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Hybrid genetic algorithms and line search method for industrial production planning with non-linear fitness function

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ABSTRACT

Many engineering, science, information technology and management optimization problems can be considered as non-linear programming real-world problems where all or some of the parameters and variables involved are uncertain in nature. These can only be quantified using intelligent computational techniques such as evolutionary computation and fuzzy logic. The main objective of this research paper is to solve non-linear fuzzy optimization problem where the technological coefficient in the constraints involved are fuzzy numbers, which was represented by logistic membership functions using the hybrid evolutionary optimization approach. To explore the applicability of the present study, a numerical example is considered to determine the production planning for the decision variables and profit of the company.

1. Introduction

It is well known that optimization problems arise in a variety of situations. Particularly interesting are those concerning management problems as decision makers usually state their data in a vague way: "high benefits", "as low as possible", "important savings", etc. Because of this vagueness, managers prefer to have not just one solution but as many of them, so that the most suitable solution can be applied according to the state of existing decision of the production process at a given time and without increasing delay. In these situations fuzzy optimization is an ideal methodology, since it allows us to represent the underlying uncertainty of the optimization problem, while finding optimal solutions that reflect such uncertainty and then applying them to possible instances, once the uncertainty has been solved. This allows us to obtain a model of the behavior of the solutions based on the uncertainty of the optimization problem.

Fuzzy constrained optimization problems have been extensively studied since the seventies. In the linear case, the first approaches to solve the so-called fuzzy linear programming problem appeared in Bellman and Zadeh (1970), Tanaka et al. (1974) and Zimmermann (1976). Since then, important contributions solving different linear models have been made and these models have been the subject of a substantial amount of work. In the non-linear case (Ali, 1998; Ekel et al., 1998; Ramik and Vlach, 2002) the situation is quite different, as there is a wide variety of specific and both practically and theoretically relevant non-linear problems, with each having a different solution method.

In this paper, the new methodology of modified S-curve membership function using fuzzy linear programming in production planning and their applications to decision making are carried out. Especially, fuzzy non-linear programming (NPL) based on vagueness in the fuzzy parameters such as objective coefficients, technical coefficients and resource variables given by a decision maker is analyzed.

Various types of membership functions were used in fuzzy linear programming problem and its application such as a linear membership function (Zimmermann, 1976, 1978), a tangent type of a membership function (Leberling, 1981), an interval linear membership function (Hannan, 1981), an exponential membership function (Carlsson and Korhonen, 1986), inverse tangent membership function (Sakawa, 1983), logistic type of membership function (Watada, 1997), concave piecewise linear membership function (Inuiguchi et al., 1990) and piecewise linear membership function (Hu and Fang, 1999). As a tangent type, of a membership function, an exponential membership function, and hyperbolic membership function are non-linear function; a fuzzy mathematical programming defined with a non-linear membership function results in a non-linear programming. Usually a linear membership function is employed in order to avoid non-linearity. Nevertheless, there are some difficulties in

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selecting the solution of a problem written in a linear membership function. Therefore, in this paper a modified S-curve membership function is employed to overcome such deficits, which a linear membership function has. Furthermore, the S-curve membership function is more flexible enough to describe the vagueness in the fuzzy parameters for the production planning problems (Vasant, 2003, 2006).

Due to limitations in resources for manufacturing a product and the need to satisfy certain conditions in manufacturing and demand, a problem of fuzziness occurs in industrial production planning systems. This problem occurs also in chocolate manufacturing when deciding a mixed selection of raw materials to produce varieties of products. This is referred to here as the Product-mix Selection Problem (Tabucanon, 1996). The objective of the company is to maximize its profit, which is, alternatively, equivalent to maximizing the gross contribution to the company in terms of US$. That is, to find the optimal product mix under uncertain constraints in the technical, raw material and market consideration. Furthermore, it is possible to show the relationship between the optimal profits and the corresponding membership values (Zimmermann, 1978). According to this relationship, the decision maker can then obtain his optimal solution with a trade-off under a pre-determined allowable imprecision.

2. Hybrid genetic algorithm for solving optimization problems

Genetic algorithms (GAs) have been used successfully to find optimal or near-optimal solutions for a wide variety of optimization problems (Gen and Cheng, 1996; Goldberg, 1989) since its introduction by Holland (1975). GAs are intelligent stochastic optimization techniques based on the mechanism of natural selection and genetics. GAs start with an initial set of solutions, called population. Each solution in the population is called a chromosome (or individual), which represents a point in the search space. The chromosomes are evolved through successive iterations, called generations, by genetic operators (selection, crossover and mutation) that mimic the principles of natural evolution. In a GA, a fitness value is assigned to each individual according to a problem-specific objective function. Generation by generation, the new individuals, called offsprings, are created and survive with chromosomes in the current population, called parents, to form a new population.

GAs often perform well in global search, but they are relatively slow and trapped in converging to a local optimal (Wang and Wu, 2004). On the other hand, the local improvement methods, such as gradient-based (line search, LS) procedures, can find the local optimum in a small region of the search space, but they are typically poor in a global search. Therefore, various strategies of hybridization have been suggested to improve performance of simple GAs (Gen and Cheng, 1996; Wang and Wu, 2004). These hybridizations usually involve incorporating a neighborhood search (NS) heuristic as a local improver into a basic GA loop of recombination and selection. That is, local improver is applied to each newly generated offspring to move it to a local optimum one before inserting it into the enlarged population (Turabieh et al., 2007). In this manner, GA is used to perform global exploration among a population (i.e. as a diversification tool), while the local improver is used to perform local exploitation around chromosomes (i.e. as an intensification tool). The general structure of the proposed hybrid genetic algorithm (HGA) for the problem is described as follows:

Step 1. Initialization: create an initial population of population size solutions using constructive heuristics and randomly generated solutions.
Step 2. Recombination: recombine the solutions in the current population using genetic operators to create new individuals.
Step 3. Improvement: apply the local improvement method (line search) to replace each offspring with a local optimum one, and insert the improved offspring into the enlarged population.
Step 4. Selection: select population size solutions from the chromosomes in the enlarged population to form the next generation, and determine the best solution in the new population.
Step 5. Iteration: repeat steps 2–4 until the termination condition is reached.

Therefore, the best solution in the last population will be final solution for the problem that ideally may be an optimal or near-optimal solution.

However, due to high computational burden of the optimal solution method, an efficient and effective hybrid genetic algorithm is proposed in this research work. In HGA, four following ways of hybridization are used:

- Incorporating simple and effective uniform heuristics into initialization step to generate good initial population.
- Incorporating two effective mutation operators of adaptive feasible and crossover operator of arithmetic to complete continuous solution of the problem with constraints.
- Incorporating an efficient neighborhood search method of gradient based (line search) as an add-on extra to the main GA algorithms to obtain optimal solutions.
- Incorporating an enumeration method into fitness evaluation function in the stopping criteria for complete continuous solution of the problem.

Computational results indicate that the performance of HGA is very promising, and it outperforms the optimal enumeration method in particular at medium- and large-scaled problems in terms of computation times and also solution quality at majority of the test problems.

L. "Dave" Davis states in the Handbook of Genetic Algorithms, "Traditional genetic algorithms, although robust, are generally not the most successful optimization algorithm on any particular domain" (1991). Davis argues that hybridizing genetic algorithms with the most successful optimization methods for particular problems gives one the best of both worlds: correctly implemented, these algorithms should do no worse than the (usually more traditional) method with which the hybridizing is done. Of course, it also introduces the additional computational overhead of a population-based search.

Davis often uses real-valued encodings instead of binary encodings, and employs "recombination operators" that may be domain specific. Other researchers, such as Michalewicz (1993), also use non-binary encodings and specialized operations in combination with a genetic-based model of search. M'uhlenbein (1991) takes a similar opportunistic view of hybridization. In a description of a parallel genetic algorithm M'uhlenbein (1991) states, after the initial population is created, "Each individual does local hill-climbing". Furthermore, after each offspring is created, "The offspring does local hill-climbing".

Experimental researchers and theoreticians are particularly divided on the issue of hybridization. By adding hill-climbing or hybridizing with some other optimization methods, learning is being added to the evolution process. Coding the learned information back onto the chromosome means that the search utilizes a form of Lamarckian evolution. The chromosomes improved by local hill-climbing or other methods are placed in