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A fuzzy genetic algorithm with varying population size to solve an inventory model with credit-linked promotional demand in an imprecise planning horizon

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ABSTRACT

A genetic algorithm (GA) with varying population size is developed where crossover probability is a function of parents' age-type (young, middle-aged, old, etc.) and is obtained using a fuzzy rule base and possibility theory. It is an improved GA where a subset of better children is included with the parent population for next generation and size of this subset is a percentage of the size of its parent set. This GA is used to make managerial decision for an inventory model of a newly launched product. It is assumed that lifetime of the product is finite and imprecise (fuzzy) in nature. Here wholesaler/producer offers a delay period of payment to its retailers to capture the market. Due to this facility retailer also offers a fixed credit-period to its customers for some cycles to boost the demand. During these cycles demand of the item increases with time at a decreasing rate depending upon the duration of customers' credit-period. Models are formulated for both the crisp and fuzzy inventory parameters to maximize the present value of total possible profit from the whole planning horizon under inflation and time value of money. Fuzzy models are transferred to deterministic ones following possibility/necessity measure on fuzzy goal and necessity measure on imprecise constraints. Finally optimal decision is made using above mentioned GA. Performance of the proposed GA on the model with respect to some other GAs are compared.

1. Introduction

GAs are general purpose search techniques, which use principles of natural evolution (Holland, 1975). Their domain of utilization is very large, a review of their implementations and some domains of applications are given in Goldberg (1989), and Michalewicz (1992). But behavior and performance of a GA are directly affected by the interaction between the parameters, which have fixed crisp values in a simple GA (Last and Eyal, 2005; Michalewicz, 1992). Poor parameter settings usually lead to several problems such as premature convergence. Extensive research work has been made to improve the performance of GA for single/multi-objective continuous/discrete optimization problems during last two decades (Bessaou and Siarry, 2001; Chang et al., 2005; Last and Eyal, 2005; Pezzellaa et al., 2008). According to literature, GAs with varying population size do better performance for search problems in various domains. Last and Eyal (2005) developed a GA with varying population size, where each chromosome is assigned a lifetime at the time of birth depending on fitness. They classified the chromosomes into three age types – young, middle-aged and old according to their age and represent them using fuzzy numbers. In their GA, crossover probability is a function of parents' age-type and is obtained using a fuzzy rule base. One difficulty in implementing this GA in the computer is that population size monotonically increases in each generation, which in turn gives memory fault in running the program after some iterations. Another drawback is that before using the fuzzy parameters in the algorithm they transform these into crisp numbers using center of gravity of fuzzy numbers. So impreciseness of genetic parameters are not properly incorporated in the algorithm.

Overcoming the above drawbacks, here, a GA with varying population size is developed where population size has an upper limit. Chromosomes are classified into young, middle-aged and old according to their age and are represented by fuzzy numbers. Here also crossover probability is a function of parents' age-type, but is obtained using a fuzzy rule base and fuzzy possibility theory Dubois and Prade (1980). It is an improved GA, where a subset of better children is included in the parent population for the next generation and the maximum size of this subset is a percentage of the size of its parent population.

GAs are extensively used for inventory control decisions during last decade. Maiti and Maiti (2007) developed a two-storage inventory model with lot-size dependent fuzzy lead-time under possibility constraints via genetic algorithm. Najafi et al. (2009) developed a parameter-tuned genetic algorithm for the resource investment

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problem with discounted cash flows and generalized precedence relations. Maiti et al. (2006) developed a two storage inventory model with fuzzy deterioration over a random planning horizon and solved using GA. Sourirajan et al. (2009) developed a genetic algorithm for a single product network design model with lead time and safety stock considerations. Maiti (2008) developed a fuzzy inventory model with two warehouses under possibility measure on fuzzy goal. Valente and Gonalves (2009) follow genetic algorithm approach for the single machine scheduling problem with linear earliness and quadratic tardiness penalties. Wee et al. (2009) developed a multi-objective joint replenishment inventory model of deteriorated items in a fuzzy environment. Taleizadeh et al. (2009) used a hybrid method of Pareto, TOPSIS and genetic algorithm to optimize multi-product multi-constraint inventory control systems with random fuzzy replenishment. Xu and Zhao (2010) used genetic algorithm to solve a multi-objective inventory problem with fuzzy rough coefficients.

Inventory models with permissible delay in payment have been extensively studied by several authors (Chang et al., 2001; Chung, 1998a,b; Goyal, 1985; Huang, 2003; Jamal et al., 2000). In these studies it is usually assumed that the supplier would offer a fixed credit-period to the retailer but the retailer in turn would not offer any credit-period to its customers, which is unrealistic, because in real practice retailer might offer a credit-period to its customers in order to stimulate his own demand. Inventory model incorporating this phenomenon was first developed by Huang (2007). He developed an EPQ model under two levels of trade credit policy, where the retailers' trade credit-period offered by the supplier, M, is not shorter than the customers' trade credit-period offered by the retailer, T_0 ($M \geqslant T_0$). A major drawback of the model is that here credit-period of customer is not same for all the customers. The persons who purchase the item earlier will get more credit-period than those purchase later. Moreover, in the model, retailers' credit-period has no effect on the demand of the item. Incorporating these shortcomings Jaggi et al. (2008) developed an inventory model under two-level trade credit policy where demand of the item depends on retailers' credit-period (T_0). They assumed that credit-period (T_0) of each customer is same and is offered during the entire planning horizon. But in reality it is normally observed that though supplier offers the credit-period to retailers during the whole planning horizon, retailer offers the credit-period to its customers during few cycles at the beginning of planning horizon to boost the demand. When demand of the item reaches a certain level, the credit-period is withdrawn by the retailer.

Again inventory models are normally developed with common assumption that lifetime of the product is infinite. Due to fluctuating world economy, cost of the raw materials as well as processing cost of an item changes rapidly. Also 'introduction of multinationals' leads to change in product specifications with new features, packets and name. So in reality, lifetime of a product is finite and normally it is imprecise in nature. Few research papers have already been published incorporating this assumption (Gurnani, 1983; Moon and Yun, 1993; Maiti et al., 2006; Roy et al., 2007).

In this research paper an inventory model of an item is developed, where lifetime of the product is assumed as fuzzy in nature and so planning horizon is assumed as a fuzzy number. Here, it is assumed that the supplier offers a credit-period (M) to the retailers to stimulate demand. Retailer also initially offers a credit-period (T_0) to its customers for few cycles to boost the demand. During these cycles demand increases with time at a decreasing rate. After withdrawals of credit-period demand remains constant for the rest of the cycles. There is only one imprecise constraint- sum of production cycle lengths is less than the length of imprecise planning horizon and the constraint will hold good to at least some necessity α. Models are formulated for both the crisp and fuzzy inventory costs. For crisp inventory parameters total profit under the above mentioned constraint is maximized using the proposed GA to take optimal decisions. When some inventory parameters are fuzzy in nature then total profit out of the system is fuzzy in nature too. As optimization of a fuzzy objective is not well defined, a fuzzy goal for average profit is set and possibility/necessity of the fuzzy objective (i.e., total profit) in respect to the fuzzy goal is optimized under the above mentioned necessity constraint in optimistic/pessimistic sense (Dubois and Prade, 1980; Maiti, 2008). Finally, the problem is transferred to an equivalent crisp model and solved using the proposed GA. The models are illustrated with numerical examples and sensitivity analysis on some inventory parameters have been made.

2. Mathematical prerequisite

Let $\tilde{a}$ and $\tilde{b}$ be two fuzzy numbers with membership functions $\mu_{\tilde{a}}(x)$ and $\mu_{\tilde{b}}(x)$ respectively. Then according to (Dubois and Prade, 1980; Zadeh, 1978),

$$pos(\tilde{a} * \tilde{b}) = sup\{min(\mu_{\tilde{a}}(x), \mu_{\tilde{b}}(y)), x, y \in \Re, x * y\}, \quad (1)$$

where the abbreviation pos represents possibility, $*$ is any one of the relations >, <, =, $\leqslant$, $\geqslant$ and $\Re$ represents set of real numbers.

$$nes(\tilde{a} * \tilde{b}) = 1 - pos\overline{(\tilde{a} * \tilde{b})}, \quad (2)$$

where the abbreviation nes represents necessity.

Similarly possibility and necessity measures of $\tilde{a}$ with respect to $\tilde{b}$ are denoted by $\Pi_{\tilde{b}}(\tilde{a})$ and $N_{\tilde{b}}(\tilde{a})$, respectively and are defined as

$$\Pi_{\tilde{b}}(\tilde{a}) = sup\{min(\mu_{\tilde{a}}(x), \mu_{\tilde{b}}(x)), x \in \Re\}, \quad (3)$$

$$N_{\tilde{b}}(\tilde{a}) = min\{sup(\mu_{\tilde{a}}(x), 1 - \mu_{\tilde{b}}(x)), x \in \Re\}. \quad (4)$$

If $\tilde{a}, \ \tilde{b} \subseteq \Re$ and $\tilde{c} = f(\tilde{a}, \tilde{b})$ where $f : \Re \times \Re \to \Re$ is a binary operation then membership function $\mu_{\tilde{c}}$ of $\tilde{c}$ is defined as

$$\text{For each } z \in \Re, \quad \mu_{\tilde{c}}(z) = sup\{min(\mu_{\tilde{a}}(x), \mu_{\tilde{b}}(y)), x, y \in \Re \text{ and } z = f(x, y)\}. \quad (5)$$

Triangular fuzzy number (TFN): A TFN $\tilde{a} = (a_1, a_2, a_3)$ (cf. Fig. 1) has three parameters a_1, a_2, a_3 where $a_1 < a_2 < a_3$ and is characterized by the membership function $\mu_{\tilde{a}}$, given by

$$\mu_{\tilde{a}}(x) = \begin{cases} \frac{x-a_1}{a_2-a_1} & \text{for } a_1 \leqslant x \leqslant a_2, \\ \frac{a_3-x}{a_3-a_2} & \text{for } a_2 \leqslant x \leqslant a_3, \\ 0 & \text{otherwise}. \end{cases} \quad (6)$$

Linear fuzzy number (LFN): A LFN $\tilde{a} = (a_1, a_2)$ (cf. Fig. 2) has two parameters a_1, a_2 where $a_1 < a_2$ and is characterized by the membership function $\mu_{\tilde{a}}$, given by

$$\mu_{\tilde{a}}(x) = \begin{cases} 0 & \text{for } x \leqslant a_1, \\ \frac{x-a_1}{a_2-a_1} & \text{for } a_1 \leqslant x \leqslant a_2, \\ 1 & \text{for } x \geqslant a_2. \end{cases} \quad (7)$$

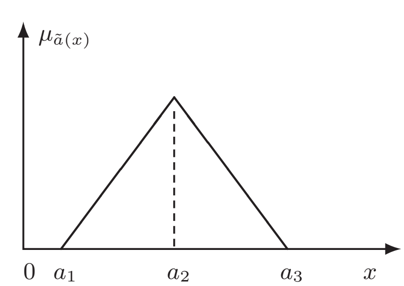

Fig. 1. Triangular fuzzy number $a = (a1,a2,a3)$.