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GA Based FGP for Resource Allocation in Farming

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INTRODUCTION

The history of human civilization shows that mankind preferred to settle on places where water and plants both are plenty, and originally human settled near river basin sides to meet the two basic needs food and water. It is thought that domestication of plants went on as far as 7000 B.C. and plant-based food production through forest gardening, the world's oldest known form of agriculture, was started as far back as 5200 B.C. The history of agriculture shows that significant improvements in agricultural techniques and technology were taken place from 12th to 13th century. Further, farming peaked in the 13th century, and stayed more or less steady until the 18th century (Campbell & Overton 1993).

However, it is worth mentioning that Green Revolution actually taken place during 1960s due to Nobel Laureate Norman Ernest Borlaug, and mathematical models were then developed for agricultural system. Then, from mid-'60s to '70s of the last century, the study on mathematical programming (MP) models to agricultural problems was first surveyed by Nix (1979).

In the context of farm planning, since optimal production of crops highly depends on proper allocation of cultivable land and adequate supply of productive resources, most of the farm problems are multiobjective in nature. As an essence, goal programming (GP) (Ignizio, 1976; Romero, 1991), fuzzy programming (FP) (Zimmermann, 1991) fuzzy goal programming (FGP) (Pal & Moitra, 2003) as prominent tools for solving multiobjective decision making (MODM) problems have been employed to farm problems (Slowinski, 1986; Biswas & Pal, 2005) in the past.

Again, to deal with the probabilistically defined uncertain data, stochastic programming (SP) (Charnes & Cooper, 1959) as well as fuzzy stochastic programming (FSP) (Sahinidis, 2004) have been studied in the past and applied to various real-life problems (Bravo, & Ganzalez, 2009). But, deep study in this area is at an early stage, and implementation to farm problems is yet to appear in the literature. Further, genetic algorithms (GAs) (Goldberg, 1989) based on the natural selection and population genetics, have appeared as volume-oriented global solution search tools for solving real-life MODM problems.

This chapter describes a *priority based* FGP approach for modeling and solving agricultural planning problems by employing GA scheme (Michalewicz, 1996; Deb, 2002) for production of various seasonal crops by allocating arable land and utilizing productive resources effectively in a plan period. In model formulation, the fuzzily described objectives are characterized by their membership functions to measure the degree of optimality of crop production. The membership functions are then converted into membership goals by assigning highest membership value (unity) as aspiration level and introducing under- and over-deviational variables to each of them. Again, chance constraints are transformed into their deterministic equivalents to employ linear FGP methodology for solving the problem. In the solution process, a GA scheme is introduced to the FGP model for evaluating the goal achievement functions to arrive at an optimal cropping plan.

The potential use of the approach is demonstrated via case example of the Bardhaman District of West Bengal (WB) in India.

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BACKGROUND

The different MP approaches for crop production planning have been widely used since Heady (1954) demonstrated the use of linear programming (LP) for land allocation problems in agricultural system. The constructive optimization models for optimal production of crops have been deeply studied (Wheeler & Russell, 1977; Glen, 1987) in the past.

Since optimal irrigation water supply is a complicated issue (Molden, 2007; Chartres & Varma, 2010), it has become a great challenge to obtain fresh water for users. The MP models for water resource planning problems with probabilistic as well as deterministic water supply constraints were studied (Askew, 1974; Revelle, Joeres, & Kirby, 1969; Yeh, 1985) in the past. Although, GA tools to different real-life MODM problems have been introduced (Sakawa & Kobuta, 2000) previously, study in the area of irrigation water supply in uncertain environment is at an early stage.

In this chapter, the FGP formulation of a farm planning problem with different fuzzily described objectives and probabilistically defined system constraints concerning achievement of socio-economic objectives is considered.

The general chance constrained FP formulation of a problem is presented in the following section.

Chance Constrained FP Problem Formulation

The generic form of a chance constrained FP problem can be presented as follows.

Find $\mathbf{X}\,(\mathrm{x}_1, \mathrm{x}_2, ..., \mathrm{x}_\mathrm{n})$ so as to satisfy:

$$F_k(\mathbf{X}) \begin{pmatrix} \gtrsim \\ \lesssim \end{pmatrix} g_k, \quad \mathrm{k} = 1, 2, ..., \mathrm{K}$$

subject to

$$\mathbf{X} \in S\{\mathbf{X} \in R^n | \Pr[F(\mathbf{X}) \begin{pmatrix} \geq \\ \leq \end{pmatrix} b] \geq p, \quad \mathbf{X} \geq 0,\ \mathrm{b} \in \mathrm{R}^\mathrm{m}\},\ A(\mathbf{X}) \begin{pmatrix} \geq \\ \leq \end{pmatrix} c, \tag{1}$$

where X be the decision vector and g_k be the imprecise aspiration level of the k-th objective $F_k(\mathbf{X})$, and where $\gtrsim$ and $\lesssim$ indicate the fuzziness of $\geq$ and $\leq$ restrictions, respectively. $F(\mathbf{X})$ is a function (linear or non-linear) of chance constraints set, b is a constant vector and $p(0<p<1)$ is the vector of satisficing probability levels, and where Pr stands for probabilistically defined constraints. A is a real matrix of coefficients set and c is a resource vector.

Characterization of Membership Function

Let $t_{\ell k}$ and t_{uk} be the lower- and upper-tolerance ranges, respectively, for achievement of aspired level g_k of the k-th fuzzy goal. Then, the membership functions, say $\mu_k(\mathbf{X})$, for the fuzzy goal $F_k(\mathbf{X})$ can be characterized as follows.

For $\gtrsim$ type of restriction, $\mu_k(\mathbf{X})$ takes the form:

$$\mu_k(\mathbf{X}) = \begin{cases} 1, & \text{if } F_k(\mathbf{X}) \geq g_k \\ \dfrac{F_k(\mathbf{X}) - (g_k - t_{\ell k})}{t_{\ell k}}, & \text{if } \mathrm{g_k} - t_{\ell k} \leq F_k(\mathbf{X}) < g_k \\ 0, & \text{if } \mathrm{F_k}(\mathbf{X}) < g_k - t_{\ell k} \end{cases} \tag{2}$$

$k = 1, 2, ..., K_1$

where $(g_k - t_{\ell k})$ represents the lower-tolerance limit for achievement of the stated fuzzy goal.

For $\lesssim$ type of restriction, $\mu_k(\mathbf{X})$ becomes:

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