO 21 2
22  J = l , JC
   NOTB=LD(J)
   IF(S(LL, NOTB).LT. 0.) GO TO 213
   FUJ=S(LL, NOTB)-AINT(S(LL, NOTB))
   GO TO 212
213  ABSY=ABS(S(LL, NOTB))
   FUJ=ABSY-AINT(ABSY)
   FUJ=1., -FUJ
212  DUJ(J)=FUJ
C  INSERT THE NEW CUT INTO MATRIX
   JJJ=JJ+1
   DO 226 I=1, II
226  S(I, JJJ)=S(I, JJ)
   DO 228 I=1, III
228  S(I, JJ)=0.
   S(III, JJ)=1.
   S(III, JJJ)=-FUO
   DO 230 I=1, INTS
   NEWCUT=LD(I)
230  S(III, NEWCUT)=-DUJ(I)
   L(III)=JJ
   JJJ=JJ
   JJ=JJ+1
   II=II+1
   III=II+1
   IF(III.EQ.50) GO TO 1
   DO 232 I=1, JJ
232  S(III, I)=0.
   REGA=1.
   GO TO 21
C  MIN XBI
500  JK=0
   IF(REGB.EQ.0.) GO TO 62
   XMIN=0.
DO 302 I=2, II
IF(S(I, JJ), ME, XMIN) GO TO 302
XMIN=S(I, JJ)
JK=I
302 CONTINUE
IF(XMIN, ME, 0.) GO TO 70
IF(XMIN, LE, 0SE-4) GO TO 70
KJ=0
XMAX=-0.5E12
DD 304 J=1, JJJ
IF(S(JK, J), ME, 0.) GO TO 304
X=S(I, J)/S(JK, J)
IF(X, LE, XMAX) GO TO 304
306 XMAX=X
KJ=J
304 CONTINUE
IF(KJ, EQ. 0) GO TO 1
GO TO 56
1 WRITE(6, 100)
100 FORMAT(///' THE FINAL MATRIX')
DO 78 I=1, III
WRITE(6, 150) I
150 FORMAT(///35X, 'ROW ', I2, /, 1X)
78 WRITE(6, 12) (S(I, J), J=1, JJ)
WRITE(6, 7)
7 FORMAT (1X, 'VARIABLE VALUE')
DO 71 I=2, II
71 WRITE (6, 5) L(I), S(I, JJ)
5 FORMAT (I4, F20.8)
STOP
END
This program uses the algorithm suggested by Dr. Ferydoom Kianfar for solving 0, 1 all integer programming problems using knapsack functions. Where II = total number of rows, JJ = total number of columns, S(I, J) = tableau for simplex method.

L(I) = variables in the basis,
B(I) = the pivot row,
LD(I) = variables not in the basis,
FT(I) = the F vector,
SS(I, J) = the initial primal feasible tableau,
P(I, I) = the P matrix,
FP(I) = the vector come from P matrix multiply by FT vector,
IDA(I) = tableau containing the value of D,
IDB(I) = tableau containing the value of D not in IDA,
IARH(I) = new value of A,
IDRR = index value for tableau IDA(I) and IDB(I),
IFP(I) = integer value of FP(I),
NARI(I) = the legitimate variables.

DIMENSION S(46, 96), B(46), L(46), FT(30), LD(30)
DIMENSION IDB(300), IDRR(30), FP(30), NARI(15)
DIMENSION SS(46, 96), P(30, 30), IFP(30), IDA(300), IARH(30)

READ (5, 4) II, JJ
III = II + 1
C READ IN THE MATRIX
DO 10 I = 1, III
10 READ (5, 12) (S(I, J), J = 1, JJ)
12 FORMAT (7F10.4)
DO 3 J = 1, III
DO 3 1 = 1, JJ
3 SS(I, J) = S(I, J)
C READ IN THE SUBSCRIPT FOR THE SLACK VARIABLE
READ (5, 4) (L(I), I = 2, II)
C READ IN VARIABLES THAT NEED TO BE INTEGER
READ (5, 4) NN, (NARI(I), I = 1, NN)
III = II - 1
REGA = 0.

21 KKK = 0
22 DO 23 I = 2, II
IF (L(I), NE, 0) GO TO 23
DO 27 J = 1, JJ
IF (S(I, J), EQ, 0.) GO TO 27
S(III, J) = S(III, J) - S(I, J)
C SEARCHING FOR THE MOST NEGATIVE ENTRY
K=III
JJJ=JJ-1
IF(REAL, EQ. 1.) GO TO 500
B(K)=0.
L(K)=0.
DO 42 J=1, JJJ
IF(S(K, J), GE. 0.) GO TO 42
IF(B(K), LE. S(K, J)) GO TO 42
B(K)=S(K, J)
L(K)=J
42 CONTINUE
C TEST FOR L(K).
45 IF(L(K)) 46, 62, 46
C FIND OUT THE PIVOT COLUMN
46 KJ=L(K)
DO 120 I=2, II
IF(S(I, KJ)) 120, 120, 121
120 CONTINUE
WRITE(6, 130)
130 FORMAT(1X, 'UNBOUNDED')
GO TO 1
C COMPUTING THE RATIO
121 JK=0
DO 50 I=2, II
IF(S(I, KJ), LE. 0.) GO TO 50
X=S(I, J J)/S(I, KJ)
IF(JK, EQ. 0) GO TO 53
IF(X, GE. XMIN) GO TO 50
53 XMIN=X
JK=I
50 CONTINUE
56 X=S(JK, KJ)
WRITE(6, 149) X
149 FORMAT(/, 'X= ', F14.6)
L(JK)=KJ
C CALCULATING THE NEW ROWS ABOVE THE PIVOT ROW
DO 57 I=1, III
57 B(I)=S(I, KJ)
IJ=JK-1
DO 59 I=1, IJ
DO 59 J=1, JJ
IF(S(JK, J)) 58, 59, 58
58 IF (B(I)) 580, 59, 580
580 S(I, J) = S(I, J) - B(I)*S(JK, J)/X
59 CONTINUE

C CALCULATING THE NEW ROWS BELOW THE PIVOT ROW
IJ = JK+1
DO 61 I = IJ, III
DO 61 J = 1, JJ
IF (S(JK, J)) 60, 61, 60
60 IF (B(I)) 600, 61, 600
600 S(I, J) = S(I, J) - B(I)*S(JK, J)/X
61 CONTINUE

C NORMALIZATION
DO 205 J = 1, JJ
205 S(JK, J) = S(JK, J)/X
KKK = KKK + 1
WRITE (6, 105) KKK, S(1, JJ), L(JK)
105 FORMAT (1X, I4, 6X, F15.2, 10X, I4)
GO TO 44

62 IF (K - 1) 70, 70, 63
63 IJ = JJ - 1

C TEST TO SEE WHETHER ALL THE ELEMENTS ON THE LAST ROW
ARE CLOSE TO ZERO.
DO 65 J = 1, IJ
IF (S(K, J) - .0001) 65, 65, 66
65 CONTINUE
WRITE (6, 103)
103 FORMAT (1X, 'FEASIBLE')
WRITE (6, 101)
101 FORMAT (1X, 'ITERATION OBJ. FUNCTION NF-W BASIC VAR.
TEST TO SEE WHETHER ALL THE ELEMENTS ON THE LAST ROW
DO 140 J = 1, JJ
140 S(III, J) = 0.
K = 1
KKK = 0
GO TO 44

66 WRITE (6, 6)
6 FORMAT (1X, 'INFEASIBLE')
GO TO 1

70 WRITE (6, 8) S(1, JJ)
8 FORMAT ('///', 1X, 'OBJ. FUNCTION.', F20.8, 1X)
WRITE (6, 7)
7 FORMAT (1X, 'VARIABLE VALUE')
DO 71 I = 2, II
71 WRITE (6, 5) L(I), S(I, JJ)
5 FORMAT (I4, F20.8)

C FIND THE LARGEST S(I, JJ)
FUO=0.
DO 202 I=2, II
REMAN=S(I, JJ)-AINT(S(I, JJ))
IF (REMAN .GE. 0. 9999995) GO TO 201
IF (REMAN .LE. 0. 0000005) S(I, JJ)=AINT(S(I, JJ))
IF RE MAN. LE. FUO) GO TO 202
FUO=REMAN
LL=I
GO TO 202
201 S(I, JJ)=S(I, JJ)+0. 0000005
S(I, JJ)=AINT(S(I, JJ))
202 CONTINUE
C TEST IF OPTIMAL SOLUTION HAS BEEN OBTAINED
IF(FUO. LE. 0. 5E-5) GO TO 1
WRITE(6, 954) JJ, FUO, LL
954 FORMAT(1X, 'JJ=', I6, ' FUO=', F10. 4, ' LL=', I6)
300 INTS=JJ-II
DO 216 I=1, INTS
216 FT(I)=0.
JC=1
DO 218 I=1, JJ
DO 220 J=2, II
220 IF(I.EQ.L(J)) GO TO 218
LD(JC)=I
JC=JC+1
218 CONTINUE
JC=JC-1
INTSS=INTS+1
P(I, 1)=1.
DO 502 J=2, INTSS
502 P(I, J)=0.
DO 504 J=1, JC
NOTB=LD(J)
IF(NOTB. LE. NN) GO TO 503
DO 506 1=2, II
506 IF(SS(I, NOTB), EQ. 1.) GO TO 508
WRITE(6, 510)
510 FORMAT(/' ERROR IN S MATRIX')
508 JT=J+1
DO 512 K=1, INTS
KT=K+1
512 P(JT, KT)=-SS(I, K)
P(JT, 1)=SS(I, JJ)
GO TO 504
503 NOT J=J+1
NOTB=NOTB+1
DO 505 MI=1, INTSS
505 P(NOTJ, MI)=0.
P(NOTJ, NOTB)=1.
504 CONTINUE
C
COMPUTE FXP
FT(1)=FUO
DO 517 I=2, INTSS
IT=I-1
IF(S(LL, LD(IT)).LT.0.) GO TO 513
REMAN=S(LL, LD(IT))-AINT(S(LL, LD(IT)))
GO TO 516
513 ABSY=ABS(S(LL, LD(IT)))
REMAN=A BSY- AINT(ABS Y)
REMAN=1.-REMAN
516 FT(I)=-REMAN
517 IF(ABS(FT(I)).GE.0.999995) FT(I)=0.
WRITE(6,916)
916 FORMAT(' FT VECTOR')
WRITE(6,12) (FT(I), I=1, INTSS)
C
FXP
DO 518 I=1, INTSS
518 FP(I)=0.
DO 521 I=1, INTSS
DO 520 J=1, INTSS
5 20 FP(I)=P(J, I)*FT(J)+FP(I)
IF(FP(I).GE.0.) IFP(I)=FP(I)+0.5
521 IF(FP(I).LT.0.) IFP(I)=FP(I)-0.5
LB=-(FP(I)-0.5)
WRITE(6,950) LB, FB(I)
950 FORMAT(1X,'LB=',I4,' FP(I)=' ,F10.4)
WRITE(6,938)
938 FORMAT(' FP(I)')
WRITE(6,12) (FP(I), I=1, INTSS)
WRITE(6,12) (IFP(I), I=1, INTSS)
INR=INTSS
C
FIND DI AND DJ, J=2,...,N
IDA(1)=0
IDA(2)=IFP(2)
KC=1
IDRR(1)=2
K=3
MM=2
J=3
538 I=1
536 IF(I.GT.MM) GO TO 532
NSTRAG=IDA(I)+IFP(J)
IF(NSTRAG .GT. LB) GO TO 534
IDP=K-1
DO 535 ICC=1, IDP
535 IF(NSTRAG .EQ. IDA(ICC))GO TO 534
IDA(K)=NSTRAG
K=K+1
534 I=I+1
GO TO 536
532 MM=K-1
J=J+1
KC=KC+1
IDR(KC)=MM
IF(J .NE. INTSS) GO TO 538
C FIND AR HEAD
KLA=LB-IFP(INTSS)
KSNR=KLA-KPLAN(KLA, IDA, K)
WRITE(6, 918) KLA, LB, IFP(INTSS), KSNR
918 FORMAT(2X, 1 KLA= I4, ' LB=', I4, 1 IFP(INTSS)=', I4,' KSNR=', I4)
IN=INR-1
IARH(IN)=IFP(INR)+KSNR
IR=IN-1
638 IF(IR .EQ. 1) GO TO 603
MINUSR=IR-1
IPLUSR=IR+1
IEADAK=LB-IFP(IPLUSR)
DO 540 I=1, IDRR(MINUSR)
540 IF(IEADAK .EQ. IDA(I)) GO TO 641
C COMPUTE DRN AND FIND AR HEARD
DO 542 I=1, IDRR(MINUSR)
542 IDB(I)=IDA(I)
I=1
K=IDRR(MINUSR)+1
MM=IDRR(MINUSR)
INR=IN-IR
CALL KNAP(INR, MM, K, IDB, IARH, LB, I, IPLUSR, IFP, &770, IR)
GO TO 638
641 IARH(IR)=IFP(IPLUSR)
IR=IR-1
GO TO 638
C STEP 3
603 IDB(1)=0
MM=2
K=3
I=1
IPLUSR=3
IDB(2)=IARH(2)
INR=IN-2
CALL KNP(INR, MM, K, IDB, IARH, LB, I, IPLUSR, IFP, &770, IR)
GO TO 638
770 DO 642 I=2, INTSS
IQU=I-1
642 FT(I)=IARH(IOU)
FT(I)=FP(I)
C GET P-1
DO 704 I=1, NN
IK=I+1
DO 706 J=2, II
706 IF(L(J), EQ, NARI(I)) GO TO 708
DO 714 K=1, INTSS
714 P(IK, K)=0.
P(IK, IK)=1.
GO TO 704
708 DO 712 K=1, INTS
KT=K+1
712 P(IK, KT)=-S(J, LD(K))
P(IK, 1)=S(J, JJ)
704 CONTINUE
C MATRIX FOP-1
DO 718 I=1, INTSS
718 FP(I)=0.
DO 720 I=1, INTSS
DO 720 J=1, INTSS
720 FP(I)=P(J, I)*FT(J)+FP(I)
WRITE (6, 930)
930 FORMAT(' FOP-1 ')
WRITE(6, 12) (FP(I), I=1, INTSS)
C INSERT THE NEW CUT INTO MATRIX
JJJ=JJ+1
DO 226 I=1, II
SS(I, JJJ)=SS(I, JJ)
226 S(I, JJJ)=S(I, JJ)
DO 228 I=1, III
SS(I, JJ)=0.
228 S(I, JJ)=0.
S(III, JJ)=1.
SS(III, JJ)=1.
S(III, JJJ)=-FP(I)
SS(III, JJJ)=-FT(I)
DO 230 I=1, INTSS
WRITE (6, 967) INTS, I, LD(I), FT(I)
967 FORMAT(14, 14, I4, Fl 6. 8)
NEWCUT=LD(I)
IQ=I+1
SS(III, I)=FT(IQ)

230 S(III, NEWCUT)=FP(IQ)
L(III)=JJ
JJJ=JJ
JJ=JJ+1
II=II+1
III=II+1
IF(III, GE, 25) GO TO 1
DO 232 I=1, JJ

232 S(III, I)=0.
REGA=1.
GO TO 21

C MIN XBI
500 JK=0
XMIN=0.
DO 302 I=2, II
IF(S(I, JJ), GE, XMIN) GO TO 302
XMIN=S(I, JJ)
JK=I
302 CONTINUE
C TEST XBR<0
WRITE(6, 997) XMIN
997 FORMAT(' XMIN= ', F10.6)
IF(XMIN, GE, 0.) GO TO 70
KJ=0
XMAX=-0.5E12
DO 304 J=1, JJJ
IF(S(JK, J), GE, 0.) GO TO 304
X=S(I, J)/S(JK, J)
IF(X, LE, XMAX) GO TO 304
306 XMAX=X
KJ=J
304 CONTINUE
IF(KJ, EQ, 0) GO TO 66
GO TO 56
1 WRITE(6, 100)
100 FORMAT('\\ THE FINAL MATRIX')
STOP
END
SUBROUTINE KNAP(INR, MM, K, IDB, IARH, LB, I, IPLUSR, IFP, *, IR)
DIMENSION IARH(30), IDB(300), IFP(30)
DO 631 J=1, INR
   636 IF(I.GT.MM) GO TO 629
      NS TR BG=ID B(1)+IARH(IPLUS R)
      IF(NSTRBG, GT, LB) GO TO 634
      IDP=K-1
      DO 635 IDD=1, IDP
         635 IF(NSTRBG, EQ .• IDB(IDD))GO TO 634
      IDB(K)=NSTRBG
      K=K+1
   634 I=I+1
      GO TO 636
   629 IPLUSR=IPLUSR+1
      MM=K-1
      I=1
   631 CONTINUE
      IPLUSR=IR+1
   632 KLA=LB-IFP(IPLUSR)
      KSNR=KLA-KPLAN(KLA, IDB, K)
      IARH(IR)=IFP(IPLUSR)+KSNR
      WRITE(6, 922) IR, IARH(IR)
   9 2 2 FOR MAT ( 1 X, 1 IR= 1 , ..., ' IARH( IR )=' , !6)
      IR=IR-1
   924 FORMAT(1X, 'IR=', I6, ' IARH(IR)=' , I6)
      IF(IR, EQ. 0) RETURN 1
   RETURN
   END

FUNCTION KPLAN(KLA, IDA, K)
DIMENSION IDA(300)
C FIND KPLAN< DRN
   KPLAN=0
   MM=K-1
   DO 530 I=1, MM
      IF(IDA(I). LT. KPLAN. OR. IDA(I). GT. KLA) GO TO 530
      KPLAN=IDA(I)
   530 CONTINUE
   WRITE(6, 924) KPLAN
   924 FORMAT(1X, 'KPLAN= ', I6)
   RETURN
   END