Computers & Industrial Engineering 87 (2015) 532–539

Contents lists available at ScienceDirect

Computers & Industrial Engineering

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

Inventory control in a centralized distribution network using genetic algorithms: A case study ☆

Dilay Çelebi *

Istanbul Technical University, Department of Management Engineering, 34367 Macka, Istanbul, Turkey

ARTICLE INFO

Article history:
Received 27 December 2012
Received in revised form 27 May 2015
Accepted 29 May 2015
Available online 6 June 2015

Keywords:
Genetic algorithms
Distribution network
Stochastic inventory control

ABSTRACT

This paper presents a case study to determine the optimal inventory levels in a spare parts distribution system. We develop a solution based on a Genetic Algorithm (GA) for an effective management of the distribution network of a Turkish automotive manufacturer under centralized control. We provide a specific approach to address the two-echelon inventory control problem in its combinatorial and sequential behavior, dealing with a large number of specific properties that are considered in practice. Findings of the case study reveal that the use of the proposed inventory control system may provide substantial cost savings to the case company. We finally draw conclusions from the case study on the company's operational practices and illustrate opportunities for improvement.

1. Introduction

The idea to coordinate activities associated with the flow of material and information through the supply chain has emerged in the early 80s and gained tremendous attention since then (Handfield & Nichols, 2002). Cooperative strategies provide opportunities for cost savings, better customer service, and competitive advantage for all companies in the supply chain. Centralized inventory control is a common cooperative strategy, where the stock control activities of the whole system become concentrated at a particular member (or a group of members), which takes full control of the inventory replenishment of the chain, and uses available demand and cost information in planning the operations. Centralizing inventory management provides cost reductions and improved service levels by decreasing uncertainty and providing better utilization of resources for production and transportation (Glock, 2012; Waller, Johnson, & Davis, 1999). However, determining optimal policies in centralized systems is complicated. Even for simple network structures, the optimal policy for distribution systems facing stochastic and time-varying demand is still unknown (see, e.g., Chen (2003)) and a challenging research question. The combinatorial and sequential character of multi-echelon inventory problems cannot be easily handled by traditional optimization techniques which employ differential calculus. Removing the convexity assumption on the function to be optimized, the differentiation technique may prove severely inefficient, as it cannot provide anything more than local information on optimality.

Over the last couple of decades, the rapid development of information technologies, along with the progress in optimization research, produced new and efficient techniques for solving complex combinatorial problems. Meta-heuristics such as Tabu Search, Simulated Annealing, and Genetic Algorithms (GA) are examples of such techniques, which have become popular for solving complex multi-echelon inventory control problems. Among these methods, GA have received considerable attention due to their potential to handle non-linear functions and to deal with multiple objectives. Unlike most traditional approaches, GA do not have any restrictions on the nature of the data employed or the problem structure that is considered. Due to its evolutionary nature, it can handle any kind of objective function or constraint, regardless of whether it is defined on discrete, continuous, or mixed search spaces (Gen & Cheng, 1997). The probabilistic evolution makes GA quite effective in performing global searches and reaching global optima. GA-based solution methods have the advantages of searching optimal points on both convex and non-convex optimization curves, and accommodating non-linearities in the objective function (Scott, Eheart, & Ranjithan, 1995).

In an attempt to investigate the success of GA in providing solutions to inventory control problems, a real-life case study motivated the development of the model and the solution technique presented in this paper. The case study presents a specific

Abbreviations: GA, Genetic Algorithms; SL, service level.

☆ This manuscript was processed by Area Editor Christoph H. Glock.

* Tel.: +90 212 2931300.
E-mail address: celebid@itu.edu.tr

http://dx.doi.org/10.1016/j.cie.2015.05.035
0360-8352/

approach to obtain a rolling horizon inventory control policy for an automotive spare parts distributor and its dealers. The paper presents a comprehensive method to address the combinatorial and sequential behavior of the problem, dealing with a large number of specific properties that are considered in practice. It first concentrates on the quantification of the inventory related cost parameters, and then provides a mathematical model to represent the stochastic cost structure of a distribution network. Considering the computational complexity of the dynamic formulations, we apply the GA structure previously proposed in Çelebi (2011) to obtain a rolling horizon inventory control policy based on the observed demand realizations.

To the authors' knowledge, this is the first study that investigates the application of GA on a capacitated lot sizing problem of a real centralized inventory distribution system under stochastic and time-varying demand. The paper is structured as follows: Section 2 gives a brief review of literature on GA applications to multi-echelon inventory problems, classified into three main categories according to the network structure they handle. Section 3 presents a summary of the system structure and gives a problem definition. Section 4 illustrates the details of the proposed inventory control system. This section includes five subsections. Section 4.1 illustrates the method of evaluating the cost parameters. Section 4.2 presents the mathematical model for a complete analysis of the inventory structure of the system. Section 4.3 provides the definition of the proposed GA structure and illustrates the steps employed in developing the proposed GA scheme. Section 4.4 gives numerical results and demonstrates potential cost savings. Section 4.5 presents the findings of the case study and its implications for practice. Finally, Section 5 presents discussions on the application of GA to inventory control problems and proposes ideas for future research.

2. Literature review: GA for centralized inventory control

Pioneered by Holland (1975), GA are powerful stochastic search and optimization techniques based on principles of natural selection and evolution. GA have been widely studied in and applied to many fields in engineering (Goldberg, 1989). They offer significant advantages over many other search optimization techniques by performing searches in a large and multi-modal state-space. GA's probabilistic nature and comprehensive structure provide advantages by allowing a search on a population of possible solutions. GA work directly with complete solutions and can quickly scan a vast set of solutions. Bad solutions do not affect the final solution negatively. Parameter estimates or bounding conditions are not required due to their inductive nature, which render GA an efficient technique for complex or loosely defined problems.

Regarding their potential as an effective optimization technique (Gen & Cheng, 2000), GA have been successfully applied to handle various complex inventory situations, which might be difficult to solve by traditional methods. Goren, Tunali, and Jans (2010) provided a comprehensive overview of the literature on the applications of GA, mainly in single-echelon lot sizing problems. There also exists a wide range of studies which implement GA to cope with the multi-echelon inventory management problem. The following sections give a brief literature review of these studies, and classify them into three major categories according to the network structure they handle.

2.1. Serial systems

Daniel and Rajendran (2005) investigated the performance of a single-product serial supply chain operating with a base-stock policy. They formulated a single-period, multi-echelon, single-product model to optimize the inventory (i.e. base stock) levels in the supply chain with the objective of minimizing the total supply chain cost, which consists of holding and shortage costs for all installations in the supply chain. Kimbrough, Wu, and Zhong (2002) and O'Donnell, Maguire, McIvor, and Humphreys (2006) managed to decrease the bull-whip effect by applying GA to a serial supply chain model based on the MIT beer game. Fakhrzad and Zare (2009) presented a combination of GA with Lagrangian multipliers for determining lot-sizes in a multi-stage, multi-product and multi-period production scheduling problem. Pasandideh, Niaki, and Nia (2011) developed an economic order quantity (EOQ) model for a two-level supply chain system consisting of several products, where the supplier's warehouse has a limited capacity which creates an upper bound on the number of orders. Ghiami, Williams, and Wu (2013) formulated an optimization model for deteriorating inventory in a single-wholesaler and single-retailer supply chain, where the retailer's warehouse has a limited capacity. They suggested a hybrid heuristic that combines GA and a neighboring search algorithm to decrease the computation time.

2.2. Assembly systems

Vergara, Khouja, and Michalewicz (2002) developed an evolutionary algorithm which calculates the production sequence at each supplier to minimize transportation, preparation, and inventory holding costs in a multi-component assembly system. They proposed a GA structure to determine a common delivery cycle and production sequence of components for each member of a synchronized supply chain. They obtained the global optimum in 97% of the cases. Berretta and Rodrigues (2004) addressed the multi-stage lot-sizing problem to determine the production lot-sizes of multiple items that minimize the production, inventory and setup costs subject to demand and capacity limitations. They used a memetic algorithm approach for solving the problem. Torabi, Fatemi Ghomi, and Karimi (2006) investigated the lot and delivery scheduling problem in a simple supply chain, where a single supplier produces multiple components on a flexible flow line and delivers directly to an assembly facility. Hnaien, Delorme, and Dolgui (2009) examined supply planning for two-level assembly systems under lead time uncertainties. They covered a single-period system where the finished product demand for a given due date is known. They evaluated optimal component release dates to minimize total inventory-related costs. Leuveano, Bin Jafar, and Bin Muhamad (2012) used a genetic algorithm to solve the integrated model developed by Chen and Sarker (2010) with the objective of synchronizing the production flow from multiple vendors to the manufacturer. A multi-period deterministic inventory model was formulated by Gorji, Setak, and Karimi (2014) for a two-level supply chain. The system consists of one retailer and a collection of suppliers with restricted capacities. They formulated a mixed-integer non-linear programming model and presented a GA structure to solve the proposed model.

2.3. Distribution systems

Syarif, Yun, and Gen (2002) considered a single-period distribution problem which covers binary decisions of opening plants and distribution centers. Yokoyama (2002) presented a model and a solution procedure based on GA for a single item distribution system with stationary and probabilistic demand. The objective was to determine the target order-up-to levels for distribution centers and transportation quantities that minimize the expected total inventory-related costs. Han and Damrongwongsiri (2005) developed a model to determine the optimal parameters of a periodic order-up to-level policy for a stochastic, multi-period, two-echelon network problem. They applied GA to derive optimal solutions through a two-stage optimization problem. Wang and Wang (2008) implemented the same method on a real industry case and noted that GA are able to derive a good inventory and distribution plan, which might lead to substantial reductions in the total cost of the system.

Nachiappan and Jawahar (2007) used a GA-based heuristic to obtain optimal operating parameters for a two-echelon supply chain with a single vendor and multiple buyers under vendor managed inventory. They formulated a mathematical model to find the optimal sales quantity for each buyer and derived optimal sales and acceptable contract prices under different revenue sharing structures. Yimer and Demirli (2010) analyzed a multi-product and multi-plant built-to-order supply chain with several supply and distribution channels. They developed a dynamic model for assembly and distribution planning of final products according to customer order specifications. Based on the outputs of this model, they formulated a planning model for components fabrication and raw-materials procurement.

Liao, Hsieh, and Lin (2011) proposed an integrated model to incorporate inventory control decisions into typical facility location models. They developed a multi-objective evolutionary algorithm to determine the optimal facility location portfolio and inventory control parameters to reach the best compromise for given conflicting criteria. Wang, Makond, and Liu (2011) handled a location allocation problem by bi-level stochastic programming. They combined GA with greedy heuristics to solve the facility location and task allocation problem of a two-echelon supply chain. Results of the paper reveal that the proposed GA can yield a near-optimal solution in stochastic demand environments. Sue-Ann, Ponnambalam, and Jawahar (2012) adopted the mathematical model illustrated in Nachiappan and Jawahar (2007). They proposed a particle swarm optimization algorithm and a hybrid GA-artificial immune system algorithm to optimize channel profit of a two-echelon supply chain model.

2.4. Managerial and theoretical implications

Despite the vast amount of studies proposing GA for solving the multi-echelon inventory management problem, its applicability in solving a practical size problem is not well-documented in the literature, particularly for complex distribution systems. The majority of studies present conceptual models for simplified problems. Inventory control systems which are built on these models may perform worse than anticipated when in use because of the negative impact of simplifying assumptions on the validity of mathematical models in real planning environments. The contribution of this paper is the specific approach it presents to address the two-echelon inventory control problem with its combinatorial and sequential character, and that it deals with a large number of specific properties that are considered in practice.

In addition to addressing a specific company's problem, this case study serves the following purposes:

- At the managerial level, it provides a mathematical model which captures the complex cost structures of a real-life problem and presents a framework to obtain the cost parameters of the model. The proposed mathematical model is comprehensive and, if required, can easily be simplified according to the needs of an application. Findings of the case study demonstrate the extent of cost savings that can be obtained by efficient inventory control and support evidence on practical benefits of advanced analytical approaches in inventory management. Reflections on the current company practices also illustrate the opportunities for improvement rather than optimization, as well as the obstacles to a successful implementation of the proposed system.
- The case study also illustrates problems and issues that may be observed in similar inventory control systems. The paper presents the main cost components of a typical distribution system, illustrates the details of a mathematical model and proposes an effective GA-based heuristic policy. The proposed GA scheme is comprehensive with respect to cost structure and does not require any restriction on the behavior of the cost function, such as convexity or linearity. To the authors' knowledge, this is the first study that investigates the application of GA on a capacitated lot sizing problem of a real centralized inventory distribution system under stochastic and time-varying demand.

3. Problem definition

The case company is one of the largest automotive manufacturers in Turkey and it is responsible for manufacturing, sales, marketing, and after-sales services of automobiles and commercial vehicles of an internationally recognized automotive manufacturer brand. The spare parts distribution system has a key function in the company operations, because of the significant profit share of the spare parts market and the impact of spare parts availability on customer satisfaction. End customer demand information is available at the distributor level, and the flow of items can be controlled centrally. Despite the high level of information sharing, management does not have an accurate estimate of the total cost associated with the flow of inventory. The company also experiences some trouble in devising good tactics for the management of spare parts, which is caused by the typically slow-moving behavior of spare parts inventory and their highly stochastic and erratic demand.

The company's distribution network provides a good example of a typical one-warehouse-multi-retailer system with a single warehouse (where the warehouse works as distribution center) and 80 exclusive dealers. All dealers are authorized to provide after sales services to end customers. The total supply from the local manufacturing facility and central warehouse in Europe generates 75% of the total purchases. The remaining 25% of the items are supplied from local suppliers. The lead times of the suppliers are unequal. On average, it takes four weeks to receive an order from the central warehouse, and 1–2 weeks from local suppliers.

The company uses an internet-based data interchange system which enables a high level of information sharing over the network, and provides online inventory and demand visibility. The system also works as a decision tool for the dealers to manage their inventories. Due to transportation restrictions, all facilities follow a periodic order policy where inventory is replenished in regular time intervals. Customer demand is probabilistic and orders are placed only at the dealers.

The study covers seven main dealers of the company in the same geographic region. For confidentiality reasons, the data has been scaled down proportionately, such that the relative magnitude is maintained. Fig. 1 illustrates that the dealers are asymmetric in terms of demand rates, and that the demand variation among the periods is generally high.

4. Development of an inventory control system

4.1. Evaluation of the cost parameters

The lack of accurate parameter estimates used in inventory control models under realistic conditions prevents many of the theoretical results in operations research from being realized (Oral, Salvador, Reisman, & Dean, 1972). An accurate calculation of cost components is important for the validity of the proposed solution

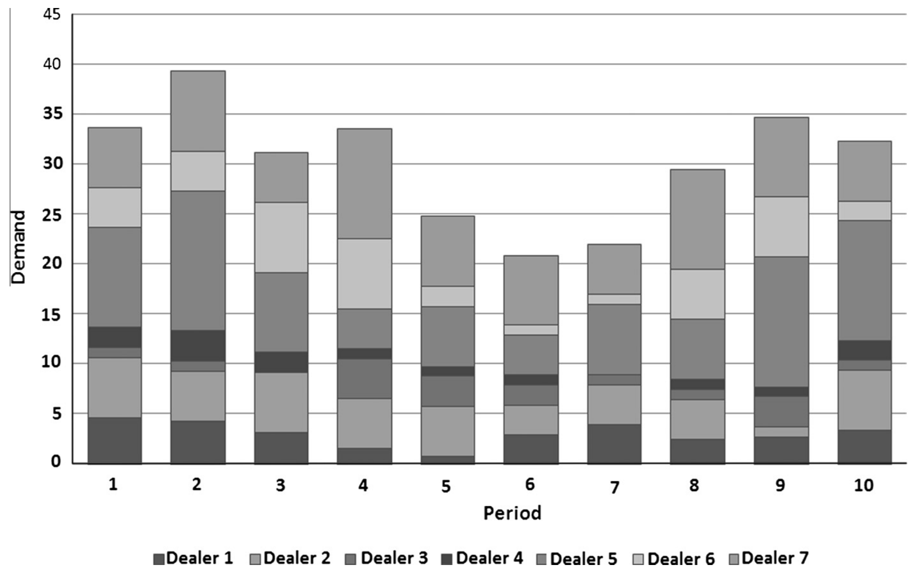


Fig. 1. Demand forecasts for dealers.

and an intuitive choice of cost parameters could lead to misunderstanding and errors in the inventory management models application (Azzi, Battini, Faccio, Persona, & Sgarbossa, 2014).

4.1.1. Inventory carrying costs

We calculate the cost of carrying inventories as the sum of capital, service and risk costs:

1. *Capital Costs:* In practice interest rate does not truly reflect the cost of capital because of the unique operating environment of each company. A reasonable approach is to categorize the inventory items into risk groups, where high risk groups (e.g. new products, non-moving items) have high desired rates of return, and low risk groups (short term inventories) are assigned to lower return rates. A matrix classification approach is useful for creating risk clusters and presenting various risk criteria over multiple dimensions.
   Table 1 illustrates the two-dimensional structure implemented in this study. The vertical dimension is the annual value of items, and the horizontal dimension groups items according to flow rates, as a function of annual demand. The risk level increases from bottom to top and from left to right, because carrying low-valued items with high volumes is less risky than carrying high-valued items with low demand rates. the case item belongs to group *A – Fast* (moderate risk level) and comprises 0.3% of the average inventory value, which corresponds to a 13.5% annual rate of return value.
2. *Inventory Service Costs:* Distributor's tax applicable to inventory is estimated as 62.2% which refers to 2.8% of the average inventory value. The premium for an all-risk-stock-insurance is 0.5% of the average inventory value. Total inventory service costs are 3.3% and 1.2%, in the warehouse and dealer locations, respectively.

Table 1
Risk groups of inventories.

ABC group	Demand rate		
	Fast	Normal	Slow & Non-moving
A	Moderate	High	High
B	Low	Moderate	High
C	Low	Low	Moderate

3. *Inventory Risk Costs:* We use the percentage scap cost to estimate the inventory risk costs. Given a relatively low rate of scrap in item level, we use aggregated scap rates over product families. We first calculate the annual cost of scrap as the difference between inventory book value and inventory value, then evaluate the value of inventory written off as a percentage of average inventory costs. Risk cost, as a percentage of average annual inventory value, is calculated as 0.7% for the warehouse and 0.84% for the dealers.

4.1.2. Order processing costs

Order processing costs are considered negligible, because the time spent for placing an order is short over an internet-based communication system which connects the manufacturer to the distributor, and the distributor to its dealers.

4.1.3. Transportation costs

The case company uses a third party logistics service provider for transporting items from the warehouse to the dealers. The price of transportation is independent of the shipment size, but dependent on the distance and the number of the vehicles used. Shipments generally consist of more than one type of items with different package sizes. The allocation of transportation cost to items is based on the box sizes, but due to the lack of package size data, we use the percentage inventory value of items as an allocation basis to estimate the fixed cost of transportation.

4.1.4. Stock-out costs

In practice, the stock-out costs are very difficult to specify because they usually represent intangible factors, such as the loss of goodwill or cost of waiting time. Very little research has been done on the estimation of the unit stock-out cost, though most of the inventory control models depend on it.

Schwartz (1966) suggested the use of a mathematical model to describe the effect of perturbed demand and estimate the effects of goodwill loses on future demand. This is not a practical approach since it depends on the restrictive assumption of a sufficiently complete customer order history and backlogs. An alternative approach is to estimate stock-out costs empirically as suggested by Jensen (1992) and Oral et al. (1972). Because of the difficulty of implementing accurate estimation methods, another common approach is to use imputed cost of stock-out occasions. Nahmias

(1993) developed a model which uses service levels as substitutes of backorder costs. He presented two models for two types of service levels. Fogarty and Aucamp (1985) formulated an inventory model with service level constraints and calculated implied time-persistent backorder cost in a deterministic environment. Cetinkaya and Parlar (1998) extended their study by introducing two types of backorder costs. They constructed a non-linear programming model with two types of service level constraints.

We use the implied costs of service level as an estimate of stock-out cost. A predetermined service level (SL) leads to a decision rule equivalent to that for backorder cost per unit short ($\hat{\pi}$) relative to the carrying charge (h) (Silver, Pyke, & Peterson, 1998):

$$\hat{\pi} = \frac{\mathrm{SL} \times h}{1 - \mathrm{SL}}. \tag{1}$$

If the management wants to implement a service level of 91%, this corresponds to a stock-out cost which is approximately 10.11 times of the annual inventory carrying cost ($\hat{\pi} = 10.11$ h).

4.2. Mathematical model formulation

We consider an inventory problem for T periods. The inventory level of dealer n at period t is denoted as x_t^n. $P(u)$ is the probability of observing u units of demand. We assume that customer demand observed by dealer n in period t follows a Poisson distribution with λ_n^t. At the beginning of each period, the distributor allocates a total of $\sum_{n=1}^{N} q_t^n$ units to N dealers. Replenishments arrive ℓ periods after the allocation decision. We assume that the outside supplier has an infinite source of supply or work at very high service levels, such that delays from the supplier side are negligible.

The model to minimize the total cost of the system is formulated as follows:

$$\text{Minimize} \quad \sum_{t=1}^{T}\left(H\left(y_t, \sum_{n=1}^{N} q_t^n\right) + \delta(Q_t) + \sum_{n=1}^{N}\left(L(x_t^n) + \delta(q_t^n)\right)\right) \tag{2}$$

subject to

$$x_t^n - D_t^n + q_{t-\ell}^n = x_{t+1}^n \tag{3}$$

$$\sum_{n=1}^{N} q_t^n \leqslant y_t \tag{4}$$

$$x_t^n \leqslant C_n \tag{5}$$

$$y_t \leqslant C_0 \tag{6}$$

where

$$\delta(q) = \begin{cases} \kappa\left\lceil \frac{q}{\theta} \right\rceil + \varsigma q + K, & \text{if } q > 0 \\ 0, & \text{if } q = 0, \end{cases} \tag{7}$$

$$H(y, q) = h_0(y - q), \tag{8}$$

$$L(x) = h\sum_{u=0}^{x}(x-u)P(u) + \pi\sum_{u=x}^{\infty}(u-x)P(u). \tag{9}$$

Here, x_t^n and y_t denote the inventory levels, and q_t^n and Q_t denote the replenishment quantities. The first two and the last two terms in the objective function show the total expected inventory-related costs. Eq. (3) is a balance constraint which adjusts the inventory levels between two consecutive periods. This is not a simple linear equation due to the random variable D_t^n, which represents stochastic demand observed by dealer n.

Eq. (4) limits the number of shipped products to all dealers by the distributor's on-hand stock in period t. Constraints (5) and (6) ensure that the dealers' and distributor's inventory holding capacities (C_n and C_0 respectively) are not exceeded.

In Eq. (7), $\delta(q)$ denotes the inventory replenishment costs of the system with a fixed ordering cost incurred with each replenishment, plus a stepwise transportation cost. K is the sum of fixed ordering cost, ς is the unit purchasing + transportation cost, and q is the replenishment quantity. Fixed transportation costs are determined by the carrier capacities. κ is the fixed cost of transporting one batch of items (of size θ) from the warehouse to any dealer.

Eqs. (8) and (9) include the costs of carrying inventories incurred at rates of h_0 and h, charged at the end of each period. Unfilled customer demand is fully back-ordered at the dealer locations, and shortages are penalized at the rate of π.

4.3. Genetic algorithm structure

The phenotype space P is the set of all combinations of order quantities for a number of T periods. Each chromosome represents the dealers' order – up – to – levels for each period and takes the form of following sequence in the encoding scheme:

$$\mathcal{C} = q_1^1 q_2^1 \ldots q_T^1 q_1^2 \ldots q_T^2 \ldots q_1^N \ldots q_T^N$$

Here, q_t^n is the direct value representation of the replenishment quantity. Each chromosome is a string consisting of $N \times T$ genes, where N is the total number of dealers and T is the number of periods. Each gene, can take on values between 0 and C_n, according to the inventory carrying capacity of retailer n. It is important to note that this design guarantees the completeness and the correctness requirements of chromosome representation. Each chromosome consists of all decision variables in the model. This structure produces a complete representation of the problem. The correctness condition is checked before fitness calculation. If the inventory on hand exceeds the capacity level for the given allocation quantity in any period, q_t^n is reduced to provide the highest feasible inventory level after allocation. As a result, the chromosomes are kept in the feasible domain without using an additional constraint.

The fitness value of a given solution (f), represented by a chromosome $\mathcal{C}$, is the minimum expected total cost of the system. To increase the performance of the algorithm, we use dynamic programming to evaluate the optimal order quantities of the distributor. The total cost resulting for any chromosome TC($\mathcal{C}$) is given in Eq. (10). The related sub-Eqs. (11)–(14) are the recursive formulations of Eq. (2) for sequential decision for the lot sizes (q^n and Q) over the lead time (ℓ and ℓ_0).

$$\mathrm{TC}(\mathcal{C}) = \sum_{n=1}^{N} g_1^n(x_1^n, q_{1-\ell}^n, \ldots, q_0^n) + f_1(y_1, Q_{1-\ell_0}, \ldots, Q_0) \tag{10}$$

where *for* $t = 1, \ldots, T-1$,

$$g_t^n(x_t^n, q_{t-\ell}^n, \ldots, q_{t-1}^n) = \left\{\delta q_t^n + L(x_t^n) + \sum_{u=0}^{\infty} g_{t+1}(x_t^n + q_{t-\ell}^n - u, q_{t-\ell+1}^n, \ldots, q_t^n)P(u)\right\} \tag{11}$$

and *for* $t = T$,

$$g_T^n(x_T^n, q_{T-\ell}^n, \ldots, q_{T-1}^n) = \left\{\delta q_T^n + L(x_T^n)\right\}. \tag{12}$$

Similarly *for* $t = 1, \ldots, T-1$,

$$f_t(y_t, Q_{t-\ell_0}, \ldots, Q_{t-1}) = \min_{Q_t \geqslant 0}\left\{\delta Q_t + H\left(y_t, \sum_{n=1}^{N} q_t^n\right) + f_{t+1}\left(y_t + Q_{t-\ell_0} - \sum_{n=1}^{N} q_t^n, Q_{t-\ell_0+1}, \ldots, Q_t\right)\right\} \tag{13}$$

and *for* $t = T$

$$f_T(y_T, Q_{T-\ell_0}, \ldots, Q_{T-1}) = \left\{ \delta Q_T + H\left(y_T, \sum_{n=1}^{N} q_T^n \right) \right\}. \quad (14)$$

We use a *Rank* fitness scaling method to convert cost values into fitness scores. The rank scaling function assigns scaled values to chromosomes, such that, the scaled value of an chromosome with rank r is proportional to $1/\sqrt{r}$. The sum of the scaled values over the entire population is equal to the number of parents needed to create the next generation. Lower raw scores have higher scaled values. The selection of mating parents is done using the *roulette wheel algorithm* (Eiben & Smith, 2007). The dynamic program of the fitness function is coded in MATLAB as a recursive formulation.

At each iteration, the current population is used to create the offspring population over a *general replacement scheme*. The chromosomes in the current population are completely replaced by the offspring, and the population size is kept constant in its initial level. The offspring generation contains three types of children: elite, crossover, and mutation.

Elite children are the individuals in the current generation with the best fitness values. These individuals are automatically passed to the next generation without any modification. Such an elite algorithm is assumed to speed up the performance of the GA significantly by preventing the loss of good solutions once they have been found (Zitzler, Deb, & Thiele, 1998). For crossover, we chose *intermediate recombination* which creates offspring genes by taking weighted average of the parent genes. We use the following function to create each gene of the child, $q_{\text{offspring}}$, from corresponding genes of two parents (p_1 and p_2):

$$q_{\text{offspring}} = \alpha q_{p_1} + (1-\alpha) q_{p_2} \quad \text{for some } \alpha \text{ in } U(0,1),$$

where α is a random number taken from the range [0,1]. The intermediate recombination method with a given α value ensures the feasibility of the chromosomes. Fractional numbers are repaired by rounding the number to the nearest integer to generate only valid order quantities. Chromosome variations are introduced by *Random Resetting* at multiple points. Genes are selected according to a probability of being mutated, P_{mut} (*mutation rate*). Selected genes are replaced with a random number generated with a uniform distribution $U(0, C_n)$.

The selections of the best genetic parameters, such as the population size, the number of generations, or the probabilities of crossover and mutation, are based on experiments over different values. A population size of 20 has given satisfactory results both in terms of convergence speed and fitness value. Larger population sizes reduce the probability of returning a local minimum by searching the solution space more thoroughly, at the expense of increased convergence time. Experimenting with varying numbers (from 0 to 10) of elite chromosomes, a number of two elite chromosomes provided best fitness results and convergence time. We determined the crossover and mutation rates through several GA experiments for linear parameter variations, as suggested by Davis (1991). The experiments were run for the combinations of three crossover fraction values (0.4, 0.6, 0.8) and four mutation rates (0.01, 0.05, 0.1, 0.2). The GA was run three times for each combination, and the performance of each configuration was calculated with the value of the objective function. Iterations were terminated either when the number of generations exceeded 500 or when no improvement of the fitness function was observed for the last 25 generations. The minimum and the average fitness function values are illustrated in Fig. 2, where average values are presented by bars and minimum values are presented by lines.

It is observed that high crossover rates generally give better results when the mutation rate is high; the best results were obtained, however, with a moderate crossover rate (0.6). A mutation rate of 0.05 was observed to perform slightly better ($\approx 1\%$) than the nearest value, which implies that, on the average, three genes from each selected chromosome were mutated.

4.4. Computational results

This section briefly explains the computational procedure and presents the results of the numerical studies. We assumed that demand at each dealer is Poisson distributed with a rate of λ_n^t. We use real demand realizations of the previous two years to forecast demand rates (λ_n^t). We run the GA to obtain the best replenishment quantities and recorded the average inventory level, service levels, and the total costs as performance measures. Fig. 3 illustrates the percentage reduction in inventory levels and the total costs under the desired service levels.

The results show that the proposed inventory control system provides 57.46% savings on the current total system cost. The average cost reduction is 52.05%, and the minimum cost reduction is 38.6%. The average inventory level of all dealers has dropped down to 8.3 from 23.33, corresponding to more than 58%. The cost reduction at the distributor is 45.16%. In a second experiment, we used past demand realisations rather than forecasted rates. Better demand information increased the average service level to 97.99%, while the average inventory level decreased to 7.46. The resulting cost reduction on the dealers' side is calculated as 61.18%, which means that the error resulting from forecasting practice creates an additional cost of 9.13%.

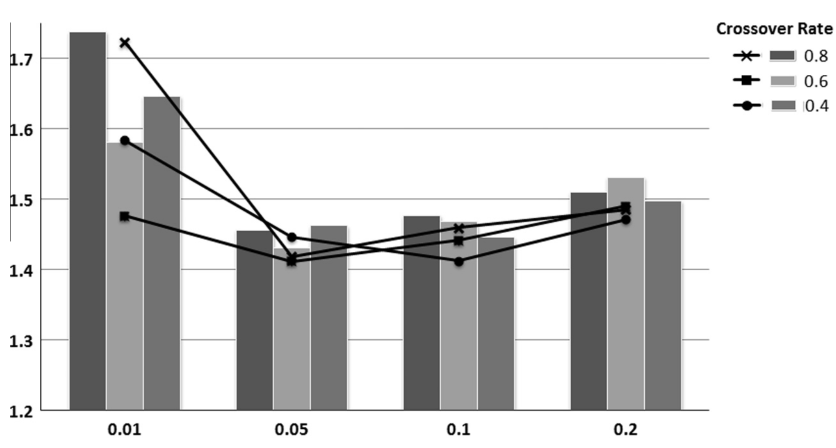
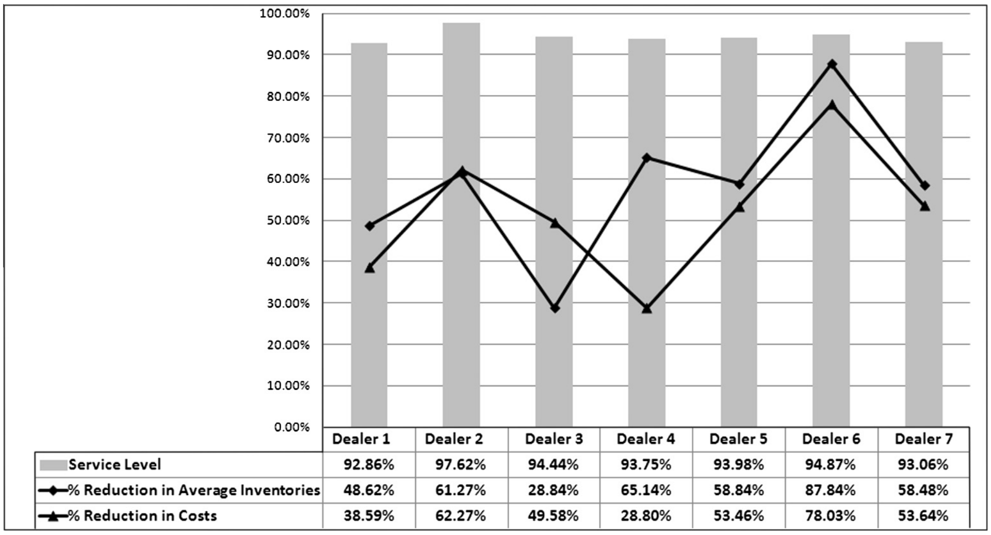


Fig. 2. Determination of best crossover and mutation rates.



	Dealer 1	Dealer 2	Dealer 3	Dealer 4	Dealer 5	Dealer 6	Dealer 7
Service Level	92.86%	97.62%	94.44%	93.75%	93.98%	94.87%	93.06%
% Reduction in Average Inventories	48.62%	61.27%	28.84%	65.14%	58.84%	87.84%	58.48%
% Reduction in Costs	38.59%	62.27%	49.58%	28.80%	53.46%	78.03%	53.64%

Fig. 3. Computational results.

The most distinct observation is that the inventory levels of the dealers under the current policy fall hardly below the inventory levels of the proposed policy. On the other hand, the dealers hardly observe back-orders. This leads to a service level close to 100%, with zero shortage costs, but at the expense of very high inventory holding costs. The average service level of the proposed system, as the percentage of demand directly supplied from the shelf, is 92.13%, which is slightly higher than the desired service level, 91%.

4.5. Findings and implications

The case study provides a general insight into the impact of the case company's current operational practices on inventory levels in the supply chain. 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 obstacle that prevents dealers from ordering more frequently is the economics of transportation. There are substantial benefits to order in large batch sizes due to the step-wise behavior of the transportation costs, so dealers have a strong incentive to fill the truck completely when they order parts from the distributor. As a reaction to mitigate the batching effect, the company decided to implement a transportation collaboration among dealers, to allow mixed shipments to multiple dealers in the same delivery, and to plan coordinated shipments to move the channel away from random ordering to balanced ordering. The company also started negotiating the terms of the contract with the third-party logistics service provider to consolidate orders from dealers who are in geographical proximity to each other, to obtain lower transportation costs for more frequent shipments.

The other reason for excess inventory levels is *Push Ordering*. The company experiences regular variations in demand, which stem from redundant orders from dealers. This behavior is related to the performance evaluation system and promotion incentive mechanism implemented by the company. Performance measurements are done quarterly, which causes end-of-quarter order surges. Salespersons who need to fulfill quotas to obtain incentives, use their bargaining power and interpersonal skills to urge dealers to place untimely orders. After the case study, the company started to investigate a new sales incentive mechanisms that was based on a rolling horizon promotion system. Under this system, performance evaluation is done continuously over the rolling periods of the last 6–8 weeks, rather than creating a high bonus period over a fixed period of time, which leads to a more constant level of effort from the salespersons.

5. Discussions and implications

This paper addressed a real-life inventory control problem in a two-echelon spare parts distribution system. The proposed mathematical model relies on implicit cost calculations that reflect the desired service levels in means of shortage costs. The results show that applying the proposed inventory control system for high cost and low demand items may provide substantial cost savings *w*th service levels maintained. Although the heuristic was developed for the specific system under study, it can be used, with appropriate modifications, in other two-stage inventory control problems with similar features.

Naturally, some barriers may exist for the successful implementation of the proposed method to other real-life problems. The complexity of today's business world entails that it is often not possible to link external sources of information into the vendor's production and inventory control processes (Stank, Keller, & Daugherty, 2001); in many cases, the same level of detailed information cannot be obtained from all distribution channels. Companies involved in strategic or incidental supply-network partnerships may be unwilling or unprepared to share information required for the coordination of the supply chain. One approach for collaboration in such a case is to design a distributed algorithm that allows the system to perform like a centralized network.

GA have been applied to a wide variety of multi-echelon inventory control problems successfully, but one should keep in mind that, as it is common with all heuristic methods, they cannot guarantee to find the global optimum in a problem space in finite time. In this paper, we relied on the fact that especially in real-life problems, the most desirable solution may not be the conventional global optimum, but instead a solution representing a robust answer to the problem at hand.

Focusing directly on the optimization of costs, rather than considering other simpler forms of improving performance, is often not the right approach. There are many other ways to improve the performance of the inventory control system, rather than directly focusing on finding the optimal solutions that are subject to a number of *givens*. It is often possible to improve the performance far more by changing one of the givens, without any optimization, rather than by optimizing subject to a given set of conditions (Silver, 1992). Changing the ways that the operations are performed, by redesigning processes or embedding new technologies, may provide high improvements in the system's performance. One of the main findings of the case study is the value of the operational changes in improving inventory control systems, such as restructuring the performance management system, reducing lead times, and coordinating transportation operations.

In future work, we intend to adapt the proposed genetic algorithm to other supply chain system structures with different network characteristics. This is not necessarily a simple extension; the additional constraints of the new structure may require a different GA encoding scheme and algorithm structure. We also plan to use the proposed models and solution methods to experimentally investigate the benefits of centralization in distribution networks. Our aim is to design a set of experiments to compare the system performances of centralized and decentralized systems through costs and service levels. The results of this research might be beneficial for understanding the motives of centralization and investigating the factors which have an increasing impact on the benefits of centralization.

Acknowledgements

I would like to express my deepest thanks to Prof. Dr. Christoph Glock for his time and extraordinary effort. His comments and suggestions helped improve this manuscript to a great extent.

References

Azzi, A., Battini, D., Faccio, M., Persona, A., & Sgarbossa, F. (2014). Inventory holding costs measurement: A multi-case study. *The International Journal of Logistics Management, 25*, 109–132.
Berretta, R., & Rodrigues, L. (2004). A memetic algorithm for a multistage capacitated lot-sizing problem. *International Journal of Production Economics, 87*, 67–81.
Çelebi, D. (2011). Evolutionary inventory control for multi-echelon systems. In M. Koeppen, G. Schaefer, & A. Abraham (Eds.), *Intelligent computational optimization in engineering. Studies in computational intelligence* (Vol. 366, pp. 329–356). Berlin/Heidelberg: Springer.
Cetinkaya, S., & Parlar, M. (1998). Nonlinear programming analysis to estimate implicit inventory backorder costs. *Journal of Optimization Theory and Applications, 97*, 71–95.
Chen, F. (2003). Information sharing and supply chain coordination. In Kok & Graves (Eds.), *Handbooks in operations research and management science: V11 supply chain management: Design, coordination and operation* (pp. 341–451). Oxford, UK: Elsevier.
Chen, Z., & Sarker, B. (2010). Multi-vendor integrated procurement-production system under shared transportation and just-in-time delivery system. *Journal of the Operational Society, 61*, 1654–1666.
Daniel, J., & Rajendran, C. (2005). A simulation-based genetic algorithm for inventory optimization in a serial supply chain. *International Transactions in Operational Research, 12*, 101–127.
Davis, L. (1991). *Handbook of genetic algorithms*. New York: van Nostrand Reinhold.
Eiben, A., & Smith, J. (2007). *Introduction to evolutionary computing. Natural computing series*. Springer.
Fakhrzad, M., & Zare, H. (2009). Combination of genetic algorithm with lagrange multipliers for lot-size determination in multi-stage production scheduling problems. *Expert Systems with Applications, 36*, 10180–10187.
Fogarty, W., & Aucamp, C. (1985). Implied backorder cost. *IIE Transactions, 17*, 105–107.
Gen, M., & Cheng, R. (1997). *Genetic algorithms and engineering design*. New York: John Wiley and Sons.
Gen, M., & Cheng, R. (2000). *Genetic algorithms and engineering optimization*. New York: John Wiley and Sons.
Ghiami, Y., Williams, T., & Wu, Y. (2013). A two-echelon inventory model for a deteriorating item with stock-dependent demand, partial backlogging and capacity constraints. *European Journal of Operational Research, 231*(3), 587–597.
Glock, C. H. (2012). The joint economic lot size problem: A review. *International Journal of Production Economics, 135*, 671–686. Green Manufacturing and Distribution in the Fashion and Apparel Industries.
Goldberg, D. (1989). *Genetic algorithms in search, optimization & machine learning*. Harlow, England: Addison Wesley.
Goren, H. G., Tunali, S., & Jans, R. (2010). A review of applications of genetic algorithms in lot sizing. *Journal of Intelligent Manufacturing, 21*, 575–590.
Gorji, M. H., Setak, M., & Karimi, H. (2014). Optimizing inventory decisions in a two-level supply chain with order quantity constraints. *Applied Mathematical Modelling, 38*(3), 814–827.
Han, C., & Damrongwongsiri, M. (2005). Stochastic modeling of a two-echelon multiple sourcing supply chain system with genetic algorithm. *Journal of Manufacturing Technology Management, 16*, 87–107.
Handfield, R. B., & Nichols, E. Jr., (2002). *Supply chain redesign: Transforming supply chains into integrated value systems*. Financial Times Prentice Hall.
Hnaien, F., Delorme, X., & Dolgui, A. (2009). Genetic algorithm for supply planning in two-level assembly systems with random lead times. *Engineering Applications of Artificial Intelligence, 22*, 906–915.
Holland, J. (1975). *Adaptation in natural and artificial systems*. Ann Arbor: University of Michigan Press.
Jensen, A. (1992). Stockout costs in distribution systems for spare parts. *International Journal of Physical Distribution & Logistics Management, 22*(1), 15–27.
Kimbrough, S., Wu, D., & Zhong, F. (2002). Computers play the beer game: Can artificial agents manage supply chains? *Decision Support Systems, 33*, 323–333.
Leuveano, A., Bin Jafar, F., & Bin Muhamad, M. (2012). Development of genetic algorithm on multi-vendor integrated procurement-production system under shared transportation and just-in-time delivery system. In *2012 2nd international conference on uncertainty reasoning and knowledge engineering (URKE)* (pp. 78–81).
Liao, S.-H., Hsieh, C.-L., & Lin, Y.-S. (2011). A multi-objective evolutionary optimization approach for an integrated location-inventory distribution network problem under vendor-managed inventory systems. *Annals of Operations Research, 186*, 213–229.
Nachiappan, S., & Jawahar, N. (2007). A genetic algorithm for optimal operating parameters of VMI system in a two-echelon supply chain. *European Journal of Operational Research, 182*, 1433–1452.
Nahmias, S. (1993). Production and operations analysis. 2nd ed., Irwin, Homewood, Illinois.
O'Donnell, T., Maguire, L., McIvor, R., & Humphreys, P. (2006). Minimizing the bullwhip effect in a supply chain using genetic algorithms. *International Journal of Production Research, 44*, 1523–1543.
Oral, M., Salvador, S., Reisman, A., & Dean, V. (1972). On the evaluation of shortage costs for inventory control of finished goods. *Management Science, 18*(6), B344.
Pasandideh, S. H. R., Niaki, S. T. A., & Nia, A. R. (2011). A genetic algorithm for vendor managed inventory control system of multi-product multi-constraint economic order quantity model. *Expert Systems with Applications, 38*, 2708–2716.
Schwartz, B. (1966). A new approach to stockout penalties. *Management Science, 12*, 538–544.
Scott, E., Eheart, J., & Ranjithan, S. (1995). Using genetic algorithms to solve a multiobjective groundwater monitoring problem. *Water Resources Research, 31*, 399–410.
Silver, E. (1992). Changing the givens in modelling inventory problems: The example of just-in-time systems. *International Journal of Production Economics*, 347–351.
Silver, E. A., Pyke, D., & Peterson, R. (1998). *Inventory management and production planning and scheduling* (3rd ed.). John Wiley and Sons.
Stank, P., Keller, S., & Daugherty, P. (2001). Supply chain collaboration and logistical service performance. *Journal of Business Logistics, 22*(1), 29–49.
Sue-Ann, G., Ponnambalam, S., & Jawahar, N. (2012). Evolutionary algorithms for optimal operating parameters of vendor managed inventory systems in a two-echelon supply chain. *Advances in Engineering Software, 52*, 47–54.
Syarif, A., Yun, Y., & Gen, M. (2002). Study on multi-stage logistic chain network: A spanning tree-based genetic algorithm approach. *Computers & Industrial Engineering, 43*, 299–314.
Torabi, S., Fatemi Ghomi, S., & Karimi, B. (2006). A hybrid genetic algorithm for the finite horizon economic lot and delivery scheduling in supply chains. *European Journal of Operational Research, 173*, 173–189.
Vergara, F., Khouja, M., & Michalewicz, Z. (2002). An evolutionary algorithm for optimizing material flow in supplpy chains. *Computers & Industrial Engineering, 43*, 407–421.
Waller, M., Johnson, M., & Davis, T. (1999). Vendor managed inventory in the retail supply chain. *Journal of Business Logistics, 20*, 183–203.
Wang, K.-J., Makond, B., & Liu, S.-Y. (2011). Location and allocation decisions in a two-echelon supply chain with stochastic demand a genetic-algorithm based solution. *Expert Systems with Applications, 38*, 6125–6131.
Wang, K., & Wang, Y. (2008). Applying genetic algorithms to optimize the cost of multiple sourcing supply chain systems: An industry case study. *Studies in Computational Intelligence, 92*, 355–372.
Yimer, A. D., & Demirli, K. (2010). A genetic approach to two-phase optimization of dynamic supply chain scheduling. *Computers & Industrial Engineering, 58*, 411–422.
Yokoyama, M. (2002). Integrated optimization of inventory distribution systems by random local search and a genetic algorithm. *Computers & Industrial Engineering, 42*, 172–188.
Zitzler, E., Deb, K., & Thiele, L. (1998). Comparison of multi-objective evolutionary algorithms: Empirical results. *Evolutionary Computation, 8*(2), 173–195.