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REVIEW ARTICLE

A review of applications of genetic algorithms in lot sizing

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Abstract Lot sizing problems are production planning problems with the objective of determining the periods where production should take place and the quantities to be produced in order to satisfy demand while minimizing production, setup and inventory costs. Most lot sizing problems are combinatorial and hard to solve. In recent years, to deal with the complexity and find optimal or near-optimal results in reasonable computational time, a growing number of researchers have employed meta-heuristic approaches to lot sizing problems. One of the most popular meta-heuristics is genetic algorithms which have been applied to different optimization problems with good results. The focus of this paper is on the recent published literature employing genetic algorithms to solve lot sizing problems. The aim of the review is twofold. First it provides an overview of recent advances in the field in order to highlight the many ways GAs can be applied to various lot sizing models. Second, it presents ideas for future research by identifying gaps in the current literature. In reviewing the relevant literature the focus has been on the main features of the lot sizing problems and the specifications of genetic algorithms suggested in solving these problems.

Keywords Production planning · Meta-heuristics · Lot sizing · Genetic algorithms

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Introduction

Lot sizing is one of the most important and the most difficult problems in production planning. Production planning is an activity that considers the best use of production resources in order to satisfy production goals over a certain period named planning horizon. It encompasses three time ranges for decision making: long-term, medium-term and short term (Karimi et al. 2003). Medium term production planning focuses on decisions related to materials requirements planning (MRP) and lot sizing. In lot sizing decisions, the objective is to determine the periods where production should take place and the quantities to be produced in order to satisfy demand while minimizing production, setup and inventory costs. Since lot sizing decisions are critical to the efficiency of production and inventory systems, it is very important to determine the right lot sizes in order to minimize the overall cost.

Lot sizing problems have attracted the attention of many researchers. There are a number of survey studies on lot sizing. De Bodt et al. (1984) discuss the state of the art of lot sizing under dynamic demand conditions, the impact of the use of rolling horizon and the influence of demand uncertainty on lot sizing decisions. Bahl et al. (1987) classify the lot sizing problems based on the demand type and resource constraints and concentrate on capacity dimensions of the production planning problem. Kuik et al. (1994) discuss the impacts of lot sizing and production planning at different decision levels in an organization. The basis of this review is a distinction of lot sizing issues related to process design/choice, activity planning and activity control. Wolsey (1995) reviews the history of the single item uncapacitated lot sizing problems by various solution algorithms, extensions and important reformulations. Drexl and Kimms (1997) present a classification on different variants of lot sizing and scheduling problems for both discrete and continuous time models. Belvaux and Wolsey (2001) show how to model the basic lot sizing problems including different extensions such as backlogging, start up costs etc. and present some computational results for various sets of problems. Karimi et al. (2003) review the studies employing exact and heuristic approaches to solve the single level capacitated lot sizing problems. Brahimi et al. (2006) review the single item lot sizing problems under uncapacitated or capacitated situations. Jans and Degraeve (2008) give an overview of recent developments in the field of modeling single level dynamic lot sizing problems.

Complexity theory and computational experiments indicate that most lot sizing problems are hard to solve (Jans and Degraeve 2007). To deal with the complexity and find optimal or near-optimal results in reasonable computational time, in recent years, a growing number of researchers have employed heuristic approaches to solve lot sizing problems (Afentakis 1987; Tempelmeier and Helber 1994; Gopalakrishnan et al. 2001; Tang 2004; Karimi et al. 2006; Pitakaso et al. 2007). Among these heuristic approaches, evolutionary computation has received the greatest attention. The most well known evolutionary computation method is Genetic Algorithms (GAs). GAs are optimization techniques that use the principles of evolution and heredity to arrive at near optimum solutions to difficult problems (Khouja et al. 1998). GAs have been employed to solve different optimization problems across various disciplines due to their flexibility and simplicity.

During the literature survey, two review studies have been noted (Aytug et al. 2003; Jans and Degraeve 2007) which discuss applications of GAs to lot sizing problems. However, the scope of these review studies is rather broad and quite different from our focus as they focus on either a broader application area or a broader set of solution approaches. Aytug et al. (2003) discuss different applications of GAs in the broad field of production and operations management problems by analyzing over 110 papers, including some lot sizing problems, while Jans and Degraeve (2007) review the recent literature employing a variety of meta-heuristics and other solution approaches (dynamic programming, Dantzig-Wolfe decomposition, Lagrange relaxation) to solve the dynamic lot sizing problem.

To the best of our knowledge, there is no previous review study particularly focusing on current applications of GAs to lot sizing problems. The main contribution of this review study is to fill the perceived gap by providing a comprehensive overview of the current literature on the applications of GAs in lot sizing area. The aim of the review is twofold. First it provides an overview of recent advances in the field in order to highlight the many ways GAs can be applied to various lot sizing models. Second, it presents ideas for future research by identifying gaps in the current literature. Moreover, this study aims also to provide a general review for lot sizing and GAs by providing a list of references for researchers. Considering the increasing number of studies in this area, we aim at reviewing the current literature extensively from two different perspectives. To highlight the research gaps in this area, the current literature is reviewed based on both the specifications of the lot sizing problems and the features of GAs in dealing with these problem specifications. The rest of the paper is organized as follows. The main problem specifications of lot sizing problems are given in Section "Lot sizing". Section "Genetic algorithms" gives a brief introduction to GAs. In Section "Review of literature", the recently published literature is discussed in detail according to the previously discussed dual focus. Finally, in the last section "Conclusion and future research directions", the concluding remarks and the future research directions are given.

Lot sizing

Research on lot sizing starts with the classical economic order quantity (EOQ) model. The EOQ model is developed for a single level production process with a single item and no capacity constraints under stationary demand. Since the assumptions of the EOQ model do not appear realistic, other models have evolved. One of them is Economic Lot Size Scheduling Problem (ELSP) which attracts many of the researchers. The ELSP is to schedule production of several different items in the same facility on a repetitive basis (Elmaghraby 1978). Thus, the ELSP is a single level multi-item problem with capacity constraints under stationary demand and infinite planning horizon. Based on the main features of lot sizing problems, the current literature can be classified as follows regarding to the classification in Bahl et al. (1987) (Fig. 1).

The first group of the lot sizing problems is the static lot sizing problems namely the Economic Lot Scheduling Problem (ELSP). The ELSP deals with the scheduling the production of a set of items in a single machine to minimize the long run average holding and set up cost under the assumptions of known constant demand and production rates. The objective of the ELSP is to determine a production cycle of i items, $i \in \{1, 2, \ldots, N\}$ in a repetitive schedule. A repetitive schedule is achieved if there is a time period T_i for each product that represents the time between successive production runs (batches or "lots") of item i (Chatfield 2007). The repetitive schedule is subject to the following conditions related to the production facility and marketplace, as stated in Bomberger (1966).

1. Only one item i can be produced at a time.
2. Set up for a certain item incurs both a specific setup cost (s_i) and setup time (t_i).

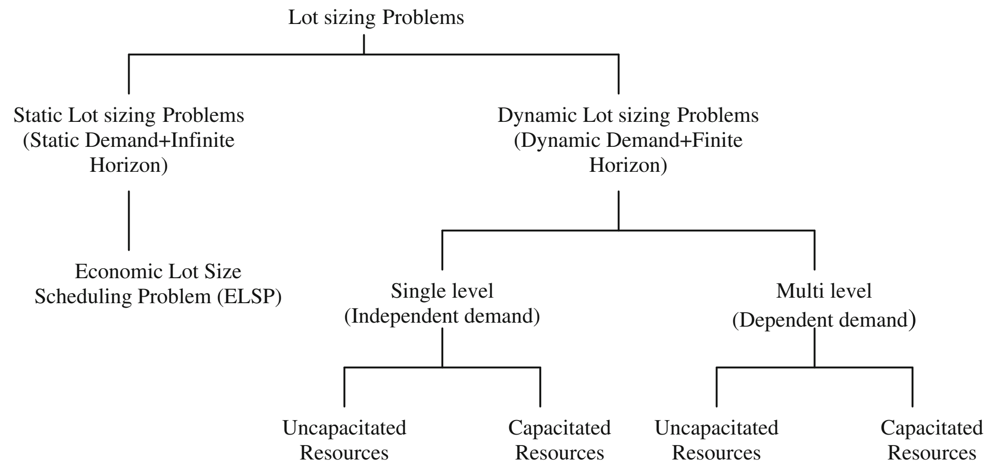

Fig. 1 A classification of lot sizing problems

3. Setup time and setup cost are determined solely by the product going into production (sequence independent).
4. Demand rate (r_i) and production rate (p_i) are known and constant for all items.
5. All demand must be met.
6. Holding costs (h_i) are determined by the value of items held.
7. Total variable cost for an item equals the average setup cost plus holding cost over a specific period of time.
8. Production time for a batch of item i, σ_i, equals the sum of the processing time and the setup time, $\sigma_i = (r_i/p_i) * T_i + t_i$.

A solution consists of a set $T = \{T_1, T_2, \ldots T_N\}$ such that T_i is sufficiently long enough to allow enough production of item i at the beginning of the cycle to meet demand during the entire cycle T_i, plus allow production of other items in the time left between the end of production of item i and the start of the next cycle. The cost per unit time for an item i is defined as in Eqs. 1 and 2:

$$C_i = (\text{average setup cost} + \text{average holding cost}) \tag{1}$$

$$C_i = \frac{s_i}{T_i} + \frac{h_i r_i T_i (p_i - r_i)}{2 p_i} \tag{2}$$

Due to the non-linearity and combinatorial characteristics of the problem, the ELSP falls into the class of NP-Hard problems. Many researches dealing with the ELSP propose different heuristic approaches which aim finding low cost schedules. For detailed description of these approaches, the reader can refer to Moon et al. (2002).

The second group is the dynamic lot sizing problems which deal with dynamic demand under a finite planning horizon. The dynamic lot sizing problem can be formulated for a single level with infinite production capacity and a single product over T periods of time as follows:

$$\text{Minimise} \sum_{t=1}^{T} (S_t Y_t + C_t X_t + h_t I_t) \tag{3}$$

$$\text{s.t. } X_t + I_{t-1} - I_t = d_t \quad (\forall t \in T) \tag{4}$$

$$X_t \leq M_t Y_t \quad (\forall t \in T) \tag{5}$$

$$Y_t \in \{0, 1\} \quad (\forall t \in T) \tag{6}$$

$$X_t, \quad I_t \geq 0 \quad (\forall t \in T) \tag{7}$$

This problem is known as the uncapacitated single-item single level lot sizing problem (Wagner and Whitin 1958), where h_t is the inventory holding cost of the product from one period to the next, d_t represents the product demand at the end of the period t, C_t is the variable unit production cost in period t, S_t is the set up cost in period t and Y_t is a binary variable that assumes value 1 if the product is produced in period t and 0 otherwise. M_t is the upper bound on the production. The decision variables X_t represent the production level in each period t and I_t represents the inventory variable of the product at the end of period t. The objective function, Eq. 3, includes total holding, setup and production costs. The inventory balance equation for each period is given in the first constraint, Eq. 4. The second constraint, Eq. 5, forces the setup variable to one if there is any production. Equations 6 and 7 are the non-negativity constraints. The reader can refer to Drexl and Kimms (1997) and Jans and Degraeve (2008) for various extensions of the single level lot sizing problems.

It should be noted that multi level lot sizing problems arise as part of MRP logic (Staggemeier and Clark 2001). In multi level lot sizing problems, there is a parent-component relationship among the items and the output of one level is input for another level (Karimi et al. 2003). Due to this dependency between items in the product structure, multi level lot sizing problems are more complicated than the single level lot sizing problems. Characteristics of more complicated models are discussed in section "Problem specifications".

Genetic algorithms

Directed random search techniques such as Genetic Algorithms (GAs) can be employed to find a near-optimal solution for many problems in complex multi-dimensional search spaces. GAs are modeled on natural evolution and inspired by the natural evolution process. It is based on the genetic process of biological organisms. Over many generations, natural populations evolve according to the principle of natural selection and "survival of the fittest". By mimicking this process and by suitable coding, GAs make the solution evolve and approach the best. Genetic operators manipulate individuals in a population over several generations to improve their fitness. Unlike simulated annealing and tabu search, GAs use a collection of solutions, from which, using selective breeding and recombination strategies, better and better solutions can be produced.

The steps that should be taken in application of the GAs can be stated as follows:

1. Choice of a representation scheme for a possible solution (coding or chromosome representation.)
2. Decision on how to create the initial population.
3. Definition of the fitness function.
4. Definition of the genetic operators to be used (reproduction, mutation, crossover, elitism)
5. Choice of the parameters of the GAs such as population size, probability of applying genetic operators.
6. Definition of the termination rule.

To start the search GAs are initialized with a population of individuals. The individuals are encoded as chromosomes in the search space. GAs use mainly two operators namely, crossover and mutation to direct the population to the global optimum. Crossover allows exchanging information between different solutions (chromosomes) and mutation increases the variety in the population. After the selection and evaluation of the initial population, chromosomes are selected on which the crossover and mutation operators are applied. Next the new population is formed. This process is continued until a termination criterion is met. The general flowchart of a simple GA can be seen in Fig. 2.

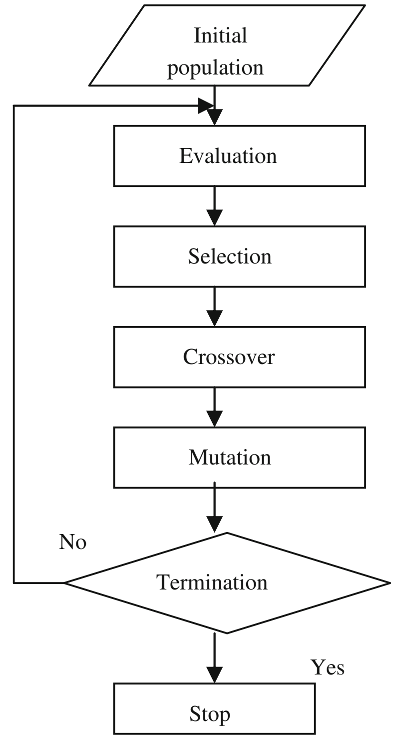

Fig. 2 Flowchart of a simple GA

Review of the literature

In this section, the present literature based on specifications of the lot sizing problem and the main features of the proposed GAs to deal with these problem specifications, are reviewed. Problem specifications contain the main features of the lot sizing problems studied such as number of levels, capacity constraints, setup time issue, planning horizon, demand type and inventory shortage. The GA specifications are related to the initialization of the population, chromosome representation and genetic operators.

Problem specifications

This study reviews the literature published in the last ten years based on the following problem specifications:

- *Number of levels*: Production systems can be single level or multi level. In single level systems, raw materials are changed into the final process after a single operation. Product demands come directly from the customer orders or market forecasts. This is the independent demand. However, in multi level production systems, there is a relationship among items which create dependent demands. The output of one level is input for another operation. Raw materials are converted into final products after several operations.
- *Capacity constraints*: When there are no limitations on the resources, the lot sizing problem is said to be uncapacitated. The capacitated lot sizing problems are more complicated than the uncapacitated lot sizing problems

since the capacity constraints directly affect the problem complexity.

- *Setup time issue*: In capacitated lot sizing problems, adding the setup time issue (Degraeve and Jans 2007) makes the problem more complex. A production changeover between different products incurs setup time and setup cost. The setup structure can be defined into two types, namely, simple and complex setup structures. If the setup time and cost in a period do not depend on the sequences, the decisions in previous periods or decisions for other products, the setup structure is said to be simple. Otherwise, it is defined as complex. Three types of complex structures can be defined. The first one involves setup carryover which allows the continuation of the production run from the previous period into the current period without any additional setup. The second one involves the family or major setup which is caused by the similarities in manufacturing process and design of group of items (this is related to decision for other products, but in the same time period). The last type of complex setup structure occurs when the setup decisions depend on the production sequence (Karimi et al. 2003).
- *Planning horizon*: The planning horizon can be defined as the time interval on which the master production schedule extends into the future (Karimi et al. 2003). The planning horizon can be infinite, finite or rolling. An infinite planning horizon is usually accompanied by stationary demand whereas a finite planning horizon is accompanied by dynamic demand. Under rolling horizon a production planning is made for a fixed number of periods for which the demand is known. The first production decision is implemented and the horizon is rolled forward to the period where the next production decision needs to be made (van den Heuvel and Wagelmans 2005).
- *Demand type*: If the value of the demand is known, it is termed deterministic which can be static or dynamic. If the value of the demand is not known exactly and occurs based on some probabilities, it is termed as probabilistic.
- *Inventory shortage*: Inventory shortage is an important specification affecting the problem modeling and complexity. If inventory shortage is allowed, it is possible to satisfy the demand of the current period by production in future periods. This is also called backlogging.

Table 1 chronologically lists the recent published literature based on the problem specifications.

Research on single level uncapacitated lot sizing problems

The main issue in single level uncapacitated lot sizing problems is to determine production lot sizes for the planning horizon so that the sum of setup, inventory holding and production cost is minimized.

The first application of GAs to a single item, single level lot sizing problem without backlogging appears in Hernandez and Süer (1999). The authors employ scaling in the fitness function to give higher reproduction probabilities to those chromosomes that represent better solutions. To evaluate how different aspects such as the population size, reproduction probability and scaling affect the results, they carry out various sets of experimental studies and state that a higher scale factor increases the chance of obtaining better solutions.

Hop and Tabucanon (2005) present a new adaptive GA for uncapacitated lot sizing problem in single level. The authors encode the timing of the replenishment as a chromosome. During the evaluation, the rates of GA operators such as mutation, selection and crossover for the next generation are automatically adjusted based on the rate of survivor off-springs. The proposed procedure gives faster and better results than using the static rates for the GAs operators.

Gaafar (2006) applies GAs to the deterministic time-varying lot sizing problem with batch ordering and backorders. The author proposes a new coding scheme for the batch ordering policy. A comparative study with the modified Silver-Meal heuristic indicates that the GAs outperform over the modified Silver-Meal heuristic.

Research on single level capacitated lot sizing problems

The presence of capacity constraints increases the complexity of lot sizing problems. The first study in this group belongs to Ozdamar and Birbil (1998) in which the authors propose a hybrid approach combining Tabu Search (TS), Simulated Annealing (SA) and Genetic Algorithms to solve capacitated lot sizing and loading problem in single level with setup and overtimes. The hybrid approach integrates a GA into a local search scheme which incorporates features from TS and SA. The approach starts with GAs and when the population tends to get stuck to the same area of the feasible/infeasible solution space, TS/SA procedure carries out the local search on randomly selected chromosomes in the current population. Computational results show that the proposed hybrid heuristic is efficient and has high potential in solving different complex problems in production planning and control.

Khouja et al. (1998) use GAs in solving economic lot size and scheduling problem. The authors propose different binary representations, crossover methods and initialization methods in order to identify the best settings and the results of comparative experiments yield good results.

In another study, Kohlmorgen et al. (1999) deal with the capacitated lot sizing problem using an island genetic algorithm. Potential solutions are genetically represented by a string of real values. The empirical study shows that the parallel genetic algorithm achieves the same solution quality with the heuristic proposed by Kirca and Kokten (1994). Hung et al. (1999) use evolutionary algorithms for production plan-

Table 1 The published literature based on the problem specification

Literature reviewed	Number of levels		Capacitated	Setup time issue	Planning horizon			Demand type			Backlogging
	Single level	Multi level			Infinite	Finite	Rolling	Deterministic demand		Probabilistic demand	
								Static demand	Dynamic demand		
Xie (1995)		*				*			*		
Khouja et al. (1998)	*		*	*	*			*			
Ozdamar and Birbil (1998)	*		*	*		*			*		
Hernandez and Süer (1999)	*					*			*		
Kimms (1999)		*	*			*			*		
Ozdamar and Barbarosoglu (1999)		*	*	*		*			*		*
Hung et al. (1999)	*		*	*		*			*		*
Kohlmorgen et al. (1999)	*		*			*			*		
Ozdamar and Bozyel (2000)	*		*	*		*			*		
Dellaert and Jeunet (2000)		*				*			*		
Dellaert et al. (2000)		*				*			*		
Hung and Chien (2000)		*	*	*		*			*		*
Prasad and Chetty (2001)		*				*	*	*	*		
Sarker and Newton (2002)	*		*		*			*			
Ozdamar et al. (2002)	*		*	*		*			*		
Moon et al. (2002)	*		*	*	*			*			
Xie and Dong (2002)		*	*	*		*			*		
Duda (2005)	*		*			*			*		*
Yao and Huang (2005)	*		*	*	*			*			
Hop and Tabucanon (2005)	*					*			*		
Chang et al. (2006)	*		*	*	*			*		Fuzzy	
Kämpf and Köchel (2006)	*		*	*		*				*	*
Megala and Jawahar (2006)	*		*			*			*		*
Moon et al. (2006)	*		*	*	*			*			
Gaafar (2006)	*					*			*		*
Li et al. (2007)	*		*			*			*		
Chatfield (2007)	*		*	*	*			*			
Jung et al. (2007)		*	*			*			*		

ning with setup decisions. Firstly, to generate new chromosomes traditional GAs are used with the conventional crossover and mutation operators. Secondly, the GA modified with the sibling operator and the conventional reproduction operators are used to produce new chromosomes. Lastly, a sibling evolution algorithm using the sibling operator is employed to reproduce. Experimental studies show that the sibling evolution algorithm performs the best among all the algorithms used.

Ozdamar and Bozyel (2000) propose three heuristic approaches including the hierarchical production planning approach, GAs and SA to solve the capacitated family lot sizing problem with setup time and overtime decisions for the single level case. The computational results show that GAs provide good performance only in small sized populations and the SA outperforms the others irregardless of the population size.

Sarker and Newton (2002) present a genetic algorithm approach to determine a purchasing policy for raw materials of a firm under a limited storage space and transportation fleet of known capacity. In order to deal with the capacity constraints, three different penalty functions namely static, dynamic and adaptive penalties, are proposed. Experimental results show that the performances of all three proposed penalty functions are similar.

Ozdamar et al. (2002) reconsider the capacitated lot sizing problem with overtime and setup times given in a previous study (Ozdamar and Bozyel 2000). Unlike the earlier study where transportation type of presentation and three different solution approaches (Hierarchical Production Planning, Genetic Algorithms, Simulated Annealing) are used, in this study the authors prefer using the direct coding and a hybrid approach consisting of GAs, Tabu Search and Simulated Annealing. The computational results show that the proposed hybrid approach is capable of finding good solutions in reasonable computational time.

Moon et al. (2002) develop a hybrid genetic algorithm for the economic lot size scheduling problem. The proposed hybrid algorithm integrates GAs with Dobson's heuristic, which has been regarded as the best in its performance for the economic lot size scheduling problem in literature. The hybrid genetic algorithm outperforms Dobson's heuristic.

Yao and Huang (2005) solve the Economic Lot Size Scheduling Problem with deteriorating items using the basic period approach under power of two heuristic. The study presents a hybrid genetic algorithm with a feasibility testing procedure and a binary search heuristic to efficiently solve the problem. The computational results show that the hybrid approach can be very helpful to derive the production scheduling and lot-sizing strategies for deteriorating items efficiently in the food industry.

Duda (2005) presents a genetic algorithm approach with repair functions for the classical discrete capacitated lot sizing problem originating from a real production environment, in single level where multi items are produced. The author employs three variants of genetic algorithm each using special crossover, mutation operators and repair functions.

Kämpf and Köchel (2006) combine GAs with simulation for the stochastic capacitated lot sizing problem. The problem involves defining a manufacturing policy consisting of a sequencing rule and a lot size rule, which maximizes the expected profit per time unit. In this study, the sequencing and lot sizing decisions are represented in a chromosome as an individual. Each individual representing a chromosome is then evaluated by using simulation under different sequencing policies such as First Come First Serve, Random and Cyclic. Experimental studies show that the proposed approach can be applied to arbitrary system structures and control policies.

Megala and Jawahar (2006) study the single item dynamic lot sizing problem using GAs and Hopfield neural network under capacity constraints and discount price structure. The authors carry out a comparative study and note that while GAs provide either optimal or near optimal solutions in most of the cases, Hopfield neural network produces satisfactory results for only small sized problems.

Chang et al. (2006) present a fuzzy extension of the economic lot-size scheduling problem for fuzzy demands. The problem is formulated via the power-of-two policy and basic period approach which allows different items to have different cycle lengths restricting each product's cycle time to be an integer multiple k of a time period called basic period (Moon et al. 2002). GAs are employed with triangular fuzzy numbers in order to find the cycle time and start time of the production.

Moon et al. (2006) apply Group Technology (GT) principles to the economic lot scheduling problem. GT is an approach to manufacturing and engineering management that seeks to achieve the efficiency of high speed and mass production by identifying similar parts and classifying them into groups based on their similarities. The GT approach often has many benefits in manufacturing systems such as shortened setup times, reduced work-in-process inventory, less material handling, and better production planning and control. The authors modify the heuristic proposed by Kuo and Inman (1990) by considering the modified cycle length and propose a hybrid genetic algorithm to solve the economic lot scheduling problem. The computational results show that the proposed hybrid heuristic outperforms the heuristic of Kuo and Inman (1990).

In another study, Li et al. (2007) analyze a version of the capacitated dynamic lot-sizing problem with substitutions and return products using GAs. The authors first identify the periods requiring setups by applying a genetic algorithm then they develop a dynamic programming approach to determine the number of new products to be manufactured or the number of return products to be remanufactured in each of these periods.

Recently, Chatfield (2007) utilizes a pure genetic algorithm for the economic lot scheduling problem. The author creates a binary encoding scheme for chromosome representation and applies it to a benchmark problem in the literature. The results are impressive such that some of them are the best ones up-to date.

Research on multi level uncapacitated lot sizing problems

Multi level lot sizing introduces dependent demands: the lot sizing and timing decisions for items at one level in the product structure depend on the decisions made for their parents (Bahl et al. 1987).

The first genetic algorithms in solving uncapacitated multi level lot sizing problems are proposed by Xie (1995). The setup patterns are coded as binary integers in the chromosome and other decision variables are computed from these patterns.

Following Xie (1995), Dellaert and Jeunet (2000) develop a hybrid genetic algorithm to solve uncapacitated multi level lot sizing problem. The authors employ the period order technique, the STIL algorithm and Wagner-Whitin based techniques to create the initial population and state that the proposed hybrid approach provides cost-effective solutions in a moderate execution time when compared with other techniques proposed in the literature.

Dellaert et al. (2000) develop a hybrid genetic algorithm to solve the multi level lot sizing problem with no capacity and product structure constraints. The authors consider the most general statement of the problem in which the inventory holding and setup costs vary from one period to the next. The simulation results show that the proposed approach considering time varying costs makes it an appealing tool to industrials.

Prasad and Chetty (2001) present a new heuristic called Bit_Mod combined with a genetic algorithm for multi level lot sizing under both fixed and rolling horizon and evaluate the influence of different parameters such as demand pattern, lot sizing rule, product structure and forecasting model under fixed and rolling horizon through simulation experiments.

Research on multi level capacitated lot sizing problems

Inclusion of capacity constraints and dependent demand between items make the problem much more complicated than the multi- level uncapacitated lot sizing problems.

Kimms (1999) presents a mixed integer programming formulation and a genetic algorithm approach for the multi level, multi-machine proportional lot sizing and scheduling problem. The author proposes a procedure in which a two-dimensional matrix is used to encode the solutions. The computational results show that the proposed approach outperforms the tabu search in terms of both run-time performance and finding the feasible solutions.

Ozdamar and Barbarosoglu (1999) propose two hybrid approaches for the multi level capacitated lot sizing and loading problem. The first one integrates GAs and simulated annealing whereas the second one consists of the Lagrangian relaxation and simulated annealing. Experimental results show that the hybrid approach consisting of Lagrangian relaxation and simulated annealing yields better results with respect to the solution quality and computation time.

Hung and Chien (2000) examine multiple demand classes in multi level capacitated lot sizing problem. Each demand class corresponds to a mixed integer programming model. The authors first generate feasible solutions by sequentially solving the mixed integer programming models each corresponding to a demand class, then they employ Tabu search, GAs and Simulated Annealing to solve the problem. Experimental results show that Tabu Search and Simulated Annealing yield better results than GAs.

Xie and Dong (2002) study the capacitated lot sizing problem with setup times and overtimes using GAs where the product structure is general acyclic network. The authors use only setup decision variables as chromosomes and other decision variables (inventory and lot sizes) are derived from these patterns. Since the problem involves capacity constraints, a heuristic approach based on lot shifting is embedded in the loop of GAs in order to eliminate the infeasible chromosomes.

Recently, Jung et al. (2007) use GAs in solving the integrated production planning problem in case of manufacturing partners (suppliers). The objective of this study is to provide efficient integrated production plans for manufacturing partners and a local firm under finite production capacity, while minimizing the total production cost. The authors formulate a mixed integer programming model by modifying the multi level lot sizing problem. With the unique chromosome structure, chromosome generation method and genetic operators, the proposed heuristic generates quite good solutions when compared with a commercial software optimization package.

Findings based on the problem specifications

In single level systems, the product demands are directly derived from customer orders or market forecasts. However, in multi level systems due to the relationship between items, the researchers need to deal with the dependent demand which makes the multi level lot sizing problem more complicated. Adding other constraints such as capacity, setup times, backlogging etc. makes this problem even more complex. In this study, it has been noted that most of the studies (i.e. 16 out of 28) focused on single level capacitated lot sizing problems.

When the capacity is tight, considering the issue of setup carryover helps in reducing the number of setups and related costs. This issue has been considered in only one study dealing with small bucket lot sizing problem involving proportional lot sizing and scheduling decisions (Kimms 1999). Dealing with the large bucket lot sizing problem using GAs under setup carryover and capacity constraints can be a promising research area.

It has been noted that the issue of backlogging has not received much attention (i.e. 7 out of 28 studies). Another important specification in lot sizing problems is the lead time. Except for Kimms (1999), Dellaert et al. (2000) and Hung and Chien (2000) nearly all studies reviewed, assume that the lead times are neglected. Moreover, in the majority of the studies reviewed, the planning horizon is assumed to be infinite or finite. Only one study deals with the multi level uncapacitated lot sizing problem employ rolling horizon (Prasad and Chetty 2001). Under rolling horizon, making revisions in the current plan according to the demand forecast, often cause disturbances in production, inventory cost and supply of raw materials and subassemblies. These disturbances are called nervousness. Thus, lot sizing techniques developed for single level under deterministic conditions may not perform well under rolling horizon. The Wagner-Whitin algorithm (1958) which gives an optimum solution with fixed horizon, does not necessarily give good solutions under rolling horizon so other lot sizing heuristics are preferred in multi level settings (Prasad and Chetty 2001). Hence, considering the fact that most real world problems are solved under rolling horizon, this issue has enough merits to take the attention of the researchers.

Genetic algorithm specifications

In developing GAs the important specifications are: representation of the solution (chromosome), the creation of the initial population, evaluation of the solution, the development of genetic operators such as mutation, crossover and the termination criterion. This section reviews the studies, which are listed chronologically in Table 2, based on these specifications.

Chromosome representation scheme

The first and the most important step in applying GAs to a particular problem is to convert solutions (individuals) of lot sizing problem into a string type structure called chromosome. This representation must uniquely map the chromosome values onto the decision variable domain. The following two classes to represent a solution have been noted:

Direct representation

MIP models of dynamic lot sizing problems contain integer variables both for the setups and possibly for the sequencing. Moreover, continuous variables for the production quantities are also present in these models. Direct representation uses the integer variables representing the setup decisions as well as sequencing decisions and continuous variables representing the production quantities in the solution of GAs when dealing with dynamic lot sizing problems. Two options for this representation can be defined as follows:

1. The first option of this group includes variables for both for the binary setup decisions and the continuous production quantities (Ozdamar and Birbil 1998; Ozdamar and Barbarosoglu 1999; Ozdamar and Bozyel 2000; Ozdamar et al. 2002).
2. The second option of this group includes only the integer variables and the production quantities can be found by solving the linear programming model, which is the original MIP problem with the integer variables fixed as in Hung et al. (1999).

In the case of multi level uncapacitated lot sizing problem (Xie 1995; Dellaert and Jeunet 2000; Dellaert et al. 2000) the set up decisions automatically determine the optimal production quantities through the zero-switch rule (Askin and Goldberg 2001).

When dealing with the economic lot scheduling problems, direct representation includes the variables for cycle times, integer multipliers and other variables related to the solution of the problem. The cycle times and integer multipliers are coded in the solution of GAs in Khouja et al. (1998) in which Basic Period Approach is used. In dealing with the ELSP using Extended Basic Period approach, Yao and Huang (2005) represent the solution as the multipliers of a basic period, Chang et al. (2006) use fundamental cycle time (basic period) in the solution encoding and Chatfield (2007) code the fundamental cycle time, integer multipliers and production beginning periods in a chromosome. In Moon et al. (2006), each gene in a chromosome represents the frequency of each product. The cycle times and other related variables are calculated based on these frequencies obtained by GAs.

Indirect Representation

The second class in the representation is indirect representation of the solution. The representation in Kimms (1999) is the only example of dynamic lot sizing problems. To represent a solution, a two dimensional matrix in which each entry represents a rule for selecting the setup state for each machine at the end of the period is employed.

Table 2 The published literature based on the GA specifications in a chronological order

Literature reviewed	Initialization of the population	Chromosome representation	Selection	Genetic operators	
				Crossover	Mutation
Xie (1995)	Randomly	Direct	Roulette wheel + elitism	One-point One point	Bit flip
Khouja et al. (1998)	Randomly	Direct	Tournament + elitism	Two point Uniform	Bit flip
Ozdamar and Birbil (1998)	Randomly	Direct	Proportional to the objective value	Two point	Randomly
Hernandez and Süer (1999)	Randomly	Direct	Roulette wheel + scaling	One-point	Bit flip
Kimms (1999)	Randomly	Indirect	Deterministically	Problem specific	Problem specific
Ozdamar and Barbarosoglu (1999)	Randomly	Direct	Proportional to the objective value	Two point	Randomly
Hung et al. (1999)	NA	Direct	Roulette wheel	Problem specific	Bit flip
Kohlmorgen et al. (1999)	NA	Direct	NA	Two point	Randomly
Ozdamar and Bozyel (2000)	Randomly	Direct	NA	Linear order (two point)	Randomly
Dellaert and Jeunet (2000)	From insertion of the solutions of different lot sizing rules	Direct	Clustering + elitism	One point	Bit flip
Dellaert et al. (2000)	Application of the mutation operator and a replenishment rule	Direct	Scaling + elitism	Problem specific	Bit flip
Hung and Chien (2000)	NA	Direct	Roulette wheel + scaling	Problem specific	Problem specific
Prasad and Chetty (2001)	Randomly	Direct	Ranking	NA	NA
Sarker and Newton (2002)	Randomly	Direct	Ranking	Two point	Bit flip
Ozdamar et al. (2002)	Randomly	Direct	Proportional to the objective value	Two point	Randomly
Moon et al. (2002)	From the solution of the nonlinear model of the ELSP	Indirect	Stochastic tournament + scaling + elitism	Partial mapped	Randomly
Xie and Dong (2002)	Randomly	Direct	Roulette wheel + elitism	One point	Bit flip
Duda (2005)	Only the predetermined part is randomly generated	Direct	Binary tournament + elitism	Problem specific	Irregular
Yao and Huang (2005)	Randomly	Direct	Roulette wheel + elitism + linear ranking	Two point Uniform	Bit flip
Hop and Tabucanon (2005)	NA	Direct	NA	One point	Bit flip
Chang et al. (2006)	Randomly	Direct	Roulette wheel	One point	Bit flip
Kämpf and Köchel (2006)	NA	Direct	Tournament + elitism	One point	One gene randomly
Megala and Jawahar (2006)	Randomly	Direct	Roulette wheel + scaling	Partial mapped	Randomly
Moon et al. (2006)	From heuristic solutions	Direct	Ranking	Uniform	Randomly
Gaafar (2006)	Randomly	Direct	Roulette wheel with elitism	Simple Uniform	Randomly
Li et al. (2007)	Randomly	Direct	Ranking + Elitism	One point	Bit flip

Table 2 continued

Literature reviewed	Initialization of the population	Chromosome representation	Selection	Genetic operators	
				Crossover	Mutation
Chatfield (2007)	Randomly	Direct	Roulette wheel + elitism + scaling	One point	Bit flip
Jung et al. (2007)	From the proposed procedure	Direct	Minimum generation gap selection	Problem specific	Problem specific

In the case of Economic Lot Size Scheduling Problems, Moon et al. (2002), who deal the problem with time varying lot size approach, use two kinds of chromosomes, the first of which represents the item number and the second one shows the absolute locations of the genes. These two chromosomes are useful in determining the frequencies of the items.

Initial population

The search in GA starts from an initial population. In the majority of the papers surveyed, the initial population is created randomly (i.e. 17 out of 28). Inclusion of heuristically generated solutions to the initial population is first reported in Dellaert and Jeunet (2000). As initial population, Moon et al. (2002) employ the nonlinear solution of the economic lot size scheduling problem. In Duda (2005), only the predetermined part (only about 3%) of the initial population is generated randomly. Moreover, Moon et al. (2006) use the heuristic solutions of Kuo and Inman (1990) in constructing the initial population.

Evaluation and selection

Following the generation of the initial population, the fitness of each individual in the population is calculated by employing an appropriate objective function. The objective function provides a measure of a chromosome's performance or fitness in the search space. The potential parents are selected to create the off-springs based on their relative fitness after the evaluation of each chromosome. It has been noted in this review study that with some exceptions (see Table 2); the roulette wheel selection is used in most of the studies. In roulette wheel selection, a sector of a roulette wheel whose size is proportional to the appropriate fitness measure is assigned to the individuals. Then a random number is generated and the parents are selected according to their random position on the wheel.

Besides the roulette wheel selection operator, a number of other different selection operators are also used in the studies reviewed. Kimms (1999) select the parents deterministically in which the individuals with the highest fitness functions are chosen to become parents. Ozdamar and Bozyel (2000) and Ozdamar et al. (2002) select the chromosomes according to their fitness values. The difference from the probability calculation in roulette wheel selection lies in the calculation of the reproduction probability which is a second degree polynomial of the inverse of the chromosome's objective function value given in Eq. 8.

$$\mathrm{Prob}_k = \frac{(1/obj^2)}{\sum_{k \in \text{population}} (1/obj^2)} \tag{8}$$

The parents are selected based on the stochastic tournament in Moon et al. (2002). In a recent study, Jung et al. (2007) propose a different selection operator based on the minimum generation gap selection method. The proposed operator randomly selects two different chromosomes from the old population and applies genetic operators to produce the off-springs. Two chromosomes with the highest fitness values are selected among two chromosomes from the off-springs and two parents and then enter the next generation. One of the strengths of this method is that it tries to preserve the good parents in the next generation, while other typical selection methods construct a set of candidates consisting of only child chromosomes so that the parents with good genes can not enter the next generation.

It has been noted that in order to control the selection process, scaling is used in a number of studies reviewed. In the proportional selection procedure, the selection probability of a chromosome is proportional to its fitness. However, this selection property exhibits some undesirable properties. For example, in early generations, there is a tendency for a few super chromosomes to dominate the selection process. In later generations, when the population has largely converged, the competition among chromosomes becomes less strong and a random search behavior emerges. Hence, scaling and ranking are proposed to mitigate these problems. Scaling maps the raw objective function to some positive real values in which the survival probability for each chromosome is determined according to these values (Gen and Cheng 1997). Hernandez and Süer (1999), Hung and Chien (2000), Dellaert et al. (2000), Moon et al. (2002), Yao and Huang (2005), and Megala and Jawahar (2006) use the scaling procedure in the selection process.

In a GA, survival is an important process that removes the individuals having low fitness. Survival is related to the population size. All the studies reviewed assume a constant population size. In steady-state GAs, which employ a constant population size a survival scheme is needed to reduce the population size to its predetermined value after generating the offsprings. In nearly half of the studies reviewed (i.e. 12 out of 28), elitism strategy is used as a survival scheme. Elitism strategy preserves the best individuals in one generation and translates them to the next generation without any change.

Another important issue in designing the GA is to decide on whether infeasible individuals should be allowed in the population or not. We noted a number of approaches dealing with the infeasible solutions. These approaches can be listed as follows:

1. To discard all infeasible solutions or attach an infinite cost to them (Kimms 1999; Dellaert et al. 2000; Dellaert and Jeunet 2000; Duda 2005; Li et al. 2007).
2. To use some penalty costs (Khouja et al. 1998; Ozdamar and Birbil 1998; Ozdamar and Barbarosoglu 1999; Xie and Dong 2002; Sarker and Newton 2002; Duda 2005; Moon et al. 2006; Chatfield 2007).
3. To repair the infeasible solutions by introducing some repair operators (Ozdamar and Birbil 1998; Ozdamar and Barbarosoglu 1999; Ozdamar and Bozyel 2000; Dellaert et al. 2000; Duda 2005; Hop and Tabucanon 2005; Jung et al. 2007).

Genetic operators

Genetic operators such as crossover and mutation are used in order to explore the search space. The crossover operator combines the chromosomes selected by the selection operator into a new chromosome. The mutation is used to maintain the diversity in the population.

During the literature survey, it has been noted that the authors develop problem-specific crossover operators to reflect the peculiarities of the lot sizing problems they study. Some of these crossover operators include *Period* (Hung et al. 1999; Dellaert et al. 2000; Jung et al. 2007), *Product* (Hung et al. 1999; Dellaert et al. 2000), *Compare* (Hung et al. 1999), *Random* (Hung et al. 1999; Hung and Chien 2000), and *Partial Mapped Crossover* (*PMX*) (Moon et al. 2002; Megala and Jawahar 2006).

Moon et al. (2002) use *PMX* Crossover which prevents two or more genes having the same value. Under PMX, two strings are aligned, and two crossing points are picked uniformly at random along the strings. These two points define a matching selection that is used to affect a cross through position-by-position exchange of operators. Duda (2005) presents a new type of crossover in which the fitness's of the parents are considered. In his representation, a chromosome shows the lots produced per shift in a day. The crossover operator randomly chooses a string of genes (representing the lots in a single shift) in two parents. If the fitness value of the first parent is better than that of the second parent, the string in the first parent is placed in the second parent. If the second parent has better fitness, the string in the second parent replaces the lots in the first parent.

Moreover, it has been noted that single bit flip mutation operator is used in most of the studies where the setup state is changed for a randomly chosen item and period (Dellaert et al. 2000; Dellaert and Jeunet 2000; Xie and Dong 2002). In a representation in which the lot sizes are also included, the mutation operator can change the lot size by a random amount (Ozdamar and Birbil 1998; Ozdamar and Barbarosoglu 1999; Ozdamar and Bozyel 2000). Specialized mutation operators are also developed to reflect the peculiarities of the lot sizing problems in a number of studies. To account for product interdependencies in multi level case, Dellaert et al. (2000) propose a mutation operator called *Cumulative,* in which the set-up periods for the predecessors are changed when mutation is performed on a given item. The mutation operator performs the same mutation on the immediate predecessors of the item under consideration and tries to ensure the feasibility. Gaafar (2006) uses different mutation operators during the genetic algorithm application such as *Random*, *Boundary*, *Ordering*, *Change ordering*, *Random swapping* and *Neighbor swapping. Random* mutation replaces a randomly chosen chromosome with a new one generated randomly. *Boundary* mutation randomly switches genes from a randomly selected position till the end of the chromosome. *Ordering* mutation maintains the number of orders in a randomly chosen chromosome. *Change ordering* mutation randomly increases or decreases the number of orders in a randomly chosen chromosome. *Random swapping* mutation swaps two randomly chosen genes in a randomly chosen chromosome and *Neighbor swapping* mutation swaps a randomly chosen gene with the neighbor gene (before or next to it) in a randomly chosen chromosome. Jung et al. (2007) propose different problem specific mutation operators matching with the chromosome representation they use. These operators along with the chromosome representation and the crossover operator proved to be efficient in terms of solution quality.

In addition to crossover and mutation operators, some different operators such as the migration and sibling operators are also proposed for lot sizing problems. The migration operator allows for a cross-over between chromosomes from different populations (Ozdamar and Birbil 1998; Ozdamar and Barbarosoglu 1999; Ozdamar et al. 2002) helping in generating good quality off-springs and variety in population. Hung et al. (1999) propose a sibling operator which performs like crossover and mutation operators. It stochastically chooses a better sibling from the neighborhood of a chromosome in the current generation and creates new chromosomes from the next generation.

Choice of the parameters of GAs

The performance of the GAs depends on the rates of the parameters such as the population size, crossover rate and mutation rate. However, the optimization of the parameter set has not attracted the attention of the researchers. Hung et al. (1999) determine the suitable parameters through conducting a series of pilot experiments. The authors use the default parameter file and vary only one control parameter at a time from the default control parameter set. Jung et al. (2007) determine the parameter set through an experimental setup including three levels for each parameter. The details of the experiments are not explained in the study. Chatfield (2007) tests different crossover and mutation rates and uses a performance metric which tracks a genetic algorithm's progress toward finding the best solution.

A new trend in parameter setting in GAs is adaptive genetic operators in which the rates of genetic operators change during the search. Ozdamar and Birbil (1998), Ozdamar and Barbarosoglu (1999), Ozdamar and Bozyel (2000), and Ozdamar et al. (2002) determine the crossover and mutation probability according to the convergence of the population's performance range. The crossover and mutation probabilities increase when the population's performance range tends to get stuck at a local optimum. Dellaert and Jeunet (2000) implement learning algorithm on the probabilities to the operators in GAs. Hung and Chien (2000) and Prasad and Chetty (2001) use the adaptive genetic algorithm proposed by Srinivas and Patnaik (1994), which dynamically adjusts the crossover and mutation probability. Starting with a high crossover rate and a low mutation rate, Yao and Huang (2005) keep decreasing the crossover rate and increasing the mutation rate until a specified level. The authors hope that in doing so the GAs can still explore the new regions in the search space and raise the diversity of the population, during the evolutionary process. Hop and Tabucanon (2005) propose using adaptive genetic operators which are based on the rate of survivor off-springs. Chang et al. (2006) use adaptive probabilities for the crossover and mutation. Namely, when the GA keeps finding the same chromosome with the highest fitness value for some number of generations, both crossover and mutation probabilities are increased gradually to further increase the chromosome diversity. Once another chromosome is found, these probabilities are set to their default values.

Termination

The search in GAs is terminated according to some rules. In this survey study, it has been noted that most of the researchers specified a maximum number of generations as a terminating condition. However, in some studies, the search is stopped if there is no improvement in the last predefined generations or the best individual does not improve more than the predetermined threshold in a predetermined number of generations.

Findings based on the GA specifications

Since the search in GAs starts from an initial population, the initial population has an important effect on the performance of the GAs. In this survey study, it has been noted that the initial population is generated randomly in most of the studies. Most of the researchers use the direct representation as a representation scheme and the indirect representation is employed only in Kimms (1999) and Moon et al. (2002).

In order to reflect the peculiarities of the lot sizing problems, a number of different crossover and mutation operators are used (see section "Genetic operators"). Despite the great variety in proposed GA operators, it has been noted that the researchers mainly employ one point crossover and single bit flip. Moreover, it has been noted that when the representation of the solution is unique to the problem type (Dellaert et al. 2000; Moon et al. 2002; Gaafar 2006; Jung et al. 2007) usually problem specific genetic operators are used. To help the convergence of the GAs, other operators such as migration (Ozdamar and Birbil 1998; Ozdamar and Barbarosoglu 1999; Ozdamar et al. 2002) and sibling operator (Hung et al. 1999) are also proposed.

Since the performance of the GAs heavily depends on the genetic operators used, the optimization of the GA parameters is another important issue in designing the GAs. However, any study dealing with this issue has not been noted during the literature review. In recent years, a new trend focusing on adaptive genetic operators has received attention in the literature. To obtain better and faster solutions, Ozdamar and Birbil (1998), Ozdamar and Barbarosoglu (1999), Ozdamar and Bozyel (2000), Ozdamar et al. (2002), Hung and Chien (2000), Prasad and Chetty (2001), Hop and Tabucanon (2005), Yao and Huang (2005), and Chang et al. (2006) propose adaptive genetic operators in which the rates of the genetic operators are automatically adjusted during the search.

From our survey study, it has been noted that when the representation of the solution is unique to the problem type, the problem specific genetic operators are used to reflect the peculiarities of the problems. This statement implies that for an effective GA design, taking into account the genetic operators together with the chromosome representation is a better idea.

As a general conclusion, regarding both problem and GA specifications the insight gained reviewing all the relevant literature listed in Tables 1 and 2 can be given as follows:

- Unlike single level lot sizing problems where the researchers employed standard genetic operators, for multi level lot sizing problems, some problem specific operators considering the interdependency among items in the product structure have been proposed (Dellaert and Jeunet 2000; Dellaert et al. 2000; Jung et al. 2007). This can be attributed to the complexity of multi level lot sizing problems. These specific genetic operators constrain the search to the set of feasible solutions rather than letting the algorithm explore infeasible solutions. This speeds the convergence of the algorithm to the optimum.

- An important issue in solving multi item stochastic capacitated lot sizing problem using GAs is to realistically deal with probabilistic demand. It has been noted that combining specially designed GAs with simulation has quite potential to find sufficiently good solutions (Kämpf and Köchel 2006).
- In most studies considering ELSPs the penalty functions are used to deal with infeasible solutions. A recent trend to enhance the feasibility testing and generate a feasible production schedule is to employ heuristics (Yao and Huang 2005). These heuristics check the feasibility of solutions generated and GAs search for the best solution among all feasible ones.
- The island GAs which are executed concurrently on several sub-populations with the added possibility of exchanging regularly good individuals between neighboring islands offer many advantages in obtaining satisfying results in a reasonable computational time. It has been noted these island GAs are employed only for single level capacitated lot sizing problem (Kohlmorgen et al. 1999). This can be attributed to the complex structure of the multi level lot sizing problem.
- In solving dynamic lot sizing problems which involve many constraints to be satisfied, repair operators are widely used to ensure the feasibility of the capacity, inventory and other constraints (Ozdamar and Birbil 1998; Kimms 1999; Ozdamar and Barbarosoglu 1999; Dellaert et al. 2000; Ozdamar et al. 2002; Duda 2005; Jung et al. 2007).
- In solving capacitated lot sizing and loading problem involving the issues of setup and overtime, the chromosome is structured to include both lot sizing and loading decisions (Ozdamar and Birbil 1998; Ozdamar and Barbarosoglu 1999).
- Unlike classical lot sizing problem in the literature, some researchers (Jung et al. 2007) take into account manufacturing partners and they propose case specific GAs approach, i.e. problem specific representation, genetic operators.

Conclusion and future research directions

GAs are increasingly used to solve many different production and operations management problems. One of the most well-known of these problems is lot sizing problems which deals with the determination of the lot sizes in order to minimize the total cost in the production system. To state the current research issues on solving lot sizing problems using GAs, this study summarizes the main specifications of the problems studied, and discusses the features of the proposed GAs to deal with these problem specifications.

From the GAs perspective, GAs are found to have better performances in terms of solution quality and speed than the results obtained by exact solution approaches and other heuristic approaches proposed for lot sizing problems in most of the published literature. The efficiency of the proposed GAs depends on various control parameters such as the population size, the probability of crossover and mutation. It has been noted in this survey study that most of the studies do not focus on the optimization of parameters to control the search effectively. However, it should be noted that it is important to have a set of robust GA parameters which work well for different data sets under different problem characteristics. Because, while one parameter set might give good results for one data set, it might fail for others. Moreover, the population initialization has not taken much attention since most of the studies preferred randomization in constructing the initial population.

As for the lot sizing perspective, more than the half of the studies reviewed, focus on the single level lot sizing problems. Since most of the real life production planning problems are multi level, a promising future research area can be solving the multi level capacitated lot sizing problems by exploiting the advantages of GAs. Another future research area can be solving the lot sizing problems under rolling horizon by GAs. Considering the fact that most real world problems are solved under rolling horizon, more attention should be given on this issue.

Based on the results of current studies it can be stated that GAs proved themselves as powerful optimization tools. To get more realistic results regarding the performance of the GAs, the focus might be on the real world lot sizing problems. Furthermore, to show the effectiveness of GAs in solving lot sizing problems, more complex lot sizing problems including features such as setup times, setup carryover, sequence dependent setup costs, parallel machines, backlogging, rolling horizon and lead times, can be taken into consideration. To the best of our knowledge, we have not noted any study dealing with single level or multi level multi-item lot sizing problem with setup carryover and backlogging using GAs. Although GAs have been applied to many different lot sizing problems, surprisingly we have not noted also any study on GAs for the regular Discrete Lot Sizing and Scheduling Problem. Therefore, these problems seem to be fruitful research area for prospective researchers.

Another perceived research gap in the currently published literature on lot sizing using GAs is that the stochastic nature of input data is ignored. Considering the fact that most real life lot sizing problems are stochastic capacitated lot sizing problems, bringing new solution approaches by integrating fuzzy logic, GAs and simulation optimization may be promising future research areas.

In recent years, the hybridization of GAs has received the attention of many researchers in lot sizing literature. The motivation of hybridizations of GAs and other solution approaches is to obtain better search algorithms that unite the advantages of the individual pure strategies (Raidl and Gunther 2006). GAs can be hybridized with other meta-heuristics or heuristic optimization techniques can be embedded into the main loop of GAs in order to obtain better solutions. An important set of solution approaches for lot sizing problems are MIP based heuristics. Hence, another interesting future pursuit may be the hybridization of GAs with these heuristics. In that case, to ensure the high performance of the GAs, the values of control parameters can be set experimentally over different instances that range in size. Also, GAs can be very important for optimal algorithms that use branch-and-bound techniques, as they can provide good solution early on which can be used to prune the tree.

Lot sizing decisions are related to determining when and how much of a product to produce in order to minimize the total cost while satisfying the demand requirements under the available capacity. Determining the right lot sizes affects the productivity and competitiveness of the system directly. With the growth of the published literature in recent years, we believe that the use of GAs for solving lot sizing problems will continue to attract the attention of the researchers in this area.

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