Journal of Manufacturing Systems 37 (2015) 217–226

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

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

Cost-service tradeoff analysis of reorder-point-lot-size inventory models

Longsheng Cheng[a], Ching-Shih Tsou[b,*], Dong-Yuh Yang[b]

[a] School of Economics and Management, Nanjing University of Science and Technology, Nanjing 210094, Jiangsu Province, China
[b] Institute of Information and Decision Sciences, National Taipei University of Business, Taipei 10051, Taiwan

ARTICLE INFO

Article history:
Received 20 March 2011
Received in revised form 9 July 2014
Accepted 24 November 2014
Available online 6 June 2015

Keywords:
Inventory control
Multi-objective optimization
Particle swarm optimization
Customer service

ABSTRACT

Inventory control involves tradeoffs between conflicting criteria such as operating cost and customer satisfaction. This paper presented two bi-objective inventory models to minimize inventory cost while maximizing customer service. Two popular measures of customer service, cycle service level and fill rate, are used in the modeling process. The decision is to search for the control policies in terms of safety factors and lot sizes that approximate the Pareto-optimal front in the objective space. Analysis adhering to multi-objective notion is conducted not only in its formulation but also in the computing and evaluation. To highlight the differences between the cycle service level model and the fill rate model, solutions from them are compared against each other thoroughly in both the objective and decision spaces. Quality measures and graphical illustration of the solutions show that control policies obtained from both models are mostly non-dominated to each other in the objective space. The fill rate model is capable of generating control policies with higher service levels. Also, it could be likely for the fill rate model to generate policies that are appealing to decision makers, such as those with adequate lot size and/or safety stock. This agrees with our intuition that cycle service level is usually less informative as a shortage measure than fill rate.

1. Introduction

Most real-world decisions involve more than one objective. Design and control of manufacturing systems, for example, usually pursue incommensurate and conflicting objectives. Wei and Gaither [1] proposed a capacity constrained multi-objective cell formation model for cellular manufacturing several decades ago. It minimizes the bottleneck cost and the intra-cell/inter-cell load balances while maximizing the average cell utilization. A heuristic was developed that assigns parts and machines to manufacturing cells, in the meantime, taking into account machine capacities, product routings, relevant costs, and several objectives of production systems. Demmel and Askin [2] suggested that the analysis of advanced manufacturing system technologies should not rely on quantitative measures alone. They presented a tri-objective model, including pecuniary, strategic, and tactical objectives, to avoid the shortcomings of traditional evaluation models. They ranked the alternatives under consideration by using the compromise programming technique.

For inventory control, Bookbinder and Chen Vincent [3] proposed a multi-criteria (or multi-objective) approach to analyze a wholesaler–retailer inventory/distribution system. They described their approach as multiple criteria decision-making (MCDM) generalizations of earlier studies [4–7]. Although their formulations are multi-objective, the solution procedure is still built on single objective optimization. Puerto et al. [8] commented on the solution procedure of Bookbinder and Chen Vincent [3] that it cannot determine the Pareto-optimal set properly. Besides giving a better procedure to generate the set, they also stated that the bi-criteria nonlinear mixed integer programming problem is well known to be the hardest kind of problem in multi-objective optimization for which no general tools have been yet developed [9].

Gutierrez et al. [10] considered the dynamic single-facility single-item lot sizing as a multi-objective combinatorial optimization problem that is mostly a NP-hard problem. The finite planning horizon is divided into several time periods whose demand distribution is unknown, although the total demand is fixed. Different combinations of the demand vector yield a set of different scenarios. The production/reorder and holding cost vectors can vary from one scenario to another. A solution method based on multi-objective branch and bound approach was proposed to solve several randomly generated problems.

* Corresponding author.
E-mail address: cstsou@ntub.edu.tw (C.-S. Tsou).

http://dx.doi.org/10.1016/j.jmsy.2014.11.008
0278-6125/

Fatrias and Shimizu [11] studied the multi-objective periodic review inventory problem in a two-echelon supply chain. Three strategies of replenishment are proposed to manage inventory efficiently while simultaneously minimizing total cost and loss rate of the supply chain. Solutions based on multi-objective differential evolution have been found that the coordination strategy between manufacturer and retailer become more effective as the uncertainty of demand increases. Recently, Hou and Hu [12] also proposed an integrated multiple-objective genetic algorithm (MOGA) approach to determine the Pareto-optimal work-in-process (WIP) level, i.e. the kanban number and size, for a JIT system.

For the continuous review inventory model, Agrell [13] presented an interactive multi-criteria framework for (s,Q) inventory control. A preferred Pareto-optimal solution was interactively found by the classic multi-objective optimization method named STEp Method (STEM), which involves solving a sequence of single objective optimization problems. However, the interactive methods require decision makers to provide choices of search direction and step size iteration by iteration until a satisfactory tradeoff is reached. Such requirement could be a cognitive burden because a clear picture of tradeoffs among criteria is not available.

Tsou [14] presented a two-stage decision framework for multi-objective inventory planning based on the Multi-Objective Particle Swarm Optimization (MOPSO) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). This approach follows the principle proposed by Deb [15] for the so-called ideal multi-objective optimization procedure. MOPSO was first used to find the non-dominated solutions with a wide range of values for objectives. After that, a compromise solution is selected by the TOPSIS according to subjective preferences from decision makers. Tsou and Kao [16] proposed a meta-heuristic based on Electromagnetism-like Mechanism (EM) to approximate the Pareto-optimal front without using any prior or interactive preference. They showed that the meta-heuristic Multi-Objective Electro-Magnetism-like Optimization (MOEMO) could find similar Pareto-optimal solutions as STEM did. Tsou [17] further showed that the evolutionary Pareto optimizers could generate tradeoff solutions potentially ignored by the well-known simultaneous method for inventory control. Another aim of Tsou [17] is to compare the backordering and the lost sales models under tri-objective settings. The emphasis here, however, is to study the two customer service measures, cycle service level and fill rate, under bi-objective settings.

Recently, Moslemi and Zandieh [18] follow our work to propose several improved strategies on using MOPSO for handling multi-objective (s,Q) model. Although all models of above studies are tri-objective, from Fig. 2 in their paper we found that the Pareto fronts actually lay on a curve instead of forming a tradeoff surface. This indicates that some of the objectives are redundant such that the use of a tri-objective model was not justified.

It is well known that various inventory systems have to operate in an efficient way while providing adequate service to customers. Various situations can be modeled and solved as a multi-objective optimization problem. Rezaei and Davoodi [19] solved the lot sizing and supplier selection problem based on three objectives about cost, quality, and service level. They found that buyers are better able to optimize their objectives compared to situations where there is no shortage. Liao et al. [20] also integrated inventory decisions with facility location problem under cost, customer service levels (fill rates), and flexibility objectives. An experimental study using practical data was used to illustrate the applicability of the proposed approach. Cycle service level is another common measure of customer service in addition to the fill rate. It will be incorporated into a bi-objective inventory control model later. The process for the tradeoff analysis of inventory cost and customer service under different service measures is shown in Fig. 1.

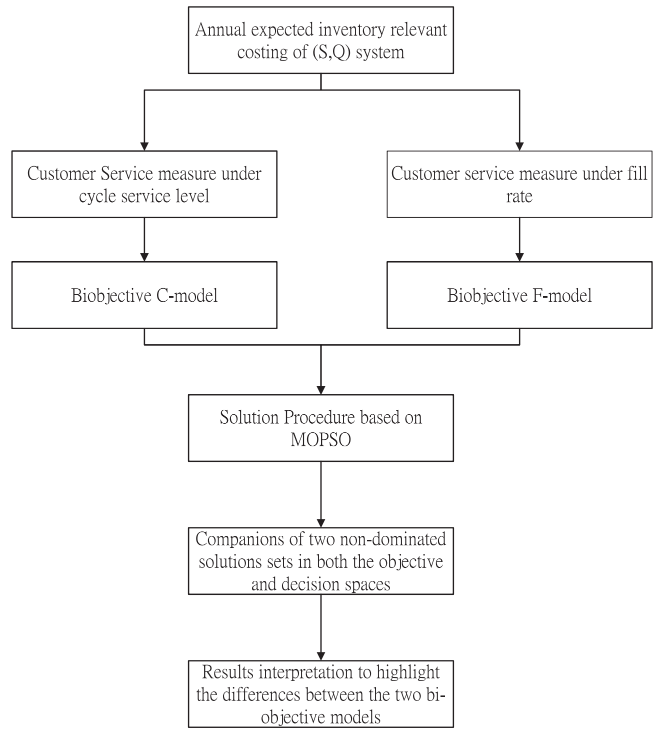

Fig. 1. Process for the tradeoff analysis of inventory cost and customer service under different service measures.

To characterize the tradeoff between inventory cost and customer service, another aim of this paper is to present two bi-objective reorder-point-lot-size inventory models under lost sales. One is based on the cycle service level; the other is based on the fill rate. Different measures of customer service are often used in inventory control systems for performance evaluation and target setting as substitutes for shortage costs that are hard to estimate. Larsen and Thorstenson [21] mentioned that the cycle service level is less commonly used than the fill rate as a performance measure for inventory control systems. However, in settings where the focus is filling customer orders rather than total quantities, the cycle service level should be the preferred measure.

On the other hand, Mangotra et al. [22] found that the fill rate is less widely used in research due to the complex form of backorder quantity term that makes it hard to model it. Furthermore, their analysis shows that the type of service measures used affects the logistics network design and inventory allocation problem. Hence, this study will compare the cycle service level and the fill rate under bi-objective inventory control settings in an aim to clarify their roles in specifying inventory policies.

Bi-objective model is the simplest form of multi-objective optimization; however, it should be studied first. To highlight the differences between two models, solutions from them are compared against each other thoroughly in both the objective and decision spaces. On the other hand, non-redundancy is assured because the criteria of operating cost and customer service are conflicting to each other. Moreover, a solution procedure based on MOPSO is applied to solve the bi-objective inventory control problems proposed here, although several studies have been adopted various multi-objective genetic algorithms (MOGAs) to attack joint replenishment problem and manufacturing system design problem [23,24]. In our opinion, the suitability of MOPSO for multi-objective inventory problems not only has been validated by prior research [17], but also the MOPSO is an easier optimizer to implement compared to MOGAs.