Gokce, M., A., Beygo, B., Emekci, T. / Journal of Yasar University, 2017, 12/45, 14-31

A Hyperheuristic Approach for Dynamic Multilevel Capacitated Lot Sizing with Linked Lot Sizes for APS implementations

İleri Planlama ve Çizelgeleme (APS) Uygulamaları için Kapasiteli Çok Seviyeli Dinamik Lot Belirleme Problemine Hiper-Sezgisel Yaklaşım

Mahmut Ali GOKCE, İzmir University of Economics, ali.gokce@ieu.edu.tr
Berkay BEYGO, berkay.beygo@gmail.com
Turgut EMEKCI, turgutekmekci@gmail.com

Abstract: *This study is concerned with solving real-life sized APS (Advanced Planning and Scheduling) problems practically. Specifically, the problem of Multilevel Capacitated Lot Sizing Problem with linked lot sizes (MLCLSP-L) is considered. The problem is a classical, practical and notoriously hard problem. We propose a new modeling technique for MLCLSP-L based on a GA-driven hyperheuristic, which enables modeling of some issues previously not modeled. Proposed model uses an indirect representation by allowing GA search through a space of low level heuristics' combinations. Each one of the low level heuristics is simple and determines the detailed production plan of a machine in a period. The solution is constructed through combination of these low level heuristics. New model is demonstrated by solving moderate size test problem along with software developed."*

Keywords: APS implementation, multilevel capacitated lot sizing problem with linked lot sizes; hyperheuristic; genetic algorithm; production planning; constructive heuristics

Öz: *Bu makale gerçek yaşam boyutlarındaki İleri Planlama ve Çizelgeleme (İPÇ)problemlerinin çözümü üzerinedir.Özellikle, kapasite kısıtı altında çok seviyeli lot boyutlandırma ve çizelgeleme problemi çalışılmıştır. Bu problem, pratik değeri yüksek ve akademik olarak da son derece zor bir problemdir. Problemin çözümü için Genetik Algoritmalara (GA) dayalı bir hiper-sezgisel yöntem önerilmektedir. Önerilen yöntem daha önce kullanılan yöntemlerleeile modellenmemiş bazı durumların modellenmesine de olanak tanır.Önerilen model, doğrudan olmayan bir temsil kullanarak, GA'nın düşük seviyeli sezgisellerin kombinasyonlarından oluşan uzayında gezinerek çözüm aramasına dayanır. Her düşük seviyeli sezgisel aslında, bir makineye, bir zaman periyodunda yükleme yapan basit algoritmadır.Esas çözüm, farklı düşük seviyeli sezgisellerin makinalarda, periyotlar boyunca kombinasyonu ile oluşturulur.Bu yeni model gerçek yaşam boyutunda bir problemin çözümünde, geliştirilen yazılım ile beraber kullanılmıştır.*

Anahtar Kelimeler: *İleri Planlama ve Çizelgeleme (İPÇ=APS) uygulaması, Çok seviyeli lot boyutlama ve çizelgeleme, hiper sezgisel, genetic algoritma, üretim planlama, yapısal sezgisel*

1. Introduction

First, we introduce Advanced Planning and Scheduling Systems and their importance. Then, multilevel lot sizing and scheduling problem is described in detail and its relationship to APS systems is established.

1.1. Advanced Planning and Scheduling Systems

The computerized production planning and control systems were developed gradually over the last thirty years, starting with Material Requirements Planning (MRP), and followed by Manufacturing Resources Planning (MRP-II), Enterprise Resource Planning (ERP) and finally Advanced Planning and Scheduling (APS) (Steger Jensen et al. 2011).

Since early 1990s, APS started to appear on the integrated systems' market. APS is formally defined as "Techniques that deal with analysis and planning or logistics and manufacturing during short, intermediate and long-term time periods. APS system describes any computer program that uses advanced mathematical algorithms and/or logic to perform optimization or simulation on finite capacity scheduling, sourcing, capital planning, resource planning, forecasting, demand management, and others. These techniques simultaneously consider a range of constraints and business rules to provide real-time planning and scheduling, decision support, available-to-promise, and capable-to-promise capabilities. APS often generates and evaluates multiple scenarios." (Blackstone and Cocks in *APICS dictionary*, 2005)

APS systems are generally used in conjunction with ERP systems, either as add-ons or direct integral components of ERP systems, creating the support mechanism for planning and decision-making (Kreipl and Dickersbach, 2008).

Figure 1 shows the conceptual framework of Advanced Planning and the Supply Chain Planning (SCP)matrix (Fleischmann et al. 2008), the multi level lot sizing and scheduling problem discussed in this paper, cover the planning tasks of lot-sizing and machine scheduling. Additionally, they are linked to short term sales planning as a capable-to-promise logic (Kilger and Schneewiss, 2005).

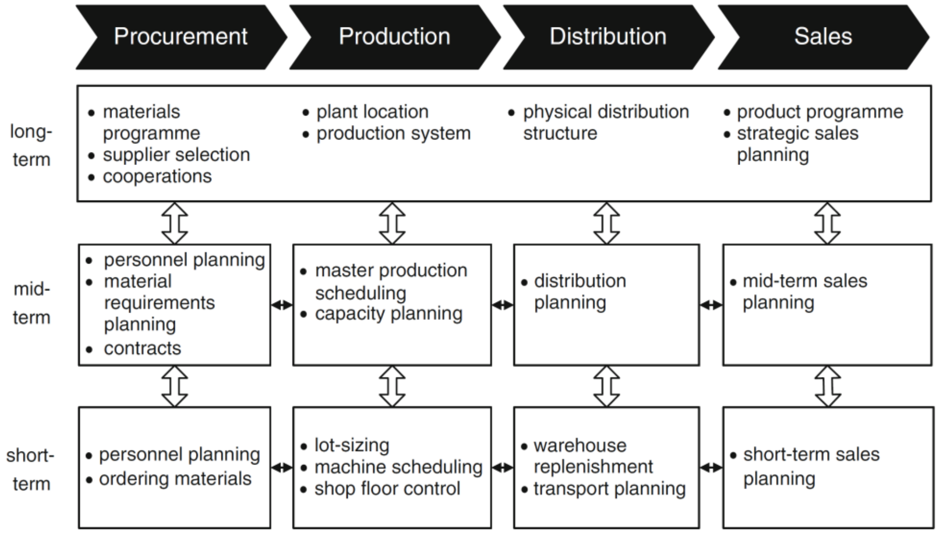


Figure 1. Supply Chain Planning (SCP) Matrix (Fleischmann *et al.*, 2008, p.87)

The great promise APS systems has been that, when implemented correctly, an APS system allows companies, use already available capacity much more efficiently, and therefore contributing more to the bottomline. This has led to a vast amount of literature on APS development.

Stadler (2005) discusses issues and challenges of today's APS will in three main categories. The first of those categories are module improvement where most importantly Production planning and detailed scheduling of APS is discussed. Lot sizing and scheduling is the main technical problem to be solved for this purpose and therefore stands as the most important technical barrier to a more successful APS implementation

The exceeding majority of the publications use MILP (Mixed Integer Linear Programming) for modeling and solving these problems. Studies suggest that there are difficulties with implementing and using APS systems (Zoryk-Schalla et al., 2004, Lin et al., 2007) and many companies report on "failed" implementations and that expected benefits have not been achieved (De Kok and Graves, 2003; Günter, 2005)

One of the main reasons of these failures is the promised benefits of being able to perform dynamic lot sizing and machine scheduling together. Unfortunately, the natural limitations of MILP modeling kick in for realistic size problems and users are either left with unsolvable problems and/or overly simplified versions of their problems leading to frustrations. Therefore there is a great need for models capable to handle real life size APS (lot sizing and scheduling) problems practically.

1.2. The Dynamic Multi-LevelLot Sizing and SchedulingProblem

In many production environments, machines (or other resources) have to go through some sort of setup before production can begin. So ideally, one would try to produce as large batches of any product as possible, once the machine is setup. This causes holding cost and the necessity of striking a balance between setup and holding costs, giving birth to lot sizing problems (Figure 2).

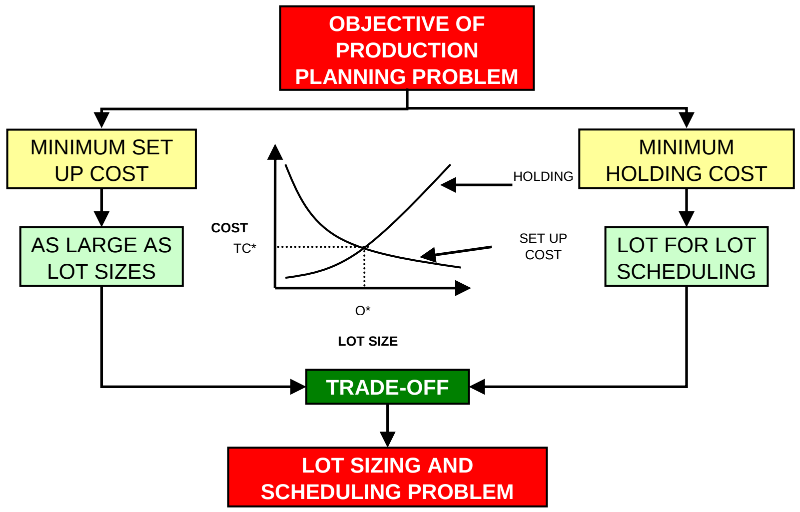


Figure 2. Objective of production planning problem

The (standard) CLSP (Capacitated Lot-Sizing Problem) includes multiple products to be produced given their demand over a planning horizon on a single machine. Production uses up machine capacity, and a setup has to be done when changing from production of one part to the other. The problem is to find an optimal production plan to satisfy demand (how many of what lot sizes of each product to produce in each period) to minimize total cost (inventory+ setup etc.). Since the capacity is limited, it might be necessary to produce some quantity of some items ahead of time and keep in inventory to incur the minimum total cost.

Classically, lot sizing and scheduling problems are categorized either as small bucket or big bucket problems. Small and big bucket problems vary based on specifications of production and the length of the planning period. Small time bucket problems allow at most one setup per machine in a period. This implies that at most two different items can be scheduled in a small time bucket problem. Big time bucket problems do not restrict the number of setups on a machine in a period. Figure 3 shows a taxonomy of lot sizing and scheduling problems according to time buckets and scheduling decisions.

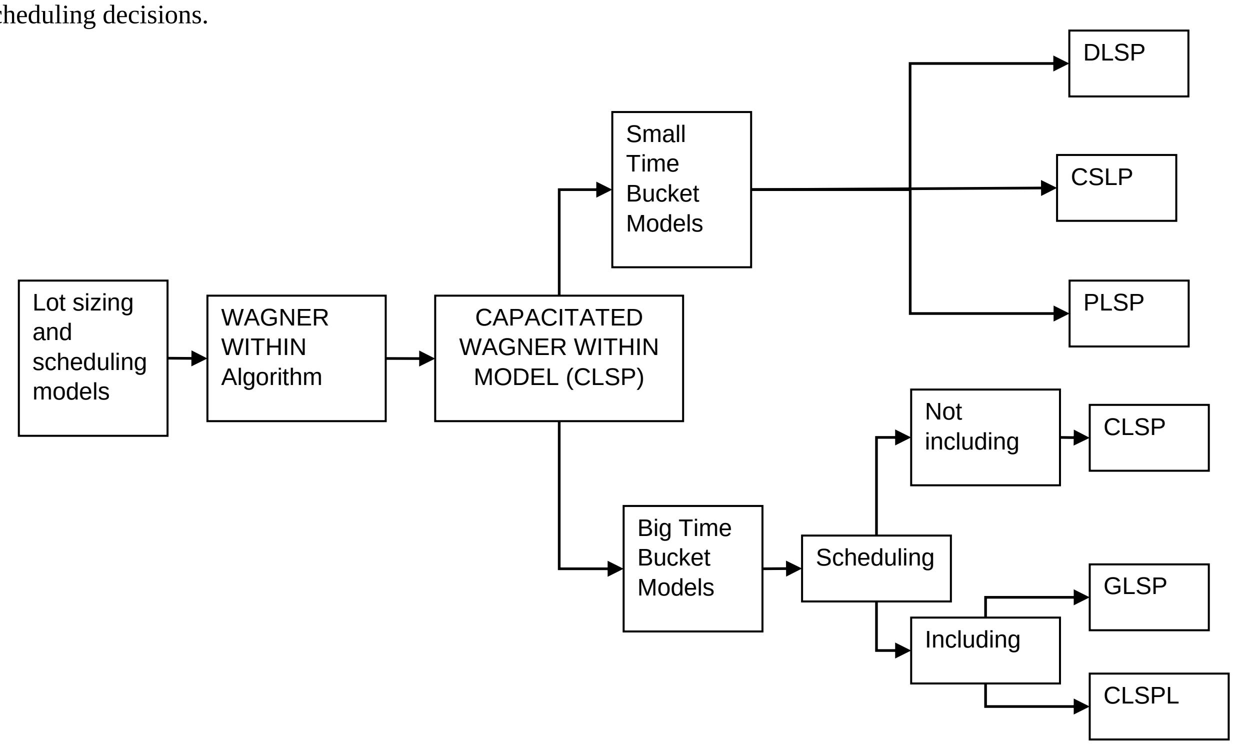


Figure 3. Taxonomy of lot sizing and scheduling problems according to time buckets and scheduling decisions

Small time bucket problems are further categorized into three classes. These are discrete lot sizing and scheduling problem (DLSP) (Fleischmann, 1990); continuous setup lot sizing problem (CSLP) (Karmarkar and Scharge, 1985); and proportional lot sizing and scheduling problem (PLSP) (Drexl and Haase, 1995).

There is an important shortcoming of the small time bucket problems. Since at most one setup per period is allowed, the number of periods for a realistic problem instance becomes prohibitively large. For this reason, small time bucket problems are most appropriate for short term planning.

The capacitated lot sizing problem is the basis of big time bucket lot sizing problems. Different from small time bucket problems, it is possible to make more than one setup on a machine in a period in big bucket models. This enables modeling longer term planning problems. Unfortunately, the problems get also very hard to solve. Multilevel capacitated lot sizing is the most realistic but probably hardest of big time bucket problems. In multilevel capacitated lot sizing problem (MLCLSP), planning is not only done for a final product, but also for the components and subassemblies that make up an end product, given its bill of material (BOM, Figure 4). Production at one level leads to demand for components at lower levels (dependent demand). The end product's demand is usually supplied by a master production schedule (MPS), which in turn is shaped by market demand. For the MLCLSP solution to be converted to a feasible production schedule, a minimum planned lead-time of one period must be introduced for each component product.

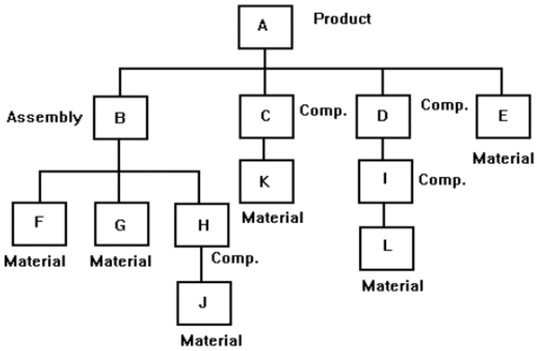


Figure 4. Bill of Material (Gozinto structure) for MLCLSP

An overview of lot sizing and scheduling problems (focusing more on small time buckets) can be found in Drexl and Kimms (1997). Meyr (1999) reviews small bucket problems with sequencing decisions.

Denizel and Süral (2006) provide various MIP formulations. Karimi *et al.* (2003) provides a review of capacitated lot sizing models. A more recent review by Quadt and Kuhn (2008) provide standard MIP formulations of CLSP and its extensions. Specifically, they provide extensions of standard MIP CLSP models based on back-orders, setup carry-over, sequencing, and parallel machines. These various extensions of CLSP result in more practical, but harder problems. Most important extensions are inclusion of parallel machines (at least one), setup carryover, backlogging and sequencing.

The existence of parallel machines implies that there is no unambiguous part-machine assignment. Each part, then, can be produced on more than one machine, possibly with different unit production and setup times.

The inclusion of setup carry-over (also referred to as linked lot sizes) mean that the machine can carry its setup state from the end of period to the start of the next period. This means last part produced on a machine in a period, can continue its production without an additional setup in the immediately following period on the same machine. Therefore a CLSP with linked lot sizes must determine the last (and first) parts on every machine for each period.

As a final extension, scheduling decisions for all parts can be included into the problem. In this case, a total sequence of parts on a machine in a period must be determined. This extension is useful in modeling when sequence-dependent setups exist. Examples for this case can be paint shops, fabric dying and chemical industry. If the setups are not sequence-dependent, this extension will add unnecessary complexity to the problem.

In many real-life problems where the utilizations are high, it is especially important to include backlogging and linked lot sizes.

The problem basically relates to the production planning process. In most real-world situations, decision-makers face multilevel gozinto structures (BOM) and therefore need solution procedures capable of dealing with these.

In this paper, we present a new modeling approach to dynamic multilevel capacitated lot sizing problem with linked lot sizes (MLCLSP-L) for general product structures based on a GA-driven hyperheuristics. MLCLSP-L is a practically important and theoretically challenging problem.

MLCLSP-L is one of the hardest and most practical of the lot sizing and scheduling problems to solve. There are mainly Mixed Integer Programming (MIP) approaches and relaxations of MIP formulations as well as direct applications of meta-heuristics to this problem.

Bitran and Yanasse (1982) and Florian et al. (1980) have shown that even single item capacitated lot sizing problem (CLSP) is NP-hard. Even the feasibility problem ("Does a solution exist?") is already NP-complete for the single-level problem if there are setup times. Chen and Thizy (1990) have proved that multi-item capacitated lot sizing problem (MCLSP) with setup times is *strongly NP-Hard*. Since MCLSP is a special case of the problem considered in this study (where every item has only single level), MLCLSPL is at least strongly NP-hard. For this reason, exact methods and commercial software packages for obtaining optimal solutions are not very helpful when the problem instances get large.

Based on these results, it is unlikely that we can develop any effective optimal algorithm for this problem. Therefore, research on developing effective heuristics has been a profitable research area for a long time.

2. Literature Review

There is a vast amount of literature on lot sizing and scheduling problems. For practical purposes, this section gives a limited review of some of the models used to solve MLCLSP-L. Also some background in hyperheuristics, especially relating to use of metaheuristics (GA)s and scheduling–planning problems is provided.

Literature on solving MLCLSP-L is composed of papers using one of the following two groups of methods.

First group includes papers based on mathematical programming and LP or Lagragean relaxations of MIP models.

Tempelmeier and Derstroff (1996) provide one of the earlier examples of a heuristic based on lagrangean relaxations of MIP models. One of the last examples of MIP based approaches comes from Tempelmeier and Buschkühl (2009). They provide a lagrangean heuristic for solving MLCLSP-L. The authors demonstrate his model with two different data sets. First set is a generated data set composed if 3-6 resources for 10, 20 or 40 parts over a planning horizon of 4,8 or 16 periods. They also demonstrate their method with an industrial data set of 77 items with one level deep BOM.

Tempelmeier (2003) and Suerie and Stadtler (2003) uses plant location analogy to get tighter bounds for their MIP formulations.

Stadtler (1996), Meyr (1999), Staggemeier and Clark (2001), Suerie (2005), Pochet and Wolsey (2006) provide excellent reviews of such models.

The second group includes papers based on meta-heuristics. When utilizing a meta-heuristic for modeling MLCLSP-L, the important decisions are which meta-heuristic to use, solution representation, evaluation, neighbourhood and/or operators to be used. Simulated annealing (SA), tabu search (TS) and genetic algorithms have been applied. Jans and Degraeve (2007) provides an excellent review on meta-heuristic approaches to dynamic lot sizing problems.

A great majority of the literature on MLCLSP-L mentioned above tries to minimize setup cost as well. For this a setup cost is assumed to be given. But in reality setup consideration is mostly based on time not cost. Also this assumes, based on setup unit time cost, a presumed weight compared to production and inventory costs. We assume a setup time, rather than a setup cost. In this setting setup consumes from available machine capacity.

The main goal of hyper-heuristics is to get rid of the need of having the heuristic have information on the problem and to enhance the generality at which meta-heuristics and optimization systems can operate, all the while providing *good quality* solutions *quickly* (Burket *et al.*, 2003). Hyperheuristics are defined simply as "*heuristics which choose heuristics* " (Burket *et al.,* 2003). Although history of the idea of using heuristics to choose heuristics goes way back, hyperheuristic name has first been used by Cowling *et al.* (2001).

Especially during the last five years, more and more research papers on hyperheuristics are published. Hyperheuristic based methods have been published for solving different scheduling problems (nurse, trainer, timetabling etc.), But except Bai *et al.* (2008) on fresh produce inventory control and shelf allocation and Tay and Ho (2008) on job shop scheduling, there are not many applications of hyperheuristic based methods for production related problems. Ochoa (2009) presents an extensive list of book chapters, conference proceedings and journal papers on hyperheuristics and related approaches. Ozcan *et al.* (2008) provides an in-depth anaylsis of hyperheuristics. An excellent review of recent developments on hyperheuristics is given by Chaklevitch and Cowling (2008).

Exact methods for MLCLSP-L suffer from the fact that solving any realistic size problem takes too long. Other heuristic based methods so far (direct applications of metaheuristics etc.) were of the kind that mostly had parameter dependent performance and required considerable parameter optimization. Different problems are faced everyday, with different characteristics. So a solution to MLCLSP-L must be robust enough to handle these differences and hopefully produce *"acceptable quality"* results.

For any solution for MLCLSP-L method to make a practical impact in industry, it should be able to solve instances with 100 or more parts which are stil not achieved. (Staedler, 2003)

To the best of our knowledge, there is no other hyperheuristic based models published for solving MLCLSP-L yet.

The proposed new modeling is more independent of problem structure than previous models. It also allows for modeling issues, previously not possible (like time heterogeneous data)

MLCLSP-L is a new challenging area for hyperheuristics. The authors believe there is great potential for use of hyperheuristics in general production related problems, especially for the industrial sizes.

In the remainder of this paper, the proposed hyperheuristic approach to MLCLSP is presented in the next section. Section 3 demonstrates the proposed model by solving a test problem and presenting results from a large experimental design. Lastly, section 4 summarizes conclusions and gives directions for future work.

3. Proposed Model

We propose a genetic algorithm (GA) driven constructive hyperheuristic method to solve MLCLSP-L. Our approach dictates a genetic algorithm managing a number of low level heuristics. Each low level heuristic myopically tries to find the production numbers and partial sequence *of jobs on a machine in a period* (the first and last parts to be produced) based on simple objectives. Therefore each low level heuristic is responsible for only determining production plan of *a* machine in *a* period. Each low level heuristic constructs part of the solution, but collection of these heuristics for all machines give a complete solution.

Due their simplicity, as easy to calculate as they are, these low level heuristics with simple objectives, do not consider the whole picture. Therefore, one would expect that if one such heuristic is applied to solve the whole problem, for all machines and for all the periods, one would attain a possibly poor, suboptimal solution. Individual low level heuristics may be especially effective at certain stages of constructing the solution while performing poorly at some latter stage. For this reason, we hope several low level heuristics combined properly may produce better solutions.

Our approach is based on the fact that an optimal solution for MLCLSP-L is a solution which balances shortage vs. inventory costs without violating capacity constraints. Low level heuristics are single objective, without considering remifications on other measures relating to the overall performance of the plan, but proper permutation of such low level heuristics might give robust *good* solutions in *reasonable* time. The hyperheuristic is responsible for searching through these combinations of low level heuristics, without any information relating to problem domain (Figure 5).

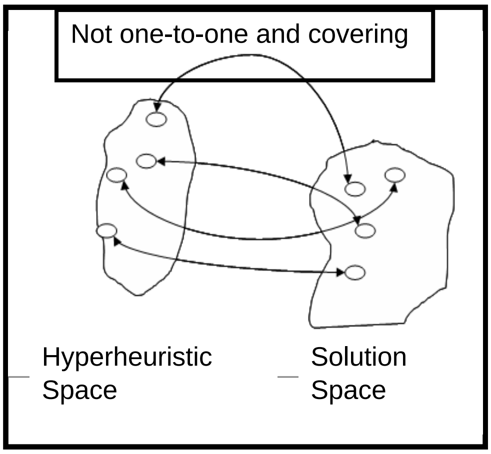


Figure 5. Heuristic vs. Solution Space

In this setting, the genetic algorithm utilizes an indirect representation of the problem. For GA, a solution is therefore just a combination of low level heuristics. Any solution in the hyper-heuristic space then has to be translated into a real solution by a deterministic simulation of low level heuristics.

3.1. Genetic Algorithm Driven Hyperheuristic Details

A genetic algorithm (GA) is a search technique used in computing to find exact or approximate solutions to optimization and search problems. It is implemented as a computer simulation of population of chromosomes (individuals) representing solutions to the problem. This population evolves through generations following a cycle of selection, crossover, mutation, toward better solutions and converging to a good solution. Genetic algorithms are a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover. Any genetic algorithm can be determined exactly by determining the following:

- Representation: GA driven hyperheuristics uses a matrix notation. A *M x T* matrix represents a solution, where *M* is the number of machines available and *T* is the planning horizon. Cell (*m*,*t*) contains the low level heuristic to be used to find production plan of machine *m* in period *t* (Figure 6).

	=1		=2			=*m*
: 1	H1	H2	.	.		H9
Iachine 2	H5	.	.	.		H5
		.	.	.		.
		.	.	.		.
Iachine *M*	H4	.	.	.		H3

Figure 6. Chromosome Representation

- Initialization: Each individual in the population is initialized by randomly assigning heuristics from the low level heuristics set (i.e. each cell in the encoded solution is assigned a low level heuristic from the list of low level heuristics with equal probability using a random number generator). As an option, the user has the possibility to generate 10 times many individuals compared to the population size and keep the best population size to get a better starting solution.
- Selection: Selection mechanism determines how individuals are picked from the population for crossover and for forming the next generation's population after crossover and mutation.

GA driven HH uses either top-to-bottom or tournament selection.

a) Top to Bottom Selection:

All the population is sorted according to their fitness values. Starting from top to bottom, the odd numbers are paired with the even numbers until the half of the population. The pairs are then mated. Then the other half of the population is filled with the children. Individual 7 and individual 8 are the children of individual 1 and individual 2.

Chromosome1
Chromosome2
Chromosome3
Chromosome4
Chromosome5
Chromosome6
Chromosome7
Chromosome8
Chromosome9
Chromosome10
Chromosome11
Chromosome12

Figure 7. Top-to-bottom selection

b) Tournament Selection:

Two individuals are randomly picked from the population. Then, these two individuals' total cost values are compared. The worse individual is disposed. This process is repeated population_size/2 times. Remaining individuals are mated to form the new population.

- Crossover: There are three crossover mechanisms used. These are row-based (RB), column-based (CB) and 2-point crossover operators.

Row-based crossover simply picks two solutions, determines a random point horizontally (along the horizontal axis, i.e. a randomly selected integer from 1 to *M*) and combines the solutions to make two new individuals.

Column-based crossover acts almost the same manner as row-based except the cut is done vertically (along the vertical axis, i.e. a randomly selected integer from 1 to *T*).

2 point crossover picks two points on the horizontal and recombines children from the two parents.

- Mutation: Three different mutation operators are used. Row based mutation picks any of the population members with user specified mutation rate, β, picks a row of this individual randomly. Each cell in this row is then changed randomly to another low level heuristic based on a uniform random distribution. Column-based mutation works in the same way as the row-based, but does it for a column.

Square-based mutation selects any individual with probability β and changes the elements in the cells covered by a randomly formed square within the encoded solution. For this purpose, a *start* column or row number is selected randomly from UNIF (1, min(*M*, *T*) and a length for the square's side based on UNIF(*start*, min (*M*,*T*))

- Evaluation: (fitness function): Evaluation of an individual requires a deterministic simulation. Since low level heuristics determine detailed production plan of a machine in a period ,one has to execute the corresponding heuristic for that machine in that period. For a heuristic for machine *m* in period *t*, low level heuristic assigned to cell (*m*,*t*) needs to know set of parts that can be produced on machine *m*, along with relevant production and setup times, inventory and backorder cost, BOM and demand information.

Starting for machine 1 to machine *M* for periods 1 through *T*, each heuristic needs demand, current backlog, part-machine assignments, setup and unit production times as input and executes to determine the production plan and sequence for that machine in that period. This deterministic simulation is done for each period in increasing machine index number. Due to the constructive nature of the GA-based hyperheuristic, only after, each corresponding heuristic is run for period *t*,

In evaluation we use backlogging allowed for level 0 items but not for lower level items. There are backlogging costs associated with lower level items, but those are used to steer GA to pick low level heuristics in a such a way to produce as many items as possible on time; not early, not late.

During the evaluation of solutions, elitism is adapted ()

- Stopping condition (Termination): There are two types of termination conditions used. Genetic algorithm either quits after a user-specified number of generations or after a certain user-specified number of non-improving generations.

A total of ten (10) low level heuristics are used for the propose solution. The details of these low level heuristics are given in the next section.

3.2. Low level Heuristics

The following notation is used to explain the low level heuristics.

t = Current period
m = Current machine
$P_{t,m}$ = Set of parts that can be produced on on machine m in period t
$D_{i,t}$ = (Remaining) Demand of part i in period t
$B_{i,t}$ = (Remainig) Backlog amount of part i at the beginning of period t.
CB_{it} = Cost matrix according to backlog for item i in period t
$CD_{i,t}$ = Cost matrix according to (potential backlogging) demand for item i in period t
$C_{m\ t}$ = (Remaining) capacity of machine m in period t
$s_{i,m}$ = Setup of item i on machine m
$p_{i,m}$ = Unit production of item i on machine m

Heuristic 1 (H1) – Minimize Backlogging Cost

H1 tries to minimize backlogging costs. It first tries to produce the backlogged items in $P_{t,m}$ in decreasing baclogging cost ($CB_{i,t}$) amount. If the machine still has enough capacity, the heuristic tries to produce the demands in period t in decreasing potential backlogging cost ($CD_{i,t}$, demand not satisifed for t becomes backlog). If the machine still has enough capacity, it tries to produce items with demand in $t+1$ in decreasing $CD_{i,t+1}$ amount and stops.

$$CB_{i,t} = \text{Min}\begin{Bmatrix} Max\_prod\_qty\_due\_to\_prerequistes, \\ Max\_prod\_qty\_due\_to\_capacity, \\ Back\log ging\_qty \end{Bmatrix} * Unit\_back\log ging\_\cos t$$

$$CD_{i,t} = \text{Min}\begin{Bmatrix} Max\_prod\_qty\_due\_to\_prerequistes, \\ Max\_prod\_qty\_due\_to\_capacity, \\ Demand\_qty \end{Bmatrix} * Unit\_back\log ging\_\cos t$$

Heuristic 2 (H2) – Minimizing Set-up Time

H2 tries to minimize the set-up cost. If there is a setup on the machine, the machine first tries to produce the backlog and all the remaining demand until the end of the planning horizon of this item. If there is still capacity left, H2 finds the item with highest number of backlogs, performs setup for this part and stops. If there are no items with backlog, finds highest demand in $P_{t,m}$, performs setup and stops. If no item with demand in $P_{t,m}$ in period t, check t+1 and stop.

Heuristic 3 (H3) – BOM_Weight

H3 first calculates BOM weight of parts in $P_{t,m}$ with positive backlog. Schedule backlogs in decreasing BOM weight. If there is stil capacity left after all items with backlogs scheduled, repeat with parts that have demand in t. If still there is capacity left, repeat for t+1. Stop.

Weight of a part is the number of that part that is required for one level 0 item.

BOM_Weight of Part i: Weight of i + (Weight of all parts i i directly goes into)

If a part is in more than one BOM, final BOM_Weight is a average of BOM_Weights from different BOMs weighted on demand of the corresponding endi tem.

Heuristic 4 (H4) - BOM_Depth

H5 first schedules backlogged items in lower levels of the BOM. Any ties based on the BOM level is broken by scheduling smaller part numbers first. If capacity left, it schedules items with demand in period t in the same manner. If still there is capacity left, H5 goes through list of items in $P_{t,m}$ with demand in period $t+1$ and stops.

Heuristic 5 (H5) - Min. Potential Backlog

H5 is a modification of H1. Instead of first going through the list of backlogged items and then items with demand in $P_{t,m}$, it schedules items in decreasing potential backloggin cost ((backlog+this period's demand)*unit backlogging cost). If all backlog and period t demand is scheduled and there is capacity left, tries to schedule items with demand in $t+1$ in decreasing $CD_{i,t+1}$.

Heuristic 6 (H6) - Quickest BOM_Depth

H6 is a modification of H4. Different from H4, H6 breaks ties between items that have same BOM depth level in favor of item with shorter processing time on machine m.

Heuristic 7 (H7) - Minimum Unit Production Time First

H7 first schedules on machine *m*, parts that can be produced fastest on machine *m*. First backlogs of these items are scheduled. If capacity remains, demand of these items are scheduled.

Heuristic 8 (H8) – Dynamic BOM_Weight

H8 is a modification of H3. Each step BOM weight of parts are updated as they are produced in the following way:

BOM Weight of part *i* = BOM Weight of part *i* * [1-(total number of part *i* produced so far/Planning horizon total demand of part *i*)]

Heuristic9 (H9) – Min. Inventory – Modified Holding Cost

H9 is a modification of H5. H9 takes the parts in $P_{t,m}$ and schedules them in decreasing cost value. The cost for part *i* in $P_{t,m}$ is calculated as:

Max. Number that can be produced of *i* * modifiedInvCost of *i*

modifiedInvCost of *i* = inventory cost of *i* - (inventory costs of all items that directly go into this item)

Heuristic 10 (H10) Resolve Capacity

H10 aims remedy possible capacity problems by pulling demand from next period to this period. H10 checks if possible capacity problems exist in period *t+1*. (This is done by finding out total setup plus production time of all items that have deman in *t+1* if they were to be produced in the fastest possible machine based on machine-part matrix. If capacity of any machine in *t+1* goes below zero, capacity problems exist)

For the machines capacity problems exist, H10 tries to move enough demand to machines with excess capacity this semester in decreasing BOM level, until capacity problem is remedied. This does not mean H10 is a repair function. But under certain conditions (existence of a possible capacity problem following period), H10 favors earlier production. If capacity problem does not exist in *t+1*, check *t+2*, and try to remedy capacity problem, then stop.

Since setup carry-over is allowed, the proposed model must be able to give the starting and ending jobs for each machine in each period. Each low level heuristic first determines the lot sizes for the machine and period it is executed for. Then every low level heuristic checks if there is already a setup on the machine and if there is a lot formed for that part. If there is the part for which the machine is already scheduled for, that part is scheduled first in that period, removing one setup. If there is no lot formed for the part the machine is already setup for, but there is a part scheduled on the same machine in previous period (not the first part) for which a lot is formed also this period. These lots are made the last and first of previous and this period, to save from the setup.

The proposed model is coded in C# with a user interface that allows easily uploading data for a different instance from a text or .csv file. The proposed model is capable of solving any general product structure.

The user interface also allows the user to see the progress of the solution, number of evaluations, current solution and details of the final solution. The detailed plan can be saved in .csv format for future use or comparisons. A screenshot along with explanations of the software is appendix 1

4. Computational Study

We present the proposed method to solve MLCLSP-L with an extended computational study on a sample problem.

The problem chosen is taken from Ozturk (2007) or Öztürk and Örnek (2009). This specific example is chosen because it is a small-moderate size problem for which the mathematical model is developed and published and results are freely accessible. The run-time to solve the mathematical model is reported to be 1800 seconds on a system with Intel Core 2 Duo 2.66 GHz CPU with 2 GB of RAM running Windows XP Professional system. The sample problem has a planning horizon (*T*) of 10 periods with 20 parts. There are three end items (level 0) with 3 and 4 levels of BOM depth. There are 12 machines on which the production takes place. The gozinto matrix is given in table 1. Figures **8** through **10** show the BOM of level 0 items. Part setup and unit production times are given in tables 2 and 3. The machine capacities are given in table 4. The test problem has demand of 89 for part 20, 179 for part 19 and 352 for part 18. The demand for lower level items are calculated through BOM explosion calculus.

We use the ten low level heuristics presented in section 2.2.

The test problem is solved with a large experimental design for parameters of GA. One of the critiques on using metaheuristics is that even when used as a hyperheuristic, significant amount of effort has to be spent parameter tuning. We would like to see if this is the case here.

The experimental design is presented in table 5. This design corresponds to a total of 3x3x2x3x3x8 = 1296 combinations of parameters. Each combination of the experimental design is run with 5 different random seeds and averaged over. Therefore the test problem is solved a total of 6480 times.

The best solution obtained by the hyperheuristic is within 96,9% of the optimal but in just 129.85 seconds a result at 96,2% of the optimal value can be obtained (pop_size= 500, gen=300, row-based mutation with 0.15 probability, column-based crossover and top-to-bottom selection). The best parameter setting is found out to be where the population size is 500, a row-based mutation is applied with a probability of 0.15, column-based crossover and pairing from top-to-bottom selection is applied for 200 generations. When larger problems are solved, the increase in the computational time of the hyperheuristic will much less compared to the increase in time required for the mathematical model.

When the problem size is doubled to 20 periods (by repeating demands for periods 1-10 for periods 11-20), it only takes hyperheuristic method 158 seconds (additional 28 seconds) to find a solution with a cost of 64012 and optimal solution from the mathematical model is stopped within 3600 seconds without finding the optimal solution.

The proposed model achieves a best solution of 96.94% of optimality. Overall average solution quality is 93.1% with a standard deviation of 1.27% for the experimental design in table 5.

The large experimentation with the parameters show almost a perfect normal distribution around the mean. 68.7% of the solutions are within +/- 1σ, 94.4% are within +/- 2σ and +/- 3σ covers the whole range.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
BOM	**P20**	**P19**	**P18**	**P17**	**P16**	**P15**	**P14**	**P13**	**P12**	**P11**	**P10**	**P9**	**P8**	**P7**	**P6**	**P5**	**P4**	**P3**	**P2**	**P1**
P20																				
P19	0																			
P18	0	0																		
P17	**2**	0	0																	
P16	**1**	**2**	0	0																
P15	0	**1**	**1**	0	0															
P14	0	0	**2**	0	0	0														
P13	0	0	**10**	**4**	0	0	0													
P12	0	0	0	**3**	**1**	**2**	0	0												
P11	0	0	0	0	**1**	0	**1**	0	0											
P10	**4**	0	0	0	0	**2**	**1**	0	0	0										
P9	0	**3**	0	0	0	0	**1**	0	0	0	0									
P8	0	0	0	0	0	0	0	**4**	0	0	0	0								
P7	0	0	**15**	0	0	0	**5**	**1**	**1**	0	0	0	0							
P6	0	0	0	**12**	0	0	0	0	0	**2**	0	0	0	0						
P5	0	0	0	0	0	0	0	0	0	**3**	0	0	0	0	0					
P4	0	0	0	0	0	0	0	0	0	**2**	0	0	0	0	0	0				
P3	0	0	0	0	**6**	0	0	0	0	0	**4**	0	0	0	0	0	0			
P2	**16**	0	0	0	0	**8**	0	0	0	0	0	**2**	0	0	0	0	0	0		
P1	0	**11**	0	0	0	0	0	0	0	0	0	**4**	0	0	0	0	0	0	0	
Lead Time	**1**	**1**	**1**	**2**	**1**	**1**	**1**	**1**	**2**	**1**	**1**	**2**	**1**	**1**	**1**	**1**	**1**	**1**	**3**	**1**
Lot Size	**15**	**10**	**5**	**30**	**30**	**20**	**10**	**60**	**100**	**60**	**30**	**20**	**240**	**120**	**200**	**150**	**100**	**120**	**100**	**100**
Backorder C.	**12,8**	**12,4**	**16,8**	**4,0**	**3,2**	**4,4**	**5,4**	**1,4**	**0,6**	**1,8**	**1,2**	**1,6**	**0,2**	**0,2**	**0,2**	**0,2**	**0,2**	**0,2**	**0,2**	**0,2**
Holding Cost	**6,4**	**6,2**	**8,4**	**2,0**	**1,6**	**2,2**	**2,7**	**0,7**	**0,3**	**0,9**	**0,6**	**0,8**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**
Starting Inv.	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Minimum SKU	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Starting Back.	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**

Table 1. Gozinto Matrix of Test Problem

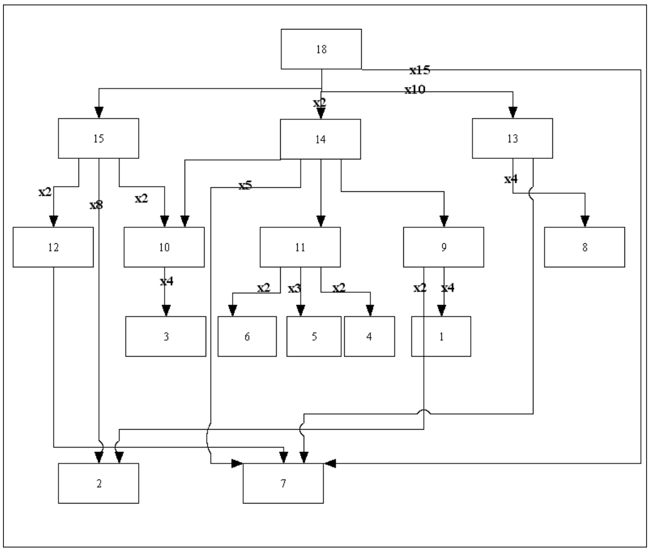


Figure 8. Part 18 BOM for test problem

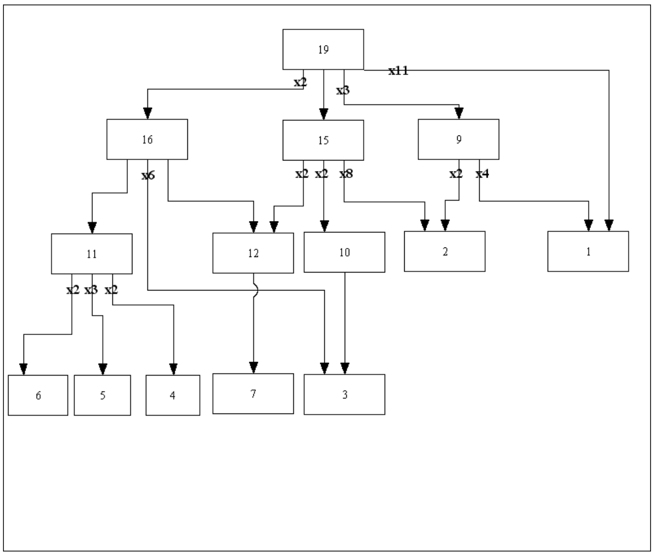


Figure 9. BOM of Part 19 for test problem

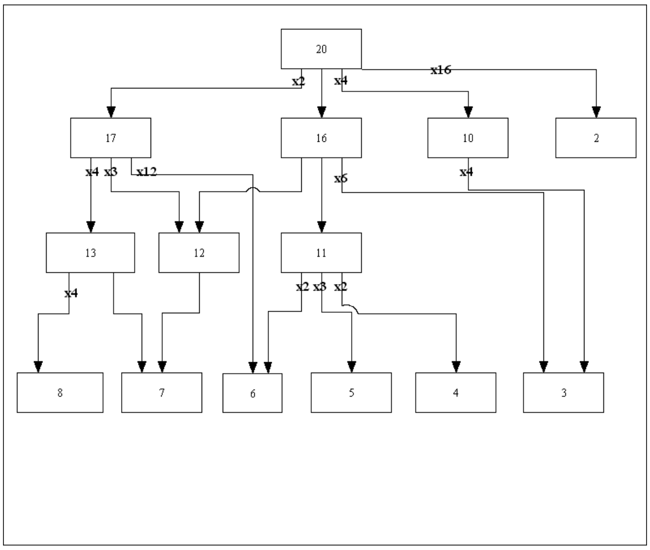


Figure 10. BOM of Part 20 for test problem

P_{im}	M12	M11	M10	M9	M8	M7	M6	M5	M4	M3	M2	M1
M20	0,25	1,50	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
M19	0,75	0,50	0,00	0,00	0,00	0,00	0,24	0,00	0,00	0,00	0,00	0,00
M18	1,50	1,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
M17	0,58	0,00	0,00	0,40	0,20	0,00	0,00	0,00	0,00	0,00	0,00	0,00
M16	0,00	0,00	0,10	0,30	0,60	0,00	0,00	0,00	0,00	0,00	0,00	0,00
M15	0,00	0,00	0,25	0,50	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
M14	0,00	0,00	0,75	0,00	0,50	0,00	0,39	0,00	0,00	0,00	0,00	0,00
M13	0,00	0,00	0,00	0,00	0,00	0,50	0,50	0,00	0,00	0,00	0,00	0,00
M12	0,00	0,00	0,00	0,11	0,00	0,20	0,10	0,00	0,00	0,00	0,00	0,00
M11	0,00	0,00	0,00	0,00	0,00	0,30	0,25	0,00	0,00	0,00	0,00	0,00
M10	0,00	0,00	0,00	0,00	0,00	0,00	0,15	0,00	0,00	0,00	0,00	0,00
M9	1,95	0,00	0,00	0,00	0,00	0,20	0,30	0,00	0,00	0,00	0,00	0,00
M8	0,00	0,00	0,60	0,00	0,00	0,00	0,00	0,00	0,30	0,00	0,10	0,00
M7	0,47	0,00	0,00	0,00	0,00	0,34	0,00	0,30	0,00	0,00	0,00	0,10
M6	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,40	0,00	0,00
M5	0,00	0,49	0,00	0,78	0,00	0,00	0,00	0,00	0,60	0,00	0,30	0,00
M4	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,20	0,20
M3	0,00	0,00	0,00	0,00	0,00	0,00	0,82	0,00	0,10	0,10	0,00	0,00
M2	0,00	0,00	0,00	0,00	0,76	0,00	0,00	0,40	0,00	0,00	0,60	0,00
M1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,30	0,00	0,00	0,25
CAP	250	250	250	250	250	500	500	750	1250	750	750	500

Table 2. Unit production times for test problem

S_{im}	M12	M11	M10	M9	M8	M7	M6	M5	M4	M3	M2	M1
P20	2,50	15,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
P19	7,50	5,00	0,00	0,00	0,00	0,00	2,40	0,00	0,00	0,00	0,00	0,00
P18	15,00	10,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
P17	5,80	0,00	0,00	4,00	2,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
P16	0,00	0,00	1,00	3,00	6,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
P15	0,00	0,00	2,50	5,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
P14	0,00	0,00	7,50	0,00	5,00	0,00	3,90	0,00	0,00	0,00	0,00	0,00
P13	0,00	0,00	0,00	0,00	0,00	5,00	5,00	0,00	0,00	0,00	0,00	0,00
P12	0,00	0,00	0,00	1,10	0,00	2,00	1,00	0,00	0,00	0,00	0,00	0,00
P11	0,00	0,00	0,00	0,00	0,00	3,00	2,50	0,00	0,00	0,00	0,00	0,00
P10	0,00	0,00	0,00	0,00	0,00	0,00	1,50	0,00	0,00	0,00	0,00	0,00
P9	19,50	0,00	0,00	0,00	0,00	2,00	3,00	0,00	0,00	0,00	0,00	0,00
P8	0,00	0,00	6,00	0,00	0,00	0,00	0,00	0,00	3,00	0,00	1,00	0,00
P7	4,70	0,00	0,00	0,00	0,00	3,40	0,00	3,00	0,00	0,00	0,00	1,00
P6	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	4,00	0,00	0,00
P5	0,00	4,90	0,00	7,80	0,00	0,00	0,00	0,00	6,00	0,00	3,00	0,00
P4	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	2,00	2,00
P3	0,00	0,00	0,00	0,00	0,00	0,00	8,20	0,00	1,00	1,00	0,00	0,00
P2	0,00	0,00	0,00	0,00	7,60	0,00	0,00	4,00	0,00	0,00	6,00	0,00
P1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	3,00	0,00	0,00	2,50

Table 3. Setup times for test problem

C_{mt}	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
C12	240	247	236	244	231	230	239	230	227	243
M11	241	240	236	241	239	230	245	249	230	228
M10	240	235	232	228	247	247	238	229	228	244
M9	239	241	226	230	229	231	241	229	226	247
M8	237	244	239	235	236	240	231	245	247	241
M7	490	487	459	472	498	488	464	467	466	466

M6	480	478	451	500	469	475	475	453	468	471
M5	681	702	688	734	749	744	725	745	698	718
M4	1150	1211	1194	1159	1134	1150	1147	1189	1137	1181
M3	749	707	750	735	698	696	713	697	707	694
M2	680	686	703	750	735	706	720	741	742	704
M1	495	458	469	492	486	452	476	477	454	456

Table 4. Machine Capacities for test problem

Population	**No. of Generations**	**Selection Rule**	**Crossover Rule**	**Mutation Type**	**Mutation Rate**
300	300	Tournament	Row-Based	Row-Based	2
500	500	Top-2-Bottom	Column-Based	Column-Based	4
1000	1000		2-Point	Square	6
					8
					10
					15
					20
					25

Table 5. Experimental design for test problem

5. Conclusion and Future Research Directions

Multilevel capacitated lot sizing problem is a very important practical problem that is faced in a wide variety of production systems. They are especially crucial for successful APS module implementations that can handle real life sized problems practically. Multilevel capacitated lot sizing problem is also an intractable problem. It is proved to be *strongly NP-Hard*.

We present a new modeling for multilevel capacitated lot sizing problem with setups and linked lot sizes (MLCLSP-L). The proposed model is based on using a GA as a hyperheuristic to manage a group of simple, single objective, low level heuristics to construct a solution for MLCLSP-L.

Each low level heuristic myopically solves the detailed planning problem of *a machine in a period*. GA driven hyperheuristic uses a $M \times T$ matrix representation, where M is the total number of machines and T is the planning horizon. Each cell (m,t) in the solution shows which of the low level heuristics to be used to determine detailed production plan of machine m in period t. The proposed method allows for the planner to understand much better what is happening with the solution and a certain

Proposed model is coded using C# with a user interface allowing very easy loading of data for different instances and ability to control model parameters as well as ability to view results in detail or save them in .csv format.

GA driven hyperheuristic can be used successfully used to model MCLSP-L. A significantly difficult test problem is modeled and solved with the proposed method. A large experimental design set is run over a wide range of parameters. GA driven hyperheuristic behaves pretty robust with different parameter settings.

Hyperheuristic approaches to especially scheduling related papers are found more during the last 5 years. But to the best of our knowledge, the proposed model is the first hyperheuristic based model for capacitated lot sizing problems. The authors believe the proposed approach has great potential in solving practical sizes of this theoretically challenging problem.

The proposed the model has the following advantages:

The proposed modeling enables some situations, which could hardly be incorporated into a solvable model. Because a matrix representation with low level heuristics are used to construct a solution piece by piece, easily one could model and solve problems with time-dependent part-machine assignments (to model breakdowns, maintenance etc.) and/or time-dependent setup - production times and/or time-dependent costs.

Also as problem sizes get significantly larger, the rate of increase in solution time for the proposed model will allow solutions to be obtained.

Future directions for this research include:

- Developing a post-solution local improvement procedure: It is highly probable due to construction of solution in pieces using simple, single objective, myopic heuristics, improvements in solution quality can be obtained by local improvements after the final solution is obtained.
- Large experimentation with different instances to measure the newly proposed model's performance: This paper presents a new model and displays advantages using a moderately complex test problem. To measure the performance of the proposed model in solving, a large variety of problems must be solved.

Investigation of possibility of a establishing a case-base from the experimental design to understand more about the structure of MLCLSP-L

REFERENCES

Bai R., Burke E.K. and Kendall G. "*Heuristic, Meta-heuristic and Hyper-heuristic Approaches for Fresh Produce Inventory Control and Shelf Space Allocation*", *Journal of the Operational Research Society*, 59(10) (2008), pages 187-1397.

Bitran, G.R., Yanasse, H.H., *"Computational complexity of the capacitated lot size problem", Management Science 28* (1982), 1174-1186.

Blackstone, John H., and James F. Cox. APICS dictionary. Alexandria, VA: APICS, 2005

Burke, E., Kendall, G., Newall, J., Hart, E., Ross, P., and Schulenburg, S., 2003, Handbook of metaheuristics, chapter 16, Hyper-heuristics: an emerging direction in modern search technology, pp. 457--474. Kluwer Academic Publishers,

Chaklevitch K., Cowling, P.:Hyperheuristics: Recent Developments. In: Cotta, C., Sevaux, M., and Srensen, K.(eds.), 2008, *Adaptive and Multilevel Metaheuristics (Studies in Computational Intelligence)*, pp 3-29, Springer Publishing Company, Incorporated

Chen, W.H., Thizy, J.M., Analysis of relaxations for the multi-item capacitated lot-sizing problem, Annals of Operations Research 26 (1990), 29–72.

Cowling, P., Kendall, G., Soubeiga, E.: A hyperheuristic approach to scheduling a sales summit. In: Burke, E., Erben, W. (eds.) PATAT 2000. LNCS, vol. 2079, pp. 176–190. Springer, Heidelberg (2001)

De Kok, A.G and Graves, S.C. (2003). Handbook in Operations Research and Management Science Vol. 11- Supply Chain Management: Design, Coordination and Operation, Elsevier, Amsterdam.

Denizel, M and Süral, H (2006). On alternative mixed integer programming formulations and LP-based heuristics for lot-sizing with setup times, *Journal of the Operational Research Society , 57 (4)*, 389-399.

Drexl A., & Kimms A. (1997). Lot sizing and scheduling – survey and extensions. *European Journal of Operations Research 99*, 221-235.

Drexl, A., Haase, K. (1995). Proportional lot sizing and scheduling, *International Journal of Production Economics 40*, 73-87.

Fleischmann, B. (1990). The discrete lot-sizing and scheduling problem, *European Journal of Operational Research 44*, 337-348.

Fleischmann, B.; Meyr, H.; Wagner, M. (2008) Advanced planning, in: H. Stadtler; C. Kilger (Eds.) Supply Chain Management and Advanced Planning, Springer, Berlin et al., 4th ed., 81–109

Florian, M., Lenstra, J.K., Rinnooy Kan, A.H.G., 1980, Deterministic Production Planning: Algorithms and Complexity, Management Science 26 (7), 669-679.

Günter, H.P. (2005), Supply Chain Management and Advanced Planning Systems: A Tutorial, Physica-Verlag HD.

Haase, K. (1998). Capacitated lot-sizing with linked production quantities of adjacent periods. Beyond Manufacturing Resource Planning (MRP II). *Advanced Models and Methods for Production Planning*, Springer, Berlin, 127-146.

Jans R., Degraeve Z., Meta-heuristics for dynamic lot sizing: a review and comparison of solution approaches, *European Journal of Operational Research* **177** (2007), pp. 1855–1875

Karimi,B., Ghomi, S.M.T.F., Wilson, J.M. (2003). The capacitated lot sizing problem: a review of models and algorithms. Omega, 31, 365-378.

Karmarker, U.S., Scharge L. (1985). The deterministic dynamic product cycling problem, *Operations Research 33*, 326-345.

Kilger, C. and Schneeweiss, L. (2005), "Demand fulfillment and ATP", In : Stadtler H., Kilger, C. (Eds.), Supply Chain Management and Advanced Planning Concepts, Models, Software and Case Studies, Springer, Berlin, , pp. 179-195. King, B. E. and Benton,

Kreipl, S. and Dickersbach, J.D. (2008). "Scheduling coordination problems in supply chain planning", Annals of Operations Research, Vol. 161, No. 1, pp. 103-123.

Lin, C.H., Hwang, S-L. and Wang, M-Y. (2007). "A reappraisal on advanced planning and scheduling systems", Industrial Management & Data Systems, Vol. 107, No. 8, pp. 1212-1226.

Meyr, H., 1999. Simultane Losgrößen- und Reihenfolgeplanung für kontinuierliche Produktionslnien. Gabler Edition Wissenschaft: Produktion und Logistik. Gabler, Wiesbaden.

Ochoa, G: A Bibliography of Hyper-heuristics and Related Approaches. ASAP research group. http://www.asap.cs.nott.ac.uk/projects/ngds/hhref.shtml (2009). Accessed 12 March 2009

Ozcan E, Bilgin B, Korkmaz E.E. (2008) A comprehensive analysis of hyper-heuristics. *Intelligent Data Analysis*, 12:1, 3-23

Ozturk C. (2007). Finite Capacity Planning in MRP systems; Problems and Issues, Msc. Thesis, Dokuz Eylul University, Graduate School of Natural and Applied Sciences.

Öztürk, C., Örnek, M.A. (2009) "Capacitated lot sizing with linked lots for general product structures in job shops", Computers and IE, 58 (2010) 151–164

Pochet Y., Woolsey L.A. (2006). *Production Planning by Mixed Integer Programming*, Springer, New York.

Quadt D, Kuhn H (2008) Capacitated lot-sizing with extensions: a review. 4OR Q J Oper Res 6: 61–83

Stadtler, H. (1996). Mixed integer model formulations for dynamic multi item multi level capacitated lot sizing. European Journal of Operations Research 94, 561-581.

Stadtler, H. (2003) "Multilevel lot sizing with setup times and multiple constrained resources: Internally rolling schedules with lot-sizing windows". Operations Research 51 (3), 487–502

Stadtler, Hartmut. "Supply Chain Management and Advanced Planning—basics, Overview and Challenges." Supply Chain Management and Advanced Planning 163, no. 3 (June 16, 2005): 575–88. doi:10.1016/j.ejor.2004.03.001.

Staggemeier, A.T.,. Clark, A.R, A survey of lot-sizing and scheduling models, 23rd Annual Symposium of the Brazilian Operational Research Society (SOBRAPO), Campos do Jordao SP, Brazil (2001), pp. 938–947.

Steger-Jensen, K. et al. (2011) Advanced Planning and Scheduling technology. Production Planning & Control, v. 22, n. 8, p. 800-808.

Suerie. C., "*Time continuity in discrete time models: new approaches for production planning in process industries"*, *Lecture Notes in Economics and Mathematical System*, 2005. Springer.

Suerie, C.,Stadtler, H., The capacitated lot-sizing problem with linked lot sizes, *Management Science* **49** (2003), pp. 1039–1054

Tay J.C and N. B. Ho, (2008) Evolving Dispatching Rules for solving Multi-Objective Flexible Job-Shop Problems, *Computers & Industrial Engineering*, vol. 54 (3), pp. 453-473.

Tempelmeier, H., A simple heuristic for dynamic order sizing and supplier selection with time-varying data, *Production and Operations Management* **11** (2003), pp. 499–515.

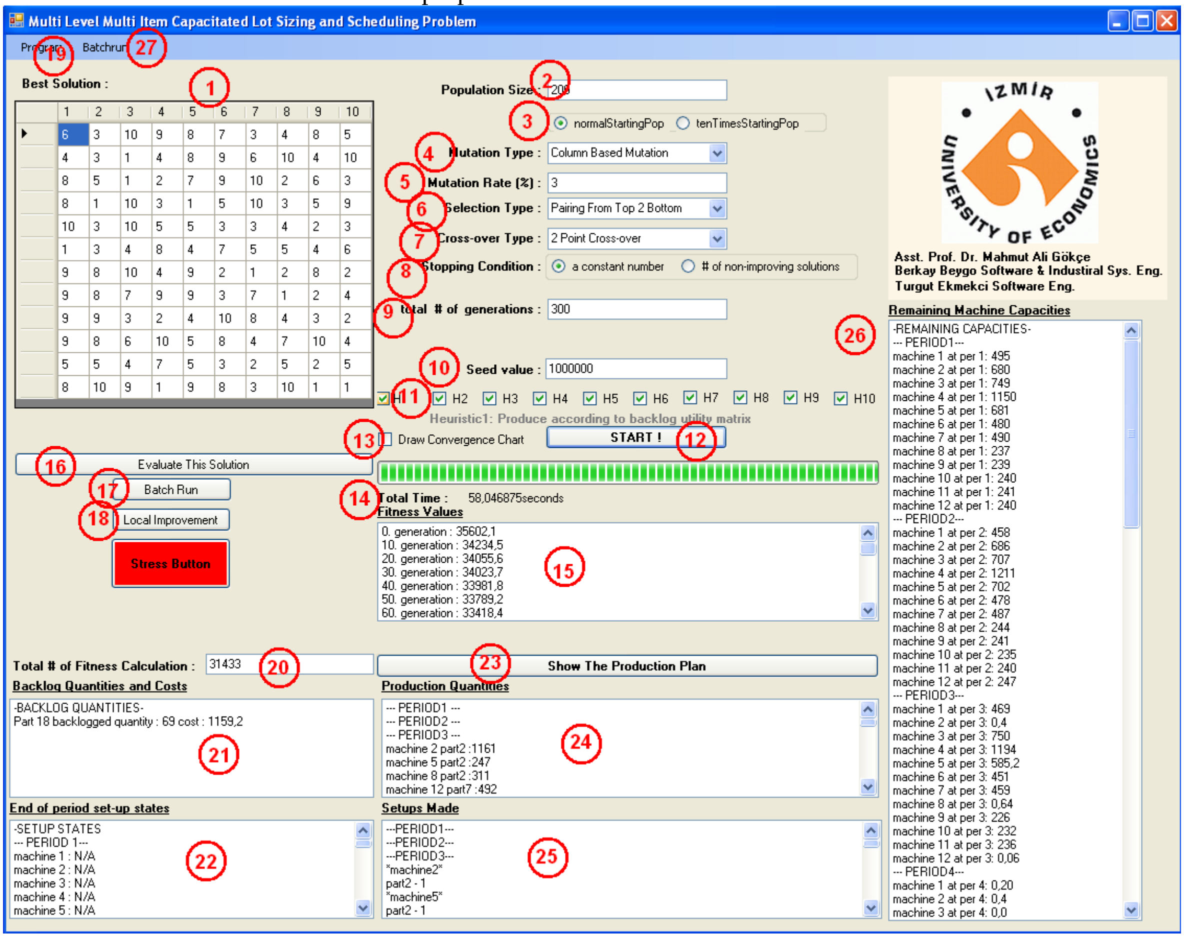
Tempelmeier, H., Buschkühl L., (2008). A heuristic for the dynamic multi-level capacitated lotsizing problem with linked lot sizes for general product structures. OR Spectrum, DOI 10.1007/s00291-008-0130-y

Tempelmier, H., Derstroff, M., (1996) A Lagrangean based heuristic for dynamic multilevel multi item constrained lot sizing with setup times, *Management Science 42*, 738-757

Zoryk-Schalla A., Fransoo J. and De Kok T.G (2004). "Modelling the planning process in advanced planning systems", Information and Management, Vol. 42, No. 1, pp. 75-87

Appendix 1

Screenshot of software for the proposed model



1) Best solution matrix is shown after the completion of the program. Also "Evaluate This Solution" button calculates the fitness of the any solution input by the user to that grid as a matrix.
2) This field is for taking "Population Size" as an input from the user. (Population size must be divisible by four if pairing from top to bottom selection is used.)
3) The two radio buttons here are for selecting how the initial population will be formed. If "NormalStartingPop" button is selected, initial population is formed according to random selection and population size given by the user. If "TenTimesStartingPop" button is selected, random population of ten times the population size determined by the user is formed and best 10% of these individual solutions are selected as the initial population.

4) Mutation Type is selected. (Column Based Mutation, Row Based Mutation, Square Based Mutation)
5) Mutation rate is input by the user from this box as a percentage.
6) The selection type is chosen here. There are two types of selection mechanisms currently used; Pairing From Top to Bottom and Tournament.
7) Cross-over type is selected. (Column Based Cross-over, Row Based Cross-over, 2 Point Cross-over)
8) User must determine the stopping condition here. Stopping condition can be input in two different forms. Either the total number of generations or the number of generations during which there are no improvements on the best solution.
9) If a fixed number of generations is chosen as the stopping condition, total number of generations to run is given through this box.
10) The seed value is input here.
11) The heuristics that will be used in the program are chosen by using these check boxes.
12) Starts the algorithm.
13) By clicking here, user might see convergence graph of the current run.
14) Total CPU time of the run in seconds is displayed.
15) This box displays best fitness values at each 10(can be changed) generations.
16) Calculates the solution in the matrix above and saves the output to an excel file. After running the program the best solution is shown in this grid and "Evaluate This Solution" button creates the excel file for that solution.
17) Runs the program with previously created batch file. Multiple runs can be done in a sequence.
18) Local improvement. To be run post optimization. Future work.

19) Problem data is uploaded via this button from a CSV (comma-separated values) file.
20) Total number of fitness calculations is shown in this textbox.
21) This box shows backlogging quantities and resulting backlogging costs.
22) This box shows set-up states of each machine at the end of each period.
23) Opens the excel file created. (The outputs are saved in an excel file consisting of 6 worksheets. Each excel file is named reflecting the parameters of the program to avoid confusion. For example if user chooses to run with a population size of 200, column based mutation, 3% mutation rate, tournament selection, column based cross-over, 300 generations, and a seed value of 10000, the file is named as Pop200_Gen300_TOUR_CBcro_CBmut3_10000.xls