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APPLICATION OF META-HEURISTIC ALGORITHMS (GENETICS) TO INVENTORY CONTROL IN FUZZY MODE: CASE STUDY OF FOOD INDUSTRY

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ABSTRACT

The inclusion of suitable inventory control and management system plays a key role in managing the financial health of a manufacturing company. In most cases, an unjustified inventory of raw materials is maintained resulting in specific losses to the company. In addition, the consideration of numerous factories manufacturing the same product results in a very complex inventory management method. The complexity of the problem improves when lead times of stocks are included. In this paper, we present our work about forecasting methods according to the fuzzy time series and genetic algorithm. The main objective of this paper is to generate a fuzzy EOQ model and to measure the optimum order quantity so as to minimize the average total cost.

Keywords: *Genetic Algorithms, Fuzzy Logic, Time Series, Inventory control, Inventory management*

INTRODUCTION

Inventory is critical to an organization from a financial and operational viewpoint. It depicts a financial investment for any company, and it is important for the provision of goods and services to the customer (Barlow, 1997). Every organization requires inventory for the smooth running of its projects. It is a link between production and distribution methods. The investment in inventories forms the most crucial part of contemporary assets and working capital in most of the undertakings (Jose et al., 2013).

It was reported by Waters (2003) and Bose (2006) that a company may fail because of the maintenance of unjustified surplus stocks. Hence, optimization in inventory control and management is very important in an organization to justify its financial health (Dutta, 1974, 1992; Bose, 2006).

Without suitable control, inventory has a tendency to grow beyond economic limits, tie up funds and enhance the cost of maintenance or carrying. At the same time, the non-availability involves the cost of stock-outs, re-ordering costs, and extra transit costs. Inventory control as an integrated method is therefore crucial for determining the time, item(s), and quantity to indent, and amount of stock, so that purchasing and storing costs become minimum without influencing production, distribution, functional success, etc. (Dutta, 1992; IIMM, 2006; Mallick et al., 2007). So, in order to analyze effective management of the distribution network of an Iranian food industry under centralized control, we developed a genetic algorithm of inventory control and management of the organization.

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LITERATURE REVIEW

In some cases, the strategic facility location decisions are highly influenced by tactical decisions such as inventory decisions. Traditionally, for modeling aims, these levels have been managed independently which may result in sub-optimal decisions, as mentioned by many researchers (Miranda and Garrido, 2004; Max Shen and Qi, 2007; Snyder et al., 2007). In other words, by considering these decisions at the same time, a notable cost saving can be obtained. Thence, integrated models have attracted much attention in the literature.

The first investigation that recommended the idea of integrating inventory cost into location models was presented by Baumol and Wolfe (1958). Cachon (2001) and Axsater (2000) developed exact techniques to assess systems cost for a two-echelon supply chain (one-warehouse-multi-retailer system), considering a periodic review and continuous review, respectively. These methods consider the order quantities and the re-order points, as fixed parameters. Ettl et al. (2000) assessed a complex network of supply processes manufacturing stages and end consumers, determining re-order-points for each site of the network, given a set of service levels for each site that serves end consumers. Puente et al. (2002) presented a fuzzy method of classifying different productive items of a company. This method allowed novel fuzzy information about the future to be included, thus allowing stricter control of the fuzzy 'A-items' that resulted from this classification.

Zhou et al. presented an extended version of Ramanathan's model. They included some balancing features for MCIC utilizing two sets of weights that are most favorable and least favorable for each item (Ramanathan, 2006). Ramanathan suggested a weighted linear optimization technique for classifying inventory items with multiple criteria. In the recommended method, a weighted additive function was utilized to aggregate the performance of an inventory item in terms of various criteria to a single score, called the optimal inventory score of an item. The weights were chosen utilizing optimization method subject to the constraints that the weighted sum for all the items must be less than or equal to one. The weighted sum was computed utilizing the same set of weights. This method used a maximization objective function. To obtain the optimal scores of all inventory items, the proposed method should be solved repeatedly by modifying the objective function. These scores can then be utilized to classify the inventory items (Ramanthan, 2006).

Chu et al. proposed an inventory control approach combining ABC and fuzzy classification. They applied this method to an example with 159 SKUs and surprisingly classified 59 items in class A, 69 items in class B, and 64 items in class C which is not consistent with the basic concept of ABC classification. However, it does not seem logical to classify roughly the same number of SKUs at three classes A, B, and C (Bernstein et al, 2007).

Chi-Yang et al. (2008) introduced an inventory classification algorithm by applying the Particle Swarm Optimization (PSO) technique. Other classification schemes require the number of item groups to be defined before classification. Besides, they are designed for specific objectives (e.g. cost minimization specific costs) or they classify items according to specific criteria (e.g. demand rate and item values). In contrast, the PSO algorithm can be utilized to incorporate various objectives. It simplifies the decision process of having to decide how many item groups should be there before item classification. The experimental design was employed for PSO parameter choice. Four objectives including cost minimization, demand correlation maximization, inventory turnover ratio maximization and a combination of the above three were considered (Chi-Yang et al., 2008).

GENETIC ALGORITHM AND FUZZY LOGIC

A genetic algorithm (or GA) is a search technique utilized in computing to find true or approximate solutions to optimization and search problems. Genetic algorithms (GAs) are search techniques according to the principles of natural selection and genetics (Fraser, 1957; Bremermann, 1958; Holland, 1975). GAs encode the decision variables of a search problem into finite-length strings of alphabets of certain cardinality. The strings which are candidate solutions to the search problem are defined as chromosomes, the alphabets are defined as genes and the values of genes are called alleles (Sastry et al., 2005).

To develop good solutions and to perform natural selection, we require a measure for distinguishing good solutions from bad solutions. The measure could be an objective function that is a mathematical model or a computer simulation, or it can be a subjective function where humans prefer better solutions over worse ones. In reality, the fitness measure must define a candidate solution's relative fitness, which will consequently be utilized by the GA to guide the evolution of good solutions.

Another essential concept of GAs is the notion of population. The population size, which is normally a user-specified parameter, is one of the significant factors influencing the scalability and performance of genetic algorithms.

We can begin to develop solutions to the search problem by utilizing the following steps:

a) Initialization. The initial population of candidate solutions is normally produced randomly across the search space. Nevertheless, domain-specific knowledge or other information can be simply incorporated.
b) Evaluation. Once the population is initialized or an offspring population is generated, the fitness values of the candidate solutions are assessed.
c) Selection. Selection allocates more copies of those solutions with higher fitness values and therefore imposes the survival-of-the-fittest mechanism on the candidate solutions. The principal idea of selection is to favor better solutions to worse ones, and many selection procedures have been suggested to accomplish this idea, including ranking selection, stochastic universal selection, roulette-wheel selection, and tournament selection some of which are explained in the next section.
d) Recombination. Recombination connects connects parts of two or more parental solutions to produce new, possibly better solutions (i.e. offspring). There are many ways of achieving this (some of which are explained in the next section), and competent performance depends on a suitably designed recombination mechanism. The offspring under recombination will not be identical to any particular parent and will rather combine parental traits in a novel manner.
e) Mutation. While recombination works on two or more parental chromosomes, mutation locally but randomly changes a solution. Again, there are many variations of mutation, but it regularly involves one or more modifications being made to an individual's

characteristic or characteristics. In other words, mutation performs a random walk in the vicinity of a candidate solution.

f) Replacement. The offspring population produced by recombination, selection, and mutation replaces the original parental population. Many replacement procedures such as generation-wise replacement, elitist replacement, and steady-state replacement methods are employed in GAs.

g) Repeat steps 2–6 until a terminating condition is met (Sastry et al., 2005).

Many diverse methods such as stochastic and non-stochastic models have been suggested in the literature for the analysis of time series. In recent years, the application of non-stochastic models has become widespread. Fuzzy time series forecasting models do not need assumptions that stochastic models do. On the other hand, most of the time, series found in real life should be considered as fuzzy time series because of the uncertainty that they contain and they should be examined with models suitable for fuzzy set theory (Alpaslan and Cagcag, 2012).

Fuzzy time series methods include three steps. These are fuzzification, identification of fuzzified relations and defuzzification, respectively. Many investigations on these three steps have been performed in literature as these steps have positive and negative influence on the forecasting performance of the process. While some of the procedures suggested in the literature include first-order forecasting models, some of them include high order forecasting models (Alpaslan and Cagcag, 2012).

Definition 1. The fuzzy set a_α of R, $0 \leq \alpha \leq 1$, is called a level α fuzzy point if

$$\mu_{a_\alpha(x)}=\begin{Bmatrix} \alpha, & x=a \\ 0, & x\neq a \end{Bmatrix}. \qquad \text{Eq. (1)}$$

Let $F_P(\alpha)$ be the family of all α level fuzzy points.

Definition 2. The fuzzy set $[a_\alpha, b_\alpha]$ of R, $0 \leq \alpha \leq 1$, is called a level α fuzzy interval if

$$\mu_{[a_\alpha,b_\alpha](x)}=\begin{Bmatrix} \alpha, & a\leq x\leq b \\ 0, & otherwise \end{Bmatrix}. \qquad \text{Eq. (2)}$$

For each $\alpha \in [0,1]$, let $F_I(\alpha) = \{[a_\alpha, b_\alpha] | \forall a < b,\ a, b \in R\}$.

Moreover, since inventory control is highly complex and can't be easily modeled only by one artificial intelligence (AI) tool, there is actually a growing tendency to gain more visibility by integrating the fuzzy logic approach in combination with neurocomputing and genetic algorithms. In this paper, a hybrid methodology is developed by combining GA, Clustering and FuzzyLogic (FL) approaches for a precise and effective evaluation of agents' performance in inventory control. It maintaines a set of fuzzy rules with their membership functions and utilizes the findings of GA to determine the significance of the decision rules in inventory control. The recommended fuzzy system is utilized to produce the performance percentage of the agent through the adoption of a fuzzy inference system (FIS) in the MATLAB fuzzy logic toolbox platform. Moreover, the optimization of the artificial market model integrates the interaction among autonomous decision-makers. Then, simulations are performed to optimize market's conditions (first step) and to assess all decisions linked to the internal cognitive structure of the agents (second step). This helps autonomous decision-makers to enhance their decision performance through adaptation and training processes within inventory control.

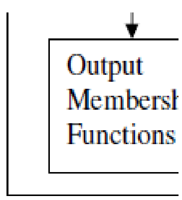

Figure 1. The system model combines GA and fuzzy logic.

MODEL FORMULATION

Multiple optimization methods in deterministic models have been utilized in the modern development of inventory control and management problems. To determine the optimal order point, first, we specify the effective factors for product consumption, including market factors and customers. Then, in order to find the value of these factors, we apply fuzzy logic and determine the optimal reorder point.

In this model, an inventory with shortage is taken into account. The purpose of this EOQ model is to find out the optimum order quantity of inventory items by minimizing the total average cost. We discuss the model using the following notations and assumptions.

C1: Holding cost per unit time per unit quantity.

C2: Shortage cost per unit time per unit quantity.

C3: Setup cost per period.

D: The total number of units produced per time period.

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$Q1$: The amount which goes into inventory
$Q2$: The unfilled demand.
Q: The lot size in each production run.

Assumptions:

(1) Demand is known and uniform.
(2) Production or supply of the commodity is instantaneous.
(3) Shortages are allowed.
(4) The lead time is zero.

Let the amount of stock for the item be Q_1 at time $t=0$ in the interval $(0, t(=t1+t2))$, the inventory level gradually reduces to meet the demands. By this procedure, the inventory level reaches zero level at time t_1 and then shortages are allowed to happen in the interval (t_1, t). The cycle repeats itself (Figure 2).

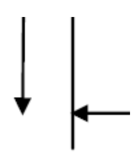

Figure 2. Inventory level.

In this investigation, the crisp EOQ model has been introduced for demand shortages so that the demand during the shortage period reduces with the shortage of time. The concerned cost function is formulated by cost, shortage cost. Then, the interval objective function was transformed into a classical multi-objective EOQ problem using the fuzzy technique. The order level Q>0 which minimizes the average total cost (Q) per unit time is given by:

$$Minimize\ c(Q) = \frac{1}{2}C_1\left(\frac{Q_1^2}{Q}\right) + \frac{1}{2}C_2\left(\frac{Q_2^2}{Q}\right) + C_3\left(\frac{D}{Q}\right)$$

Up to this stage, we are assuming the demand, ordering cost, holding cost, etc. as real numbers i.e .of fixed value. But in real-life business situations, all these components are not always fixed, rather these are different in different situations. To overcome these ambiguities we approach with fuzzy variables, where demand and other cost components are considered as triangular fuzzy numbers.

Fuzzy EOQ model

From the crisp model (1) we have seen that except the time variables t_1 and t_2, all other terms are constant coefficients. To cope with the real world situation, let them consider a triangular fuzzy number. Then, the problem (7) reduces as follows:

The inputs for the fuzzy toolbox that consist of the selected features and their membership functions are framed as follows:

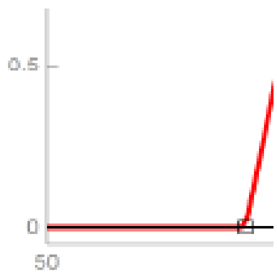

Figure 3. The input variables and their membership functions

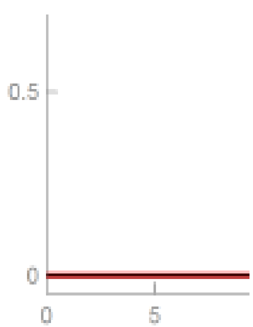

Figure 4. The input variables and their membership functions

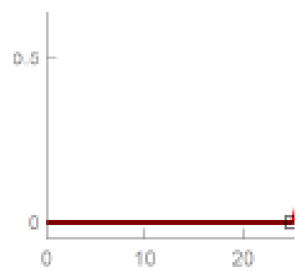

Figure 5. The input variables and their membership functions

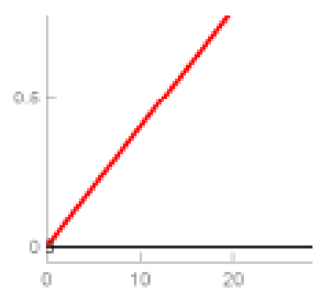

Figure 6. The output that declares whether the patient has diabetes or not.

Figures 3, 4, and 5 show the input variables and their membership functions and Figure 6 is the output that declares whether the patient has diabetes or not.

FINDINGS AND IMPLICATIONS

Inventory management is an important component of inventory control. The results show that the ordering patterns of the dealers are more erratic than the consumption patterns. The discussion of the results with company experts revealed possible explanations for excess inventory levels observed at the dealers. The main reason is the length of the current ordering period of the dealers. One obstruction that prevents dealers from ordering more regularly is the economics of transportation. There are substantial advantages to order in large batch sizes because of the step-wise behavior of the transportation costs, so dealers have a strong motivation to fill the truck completely when they order parts from the distributor. As a response to lessen the batching influence, the company decided to perform a transportation collaboration among dealers, to provide mixed shipments to various dealers in the same delivery, and to plan coordinated shipments to move the channel away from random ordering to balanced ordering. The company also began negotiating the terms of the contract with the third-party logistics service provider to combine orders from dealers who are in geographical closeness to each other, to get lower transportation costs for more frequent shipments.

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