Expert Systems with Applications 38 (2011) 12051–12057

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Comparisons of some improving strategies on MOPSO for multi-objective (r, Q) inventory system

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ARTICLE INFO

Keywords:
Multi-objective particle swarm optimization
Inventory planning and control
Crowding distance
ε-Dominance

ABSTRACT

This paper presents comparisons of some recent improving strategies on multi-objective particle swarm optimization (MOPSO) algorithm which is based on Pareto dominance for handling multiple objective in continuous review stochastic inventory control system. The complexity of considering conflict objectives such as cost minimization and service level maximization in the real-world inventory control problem needs to employ more exact optimizers generating more diverse and better non-dominated solutions of a reorder point and order size system. At first, we apply the original MOPSO employed for the multi-objective inventory control problem. Then we incorporate the mutation operator to maintain diversity in the swarm and explore all the search space into the MOPSO. Next we change the leader selection strategy used that called geographically-based system (*Grids*) and instead of that, crowding distance factor is also applied to select the global optimal particle as a leader. Also we use ε-dominance concept to bound archive size and maintain more diversity and convergence in the MOPSO for optimizing the inventory control problem. Finally, the MOPSO algorithms created using these strategies are evaluated and compared with each other in terms of some performance metrics taken from the literature. The results indicate that these strategies have significant influences on computational time, convergence, and diversity of generated Pareto optimal solutions.

1. Introduction

Inventory control is one of the major issues in the field of operational research and production management. For this reason, it has been researched over the past several decades. Inventory planning and control systems manage what is needed and when. Most of the problems about this issue are modeled as single objective optimization as it aggregates several cost concepts and service level into a single objective. However, estimation of cost parameters for the stockout case with considering one objective is difficult in practice. Also, optimization of cost concepts and service level into one objective should not be modeled practically, because these objectives are conflicting with each other. Hence, researchers have studied various multi-objective approaches for these problems, over the past years, where scalar transformation of conflicting objectives can be avoided.

Bookbinder and Chen (1992) analyzed multi-echelon inventory and distribution systems with a multi-criteria approach which uses MCDM concepts of exchange curve (analyzing of cycle stock investment and workload), optimal policy curve, and response surface.

Agrell (1995) presented interactive multi-criteria framework for an inventory control decision support system that simultaneously determines lot size and safety stock or service level. This framework modeled the problem with no need to estimate the shortage cost that is being considered indirectly in the evaluation of the customer service. An interactive method optimizes a sequence of single objective optimization problems that finally results in an optimum solution such that the decision maker (DM) needs to be involved in every step of the algorithm.

Puerto and Fernandez (1998) solved a multi-criteria deterministic and stochastic inventory control problem using advanced mathematical derivations for obtaining Pareto-optimal solution sets.

Mandal, Roy, and Maiti (2005) applied geometric programming method to solve a multi-item multi-objective fuzzy inventory model for finding demand, lot size, and stock out level for each item.

All the researches mentioned so far have used traditional preference-based or utility-based multi-objective optimization procedure. These approaches contradict our intuition that single objective optimization is a degenerate case of multi-objective

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doi:10.1016/j.eswa.2011.01.169

optimization problem (MOOP) (Deb, 2001). Also MOOP does not have a solution that simultaneously optimizes all objectives. Therefore, a requirement to apply multi-objective optimizers to MOOPs is essential. Through these optimizers, a set of solutions are generated that are called non-dominated solutions. These efficient solutions are not superior to one and other in the objectives space. Non-dominance means that the improvement of one objective could only be provided at the loss of other objectives.

Multi-objective optimizers and meta-heuristics like evolutionary algorithms or swarm intelligence methods have proved their ability to deal with MOOPs either convex objective space or non-convex objective space. In over recent years, multi-objective evolutionary algorithm like non-dominated sorting genetic algorithm-II (NSGAII) (Deb, Pratap, Agarwal, & Meyarivan, 2002), strength Pareto evolutionary algorithm-II (SPEAII) (Zitzler, Laumanns, & Thiele, 2001), etc. and also multi-objective particle swarm optimization (MOPSO) algorithms have been applied to solve MOOPs.

Recently, Tsou (2008, 2009) has applied some meta-heuristics such as MOPSO, multi-objective electromagnetism-like optimization (MOEMO) and strength Pareto evolutionary algorithm (SPEA) to resolve the multi-objective (r, Q) inventory system presented by Agrell (1995) that was mentioned earlier. Tsou (2008) employed MOPSO algorithm based on the seminal work of Coello-Coello and Lechuga (2002) to solve the inventory system that was mentioned and then used a ranking method of multi-attribute decision making (MADM) called TOPSIS (Yoon & Hwang, 1995) to provide a sorting procedure of non-dominated solution and select a compromise solution to deliver to the decision maker. Tsou (2009) employed an improved version of MOPSO (IMOPSO). In IMOPSO, a local search is used to enhance the convergence to the Pareto-optimal front. Also a clustering technique is applied to the non-dominated archive to control archive size such that it can speed up the search and maintain diverse solutions by this technique. Then, IMOPSO was compared with MOEMO and SPEA. Regarding the results, the MOPSO was chosen as a better algorithm for solving the multi-objective (r, Q) inventory system.

This paper tries to employ crowding distance factor (Reyes Sierra & Coello-Coello, 2005), ε-dominance concept (Mostaghim & Teich, 2003) and a mutation operator to MOPSO for the inventory control problem by Agrell (1995). Then the results are compared with the works of Tsou (2008, 2009). Mostaghim and Teich (2003) indicated that ε-dominance decreases computational time more than clustering techniques and has also influence on convergence and diversity of solutions created by MOPSO (in some cases even ε-dominance is better than clustering techniques). For this reason, by additionally applying crowding distance and mutation operator, we incorporate this concept instead of using clustering techniques into MOPSO for the multi-objective inventory control problem.

The rest of the research is organized as follows: Section 2 describes the multi-objective inventory planning and control model mentioned earlier. Definitions of Pareto optimality and ε-dominance are mentioned in Section 3. Next we describe the MOPSO algorithms in Section 4. All the comparisons are presented in Section 5. Finally, we present our conclusions and future works in Section 6.

2. Multi-objective (*r*, *Q*) inventory system

The control of inventories has been a major issue in the field of industrial engineering and operational research for a long time. As an essential activity for any enterprise, inventory planning tries to determine the decisions about when to order and how much to order for different control mechanisms. A common control policy is a continuous-review (r, Q) system in which an order of size Q is placed whenever the inventory position drops to the reorder point, r (Silver, Pyke, & Peterson, 1998). Determination of (r, Q) depends on the lead time and the fluctuation of demand which aims to minimize inventory cost and maximize customer service. Agrell (1995) set up three objectives about cost and stock-out to plan for two control parameters, the order size Q and the safety factor k which is a term of the reorder point r. It is assumed that only a single product is considered here. After a fixed lead time, L, the order is received all at once and placed into inventory. The demand within lead time, D_L, is a random variable that is normally distributed with density function, $\varphi(x)$, mean μ_L and standard deviation σ_L. The system is also characterized by the following parameters (Tsou, 2008).

D is the average annual demand.
A is the ordering cost.
c is the unit item cost.
h is the inventory carrying rate.
SS is the safety stock. That is, $SS = k\sigma_L$.
k is the safety factor.
r is the reorder point, which equals to the average lead time demand plus the safety stock.

$$\text{Min} \quad C_B(k, Q) = \frac{AD}{Q} + hc\left(\frac{Q}{2} + k\sigma_L\right) \tag{1}$$

$$\text{Min} \quad N(k, Q) = \frac{D}{Q}\int_k^\infty \varphi(x)dx \text{ and} \tag{2}$$

$$\text{Min} \quad S(k, Q) = \frac{D\sigma_L}{Q}\int_k^\infty (x-k)\varphi(x)dx, \tag{3}$$

Subject to

$$0 \leqslant Q \leqslant D \tag{4}$$

$$0 \leqslant k \leqslant D/\sigma_L \tag{5}$$

Eq. (1) minimizes the expected total relevant cost annually, Eq. (2) minimizes the expected frequency of stockout occasions annually, and Eq. (3) minimizes the expected number of items stocked out annually. Eq. (4) ensures that the order size must be non-negative and no greater than annual demand. Finally, Eq. (5) guarantees that the safety stock will not be higher than the annual demand.

3. Definitions of Pareto optimality

A multi-objective optimization problem can be defined as follows:

$$\text{Minimize} \qquad \vec{f}(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), \ldots, f_k(\vec{x})]^T \tag{6}$$

$$\text{Subject to:} \quad g_j(\vec{x}) \leqslant 0 \quad j = 1, 2, \ldots, m \tag{7}$$

where $\vec{x} \in R^n$ is a n-dimensional vector, each x_j $(j = 1, 2, \ldots, n)$ can be real-valued, integer-valued or Boolean-valued. Objective functions $f_i : R^n \to R$ $(i = 1, 2, \ldots, k)$ and constraints g_j $(j = 1, 2, \ldots, m)$ can be linear or non linear arbitrary functions.

To describe the concept of optimality in which we are interested, we will review definitions of domination and ε-domination. More definitions of Pareto optimality can be found in the seminal works of Mostaghim and Teich (2003).

3.1. Domination

We say that a decision vector, $\vec{x}_1$, dominates a decision vector $\vec{x}_2 (\vec{x}_1 \prec \vec{x}_2)$ if the decision vector $\vec{x}_1$ is not worse than $\vec{x}_2$ in all objectives, i.e., $f_i(x_1) \leqslant f_i(x_2)\ \forall i = 1, 2, \ldots, m$.