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FARM AGRICULTURAL PLANNING USING GOAL PROGRAMMING TECHNIQUES

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Abstract

Agriculture in India is one of the most prominent sectors to its economy. About 70% of the population depends on Agriculture. India's wide range of Agro-climatic region, vast extend of land and forest and rich variety of Bio-diversity, rank it among the most naturally endowed nation of the world. However, India still has many growing concerns. While agriculture in India has achieved grain self-sufficiency but the production is, resource intensive, cereal centric and regionally biased. The resource intensive ways of Indian agriculture has raised serious sustainability issues too. Increasing stress on water resources of the country would definitely need a realignment and rethinking of policies. Desertification and land degradation also pose major threats to agriculture in the country. India also needs to improve its management of agricultural practices on multiple fronts. An overview of the different goal programming formulations, their assumptions, limitations and implications for agricultural decision making has been presented. The concept of standardized dual variables in goal programming is introduced through a simple example of farm agricultural planning.

Keywords: Goal Programming, Decision Making, Farm Planning.

Introduction

Goal programming technique, has its potential, particularly in the decision-making environments involving multiple objectives like farm agricultural planning and management. In many situations farmers are often faced several objectives simultaneously and has no easy single choice. For example: maximization of net revenue; minimization of capital borrowing and hired labour ; and minimization of the risk associated with yield and field. On a regional or national level, the agricultural decision maker may be faced not only with decisions about economic growth, but also about population nutritional requirements, strategic planning, environmental and other institutional issues. In this paper, we present aspect of goal programming based on duality theory in farm agricultural planning.

GOAL Programming Model

A generic-type goal planning model can be :

Minimize: $w^{+}d^{+} + w^{-}d^{-}$ .... (1)

Subject to: $Gx + d^{+} - d^{-} = g$ .... (2)

1

$$Ax \le b \qquad \text{......... (3)}$$

$$x, \quad d^+, \quad d^- \ge 0 \qquad \text{......... (4)}$$

where x is a (n×1) vector of decision variables, G is a (p×n) matrix of goal contribution coefficients; g is a (p×1) vector of desired goal levels; d^+ and d^- are (p×1) vector representing, respectively, positive and negative deviations from goals; A is a (m×n) matrix of technological coefficients; b is a (m×1) vector of resource levels. In addition, w^+ and w^- are (1×p) vectors of weights which may or may not be preemptive.

Duality Interpretation of GOAL Programming

When a goal programming is solved as a minimum sum of weighted deviations, the problem of choosing the weights has been the focus of a lot of work because of its complexity. The commonly used weighting procedure is to have the decision maker associate the highest weights with the most important goals. The use of duality theory may help provide a new insight into the design and interpretation of time weights. We focus on the interpretation of duality in goal programming and its usefulness in decision making.

Without loss of generality, we restrict our attention to a primal problem with only goal constraints. In addition, the distinction between preemptive and non-preemptive formulations will be implicit in the distinction between a single dual or a sequence of prioritized duals.

Consider the following primal goal programming and dual goal programming formulations in compact form:

Primal : Minimize: $Z = w^+ d^+ + w^- d^-$

Subject to: $Gx + d^+ - d^- = g$

$x, \; d^+, \; d^- \ge 0$

Dual : Maximize: $y = v^t g$

Subject to: $G^t v \le 0$

$-w^- \le v \le w^+$

where v is a vector of dual variables, y is the value of the dual objective function, the problem dimensions are as in (1) – (4), and t is used to indicate transpose.

In goal programming, the primal may still be interpreted in physical terms where an optimal product mix contributes to the achievement of a certain number of goal targets. However, the corresponding dual is a "pricing problem of the goal targets" in terms of the decision maker's preferences. Hence, the dual should have preference–utility interpretation with the dual variables representing absolute marginal utilities of the different goals. We show below that a more useful interpretation of the dual variables is in relative terms, and we provide a numerical illustration.

From primal-dual relationships between primal goal programming and dual goal programming, we have the following:

$$y \le z \text{ (for any pair of feasible solutions)} \qquad \text{......... (5)}$$

$$y^* = z^* \text{ (at optimality)} \qquad \text{......... (6)}$$

$$\frac{\partial z^*}{\partial g_i} = v_i^* \qquad \text{......... (7)}$$

$$\frac{\partial y^*}{\partial d_i^*} = w_i \qquad \text{......... (8)}$$

The first two relations can be interpreted together as follows: the total disutility of deviation from the goal targets (i.e., z) is always at least as large as the total utility of these goal targets (i.e., y), and equal to it at optimality.

Relation (7) states that the i^{th} optimal dual variable represents the marginal effect of the i^{th} goal target of total disutility (or utility). Relation (8) is a restatement of the weights attached to deviations (either positive or negative) as marginal effects of these deviations.

Finally, from (7) and (8) we also obtain the following relations:

$$v_i^* (\partial g_i) = w_i (\partial d_i^*) = \partial z^* = \partial y^* \qquad \text{......... (9)}$$

$$v_i^* / w_i = \partial d_i^* / \partial g_i \qquad \text{......... (10)}$$

From (9) we see that the same marginal disutility / utility effect can be derived from either changing the goal targets or changing the corresponding deviations. But the most interesting result is given by (10) which defines a "marginal rate of substitution" between a goal target and the distance away from it as equal to the marginal utility of the Goal divided by its weight. Hence, we can use these standardized dual variables (v_i^*/w_i) as a measure of Goal achievement across all Goals. This provides a way of properly interpreting and using the dual variables in Goal programming with or without preemption.

Numerical Illustration

The following example is used to illustrate the analysis. Two variables and two constraints have been taken to have graphical interpretations for both the primal and the dual. Consider a farmer who can grow either Wheat or Gram. He has 20 acres of land and would like to achieve at least Rs. 750000 of revenue while minimizing total production cost.

Table 1 : Cost / Revenue Data

	Wheat	Gram
Yield Quintal/Acre	20	8
Price Rs/Quintal	1350	4000
Cost Rs / Acre	9000	8000

This problem is formulated as the following linear programming problem:

(LP) Minimize: $z = 9000\,x_1 + 8000\,x_2$

subject to: $x_1 + x_2 \leq 20$

$27000x_1 + 32000x_2 \geq 750000$

$x_1,\ x_2 \geq 0$

where x_1 and x_2 represents acres of wheat and gram respectively.

Clearly, the problem has no feasible solution, as shown in figure 1. To get around the infeasibility and still find an acceptable "compromise" solution, the following simple Goal programming formulation is used:

(GP) Minimize: $z = \alpha_1 \left(\frac{d_1^-}{20}\right) 100 + \alpha_2 \left(\frac{d_2^+}{750000}\right) 100$

Subject to: $x_1 + x_2 + d_1^+ - d_1^- = 20$

$$27000x_1 + 32000x_2 + d_2^+ - d_2^- = 750000$$

$$x_1,\ x_2,\ d^+,\ d^- \geq 0$$

where α_1 and α_2 are weights attached to the deviation variables. In this form the objective function is expressed as a weighted sum of percent deviations from targets. For illustration purposes a particular set of weight is $\alpha_1 = \alpha_2 = 1$ meaning equal importance, is given to both Goals. We let

$$\frac{100\alpha_1}{20} = w_1; \quad \text{and} \ \frac{100\alpha_2}{750000} = w_2$$

This formulation is easily interpreted in light of Figure 1 as one which seeks to minimize the total infeasibility in the constraints of the original linear programming problem. The resulting Goal programming solution is $x_2 = 20$ (grow 20 acres of gram) and $d_2^+ =$ Rs. 110000 (revenue shortage) and corresponds to P_1 in Figure 1. For the farmer this solution will guarantee as Rs 640000 total return.

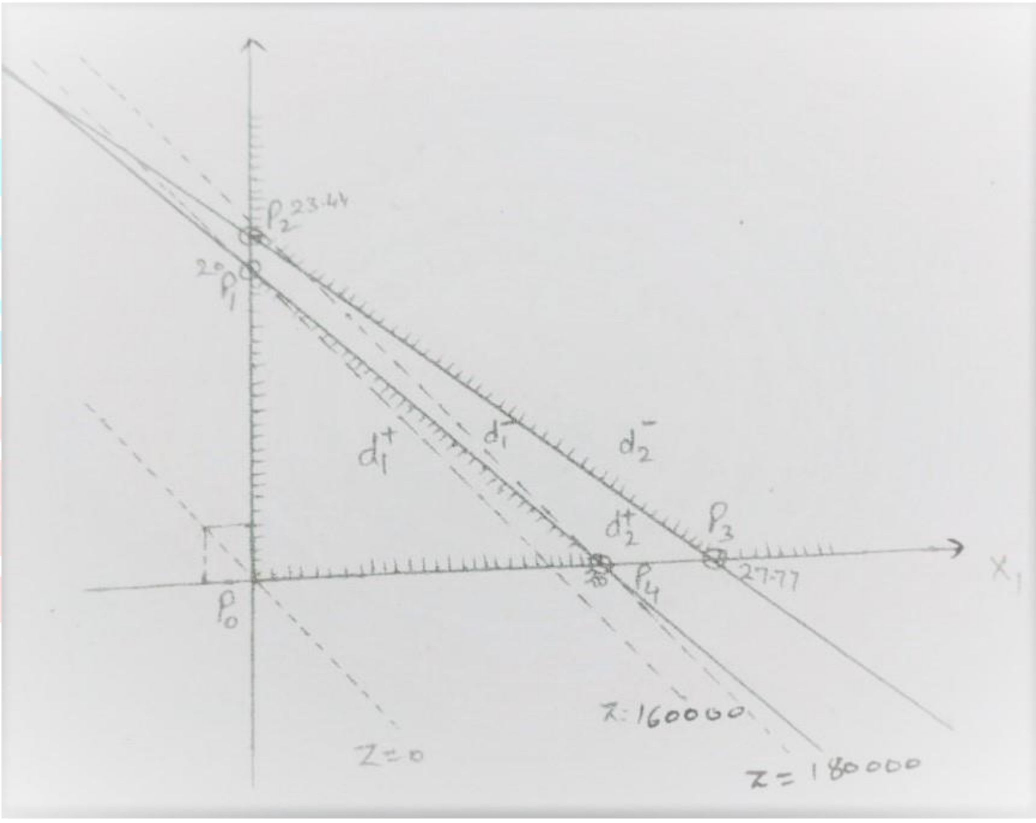

Figure 1: Solution of Farm Example

Now, suppose that the farmer looks at this solution and requires that an absolute first priority is not violating the revenue constraint because it may be a bankruptcy level. Once this is achieved, a minimization of the infeasibility of the total land constraint will be sought. This requirement is formulated as a lexicographic (or prioritized) Goal programming with objective function $\{(d_2^+),(d_1^-)\}$ solved in two iterations:

Iteration One:

Minimize: $z = \{d_2^+\}$

Subject to : $27000\ x_1 + 32000\ x_2 + d_2^+ - d_2^- = 750000$

$$x_1,\ x_2,\ d_1^+,\ d_1^- \geq 0$$

with optimal solution:

$$d_2^+ = 0,\ 27000\, x_1 + 32000\, x_2 - d_2^- = 750000$$

(Line segment $P_2 P_3$ in Figure 1)

Iteration Two :

Minimize: $z = \{d_1^-\}$

Subject to: $x_1 + x_2 + d_1^+ - d_1^- = 20$

$27000\, x_1 + 32000\, x_2 + d_2^- = 750000$

$x_1,\ x_2,\ d_1^+,\ d_2^+,\ d_2^- \geq 0$

with optimal solution:

$x_2 = 23.44$, $d_1^- = 3.44$ (P_2 in Figure 1)

The case of an optimal but dominated solution, due to alternative optima, can also be illustrated. Consider the case where the farmer wants to use up all the land available (20 acres). The corresponding Goal programming will have objective function $\{d_1^+ + d_1^-\}$. A regular simplex code gives the following solution: $x_1 = 20$, $d_2^+ = 180000$ (P_4 in Figure 1). But an alternate optimal solution is easily found to be: $x_2=20$, $d_2^+ = 110000$ (P_1 in Figure 1). In terms of the original problem the two solutions are compared in Table 2, from which clearly the first solution is dominated.

Table 2 : Comparing Alternate GP Solutions

	Optimal Solution $x_1 = 20; x_2=0$	Alternate Optimal Solution $x_1=0 ; x_2=20$
Cost	180000	160000
Revenue	540000	640000
Deficit	210000	110000

To illustrate the duality result, consider the following Goal programming model corresponding to the original linear programming problem, which is inconsistent:

(GP) Minimize : $z = w_1^- d_1^- + w_2^+ d_2^+$

Subject to : $x_1 + x_2 + d_1^+ - d_1^- = 20$

$27000 x_1 + 32000 x_2 + d_2^+ - d_2^- = 750000$

$x_1,\ x_2,\ d^+,\ d^- \geq 0$

where w_1^- and w_2^+ are chosen in a way that will make the objective function consistent and should reflect the importance of each Goal. If we use the opportunity costs of incurred shortages as a measure of relative importance, then $w_1^- = 155000$ is interpreted as the cost of providing an additional acre of land and $w_2^+ =$ 1.00 is the cost per unit of additional revenue foregone.

Now, we consider the dual problems of both linear programming and Goal programming above:

(DLP) Maximize: V = $-20y_1 + 750000y_2$

Subject to:

$$-y_1 + 27000y_2 \le 9000$$

$$-y_1 + 32000y_2 \le 8000$$

$$y_1,\ y_2 \ge 0$$

(DGP) Maximize: V = $-20y_1 + 750000y_2$

Subject to:

$$-y_1 + 27000y_2 \le 0$$

$$-y_1 + 32000y_2 \le 0$$

$$0 \le y_1 \le 155000$$

$$o \le y_2 \le 1$$

Figure 2, depicts both problems with the hatched area corresponding to dual linear programming and the cross-hatched area corresponding to dual Goal programming.

Since the original linear programming problem was inconsistent, by duality theory, we know that its dual linear programming is unbounded. The Goal program which was formulated to resolve the inconsistency is a linear program which has feasible solutions. Its dual Goal program, has the finite optimal solution: $y_1 = 32000$, $y_2 = 1$ as can be seen from Figure 2. This solution corresponds to shadow prices of Rs. – 32000 for land and Rs. 1.00 for total revenue, with the following interpretations, based on (5) – (10) above:

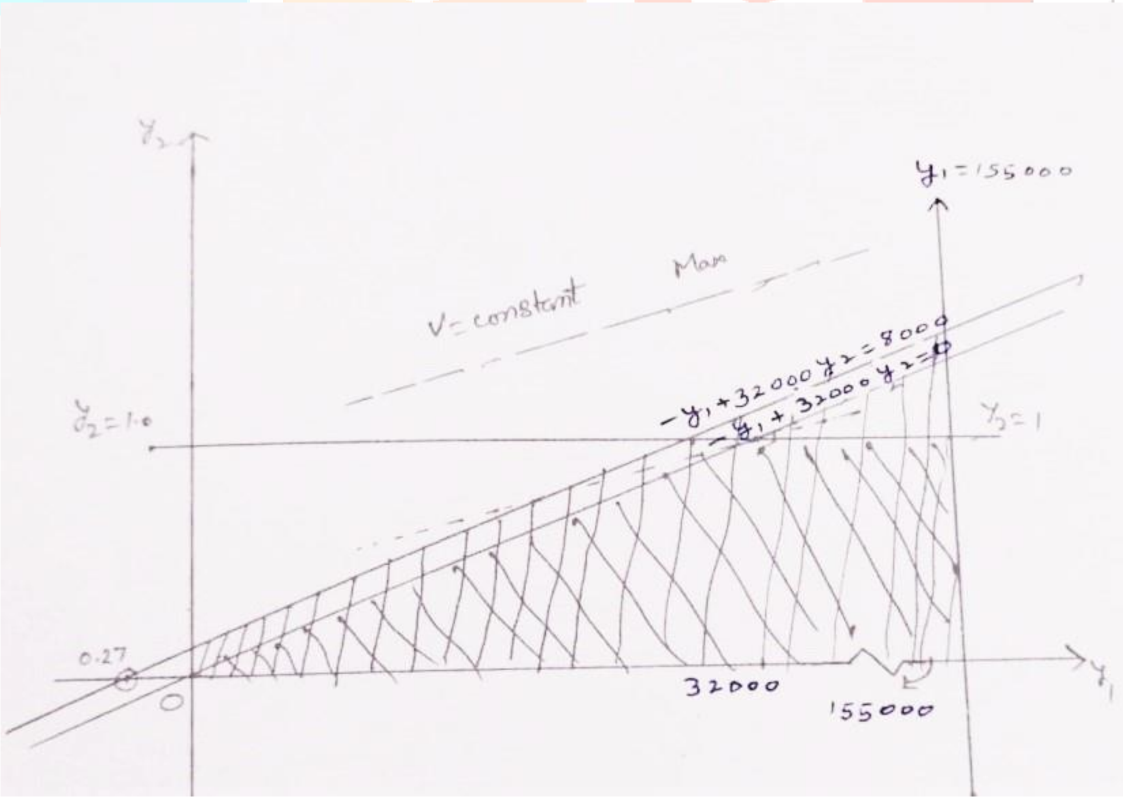

Figure 2 : Dual Solutions for (DLP) and (DGP)

(1) In absolute terms, the magnitude of the shadow prices can be misleading in terms of the ranking of the constraints with respect to total Goal achievement. That is, an additional acre of land will improve the total Goal achievement by Rs. 32000 even though it may cost at least Rs. 155000 to acquire; on the other hand, an additional rupees of revenue forgone will only improve the total Goal achievement by one rupee.

(2) In relative terms, when comparing the achievement of both Goals, the ratios of the shadow prices to their corresponding primal weights (standardized dual values) convey more meaningful information:

$$\frac{y_1}{w_1^-} = \frac{32000}{155000} = 0.20 and \frac{y_2}{w_2^+} = \frac{1}{1} = 1.00$$

These ratios reveal that on a per unit basis total revenue contribute 100 percent to Goal achievement compared to 20 percent for land. This is can be seen from the fact that the Rs 155000 opportunity cost of land will yield Rs. 155000 improvements instead of Rs. 32000 for land. This suggests that care should be taken in practically interpreting shadow prices in Goal programming.

Conclusion

The Goal programming approach the priorities that how to associate the results of a given solution to the satisfaction of the ranking and also how to generate them and what they mean. The duality interpretation of the weights can help both the analysts and the decision makers in the design and solutions of meaningful multicriteria decision problems in farm agricultural planning and management.

References

1. Candler, W., and Boehlje, M. "Use of Linear Programming in Capital Budgeting with Multiple Goals." American Journal of Agricultural Economics. 53, 325-330, 1971.
2. Lee, Sang M. Goal Programming for Decision Analysis. Auerbach Publishers, Inc. Philadephia. 1972.
3. Harper, W.M., and Eastman, C. "An Evaluation of Goal Hierarchies for Small Farm Operators." American Journal of Agricultural Economics. 62, 742-747, 1980.
4. Willis, C.E., and Perlack, R.D. "A Comparison of Generating Technologies and Goal Programming for Public Investment, Multiple Objective Decision making". American Journal of Agricultural Economics. 62, 66-74, 1980.
5. Bazaraa, M.S., and Bouzaher, A. "A Linear Goal Programming Model for Developing Economics with an Illustration from the Agricultural Sector in Egypt." Management Science. 27(4), 396-413, 1981.
6. Barnett D., Blake B., and McCarl B.A. "Goal Programming Via Multidimensional Scaling Applied to Senegalese Subsistence Farms." American Journal of Agricultural Economics. 64, 720-727, 1982
7. Schniederjans, M. J., and Kwak, N.K. "An Alternative Solution Method for Goal Programming Problems: A Tutorial." Journal of the Operational Research Society. 33(3), 247-251, 1982.
8. Markowski, C.A., and Ignizio, J.P. "Duality and Transformations in Multiphase and Sequential Linear Goal Programming" Computer and Operations Research. 10(4), 321-333, 1983.
9. Romero, C., and Rehman, T. "Goal Programming and Multiple Criteria Decision-Making in Farm Planning: Some Extensions." Journal of Agricultural Economics. 36, 171-186, 1985.
10. Fahmy, D., and El-Shishiny, H., "A Goal Programming Model for Desert Farm Planning". Advanced Desert Arid Land Technology Development. 5, 69-86, 1991.
11. Ghosh, D., Pal, B.B., and Basu, M. "Determination of Optimal Land Allocation in Agricultural Planning Through Goal Programming with Penalty Functions". Opsearch. 30(1), 15-34, 1993.
12. Piech, B., and Rehman, T. "Application of Multiple Criteria Decision Making Method to Farm Planning: A Case Study". Agricultural Systems. 41(3), 305-319, 1993.
13. Ghosh, D., Pal, B.B., and Basu, M. "Determination of Optimal Solution for a MCDM Model in Agricultural Planning: A Strategy". International Journal of Management and Systems. 11(2), 267-283, 1995.