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Scatter search based interactive multi-criteria optimization of fuzzy objectives for coal production planning

Parag C. Pendharkar*

School of Business Administration, Pennsylvania State University at Harrisburg, 777 West Harrisburg Pike, Middletown, PA 17057, United States

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ABSTRACT

We present an interactive multi-criteria procedure that uses user defined tradeoff-cutting planes to identify promising feasible solution search space. New solutions in the promising feasible solution search space are constructed using combination of scatter and random search. The procedure of identifying tradeoff-cutting planes and scatter search continues for either a predetermined fixed number of iterations or until no solutions in the promising feasible solution search space are found. We formulate a coal production planning problem with fuzzy profit and fuzzy coal quality decision-maker utilities, and apply our procedure for additive and multiplicative decision-maker utilities.

1. Introduction

Fuzzy logic is recognized as an important decision support tool due to its capability to incorporate linguistic non-crisp variable values (Elamvazuthi et al., 2012). The availability of software platforms such as Matlab with fuzzy toolbox is making the use of fuzzy logic very easy in production planning (Vasant, 2003; Vasant et al., 2004). As a result, a variety of fuzzy linear programming (FLP) and heuristic (Vasant and Barsoum, 2010) applications have emerged from variety of industries ranging from textiles (Elamvazuthi et al., 2009), crude oil refinery (Vasant et al., 2012) to coal mining (Pendharkar, 1997). Interactive FLP has been applied to production planning in textile firms, transportation planning and crude oil refinery industries (Vasant et al., 2011; Pedro and Vasant, 2011; Vasant et al., 2010a). Among the popular membership functions in FLP are linear and S-shaped membership functions (Bhattacharya and Vasant, 2007; Vasant et al., 2010b). Diaz-Madrronero et al. (2010) describe different membership functions used in FLP and their benefits. Generally, linear membership functions are easy to use and have higher computational efficiency. S-shaped membership functions provide flexibility in describing uncertain and ill-known fuzzy problems (Elamvazuthi et al., 2010).

Interactive multi-criteria problems involve simultaneous optimization of two or more conflicting objectives (Bas, 2012; Vasant et al., 2007). Assuming an n-dimensional decision variable vector $\boldsymbol{x}=[x_1,\ldots,x_n]^T$, a feasible solution set X such that the feasible set of decisions satisfy $\boldsymbol{x}\in X$, a set of $h\geq 2$ criteria functions $f_h(\boldsymbol{x})$, and a group/individual utility function u, the interactive multi-criteria optimization problem is described as follows (Troutt, 1994; Steuer, 1986):

$$\max\{u(f_1(\boldsymbol{x}),\ldots,f_h(x)) : \boldsymbol{x}\in X\sqsubset\mathbb{R}^n\} \quad (1)$$

Assuming that $u(f_1(\boldsymbol{x}),\ldots,f_h(\boldsymbol{x}))$ is concave, twice differentiable and satisfies *strict non-satiety*[1] assumption, any solution that maximizes (1) is called the best compromise solution (Troutt, 1994; Steuer, 1986).

Most popular methods to find a compromise solution require user interaction to identify the compromise solution. These methods use cutting planes (Shin and Ravindran, 1991), Marginal Rate of Substitution (MRS) (Geoffrion et al., 1972), or abstract mass concept (AMC) (Troutt, 1994) to obtain the compromise solution. While all of these methods are similar in their implementation of user interaction, they are different in their assumptions and the manner in which they process information. The MRS method seeks tradeoff rates between different criteria to narrow the location of compromise solution. The AMC method is an advanced method that seeks the cutting plane information from the user to solve a continuous

* Tel.: +1 717 948 6028; fax: +1 717 948 6456.
E-mail address: pxp19@psu.edu
URL: http://www.personal.psu.edu/pxp19/

[1] Means more units of an attribute is preferred to the less of the same, i.e., $\partial u/\partial f_h\geq\epsilon$, where ϵ is infinitesimally non-Archimedean.

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piecewise polynomial system of equations that yields direction specific gradients for different criteria, which are then used to identify a compromise solution half-space. The AMC is useful when the decision maker's utility function is not known or when the decision maker's utility function is known but there are too many criteria to optimize which renders MRS method too difficult to use. When the decision maker's utility function is known and the decision-making criteria are reasonably small then constructing cutting planes is very simple. Shin and Ravindran (1991) illustrate how these cutting planes can be constructed. Generally, the construction of these cutting planes requires interaction from the user on his/her satisfaction about a computer generated solution. Typically, a possible solution is shown to the user and if the user is not satisfied with the shown solution then a cutting plane is constructed by using the value of shown solution and partial derivatives of utility function with respect to different criterion.

Once a half-space for compromise solution is identified, finding the next feasible solution in half-space becomes the next problem to solve in an interactive multi-criteria optimization. A popular method that is used to identify feasible solutions in the half-space is called parameter space investigation (PSI) method (Steuer and Sun, 1995). The PSI method uses Monte Carlo strategy to randomly search for solutions in the solution half-space and retains solutions that belong to the solution half-space and rejects any other solutions. While the PSI works well and is independent of the number of criteria and the number of constraints, its performance is highly sensitive to the dimension of variable vector $\boldsymbol{x}$ (Steuer and Sun, 1995). For example, assuming that $p(\boldsymbol{x}_s)$ is the probability that a randomly generated sth element of vector $\boldsymbol{x}$, for $s \in \{1,\ldots,n\}$, from the PSI method's Monte Carlo strategy belongs to the feasible solution space then the probability that all elements belonging to the feasible solution space is given by $\prod_{s=1}^{n} p(x_s)$. When cutting/cutoff planes are added due to user interaction, half-space for the compromise solution only shrinks leading to new probabilities $p^{\text{new}}(x_s) \le p(x_s)$, $\forall x_s$. For large dimension of $\boldsymbol{x}$ or for several user interactions with reasonable dimension, finding feasible solutions using the PSI method gets difficult because $\prod_{s=1}^{n} p^{new}(x_s) \to 0$ with higher dimension of $\boldsymbol{x}$ and increasing user interactions. Steuer and Sun (1995), using a multi-criteria linear programming problem, report that for $n=10$, PSI method finds only 10 feasible solutions in 100,000 trials and for $n=20$ no feasible solution can be found in 100,000 trials. Since user interaction only decreases the feasible region resulting in lower $p^{\text{new}}(x_s)$, using PSI method may be inefficient for even small problems with $n=5$ and five user interactions.

An alternative to the use of PSI method is the scatter search approach (Glover et al., 2000). Scatter search is an alternative approach to random search approach where generalized path construction in Euclidean space is used to construct solutions. In a scatter search approach, initial sets of solutions are randomly generated. Of these random solutions, the set of solutions that belong to the feasible region are called the *reference set* (Laguna and Marti, 2003). The solutions from reference set are combined, using convex and non-convex combinations, to identify new reference set solutions. A typical reference set contains 5–20 solutions and two solutions are combined at a time to generate new reference set solutions. If the new reference set solutions are better quality solutions than the solutions in previous reference set then the previous reference set is updated to contain the best 5–20 solutions. Occasionally, *intensification* and *diversification* strategies are used to explore solution search space (Glover et al., 2003; Laguna, 2002). Intensification uses minor Euclidean space perturbations to the existing reference set solutions to identify improvements. In diversification, either a random search or a line search is used in an attempt to identify solutions that are far away from the current reference set solutions.

In this paper, we propose a multi-criteria coal production planning problem with fuzzy profit and fuzzy coal quality criteria. Next, we propose a scatter-search based interactive multi-criteria optimization procedure to identify promising solutions, and test the procedure using an example with additive and multiplicative decision-maker utilities. The rest of the paper is organized as follows. In Section 2, we propose the fuzzy multi-criteria model for coal production planning. In Section 3, we describe the scatter search based interactive multi-criteria optimization procedure for solving interactive multi-criteria optimization problems. In Section 4, we describe a production planning example, apply scatter search procedure and provide the results of our experiments. In Section 5, we provide a discussion on the proposed procedure. In Section 6, we conclude our paper with a summary.

2. Fuzzy multi-criteria coal production planning problem

We divide this section into three sub-sections. The first sub-section contains brief overview of coal mining and coal composition. The second sub-section describes fuzzy membership function design and implementation for fuzzy profit and fuzzy quality attributes. Finally, the third sub-section describes constraints to delineate feasible solution region.

2.1. Overview of coal mining and coal composition

The United States (US) has the largest coal reserves in the world, and coal has been mined in the US since the early 1800s. Recent estimates show that annual coal extraction in the US is slightly over one billion short tons[2] (Freme, 2009). The primary markets for US coal are electric utility companies, independent power producers and commercial/industrial plants. The selling price for coal to these markets varies depending on the consumer. For electric utilities the selling price of coal is approximately \$44.72/t, and for independent power producers the selling price is approximately \$39.72/t. The selling price for commercial and industrial plants slightly higher and varies between \$64.87/t and \$97.28/t. The high selling price for commercial and industrial plants is, in part, due to higher transportation (delivery) costs to these locations (Freme, 2009).

Coal is classified into different categories depending on its elemental carbon content. There are three primary types of coal: Anthracite, Bituminous and Lignite. Anthracite is the highest quality of coal containing between 86 and 96% elemental carbon and has the highest heat value of between 13,550 and 15,600 Btu/lb. Bituminous and Lignite have lower percentage of elemental carbon with ranges of 46–86% for Bituminous coal and 46–60% for Lignite, respectively. All of these three forms of coal contain other elements present in organic matter, which include ash, sulfur and nitrogen.

Coal is sold to electric power plants through long-term contracts and spot sales for increased demand due to higher than anticipated economic growth or unusual weather conditions leading to higher electricity demand (Freme, 2009). Most mine contracts, due to varying heat value of coal and environmental protection agency (EPA) regulations, contain coal specifications that specify limits on delivered coal heat value, sulfur, and ash content. Since coal mine locations and coal quality are governed by geology, mining companies mine different quality of coal from different mines, and blend it so that the blended coal adheres to the contractual obligations (Pendharkar, 1997). If blended coal does not meet the quality standards then it can be further processed through coal washing plants to improve its quality.

Pendharkar (1997) argued that while coal companies must meet their contractual obligations, there is slight leeway on coal specifications. For example, a maximum sulfur limit of 1.2% does

[2] One short ton=2000 lbs.