**“DISCUSSION FOR ECONOMIC AGRICULTURE THROUGH MATHEMATICAL PROGRAMMING”**

**1Chetan Kumar Sharma, 2Mohammad Zuhaib\*, 3Nitin Kasana, 4Neeraj Singh**

1Associate Professor,Department of Mathematics, Noida International University, G B Nagar, U.P., INDIA

2Associate Professor,Department of Agriculture, Noida International University, G B Nagar, U.P., INDIA

3,4Research Scholar, Department of Mathematics, Noida International University, Greater Noida, U.P., INDIA

***1******cks26april@gmail.com******,  3******nitingujjar2323@gmail.com****4****nagarkoti0007@gmail.com***

**\*Corresponding Author**

*Mathematical programming in agriculture had its origin in attempts to model the economy of agriculture production including its dimensions. Supply response programs are now being included in economic studies, In view of economic studies, we have to discuss the structure and solution of single-period, deterministic linear programming models, which help farmers to improve their economic growth, to achieve happiness and prosperity in life. The improvements have been in the direction of incorporating more economic theory and economic reality into the models. Linear programming is a method of determining a profit-maximizing combination of farm enterprises that is feasible with respect to a set of fixed farm constraints.*

**Keywords:** Linear Programming Model, Quantitative Methods, Agriculture Economics, Farm-level, Sector-level

**Introduction**

From the earliest days, statically and quantitative methods have played an important role in the agriculture field, especially in agriculture economics and another area of applied economics. As a contribution of Linear programming has proven to be one of the most applicable tools for the analysis of resource allocation choices at the agricultural firm and sector level. This mathematical programming has been used in the field of agriculture economics for more than three decades. It has been such a useful tool of analysis that its basic principles are taught in all colleges and Universities of Agriculture, particularly in the last decade there also have been several methodological advances in the field of agriculture, and mathematical programming models for agriculture have been used in a large number of developed and developing countries. The improvements have been in the direction of incorporating more economic theory and economic reality into the models. The models provide the link between economic theory and data, on the one hand, and practical appreciation of real problems and policy orientations on the other hand. Mathematical programming in agriculture had its origin in attempts to model the economics of agriculture production including its dimensions. The mathematical programming structure also known as *process analysis* or *activity analyses are* particularly suitable for economic agriculture. Agronomists and other agriculture specialists in developed and developing countries think about agricultural inputs and outputs coefficient in terms of the annual crop cycle and per acre or hectare or other units of land. At the sector level, parametric variations can be used to generate response functions that are implicit in the model's structure in this condition the model becomes a device for translating micro-level (farm level) information into macro-level (sector level) functions, that are more familiar to many economists.

A set of estimated supply and demand functions at the sector level can indicate equilibrium production and price levels, towards which the sector would tend to move. The main problem with relying only on econometrics is data difficulties and changes in underlying economic structure. The data problem arises because in many cases, many crops compete for the available fixed resources; therefore, cross-supply effects are important components of the supply functions. Normally there are not enough degrees of freedom in a time series data set to estimate both own and cross-supply elastic tics. In addition to these considerations, a programming model’s supply functions provide information on the associated response of inputs, such as labor, agrochemicals, and the like. In its simplest form, linear programming is a method of determining a profit-maximizing combination of farm enterprises that is feasible concerning a set of fixed farm constraints. Early applications of linear programming in farm planning assumed profit-maximizing behavior, a single-period planning horizon (no growth), and a certain environment.

**Structure of Linear Programming Model**

Individual farmers must repeatedly make decisions about what commodities to produce, by what method, in which seasonal periods, and arise in pre-casted yields, costs, and prices for the individual farm enterprises, and enterprise requirements for fixed resources and in the total supplies of the fixed resources available. In its simplest form, linear programming is a method of determining a profit-maximizing combination of farm enterprises that is feasible concerning a set of fixed farm constraints. For a given farm situation the linear programming model requires the specification of

* The alternative farm activities, their units of measurement, their resource requirements, and any specific constraints on their production.
* The fixed resource constraints of the farm
* The forecast activity returns net of variable costs, hereafter called gross margins.

To formulate the problem mathematically we introduce the following notation:

* The level of the farm activity, such as the acreage of … grown

Let denote the number of possible activities; then

* The forecasted gross margin of a unit of the activity (*e.g.,* Rupee per ace)
* The quantity of the resource (*e.g.,* acres of land or days of labor required to produce one unit of the activity )

Let denote the number of resources; then

* The amount of the resource available (*e.g.,* acres of land or days of labor)

With the notation, the linear programming model can be written as follows:

 … (eqn. 1)

Such that,

 … (eqn. 2)

And,

 … (eqn. 3)

In view, the problem is to find the farm plan (defined by a set of activity levels,) that has the largest possible total gross margin**,** but which does not violate any of the fixed resource constraints (eqn. 2), or involve any negative activity levels (eqn. 3). This problem is known as the primal linear programming problem.

**Table 1: A Linear Programming Tableau**

|  |
| --- |
| Structure of Linear Programming |
| Objective function Resource constraints |  |  | **…** |  | **RHS** |
| 1 |  |  | **…** |  | **Maximize** |
| 2 |  |  | **…** |  |  |
| 3 |  |  | **…** |  |  |
| ... | **.****.****.** | **.****.****.** | **.****.****.** | **.****.****.** | **.****.****.** |
| m |  |  |  |  |  |

A matrix showing all the coefficients of the algebraic statement of the model. By convention, this way of presenting a structure of linear programming. Several conventions have been introduced in Table 1.

***First,***the equation to be maximized is called the objective function. In the current problem, the objective is the total gross margin (eqn. 1) but other objective functions are also possible.

***Second,***the constraints are called rows and the activities are called columns.

***Third,***the fixed resource supplies, and the Maximize coefficient are called the Right Hand Side (or, RHS) of the problem. They have all been stipulated as less than or equal () constraints, though it is also possible to include equality constraints (=) or greater than or equal () constraints.

**Assumptions**

A number of assumptions vary the nature of the production process, the resources and, activities are latent in the linear programming model in eqn. 1 to eqn. 3.

**Optimization:** An appropriate objective function is either maximized or minimized.

**Fixedness:** At least one constraint has a non-zero RHS coefficient.

**Finiteness:** The solution may be sought if there are only a finite number of activities and constraints to be considered.

**Determinism:** In the model, all constants are and

**Continuity:** Resources can be used and activities produced in quantities that are fractional units.

**Homogeneity:** All units of the same resources or activity are identical.

**Additives:** The activities to be additive when two or more are used their total product is the sum of their individual products.

**Proportionality:** The gross margin and resource requirements per unit of activity are assumed to be constant regardless of the level of the activity used.

Let, and constant returns to scale mean that if all the fixed resources are increased by a factor of proportionality then the value of the objective function also increases by .

Specifically,

Since,

If the coefficient are constant, it follows that

Thus, if the supplies of the fixed factors are increased by a factor of proportionality then the optimal activity levels also increase by.

This states that if each factor is valued as its marginal product, then the sum of the factors multiplied by their marginal products is equal to the total output. The assumptions of additively and proportionality together define linearity in the activities namely, linear programming and assumptions underlying the linear programming model. While these assumptions must hold for all rows and columns of a model, they don’t have to hold for the farm production processes themselves. Many ingenious methods of increasing the flexibility of the model are possible without violating the assumptions.

The fixedness assumption can be relaxed through dynamic multi-period specifications which allow growth and changes in the resource constraints over time. Also, methods have been developed for modeling stochastic and coefficients and for incorporating less than perfectly elastic input supplies.

**Principles of Solving Mathematical Programming Problems**

The solution to a linear programming problem is usually a unique farm plan in terms of the optimal activity. Consider the following linear programming problem:

Such that resource

 resource

If we plot the activity levels on the axes of a graph, the constraints of this problem can be portrayed as below figure:

 Common Feasible Area

 St. Line 1

 St. Line 2

 A B

 O C

Figure 1: The Feasible Set

Each constraint is represented by a straight line that intersects the axes at the maximum level of each activity that can be produced with the assumed supply of the associated resource. For the activity and the resource, the maximum activity level is

Intermediate points along a constraint depict linear combinations of the activity that also exactly exhaust the resource. For a farm plan to be eligible for consideration as the optimal solution to the linear programming problem, it must be feasible for all the resource constraints. In this limits consideration to those combinations of and contained in the area OABC. ABC is known as the production possibility frontier, it defines the maximum amount of and that can be produced for all possible ratios of the levels of these activities. To identify the optimal farm plan, we need to introduce the objective. This is done by drawing revenue lines that define the combinations of and that can be used to attain some fixed amount of total gross margin . These revenue lines are always parallel, and the ones corresponding to larger values of always lie above and to the right of those corresponding to smaller values of .

 U

Increasing Revenue

 T

 S

 O P Q R

Figure 2: The Revenue Lines

At we want to maximize Z, the total optimal farm plan is clearly the feasible plan that lies on the highest attainable revenue line.

The optimal Point

 A B

 O C

Figure 3: The Optimal Solution

In Figure 3, revenue lines have been superimposed on the set of feasible farm plans from Figure 1. The highest revenue on the set of feasible farm plans from frontier at B. B is therefore the optimal solution to the linear programming problem. The key to the simplex method is to reduce the feasible farm plans that need to be considered to a finite number. In Figure 3, we were to rotate the revenue line to reflect alternative ratios of the activity gross margin. It should be clear that the optimal solution for each rotational shift must not only lie on the production possibility frontier ABC, but it will be either points A, B, or C. Some ambiguity arises if the revenue lines are exactly parallel to either segment yielding the same value of Z, so one can choose a plan lying at the end of the segment as the optimal solution The end-point solutions are again A, B, and C.

**Computational Difficulties in Mathematical Programming**

Mathematical Programming problems cannot always be solved where optimal solution may simply not exist, In other cases, an optimal solution may exist, but the simplex procedure may converge only slowly, or not at all because of degeneracy problems. We have to discuss each problem.

**Infeasibility:** A linearprogramming problem is said to be infeasible if there is no single solution that satisfies all the constraints. Infeasibilities usually arise in practice because of mistakes in preparing the data for a linear programming problem. In large and complex problems they may also arise because the analyst fails to take adequate account of all the logical relations within the model.

**Unboundedness:** A linearprogramming problem is said to be unbounded if a feasible solution exists that has an infinite value for the objective function. Unboundedness is most commonly encountered because of errors in preparing the data for a linear programming problem.

**Degeneracy:** Degeneracy exists in a problem if the value of the objective function does not change when moving from one iteration to the next. This happens when the best incoming activity can only enter the basis at zero level. Another problem associated with degeneracy is that of ties. A tie occurs when there are two or more possible incoming activities at a given iteration that are equally good in terms of the resultant increase in the objective functions.

**Post-optimality Analysis**

In solving a linear programming problem, all the and coefficients are assumed to be known constant. However, the user may not always be sure of his data, particularly his forecasts of activity gross margins. Some coefficients, such as price and yields, may also vary from year to year because of weather or economic changes beyond the farmer’s control. One way of dealing with these uncertainties in the data is to solve the model for different but realistic sets of assumptions about the data to determine the stability or robustness of the optimal farm plan. Such post-optimality analysis is also useful for evaluating longer-term farm decisions, or changes in the economic and technological environment, which affect the fixed constraints of the farm.

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