Expert Systems with Applications 37 (2010) 2599–2608

Contents lists available at ScienceDirect

Expert Systems with Applications

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

Applying the linear particle swarm optimization to a serial multi-echelon inventory model

Ming-Feng Yang *, Yi Lin

Department of Information Management, Yu Da University, Miaoli County 361, Taiwan, ROC

ARTICLE INFO

Keywords:
Multi-echelon inventory model
Uncertain delivery lead time
Quality unreliability
Particle swarm optimization

ABSTRACT

In the aspect of supply chain management; responding to the accurate needs of customers and effectively reducing the total costs are of significance activities for companies to achieve their competitive edges and to have opportunities to gain large amounts of advantages in the current highly competitive global supply chain management environment. Therefore, this article provides a serial multi-echelon integrated just-in-time (JIT) model based on uncertain delivery lead time and quality unreliability (SMEIJI model) considerations. Hence, we will apply the particle swarm optimization (PSO) as a method to result an improved solution solving a mixed nonlinear integer problem. Based on our fitting parameter settings, the final result show that the linear decreasing weight particle swarm optimization (LDW-PSO) will be efficiently performable and have a primary solution in solving the multi-echelon inventory problem.

1. Introduction

The main discussion of this article is to create a serial multi-echelon integrated just-in-time inventory model with an uncertain delivery lead time and quality unreliability consideration; above all, we focus on comparing LDW-PSO with the non-liner decreasing weight particle swarm optimization (NLDW-PSO). Accordingly, Ha and Kim (1997) indicates that the just-in-time method attempts to eliminate all waste from a firm's operation, and ultimately, help the firm achieve zero inventories by facilitating frequent shipment of purchased parts in small lots and manufacturing small lots frequently. Even though the performance of whole supply chain is above that of a single echelon member in this global competition environment, most companies still hardly to avoid this disadvantage. The possible contribution factor is that buyers may not adjoin vendors geographically in real situation. The uncertain delivery lead time might be happened and exposure to the safety inventory stock. We can say that, it is directly decreasing customer satisfaction and rising by higher defective rate. Hence, we have to find out an optimal inventory model that can ameliorate the total cost of whole supply chain under uncertain delivery lead time and quality unreliability.

The key factor of an enterprise to gain advantage in supply chain management is to create an optimal inventory development. Especially, enterprises have trying to respond to the real requirements of all customers and reduce total costs effectively. In traditional inventory system, both venders and buyers only focus their own optimal economic lot sizes; however, this does not obtain in an optimal policy for the entire supply chain. To be specific, an old-fashioned inventory policy might not be economically realistic in the current highly competitive global supply chain environment. Consequently, an integrated inventory approach may help determine an optimal order quantity and shipment policy.

The structure of this article is indicated as follows: the material and method reviews of serial multi-echelon just-in time inventory, LDW-PSO and NLDW-PSO. And then, based on our proper parameter settings; the computational experiments will be performed with the particle swarm optimizations that have good initial solutions. Comparing the assumption results with the ideal solution found by LINGO 9.0 is our main discussion; and finally, we will display all computational results to have conclusions and suggestions.

2. Materials and methods

Goyal (1977) indicated an integrated inventory model to minimize the joint total cost for a single-supplier single-customer problem. And then, (Banerjee, 1986) extended Goyal's model which expressed the employed a lot-for-lot policy to develop a joint economic lot size (JELS) model. By loosening Banerjee's lot-for-lot assumption, (Goyal, 1988) proposed a more general model that produces a lower-joint total cost. In the past few years, several researchers developed Goyal's model and the JELS model into a two-echelon JIT supply chain model in order to find the optimal vendor–buyer cooperative policy. Chen (2000) generalized the Clark–Scarf model by allowing inventory batch transfers, extending the model to the serial and assembly multi-echelon inventory

---

* Corresponding author. Tel.: +886 37 651188; fax: +886 37 652256.
E-mail addresses: yang60429@ydu.edu.tw (M.-F. Yang), iwc3706@yahoo.com.tw (Y. Lin).

0957-4174/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2009.08.021

system where materials flow in fixed batches. Chiu and Huang (2003) proposed a multi-echelon integrated JIT inventory model with a random delivery lead time. Seo (2006) proposed an improved reorder decision policy for controlling general multi-echelon distribution systems. This system utilizes shared stock information. The objective of multi-echelon inventory management is to deliver the desired end customer service level at a minimum joint total cost, with the inventory divided among the various echelons (Lee, 2003a, 2003b).

For lead time reduced effectively, a well-thought vendor will work with a purchaser as closely as possible. It is acceptable of the purchaser while allowing the vendor to maintain a stable production and a delivery schedule. On the other hand, as this paper indicated in the earlier section, some buyers may not be much adjoining to their vendors in the real competitive environment. Thus, the long-distance transportation will cause uncertain lead time and quality unreliability. The inventory policy of an imperfect strategy will take firms to posit in the disadvantageous competition environment. Hence, many two-echelon or multi-echelon inventory studies assume that the delivery lead time is known and modified. Yano (1987) developed a serial three-echelon inventory model to determine the optimal planned lead time. Graman and Rogers (1997) extend this model to a multi-echelon inventory model, based on the buffer stock policy, to deal with random delivery lead times. Chiu and Huang (2003) proposed a multi-echelon integrated JIT inventory model using time buffer and emergency borrowing policies to deal with random delivery lead times. However, stock and time buffers cannot completely avoid shortages if the buffer is not large enough. The shortages can be avoided in Chiu's model, and costs can be reduced by the trade-off between emergency borrowing costs and time buffer costs (Chiu & Huang, 2003).

The optimal result of JIT theorem is timely satisfying the immediate consumption of purchasing and manufacturing activities. Ha and Kim (1997) indicates that JIT method attempts to eliminate all waste from a firm's operation, and ultimately, help the firm achieve zero inventories by facilitating frequent shipment of purchased parts in small lots and manufacturing small lots frequently. The major focus of JIT manufacturing system is to improve the quality of all products and resources and productivity through the elimination of all waste from all operation activities.

PSO is an evolutionary computation model based on swarm intelligence that discovered by Dr. Eberhart and Dr. Kennedy in 1995. Inspiring by social behavior by bird flocking and fish schooling, with his observation, a group of birds is characteristic by searching food in one area randomly and each bird did not know where the food is located. The most effective and efficient strategy for searching the food is to follow to the bird adjoining to the food (Allahverdi & Al-Anzi, 2006).

In the basic PSO model, each bird has its own single flying direction as a solution in the searching space; we indicate that it is a particle in the PSO model. Instead of using genetic operators, these particles are evolved by cooperation and competition among the particles themselves through generations. Basically, the particle model consists of ***m*** particles moving in a ***D***-dimensional search space. Each particle is a potential global optimum solution of the objective function $f(x)$. Each particle keeps track of the best solution (fitness) it has achieved so far in the search space. This value is called *pbest*. The best solution obtained so far by any particle in the population is called the global best, or *gbest*. Each particle is updated by the above-mentioned two "best" values (Eberhart & Kennedy, 1995; Eberhart & Shi, 2000).

We assume A–E as a single searching particle, and T is the target. At the beginning, all single particles are uniformly distributed. That is to say, the particle B is most closely to the target which has the best solution in this space. The particle B is called the global best, or gbest as Fig. 1. As time goes on several times, each particle keeps track of the best solution it has achieved so far in the search space. At this time, the particle D will find the best solution which called pbest as Fig. 2.

The following two equations indicate that each particle updates its coordinates and velocity after discovering the two best values.

$$V_{id} = V_{id} + c_1 \times Rand() \times (pbest_{id} - X_{id}) + c_2 \times Rand() \times (gbest_d - X_{id}) \tag{1}$$

$$X_{id} = X_{id} + V_{id} \tag{2}$$

There are three components composing of Eq. (1): the previous velocity of the particle, the particle experience, and the swarm experience. Particles will keep "moving" at the current speed in the same direction until they hit the search space boundary without these two kinds of experience. According to Eberhart and Shi (2001); the maximum velocity is constrained that controls the global exploration ability of a particle swarm in the original PSO model. Different problems should have different balances between the local search ability and global search ability.

The Eq. (2) was built by Shi and Eberhart (1998) as an advanced PSO model to improving convergence efficiency and balance local and global search abilities. An inertia weight w is brought into the Eq. (1) as shown in Eq. (3).

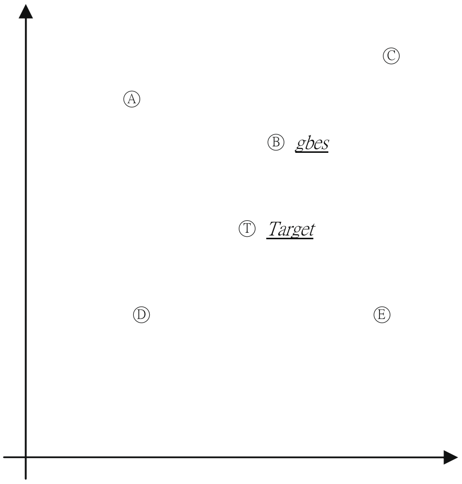

Fig. 1. The particle B as the gbest originally.

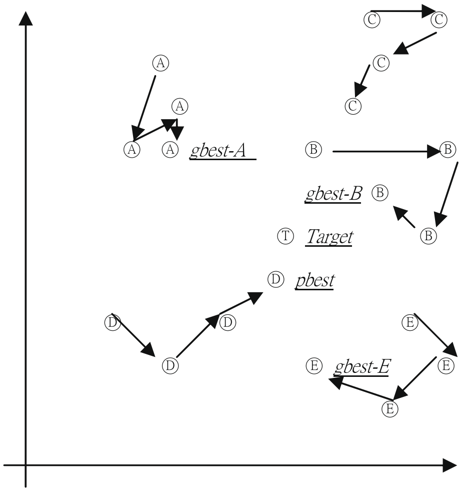

Fig. 2. The particle D as the pbest subsequently.