IWLS 2018

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August 22-24, 2018

9th International Workshop on Lot Sizing

Celebrating the 60th anniversary of the pioneering papers by Manne and Wagner & Whitin

Proceedings

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Bem-vindo à Ubatuba!

It is a great pleasure to warmly welcome you in Ubatuba! We hope this beautiful city in the Brazilian coast will be the perfect place for making the workshop as successful as in all its previous versions. We will have plenty of time to discuss the latest developments in the lot sizing community as well as enjoy nice weather and beautiful landscapes in very good company!

As in the previous workshops, the goal of the IWLS is to cover recent advances in lot sizing: new approaches for classical problems, new relevant problems, integration of lot sizing with other problems such as scheduling, distribution or vehicle routing, presentation of case studies, etc. The workshop will also aim at favoring exchanges between researchers and enhancing fruitful collaboration.

This is the 9th IWLS and we are glad to host the workshop this time in Brazil. This year, in special, we celebrate the 60th anniversary of two seminal papers for the lot sizing literature, one by Manne and the other by Wagner & Within. These authors have made important contributions to our community, which stimulated the attention to lot sizing problems.

We would like to thank you for attending the workshop, especially if you are coming from far way. We really appreciate your effort in coming to Brazil and sharing your time with us during the workshop. We are also thankful to our sponsors, which literally made this workshop possible, and to everyone that contributed somehow with the organization. We hope you will enjoy your time in Ubatuba!

Obrigado :)
Silvio, Pedro, Kelly, Mari

IWLS 2018 Program:

Tuesday , August 21, 2018
19:00-20:00 - Welcome Reception (Workshop)
20:00-22:00 – Dinner (served by the hotel to guests) + Drinks (Workshop)

Day 1: Wednesday, August 22, 2018
08:15-08:45 Registration
08:45-09:00 Opening & Welcome
09:00-10:30 Session - Applications (chair: Alistair Clark)

Applications of Lot-Sizing
Alistair Clark

A Case Study in the Glass Container Industry: Thermos flask production
Magna Paulina de Souza Ferreira, Flaviana Moreira de Souza Amorim, Márcio da Silva Arantes, Claudio Fabiano Motta Toledo

A Lot Sizing Perspective for the Battery Storage Coordination in Power Distribution Systems
Caio Santos, Ellen Cavalheiro, Petra Bartmeyer, Rodrigo Lima, Christiano Lyra

10:30-11:00 Poster Introductions (chair: Maristela Santos)
11:00-11:30 Coffee Break/Poster Session
11:30-13:00 Session - Integrations (chair: Kelly Poldi)

Decomposition methods for a capacitated three-level lot sizing and transportation problem with a distribution structure
Matthieu Gruson, Jean-François Cordeau, Raf Jans

Integrated lot sizing and cutting stock problems in paper industries
Livia Maria Pierini, Kelly Cristina Poldi

Leveraging Capacity Planning with Maintenance Insights
Manuel Díaz-Madroñero, Luís Guimarães, Bernardo Almada-Lobo, Ayse Akbalik, Christophe Rapine

13:00-14:30 Lunch (served by the hotel to guests)
16:30-18:30 Happy Hour (Workshop)
19:00-20:30 Dinner (served by the hotel to guests)

Day 2 Thursday, August 23, 2018
09:00-10:30 Session – Stochastic and Robust (chair: Kerem Akartunali)

Reformulations for Robust Lot-Sizing Problem with Remanufacturing Option and Backlogging
Öykü Naz Attila, Agostinho Agra, Kerem Akartunali, Ashwin Arulselvan

Heuristics for the stochastic economic lot sizing problem with remanufacturing
Onur A. Kilic, Huseyin Tunc

Stochastic lot-sizing for remanufacturing planning with lost sales and returns
Franco Quezada, Céline Gicquel, Safia Kedad-Sidhoum

10:30-11:00 Coffee Break/Poster Session
11:00-12:30 Session - Extensions (chair: Nabil Absi)

Detailed production planning models with flexible lead time constraints
Sébastien Beraudy, Nabil Absi, Stéphane Dauzère-Pérès

A strategic production problem balancing cost and flexibility
Etienne de Saint Germain, Vincent Leclère, Frédéric Meunier

12:30-14:00 Lunch (served by the hotel to guests)

14:00-15:30 Session – Heuristics (chair: Pedro Munari)

A column generation based heuristic for Inventory routing with practical constraints
Pedro Munari, Aldair Alvarez, Reinaldo Morabito

New progresses on a greedy construction heuristic for capacitated lot-sizing problems
Christian Almeder

A Lagrangian heuristic for the capacitated lot sizing and scheduling problem on parallel related production lines
Willy A. Oliveira, Maristela O. Santos, Kerem Akartunali

15:30-16:00 Coffee Break/Poster Session

16:00-17:30 Session – Stochastic and Integrations (chair: Raf Jans)

Stochastic Lot Sizing Problem with Joint Service Level Constraints
Narges Sereshti, Yossiri Adulyasak, Raf Jans

Multi-stage stochastic capacitated lot sizing under tight service constraints
Fabian Friese

A single-item lot-sizing problem with a by-product and inventory bounds
Elodie Suzanne, Nabil Absi, Valeria Borodin, Wilco van den Heuvel

17:30-18:00 Meeting of the EURO Working Group on Lot-Sizing

20:00-23:00 Workshop’s Dinner (Beach Party)

Day 3 Friday, August 24, 2018

09:00-10:30 Session - Complexity and Algorithms (chair: Wilco van den Heuvel)

Approximation algorithms for lot-sizing problems using sandwich functions
Guillaume Goisque, Christophe Rapine, Wilco van den Heuvel, Albert P. M. Wagelmans

Revisiting the Zero-Inventory Property in Remanufacturing
Meltem Denizel

Comparison of different cuts to interactively solve production lot-sizing and scheduling problems in cases of infeasibilities
Fernanda Alves, Maurício C. de Souza, Thiago H. Nogueira, Martín Ravetti

10:30-11:00 Coffee Break

11:00-12:30 Session - Applications and Integrations (chair: Silvio Araujo)

A supply chain tactical planning approach for optimizing the tomato processing industry
Cleber Rocco, Reinaldo Morabito, Luís Guimarães, Bernardo Almada-Lobo

Integrated Lot Sizing, Scheduling and Cutting Stock Problem
Gislaine Mara Melega, Silvio Alexandre de Araujo, Reinaldo Morabito

Integrated lot sizing and blending problems
Diego Jacinto Fiorotto, Raf Jans, Silvio Alexandre de Araujo

12:30-14:00 Lunch (served by the hotel to guests)

Poster Session:

Integrated Lot Sizing and Cutting Stock Problem Applied to a Spring Industry
Pedro Rochavetz de Lara Andrade, Silvio Alexandre de Araujo, Adriana Cristina Cherri Nicola

Heuristics for the lot sizing and scheduling problem of production with demand order management
Rudivan Barbosa, Willy Oliveira, Maristela Oliveira Santos

Machine Flexibility in Lot Sizing Problems: Construction of Heuristics
Melka Catelan, Silvio Araujo, Diego Fiorotto

The Integrated Lot-Sizing and Cutting Stock Problem Applied to a Mattress Industry
Maurício Móz Christofoletti, Silvio Alexandre de Araujo, Adriana Cristina Cherri, Raf Jans

An optimization model for the general lot sizing and scheduling problem in beverage production
Deisemara Ferreira, Victor Mario Noble Ramos

A fix-and-optimize with objective function exchange applied to the production planning in pulp and paper industry.
Marcos Mansano Furlan, Maristela Oliveira Santos, Reinaldo Morabito

Reformulations for the Lot Sizing Problem: an initial study
Maurício Rocha Gonçalves, Silvio Alexandre de Araujo

Capacitated lot sizing and replanning problem for machining industry
Matheus Artioli Leandrin, Adriana Cristina Cherri, Luiz Henrique Cherri

Production planning considering cutting and scheduling aspects
Felipe Kesrouani Lemos, Silvio Alexandre de Araujo, Adriana Cristina Cherri, Horácio Hideki Yanasse

A new model integrated in the planning and programming of furniture production
Guilherme de Oliveira Macedo, Carla Taviane Lucke da Silva Ghidini

Integrated Lot Sizing and Cutting Stock Problem with Usable Leftovers
Douglas Nogueira do Nascimento, Silvio Alexandre de Araujo, Adriana Cristina Cherri

A lot sizing and cutting stock problem in a trusses slabs industry
Sônia Cristina Poltroniere, Ângelo Henrique Dinhane Vassoler, Silvio Alexandre de Araujo

Production planning integrated to the optimization problem of the use of molds
Caroline Signorini, Silvio Araujo, Gislaine Melega

The integrated lot sizing and transportation problem
Samanta Teixeira, Silvio Araujo, Diego Fiorotto

Extended abstracts

Short abstracts

Extended abstracts

New progresses on a greedy construction heuristic for capacitated lot-sizing problems

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Abstract

Finding good or even feasible production plans for capacitated lot-sizing problems is usually (NP-)hard. Using state-of-the-art model formulations and MIP-solvers still leads in many cases to excessive long computational time. Construction heuristics are tremendously faster and have been discussed in the research literature already more than 30 years. In some cases those heuristics produce good quality results. But on *scattered* and capacity tight problems, where irregular or lumpy production plans are necessary, the results are usually not as good. In this work we have a look on a new class of construction heuristics which build production plans stepwise by adding demand to an existing partial plan. This extension of a partial plan is based on simple common sense rules. The essential part influencing the quality of the final production plan is determined be the order in which demand is added to the plan. With this method we can generate fast good quality production plans.

1 Introduction

There are two well-known construction heuristics for the capacitated lot-sizing problem without setup times. The Dixon-Silver-heuristic (cf. [1]) builds up a production plan period-by-period starting from the first one. Its main idea is to make a "local" cost-based decision about the extension of a production lot in the current period. Furthermore, it considers the necessity of preproduction due to capacity limitations in later periods. The ABC-heuristic (cf. [3]) consists of 72 variants of a construction heuristic. These variants differ in the order of the products to be lot-sized and the lot-sizing rule. Basically the production plan is constructed step wise from the first to the last period similar to the Dixon-Silver-heuristic.

Recently a new extension of the Dixon-Silver-Heuristic has been proposed where this local decision criteria is optimized using genetic programming (cf. [?]). After a preprocessing (training) phase the resulting heuristic is able to outperform Dixon-Silver and ABC in terms of solution quality while being less computational intensive than ABC.

But all of the above mentioned heuristics cannot handle setup times. In general, in the presence of setup times it is not possible to generate a feasible production plan in polynomial time, since this problem is NP-complete.

[4] proposed a simple construction heuristic embedded in a metaheuristic for the practical lot-sizing problem of a pharmaceutical company. This construction heuristic is a simple, rule-based method to add new demand to an existing production plan. The order in which demand is added to the plan is optimized by a genetic algorithm. The heuristic proposed in this work is based on similar ideas.

2 Greedy construction heuristic for the capacitated lot-sizing problem

The main idea of the algorithm is to add step-by-step demand to a production plan. So the first step is taking all positive demands $d_{i,t} > 0$ for all products i and all periods t and put them in a list $dl =< d_{i_1,t_1}, d_{i_2,t_2}, \ldots, d_{i_K,t_K} >$ of K elements. We start with an empty production plan, i.e., no setup and no production is scheduled yet. One-by-one a demand from the list is added to the production plan by applying the following rules:

1. **Shift an already scheduled demand or part of it forward.** This rule serves as a look-forward feasibility check mechanism. If there is not enough capacity available in the current and all previous periods, the currently considered demand cannot be included in the plan. In this case, the production of the item with the lowest setup cost among the items with positive inventory in the current period is shifted into later periods. If this does not free up enough capacity production of other items is shifted as well.

2. **Use inventory to satisfy current demand.** If the inventory level of item i at the end of period t is positive and the sum of remaining capacity in the future periods is positive as well, then this inventory is used to satisfy the current demand. In order to compensate for the inventory consumed prematurely, a new demand is created for the subsequent period.

3. **Directly schedule current demand.** If the considered demand belongs to the first period, i.e. if $t = 1$, it must be directly added to the production schedule in this period regardless of the costs incurred.

4. **Extend current lot.** If a setup for item i in period t already exists and there is still some remaining capacity in this period, the corresponding lot is extended. If the remaining capacity is not sufficient to cover the whole demand d_{it}, a new demand for the remaining amount is created for the previous period.

5. **Create a new lot in the current period or extend previous lots.** This scheduling alternative is used if there is no setup for item i in the current period t, but there would be enough capacity for producing the whole demand in t. Here, two possible operations are considered: (i) Create a new lot and produce everything in the current period. (ii) Cover the demand by extending existing lots in previous periods. The cheaper option is used.

6. **Create a new lot in a previous period or split the demand.** In this case, again some alternatives are tested: (i) Cover the demand by extending existing lots in previous periods. (ii) Find the most recent period where the whole demand could be produced with a new lot. (iii) Create a new lot in the current period, produce the maximum amount, and cover the remaining demand by extending existing lots in previous periods. (iv) Cover the demand by creating two lots, one in the current period and one in a previous period (v) Schedule the production of the demand as late as possible, regardless of the number of new lots created. The cheapest option is used.

For each element of the demand list dl the rules are applied one after each other starting from Rule 1 until the demand is integrated in the production plan. The final production plan depends on the order of the demand elements in the demand list.

3 Testing different sorting criteria

So sorting the demand in the right way is crucial to obtain a good production plan. For testing we used 1591 test instances of [3] and of [**?**]. In total 75 sorting rules have been tested. A first statistical test proved that there is a strong relation between time-between-orders (TBO) of an instance and the obtained solution quality. There are also weaker correlations with problem size and capacity tightness.

Considering the best sorting rules Table 1 shows the deviation from the optimal solutions for the different instance classes.

4 Conclusions

So far the results are good but not satisfactory. The greedy heuristic is able to obtain similar results as Dixon-Silver but cannot reach the ones obtained by the ABC-heuristic. So further analysis of the rules and the sorting criteria is necessary. The biggest advantage of the heuristic is its flexibility because it can be applied easily to many variants of the CLSP.

		ABC test instances			Suerie test instances		
		capacity	TBO	size	capacity	TBO	size
	GCH	6.11%	0.90%	4.32%	3.83%	2.03%	4.28%
low/small	DS	2.36%	0.78%	4.16%	2.59%	1.75%	3.90%
	ABC	2.01%	0.73%	3.24%	1.67%	1.36%	2.05%
	GCH	4.53%	-	-	5.62%	-	5.95%
medium	DS	3.48%	-	-	6.20%	-	8.45%
	ABC	3.10%	-	-	3.48%	-	4.28%
	GCH	4.76%	9.37%	5.74%	8.66%	7.75%	5.15%
high/large	DS	5.15%	6.55%	3.29%	16.96%	9.23%	5.42%
	ABC	4.52%	5.69%	3.19%	8.23%	4.76%	3.23%
	GCH		5.13%			5.14%	
all	DS		3.66%			5.81%	
	ABC		3.13%			3.21%	

Table 1: Results for all sorting rule (GCH - greedy construction heuristic, DS - Dixon-Silver)

References

[1] Dixon, P.S., Silver, E.A., A heuristic solution procedure for the multi-item, single-level, limited capacity, lot-sizing problem. Journal of Operations Management 2, 23—39 (1981)

[2] Hein, F., Almeder, C., Figueira, G., Almada-Lobo, B., Designing new heuristics for the capacitated lot sizing problem by genetic programming. Computers & Operations Research 96, 1—14 (2018)

[3] Maes, J., Van Wassenhove, L.N., A simple heuristic for the multi item single level capacitated lotsizing problem. Operations Research Letters 4, 265—273 (1986)

[4] Oyebolu, F.B., van Lidth de Jeude, J., Siganporia, C., Farid, S.S., Allmendinger, R., Branke, J., A new lot sizing and scheduling heuristic for multi-site biopharmaceutical production. Journal of Heuristics 23, 231-–256 (2017)

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

Comparison of different cuts to interactively solve production lot-sizing and scheduling problems in cases of infeasibilities

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Abstract

The integrated production planning and scheduling decisions are essential for cost minimization and to avoid infeasibilities. This work aims to present three interactive strategies for the cases in which such infeasibilities occur when solving a production lot-sizing and scheduling problem in a single machine scenario. Initially, both problems are sequentially solved, if an infeasibility occurs at the scheduling level, i.e., the shop-floor has not enough capacity to do the planned activities, cuts are added to the lot-sizing problem based on information resulting from previous iterations, characterizing an interactive approach. Computational experiments show that interactive strategies are effective and efficient to solve the problem, finding better results when compared to an integrated approach for most of the tested instances.

1 Introduction

Production lot-sizing and scheduling problems are usually considered individually in real situations in industries. However, considering them separately can generate infeasibility to the production plan, since the scheduling problem receives input data from the lot-sizing problem. This work aims to compare three different interactive strategies to solve production lot-sizing and scheduling problems in cases of infeasibility, comparing results with an integrated approach. If an infeasible sequence is found, cuts are added to the lot-sizing problem. In this work, we study a single machine scenario considering sequence-dependent setup times and limited production capacity. The factory has the option of stocking products or to backlog. Therefore, the costs to be minimized are inventory and backorder costs. The literature articles that most resemble this work are [1], [2] and [3], in which interactive approaches are proposed to solve production lot-sizing and scheduling problems.

2 Solution methods

This section presents three interactive strategies for solving the problem in cases of infeasibility scheduling sequences. For the sake of comparison, we also solve the problem with an integrated continuous time horizon model. The rolling horizon technique is applied to both methods. The sets, parameters and decision variables used are presented in Table 1.

Data	Description
J	Set of products
L	Set of iterations solved until find a feasible solution
$L1$	Set of iterations in which Constraints 1 are added to the lot-sizing problem
$L2$	Set of iterations in which Constraints 2 are added to the lot-sizing problem
Ω_l	Set of products that were scheduled at iteration l, with $l \in L$
t^*	Period of the rolling horizon being scheduled
C	Production capacity (hours)
D_{jt}	Demand of product j in period t
p_j	Processing time of product j
St_{ij}	Setup time for production of product j after the production of product i
M	Big value, defined as $M = \sum_{j \in J} p_j D_{jt^*} + \sum_{j \in J} max_{i \in J} St_{ij}$
SS_l	Total setup time of the sequence defined at iteration l, with $l \in L$
K_l	Total number of products belonging to the set Ω_l at iteration l, with $l \in L$
MKS_l	Makespan of the sequence defined at iteration l, with $l \in L$
q_{jt}	Integer variable indicating the quantity produced of job j in period t
w_{jt}	Binary variable indicating if there is production of job j in period t

Table 1: Sets, parameters and decision variables.

The Interactive Strategy I (ISI) and Interactive Strategy II (ISII) are presented in a previous work [3], while Interactive Strategy III (ISIII) is proposed here. In all cases, we begin solving the capacitated lot-sizing model; its output consists of which products are chosen to be produced (w_{jt}) and their production quantities (q_{jt}). Based on this information a scheduling problem is solved with an Iterated Local Search (ILS) heuristic, obtaining the production sequence and its makespan value (MKS_l). In case of infeasibility due to the lot-sizing capacity constraints, cuts are added to the lot-sizing formulation, which is solved again. This procedure runs interactively until a feasible solution is found.

In ISI one of two types of cuts (Constraints 1 and 2) is inserted into the lot-sizing formulation. At the l iteration, the set of cuts to be added is chosen based on the total setup time of the scheduling sequence (SS_l). If its value is less than or equal to the production capacity, the cuts represented by (1) are used. Otherwise, the cuts represented by (2) are added to the lot-sizing model. These cuts allow the model to keep the same set of products changing only their production quantities or even change the whole set of products to be produced.

$$SS_l + \sum_{j \in \Omega_l} p_j q_{jt^*} \leq C \qquad \forall l \in L1 \tag{1}$$

$$SS_l + \sum_{j \in \Omega_l} p_j q_{jt^*} \leq MKS_l - 1 \qquad \forall l \in L2 \tag{2}$$

In the ISII strategy, the set of cuts to be added to the lot-sizing problem cause an alteration of the previous infeasible sequence (Constraints 3). At least one product will be removed from this sequence.

$$\sum_{j \in \Omega_l} w_{jt^*} \leq K_l - 1 \qquad \forall l \in L \tag{3}$$

The cuts proposed for ISIII (Constraints 4) indicate that if the products defined to be produced in the previous iteration are maintained, the production quantities must be altered. If the products are changed, the constraints are limited by a large value, M, allowing the model to select the production quantities freely.

$$\sum_{j \in \Omega_l} p_j q_{jt^*} + SS_l \leq C + M(K_l - \sum_{j \in \Omega_l} w_{jt^*}) \qquad \forall l \in L \tag{4}$$

3 Computational experiments

We considered instances with 4, 6, 8, 10, 12, 15 and 20 products. For each size, 10 values are generated totalizing 70 instances. We select the ones that are initially infeasible to compare the interactive strategies. The resolution time is limited to 3600 seconds for the integrated model and 30 seconds for each iteration of the interactive approach.

Table 2 presents the average results for the tested instances. For instances with 4 and 6 products, the integrated approach managed to obtained better solutions. However, for cases with 8 and more products, the interactive strategies find results up to approximately 11% better than the integrated model. Furthermore, all interactive strategies present smaller computational times if compared with the integrated approach. All interactive approaches show similar objective function values. However, when evaluating the computational time, ISII presents higher average values. The proposed strategy manage to maintain the same level of performance with better computational times.

	Integrated		ISI			ISII			ISIII		
Instance	**OF**	**Time (s)**	**OF**	**Gap**	**Time (s)**	**OF**	**Gap**	**Time (s)**	**OF**	**Gap**	**Time (s)**
4	1376,90	0,64	1380,20	0,24%	0,31	1380,20	0,24%	0,30	1380,20	0,24%	0,33
6	2132,50	16,88	2145,00	0,58%	2,03	2145,00	0,58%	2,21	2145,00	0,58%	2,10
8	2562,90	1472,55	2551,10	-0,46%	22,69	2551,10	-0,46%	17,30	2551,10	-0,46%	21,70
10	3391,40	3620,07	3345,10	-1,38%	44,57	3345,10	-1,38%	122,77	3345,10	-1,38%	49,44
12	4332,50	3617,42	4286,30	-1,08%	207,78	4286,30	-1,08%	703,87	4286,30	-1,08%	247,08
15	5555,40	3615,20	5384,50	-3,17%	549,37	5385,40	-3,16%	2022,00	5385,00	-3,16%	458,47
20	4554,25	3619,69	4094,63	-11,23%	1030,19	4095,60	-11,20%	3142,00	4094,75	-11,22%	863,25

Table 2: Computational results.

4 Conclusions

For most of the tested instances, the interactive strategies find better results with smaller average computational times than the integrated approach. All the cuts strategies present efficient and similar performances. However, the proposed strategy ISIII seems to be faster when compared to ISI and ISII as the number of products increases. For future works we intend to test cuts considering other parameters, e.g., increasing the number of products, and work on different interactive strategies.

5 Acknowledgments

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Reformulations for Robust Lot-Sizing Problem with Remanufacturing Option and Backlogging

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Abstract

Production systems with item recoveries, such as remanufacturing, can reduce overall production costs and waste through restoring deformed products to their usable state. Despite the wide range of research on lot-sizing problems, only limited number of studies have focused on lot-sizing problems with remanufacturing. Although these studies have shown the effectiveness of various methods, much less is known about the impact of uncertainty. In this talk, we explore the implications of parameter uncertainties within the framework of robust optimization. In particular, we investigate extended reformulations. We present detailed computational results and discuss future opportunities.

1 Deterministic Problem with Backlogging

Different from traditional manufacturing settings, item recovery allows used products to return to the production cycle in part or in full. From various product recovery approaches, remanufacturing is the most effective one both economically and environmentally, as it aims to return a used product at least to the same quality level of a newly manufactured product. Although remanufacturing is receiving increasingly more attention from the research communities of a broad range of disciplines from design and manufacturing engineering to environmental science, the research is in general in its early stages, in particular in operations research.

One particular area of interest in remanufacturing is lot-sizing. Over the last 6 decades, research in lot-sizing of traditional manufacturing has contributed to significant savings and much more effective production systems in practice, and such a potential cannot be ignored for the newly developing systems involving remanufacturing. Despite this significance, the research in lot-sizing with remanufacturing has been rather limited, and we refer the interested reader to the recent study of [5], which provides a detailed review of accomplishments to date.

Before discussing the role of uncertainty, we define the problem of interest in the deterministic setting. We follow the problem as presented in [1], with a given time horizon T, and a set of demands, $\mathcal{D} = \{D_1, D_2, \ldots, D_T\}$, and returns, $\mathcal{R} = \{R_1, R_2, \ldots, R_T\}$. Demand can be satisfied by items that are either manufactured from scratch or remanufactured from returns, both of which achieve the required minimum quality level, and we refer to these as "serviceable items". Serviceable items may be carried in inventory to satisfy future demands, or they may be backlogged to satisfy demand of earlier periods. For simplicity, we assume costs to be time invariant, and define cost m (resp. r) per item manufactured (resp. remanufactured), a fixed joint set up cost K if an item is produced in a period, and cost h^s (resp. b) per period per serviceable item carried in inventory (resp. backlogged). Moreover, in each period, we can remanufacture the returned items or carry them over to the next period in the "return inventory" at a cost of h^r per item, or dispose them at a cost of f per item. For the sake of notation, let $x^m := (x_1^m, x_2^m, \ldots, x_T^m), x^r := (x_1^r, x_2^r, \ldots, x_T^r), d := (d_1, d_2, \ldots, d_T)$, and $y := (y_1, y_2, \ldots, y_T)$ to be the vectors associated with production (manufacturing and remanufacturing), disposal and joint setup variables, respectively. We also define H_t^s (resp. H_t^r) to indicate serviceable items inventory cost incurred in period t (resp. returns inventory). We also define the vector $\mathbf{x} := (x^m, x^r, d, y)$. W.l.o.g., we assume initial inventory is zero. Then, we can present a mixed integer program (MIP) formulation for the deterministic problem as follows:

$$\min \quad \theta^{D,R}(\mathbf{x}, d, y) + \sum_{\mathrm{t=1}}^{\mathrm{T}} (H_t^s + H_t^r) \tag{1}$$

$$\text{s.t.} \quad H_t^s \geq h^s \sum_{i=1}^{t} (x_i^m + x_i^r - D_i) \qquad \forall t = 1 \ldots T \tag{2}$$

$$H_t^s \geq -b \sum_{i=1}^{t} (x_i^m + x_i^r - D_i) \qquad \forall t = 1 \ldots T \tag{3}$$

$$H_t^r \geq h^r \sum_{i=1}^{t} (R_i - x_i^r - d_i) \qquad \forall t = 1 \ldots T \tag{4}$$

$$M_t y_t \geq x_t^m + x_t^r \qquad \forall t = 1 \ldots T \tag{5}$$

$$x^m, x^r, d \geq 0, \tag{6}$$
$$y \in \{0,1\}^T \tag{7}$$

Here, we note that the objective function minimizes the total cost, where

$$\theta^{D,R}(\mathbf{x}, d, y) = \sum_{\mathrm{t=1}}^{\mathrm{T}} (K y_t + m x_t^m + r x_t^r + f d_t)$$

Constraints (2) and (3) ensure that either holding or backlogging cost will be accounted for the serviceable items in period t. In a similar fashion, constraint (4) dictates returns inventory cost. Joint setups are enforced by the constraint (5) whenever manufacturing and/or remanufacturing takes place in period t. Finally, nonnegativity and integrality restrictions are achieved by constraints (6) and (7).

2 Uncertainty and Reformulations

Making decisions for future periods, where demands and returns will take place, presents a significant challenge in identifying accurate input parameters. Even in a make-to-order production system, where future orders need to be received in advance and hence demand quantities can be more easily justified, the uncertainties involved in returns will most often remain intact. Therefore, there is a need to appropriately address the issue of input parameter uncertainties, in particular in demands and returns. Robust optimization offers a suitable framework for this case. Different than stochastic optimization, which requires probability distributions for uncertainties (often an unrealistic case for even demand quantities), robust optimization aims to achieve solutions that remain feasible over a so-called "uncertainty set". Since the work of [2], there have been significant advances in the arena of robust optimization, see the extensive review of [3].

As in our preliminary work [1], we define the uncertainty sets for demands and returns as budgeted polytopes [4]. For each period $t = 1, \ldots, T$, we define nominal demands (resp. returns) $\overline{D}_t$ (resp. $\overline{R}_t$), and the maximum deviation from the nominal value $\hat{D}_t$ (resp. $\hat{R}_t$). Therefore, the demand (resp. return) D_t (resp.R_t) in period t takes a value in $[\overline{D}_t, \overline{D}_t + \hat{D}_t]$ (resp. $[\overline{R}_t, \overline{R}_t + \hat{R}_t]$). Then, we define the variables $z_t^D \in [0,1]$ (resp. $z_t^R \in [0,1]$), which indicate the proportion of deviation we have from the nominal demand (resp. return) in period t. In order to avoid over-conservative estimates for z_t^D (resp. z_t^R), we also define the parameters Γ_t^D (resp. Γ_t^R):

$$Z^D(\Gamma^D) := \{z^D \in [0,1]^T : \sum_{i=1}^{t} z_i^D \leq \Gamma_t^D, \ \forall t = 1, ..., T\}$$

$$Z^R(\Gamma^R) := \{z^R \in [0,1]^T : \sum_{i=1}^{t} z_i^R \leq \Gamma_t^R, \ \forall t = 1, ..., T\}$$

Then, the uncertainty sets for demands and returns are defined as:

$$U^D(\Gamma^D) := \{D \in \mathbb{R}_+^T : D_t = \overline{D_t} + \hat{D}_t z_t^D, z^D \in Z^D(\Gamma^D)\}$$

$$U^R(\Gamma^R) := \{R \in \mathbb{R}_+^T : R_t = \overline{R_t} + \hat{R}_t z_t^R, z^R \in Z^R(\Gamma^R)\}$$

An alternative characterisation for these sets can be provided in terms of the convex hull of its extreme points, which allows a decomposition approach as presented in [1]: a restricted version of the robust problem with only a subset of extreme points, called "Decision Maker's Problem" (DMP), can be solved iteratively with an "Adverserial Problem" (AP), which generates extreme points to add to DMP. From our computational experience, we have observed that although AP can be solved very fast, DMP can become a bottleneck in the process. In this talk, we will present a number of extended reformulations for DMP, including approximate extended reformulations [6], and discuss our extensive computational experiences with such reformulations.

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Detailed Production Planning Models with Flexible Lead Time Constraints

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Abstract

Semiconductor manufacturing facilities (fabs) probably include the most complex manufacturing processes, with hundreds of products, each requiring hundreds of operations on hundreds heterogeneous machines. Moreover, a product is processed in the same workshops dozens of times in its route. This leads to congestions in the facility and to cycle times of two to three months. Capturing all these characteristics in production planning is not an easy task. The current literature focuses on modeling congestion effects efficiently. Iterative simulation-optimization methods or modeling congestion using clearing functions have been shown to be efficient, but using fixed lead times remain an accurate and fast modeling approach. In this work, we investigate linear programming models with new constraints as an alternative to the classical fixed lead time constraint in order to offer more flexibility. Our models are first validated on small instances, and then tested on large industrial instances.

1 Introduction

In front-end semiconductor manufacturing (also called wafer manufacturing), production planning is very complex due to the system characteristics such as re-entrant flows, hundreds of operations to perform for each product, many heterogeneous machines of different types, etc. Efficient production planning is even more crucial in high-mix facilities, i.e. with many products, which correspond to most European semiconductor manufacturing facilities.

In production planning, quantities of products to be started at every period of the planning horizon must be determined to meet demands at lowest cost while satisfying capacity constraints. Detailed planning also aims at allocating capacity to products on their manufacturing routes. A large part of the research literature in semiconductor manufacturing has focused on modeling congestion effects. A first approach is to use fixed Lead Times (LT), i.e. a fixed delay in number of periods between the arrival of products at an operation and their completion. However, fixed lead times do not take into account that the actual lead times depend on the production quantities of the different products. In 1996, Hung and Leachman [3] tackle this circularity issue by proposing an approach that iterates between an optimization model and a simulation model. The optimization model optimizes the production plan given fixed lead times, and the simulation model determines the lead times given the production plan. A more recent way to model congestion is the use of (see e.g. [2] and [1]), i.e. non-linear functions that determine the output according to the workload.

2 Generic model for production planning

In this section, a generic model is introduced for planning the production of wafers, namely the production of P products over a discrete time horizon that has two timescales. The time horizon is decomposed into T days and S weeks. Demands are expressed per product and per week. Each product needs a sequence of operations $\mathcal{L}_p$ to be processed on a set of workshops. Each workshop can process a finite set of operations and has a finite capacity.

The plan is determined by optimizing internal production flows. The goal is to decide quantities X_{plt} to be released per product p, per operation l and per period t (day). The set of operations for each product and their resource consumption provide the timing of operations. In order to trace production flows, a variable W_{plt} that represents the work in process per product, per operation and per period (day) is introduced. The goal is to satisfy demands while minimizing inventory, backlogging and work in process costs. Lead Time constraints are also considered in this model, which are discussed in the following section.

3 Lead Time constraints

3.1 Fixed Lead Times

Constraints (1) ensure that the production of product p at operation l in period $t+LT$ (where LT stand for the lead time) is equal to the quantity that enters the queue in period t.

$$X_{plt} = Y_{pl(t+LT_{pl})} \qquad \forall p,\ \forall l \in \mathcal{L}_p,\ \forall t \in \{1, \ldots, T - LT_{pl}\} \tag{1}$$

Using Constraints (1) helps to quickly solve large linear programs because all production flows are determined by the production starts. Hence, there are "only"

$T * P$ important decision variables. But these constraints introduce some biases. First, the workload is associated with the last period of the lead time, which is not realistic. Second, when fixed lead times are too "tight", production flows are too constrained which leads to larger total costs (see Table 1). Third, fixed lead times must be adapted when the product mix is changing.

3.2 Flexible Lead Times

To tackle the limits of the fixed lead times and better smooth production, we propose to use new constraints to model flexible lead times. We define groups of operations in the route of products that can be processed in the same period. The parameter $o_p^{max}(l)$ defines the maximum number of operations before operation l in the route of of product p where a given production quantity can be processed in the same period than l. Note that $o_p^{max}(l)$ is set to $+\infty$ if all operations preceding operation l of product p can be processed in the same period. Let us replace Constraints (1) by Constraints (2).

$$Y_{plt} \leq \sum_{k=l-o_p^{max}(l)}^{l} W_{plt} \qquad \forall t,\ \forall p,\ \forall l \in \mathcal{L}_p \quad \text{s.t. } o_p^{max}(l) \neq +\infty \tag{2}$$

Constraints (2) specify that, at period t and for operation l of product p, only the production quantities that already are in the queue of operation l and the $o_p^{max}(l)$ previous operations of the route can be processed. Note that Constraints (2) ensure a minimum cycle time for each product, but are not as constraining as considering fixed lead times. Capacities are better smoothed on the planning horizon, and the additional flexibility helps to improve sharing the capacity of workcenters between products and at different levels of their routes.

4 Conclusions

In the workshop, models with Constraints (1) and with Constraints (2) will be compared using a small data set and an industrial data set. The following main indicators are considered: Total cost (inventory and backlog costs), total production output of finished products and planned lead times. The models are solved using a commercial linear programming solver. Some preliminary results on the small data set can be found in Table 1. The fixed lead times are determined based on the knowledge of the production system, and the flexible lead times are all set to 3.

In a context of high demand, between a solution with fixed lead times and a solution (unrealistic) with no lead times, the model with flexible lead times helps to find better solutions. This preliminary experiment shows that some flexibility on lead

Models	Fixed Lead Times	Fixed Lead Times = 0	Flexible Lead Times	Without Lead Times
Objective: Total cost	27,203	29,850	25,366	19,067
Total production output	553	546	556	571

Table 1: Comparison of different lead time models (unfeasible demand with small data set)

times allows for slightly more products to be produced than with fixed lead times and for a significantly lower (6.8% lower) total cost.

Our perspectives include the comparison of a model using a series of fixed lead times with a model using a series of flexible lead times, both models with the same overall expected cycle time. We are also working on validating our models on industrial data to validate the relevance of the production plans. Finally, new objective functions are being considered, in particular profit maximization.

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Applications of Lot Sizing

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Abstract

Lot-sizing lies traditionally in the manufacturing sector, but it is applicable not just to related areas such as process industries and supply chains, but also to innovative areas such as humanitarian logistics. We look at some of the applications that can be modelled using lot-sizing.

1 Introduction

This extended abstract simply lists some (but not all) of the articles that illustrate the variety of applications discussed in the presentation. The slides with a full list of references can be downloaded from `https://go.uwe.ac.uk/AlistairClark`

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Revisiting the Zero-Inventory Property in Remanufacturing

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Abstract

In a remanufacturing environment, a recovery option is to disassemble the acquired end-of-life products, known as “cores”, for their component parts. After they are refurbished, these parts can be sold as spare parts or used in new production. This process is referred to as parts harvesting in the remanufacturing literature. There may be different cores from which the parts can be harvested and the tactical level planning for the disassembly operations involves meeting the separate demands for the components parts over a planning horizon. Although this problem resembles the uncapacitated lot sizing problem, there are significant differences between the two. The well-known *zero-inventory property*, does not hold, since although there is still a trade-off between the setup and inventory holding costs, the setup cost is incurred when a core is dismantled to produce more than one unit of more than one component parts, which will in turn be carried in inventory and incur inventory holding costs. We address this issue and show how the zero-inventory property manifests itself in this context. For this purpose, we first provide a standard lot sizing formulation for the *single core* problem and present the adaptation of the zero-inventory property that will hold in an optimal solution to the problem. We also provide a reformulation of the problem and show that it can be solved in $O(T)$ time. We then extend the results to the case of multiple cores.

1 Introduction

One of the common disposition options in product recovery is parts harvesting. Component parts harvested from the returned or acquired end-of-life products (referred as cores) are refurbished and used as spare parts or in new production. When remanufacturers plan production they need to determine the lot sizes in which the cores are dismantled to harvest the required number of component parts demanded over a finite planning horizon. When a setup is incurred each time a new lot is processed, the problem becomes one of Uncapacitated Lot Sizing Problem (SRLS). It, however, differs significantly when parts have different demand requirements and the bill of material changes from part to part. Bill of material for component parts in a product may be of varying quantities such as; there is one mother board in a computer but more than one RAM cards. In this case, the *zero-inventory property*, first identified by Wagner and Whitin (1958) for the SRLS, does not apply even if all parts are demanded in the same amount. The well-known zero-inventory property suggests that there is production for a product in a period only when the inventory on hand for that product in the beginning of the period is zero. In remanufacturing, when there are more than one of the same component part in a core or the demand is different for different component parts, the zero-inventory property does not work. It is possible that the total number of parts harvested are more than the total demand over the periods considered.

We address this problem and suggest a modified rule that can be used similar to the zero-inventory property in solving lot sizing problems in remanufacturing.

Remanufacturing generally involves several disposition options such as; refurbishing, dismantling for parts harvesting, recycling, and/or salvaging. In order to keep our focus on the problem that we address in this paper, we include only parts harvesting, since it is this feature of the problem that presents the interesting violation of the zero-inventory property in SRLS.

For this purpose, we will first present a multi-core capacitated problem where, the demand for different component parts to be satisfied over a finite number of periods is known. When a core is dismantled the parts obtained can be used immediately to meet current periods demand or they can be inventoried to be used to meet the demand of future periods. There is a setup incurred before a batch (lot) of cores is dismantled. Similar to the UCLS problem the tradeoff is between the inventory holding and the setup costs. However, note that while the demand is for the parts harvested from the available cores, the setup is for dismantling the cores. Hence the tradeoff is not between the setup and the inventory holding costs for a core. It is between the setup cost for dismantling a core and the inventory holding costs of parts harvested from that core each of which may have a different demand. It is safe to assume that the holding cost for a core is low enough to be ignored or it is lower than the total holding costs of the dismantled and furbished parts. We also assume that core availability is higher than the demand or cores can be acquired in the desired amount just in time.

2 The Multi-Core Remanufacturing Lot Sizing Model MRLS

In this section we present our model that formulates the problem described in its classical form after providing the due definitions.

Indices:

i, m, n: core types in $\{1, \ldots, N\}$
t, k: time periods in $\{1, \ldots, T\}$

Decision Variables:

z_{it}: amount of core type i dismantled in period t;
u_{jt}: amount of inventory of part j at the end of period t;
y_{it}^d: 1 if a core type i is dismantled in period t; 0 otherwise;

Parameters:

d_{jt}^p: the demand for part j in period t;
c_i^d: the unit dismantling cost of a core;
K_i^d: the set-up cost for dismantling cores;
h_j^p: the unit inventory holding cost for part j;
a_{ij}: the number of part j obtained by dismantling core i;
M_{it}^d: an upper bound on the number of cores i dismantled in period t.

(MRLS):

$$\textsf{min} \quad \sum_{t=1}^{T} \left[\sum_{i=1}^{N} c_i^d z_{it} + \sum_{i=1}^{N} K_i^d y_{it}^d + \sum_{j=1}^{M} h_j^p u_{jt} \right] \tag{1}$$

$$\textsf{st.} \quad u_{j(t-1)} + \sum_{i=1}^{N} a_{ij} z_{it} - u_{jt} = d_{jt}^p, \quad j: 1, \ldots, M; \;\; t: 1 \ldots, T \tag{2}$$

$$z_{it} \leq M_{it}^d \, y_{it}^d, \quad i: 1, \ldots, N; \;\; t: 1 \ldots, T \tag{3}$$

$$z_{it} \geq 0, \quad i: 1, \ldots, N; \;\; t: 1 \ldots, T \tag{4}$$

$$u_{jt} \geq 0, \quad j: 1, \ldots, M; \;\; t: 1 \ldots, T \tag{5}$$

$$y_{it}^d \in \{0, 1\}, \quad i: 1, \ldots, N; \;\; t: 1 \ldots, T \tag{6}$$

The objective function minimizes the total processing and setup costs for dismantling and the total inventory holding cost for parts. Constraints (2) are the inventory balance constraints for the harvested parts. We assume no initial inventory for $t = 1$, since any such inventory can be subtracted from the demand. In the second term, we sum over all core types to find the total harvested amount for part j. For two core types m and n, the number of part j available in core m (a_{mj}) may or may not be the same with that in core n (a_{nj}). Constraints (3) are the set-up constraints for dismantling. Constraints (4) and (5) assure the non-negativity of the decision variables. Constraints (6) are for the binary variables indicating whether a core is dismantled in a period or not.

Problem MRLS looks similar to a SRLS, however, there are important differences:

i) The tradeoff in the objective function is between the setup cost for dismantling a core versus the inventory holding costs of the parts harvested from that core.

ii) The zero-inventory property does not hold. As well known the zero-inventory property says that there may be production in a period only when the beginning inventory of that period is zero. Since different parts (j) harvested from one core (i) may differ not only in number (a_{ij} values may be different) but also in their demand (d^p_{jt}) in any period (t), the zero-inventory property in its existing form does not hold.

To study how the zero-inventory property behaves in MRLS, we first consider its special case where, there is only one core type ($N = 1$). We also provide a reformulation of the problem and show that it can be solved in $O(T)$ time. We then extend the results to the multi core case.

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Leveraging Capacity Planning with Maintenance Insights

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Abstract

Production planning allows companies to manage the use of productive resources to meet the customers demand at a competitive cost. A recent trend in some industries is the simultaneous planning of production and capacity levels of those resources. Traditionally, these two problems have been addressed separately by the scientific community. In some manufacturing environments, the continuous productive resources are specialized and are subject to frequent repair and renewal operations to ensure their performance. Under these circumstances, capacity planning must be jointly tackled with production and maintenance decisions both to account for the unavailability periods, but also, to adjust capacity thanks to repair and renewal operations representing new opportunities. In this talk, we first study a strategic problem, where we have to decide which furnaces to replace/refurbish, which ones are to be upgraded to have higher capacities. We show by means of mathematical programming how the integration of the aforementioned processes can be performed in order to maximize respective benefits, building on a real-word case from a two-stage process glass container industry. We then tackle the tactical problem to decide when to schedule maintenance activities more precisely within a given production calendar. For this latter, we propose polynomial time algorithms for simpler versions of the global problem.

1 Introduction

Process industries are capital intensive leading to a strong focus on improving efficiencies and reducing costs to remain competitive. It is imperative that demand is satisfied in the most cost-effective manner. The main operational driver is to maximize the facilities throughput by means of processes' specialization to decrease downtimes. This is the case of the glass container industry that holds additional characteristics, such as high degree of competition between firms, highly seasonable and variable demand, and low profit margins. This industry has a two-stage production system, the furnaces produce glass paste that is then fed continuously to a set of parallel molding machines of different configurations that form the container. The furnace can only melt glass of one color at a time and, consequently, all machines attached to it produce containers of this color. The production of more than one color in a furnace generates important sequence-dependent setup times and costs related to color changeovers, reducing productive time. Therefore, a common practice in the glass industry is the specialization of a small set of colors to each furnace in order to minimize production capacity losses.

Moreover, furnaces and molding machines work in a continuous manufacturing process subject to repairing and renovation operations to ensure their correct performance and production capacity levels. Furnaces have a limited life cycle (approximately 20 years), requiring cyclical maintenance activities to be more performant and less costly. The replacement/refurbishment of a furnace can take several weeks during which the production of the glass is entirely stopped on this furnace. This non-production period is thus very costly for the firm. Which furnaces to replace and which ones to repair is a decision taken months in advance by the planners. Whenever a furnace is replaced, its capacity levels and downstream molding machine configurations might be adjusted. Under these circumstances, the simultaneous planning of production, capacity levels and maintenance of the productive resources is mandatory [2].

We first introduce a comprehensive mathematical programming model that integrates the aforementioned planning decisions, considering the two-stage production environment, at a strategic decision level. The aim is to decide which furnaces to replace or to repair, taking into account capacity and production planning, over a long time planning horizon. A decomposition MIP-based strategy is employed to solve this latter, and to show the impact of integrating such decisions. We then focus on a tactical problem, where the aim is to plan the replacement or the maintenance activities in a mid-term horizon while minimizing the total cost of production and inventory holding. We study several variants of the overall problem, and propose new polynomial time algorithms to exactly solve simpler subproblems.

In both approaches, we discretize the time horizon into T periods, a period corresponding typically to one month in the initial industrial case. We also assume that once the production of a specific color begins on a furnace, it lasts at least one period (one month). This constraint is related to the expensive changeovers detailed below in cost assumptions.

- The end-products are glass containers of different colors and different sizes. The color changes are made into the furnaces, and the change-over time between different colors takes one to four days which can be quite costly. It is thus important to consider sequence-dependent changeover costs and times.
- The unit production cost increases with the age of the furnace. This is due to the fact that an aged furnace is less energy efficient, and more natural gas is required to achieve the same production level. After a repair/replacement activity, this cost naturally decreases.

2 Strategic maintenance planning problem

In this strategic problem, we have to decide which furnaces are to be replaced or refurbished, which ones are to be upgraded to have higher capacities. We propose a mathematical model to show the impact of the integration of aforementioned activities into the classical production planning.

2.1 Comprehensive MIP model

This model decides on the timing of repair and renewal activities on each furnace along the planning horizon, together with the typical production planning (in this case, lot sizing) decisions. In case of a furnace renewal, both new capacity level of the furnace and configurations of the underlying machines can emerge. Our model attempts at minimizing the total costs associated to production cost of fluid glass at the furnace and the corresponding energy costs, production cost of the end products at molding machines and their corresponding energy costs, inventory holding costs, backorder costs, setup costs for products and configuration changes in machines.

2.2 Decomposition algorithm

Given the complexity emerging from the integration of the several decision making dimensions, we resort to a decomposition algorithm to be able to generate good quality solutions within reasonable computational time. We explore the hierarchical nature of the decisions to design an efficient search algorithm by identifying and exploring the most promising periods to perform the maintenance actions. The search is carried out within a tree which guides the quest for better solutions.

3 Tactical maintenance planning problem

The objective is to decide when to schedule the replacement or repair activities more precisely in the production calender in order to minimize the overall production and holding cost, while satisfying customer's deterministic demand [3]. Thus, this problem can be classified into the lot sizing problem literature integrated with the maintenance scheduling for multi-furnaces producing multi-colors. To devise polynomial time-algorithms, we consider that repair/replacement activities on the furnaces have been already decided over a given time horizon (e.g. over 2 or 3 next years). Hence, given a subset of furnaces where repair/replacement activities must be conducted, we have to decide a date for each activity together with a production planning taking into account the loss of capacity due to the unavailability of some furnaces. We focus on the upstream level, the furnaces, aggregating the products into color families.

The furnaces are continuously producing glass melt (24h/24h, 7days), at their full capacity. Since each furnace produces a single color per period, and at most one changeover can take place in each period, the lot-sizing problem can be modelled as a multi-machine multi-item discrete lot-sizing and scheduling problem (DLSP) with sequence-dependent changeover costs and times. DLSP is known to be NP-hard even in case of 2 items and a single resource [1]. Assuming a stationary capacity C, we derive a polynomial time algorithm, based on dynamic programming, when the number of colors is fixed. Our algorithm can be extended to consider the shortage of demand, through backlogs or lost sales.

We also consider the more general model with single-changeover per period. In this case, the all-or-nothing constraint of DLSP is relaxed. On one hand, the furnace has a limited capacity C^{max} to not exceed in each period, which represents the total quantity in tonnes of glass melt during a period. On the other hand, the quantity produced cannot be lower than C^{min}, due to the technical issues of the furnaces and efficiency considerations. Hence, in each period where the furnace is operating, the quantity procuced must lie between C^{min} and the above-mentioned maximum level C^{max}. Notice that DLSP is a special case of this problem when $C^{min} = C^{max} = C$. We also adapt our dynamic programming to this version of the problem.

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An optimization model for the general lot sizing and scheduling problem in beverage production

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Abstract

The present research studies the general integrated lot sizing and scheduling problem for nonalcoholic beverage settings with synchronized production stages. To the best of our knowledge, it is the first effort in using time windows to model preventive maintenances and perishability. Preliminary computational tests indicate that the model is flexible and adherent to represent practical scenarios.

1 Introduction

Over the past 20 years, academics and practitioners have been developing a large number of papers that propose mathematical models to represent integrated decisions of lot sizing and scheduling. In particular, there has been a substantial effort in devising optimization approaches applied to the beverage industry. However, most of the existing models ([6], [1], [2]) reflect specific characteristics of real plants and it is not easy to adapt them to represent general processes.

In this paper, we present a novel mixed-integer linear optimization model to deal with the general lot sizing and scheduling problem in the beverage industry in which the production process is composed of two stages. Differently from the available models in the literature, our formulation does not require that the machines from the first stage be dedicated to a set of machines of the second stage. In addition, we include time windows to schedule preventive maintenance and to consider the perishability of the raw material.

2 Problem description

The beverage production process consists of two main stages. In the first stage, the flavour of the beverage, called syrup from now on, is prepared in tanks with a dilution of ingredients. In the second stage, the final product is finalized in the bottling lines. It is added gas and water in the syrup then they become a soft drink ready to fill the bottles.

During the first stage, only one flavor can be prepared for each batch and it is necessary that the mixed tank is completely empty before a new batch can be produced. To ensure the homogeneity of the liquid produced, it is required a minimum amount of liquid sufficient to cover completely the mixer blades [2]. There is a maximum capacity of each tank in liters. In the second step, the beverage is bottled. The syrup is perishable so there is a maximum time to bottle it.

The bottling lines have a conveyor belt that moves these containers throughout the processes. After the bottles have been sanitized, these containers are filled with the beverage up to its limits. Each bottling line produce different set of items depending mostly on the bottle size. Their capacities are limited and measured in minutes. The processing time is different for each item.

The setup of the lines corresponds to the cleaning of the equipment and some mechanical adjustments due the bottle sizes. In the first stage, the setup refers to the cleaning and the syrup preparation. As the tanks capacities are limited, high demands of one item may result in a preparation of many batches. The cleaning are sequence-dependent in both stages. Because of the syrup preparation, there is setup time even between batches of the same flavour in the first stage, whereas there is setup time only between different items in the second stage.

The bottling lines cannot receive syrup from more than one tank per time, while a tank can supply many lines simultaneously. The interdependency between the stages and the sequence-dependent setup times might yield in waiting times from one stage to the other when the production programming is defined, which can result in the lost of syrup due its perishability. Thus, it is essential to guarantee that the syrups are produced only if they can be bottled by the second stage lines. In this way, the setup times and the preventive maintenance might be included in the schedule.

3 Proposed model and conclusions

For the sake of brevity we are presenting only the ideas of the main constraints.

In the mathematical model, the objective function minimizes the total costs of inventory, backlogging, and setup. The classical constraints of integrated lot-sizing and scheduling problems are well known in the literature (see for example, [1] and [6]) and they are present in the formulation.

In the preset paper the time windows for maintenance must be inserted before or after the line produce its period production plan. In the classic lot-sizing models the machine capacity constraints are associated with the period capacity constraint. So, to limit the capacity of the machine it is reduced the period size. However, in multi-stage problem it is interesting to control the exact moment in which the the machine is available to produce into the period, disassociating it from the period capacity.

To deal with time windows for the maintenance and perishability of syrup it was created constraints to control the capacities (or availability of production) lines/tanks in the period. It must be permitted that lines start the production in the middle of the period, and/or stop before the end of a period, allowing maintenance to occur out of the production time windows. Notice that this is different from only reducing the capacity of the lines.

To test the effectiveness of model and the impact of time windows for maintenance and syrup utilization it was generated sets of instances based on literature data. The results showed that in fact the model is adherent and flexible to represent several types of production plants that can be found in practice of industry.

Based on the results, it can be concluded that characteristics such as the perishability of syrups and the scheduling of preventive maintenance can significantly affect the production plans and consequently the total costs.

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A Case Study in the Glass Container Industry: Thermos flask production

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Abstract

The present paper reports a case study based on the production process of a Glass Container Industry located at Minas Gerais State, Brazil. The industry produces thermos flask with glass inner where there is a single oven connected to two machines. These machines manufacture three different ampoules. Currently, the decision-making process is based on the experience of the person in charge of production and it does not apply any technique to optimize the production process. During this case study, a tailor-made mathematical formulation was elaborated to describe the production planning. Next, an exact approach, based on branch cut algorithm from Cplex Solver, is applied to solve this problem as well as an evolutionary algorithm. The results achieved by these methods solving a set of instances are reported and analyzed on this paper.

1 Introduction

The production process in the Glass Container Industry (CGI) is usually composed of two main stages. In the first stage, the glass raw materials are melted by a furnace. In the second step, the containers are produced by molding machines [1],[2]. In our case study, the GCI produces different types of thermos flask to meet a specific demand within a time horizon. The main contribution of this paper is the proposal of a mathematical model based on information gathered from the GCI. We will refer to the problem here approached as Problem in Glass Industry - Thermos Flask (PGI-TF). The paper also reports the application of an exact method and a simple Genetic Algorithm (GA) based on [4] to solve the PGI-TF. The model allows the application of the B&C method from CPLEX solver, aiming to solve optimally the PGI-TF instances. The GA seeks to achieve viable solutions for the same instances within a reasonable computational time.

2 Problem and Model

The model parameters and decision variables are summarized next:

Sets:

- k: Machines available $(k = 1, ..., K)$.
- i: Products to be manufactured $(i = 1, ..., m)$.
- t: Time horizon $(t = 1, ..., T)$.

Parameter:

- F: Capacity of the furnace (kg)
- C_i: Cost of the product i
- D_{it}: Demand of product i in period t.
- P_i: Product weight i. (Kg)
- Q_{ik}:Lot size of thermos flask i produced by machine k without setup.
- R_{it}: product i scrap in period t.

Variables:

- I_{it}: Inventory of product i in period t.
- Y_{itk}:1 if product i is produced in period t by machine k; 0 otherwise.
- PL_{itk}: Net output of product i within period t in machine k.
- PT_{itk}: Total output of product i in period t from machine k.
- S_{itk}: 1 Setup of product i in period t on machine k; 0 otherwise.

Mathematical Formulation:

$$Max \sum_{i=1}^{m}\sum_{t=1}^{T}\sum_{k=1}^{K} PL_{itk}.C_i \tag{1}$$

s.a:

$$I_{it} = \sum_{k=1}^{K} PL_{itk} + I_{it-1} - D_{it} \qquad \forall \quad (i, t > 0) \tag{2}$$

$$\sum_{i=1}^{m}\sum_{k=1}^{K} PT_{itk}.P_i \leq F \qquad \forall \quad (t) \tag{3}$$

$$PL_{itk} = PT_{itk} * (1 - R_{it}) + Q_{ik} * S_{itk} * (-\frac{1}{3} + \frac{1}{3}R_{it}) \quad \forall \quad (i, t, k) \tag{4}$$

$$PT_{itk} = Q_{ik} * Y_{itk} \qquad \forall \quad (i, t, k) \tag{5}$$

$$\sum_{i=1}^{m} Y_{itk} = 1 \qquad \forall \quad (t, k) \tag{6}$$

$$S_{itk} \geq Y_{itk} - Y_{i(t-1)k} \qquad \forall \quad (i, t > 0, k) \tag{7}$$

$$S_{itk} = Y_{itk} \qquad \forall \quad (i, t = 0, k) \tag{8}$$

$$Y_{itk} = Y_{it(k-1)} \qquad \forall \quad (i, t, k > 0) \tag{9}$$

$$Y_{itk}, S_{itk} \in \{0, 1\} \tag{10}$$

$$I_{it}, PL_{itk}, PT_{itk} \geq 0 \tag{11}$$

The objective function (1) maximizes net production. The constraints (2) represent the inventory balancing equation. The constraints (3) limit the total production to the melting capacity of the furnace within the period.The constraints (4) state that the net production of the thermos flask will be the total production minus the number of thermos flask lost during the production process, considering whether there was a *set-up* or not during the period. The constraints (5) describe that the total output must be equal to the production capacity of the machine, within a regular day, only if the product is produced. The production will be zero, if the product is not assigned to machines. The restriction (6) allows only one product to be produced by a machine within a time period. The constraints (7) and (8) represent setup, where the difference between the active product in the current period and the previous period will determine whether or not there is setup. The constraints (9) state that the same product must be produced by machines within a time period. The constraints (10) and (11) give the domains of the decision variables.

3 Results and Discussions

The exact method B&C and the GA are applied to solve 17 instances of the PGI-TF, where the instances data were provided by the CGI. The genetic algorithm was developed using the Professional Optimization Framework (ProOF) [3]. The methods run within the short time limit of 30 sec. The GA is executed 10 times over each instance. Figure 1 compares the methods performance taking into account the CPU time. The B&C and GA are compared in Figure 1(a), while the GA is evaluated based on its minimum, maximum and average time in Figure 1(b).

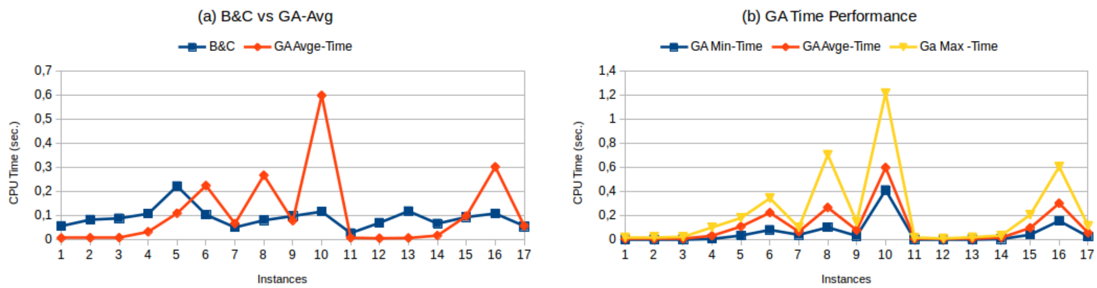

Figure 1: Methods Execution Time

4 Conclusion

The exact and evolutionary methods were able to find the optimal solution for all instances. The GA also returns the optimal solutions for all 10 executions over each instance. The B&C achieves optimal solutions before the time limit of 30 sec. The GA finds on average optimal solution faster than BC for 13 out of 17 instances.

Acknowledgment

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Integrated Lot Sizing and Blending Problems

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Abstract

The standard blending problem consists of combining ingredients to produce a final product with a given demand, while satisfying specific criteria with respect to the global blend and minimizing the total cost. The Bill-Of-Material (BOM) (or recipe) indicates which ingredients are used and in which proportion. In some cases, there is some flexibility in the planning process with respect to the proportion imposed for each of the ingredients, where it can vary between a minimum and a maximum level instead of being fixed. This problem has been widely studied in a single period setting. However, the problem becomes more complex when we take into account a longer time frame. In such a case, demand for the final product occurs in several time periods, and both the final product and the ingredients can be held in stock. In the integrated lot sizing and blending problem, the decisions relate to the production of the final product via the blending process, and the production (or procurement) of the ingredients over an extended time horizon.

We propose mathematical formulations for this integrated problem. In a computational experiment, we analyse the impact of important parameters such as the level of flexibility in the BOM, the variance in the procurement cost among the ingredients, and the variance of the proportion of the ingredients in the total mix. Furthermore, we analyse the value of integration by comparing the solutions of the integrated models to the solutions of approaches that do not fully capture this integration such as a lot-for-lot approach, models without inventory for the final product or ingredients, and a hierarchical approach.

1 Introduction

Most end products are produced using several components and subassemblies. In many cases, the Bill-of-Material is fixed, meaning that for each final product, it is known in advance how many units of each component will be needed. However, in some cases there might be some flexibility with respect to the proportion imposed for each of the ingredients, where it can vary between a minimum and maximum level instead of being fixed. One case that has already been studied in the lot sizing literature is the case of alternative components, where the company has the choice between different versions of a component. This is the case of lot sizing with component substitution (see e.g., Balakrishnan and Geunes 2000). In these cases, there are preferred components to meet a specific demand which may be eventually replaced by alternative products, leading to a replacement cost. Practical applications for lot sizing problems with component substitution can be found, for example, in the electronics and metallurgical industries (Denton and Gupta, 2004, Galego et al., 2006, Lang and Shen, 2011). In certain industries (e.g., food, steel), however, there is some flexibility with respect to the amount or volume that is needed of each component (sometimes referred to as ingredients). The proportion of the different ingredients in the final mix can vary as long as certain constraints are satisfied. In a single-period setting, this problem is well-known and is referred to as the blending problem. However, in a medium term planning perspective, this problem does not only require a solution for the blending problem in each production period, but also the planning of the production of the end items and components.

2 Analysis of BOM Flexibility

We consider different levels of BOM flexibility and analyse the value of the BOM flexibility in relation to the base case without flexibility. The results show that the value of BOM flexibility depends on the characteristics of the instances. For all levels of BOM flexibility, we observe that the benefits, which is measured as the percentage decrease in the objective function value compared to the base case, are the highest for the instances with 10 ingredients, low setup cost for the end product and high production cost of the ingredients and the benefits reach 16.5% for these classes of instances. In relation to the classes of instances, note that when the capacity is tight the benefits of BOM flexibility decrease. By increasing the number of ingredients the benefits of flexibility also increase. The time between order for the ingredients (TBO) has no significant impact on the benefits of the BOM flexibility. When the setup cost of the en products is low the benefits of BOM flexibility are bigger than the instances with high setup cost of the end products. Finally, when the production cost of the ingredients is high, the benefits of BOM flexibility are bigger than the instances with low production cost of the ingredients.

3 Analysis Value of Integration

In this section we analyse the value of the integration of the lot sizing and blending problem considering the approach in which the models are solved separately. In other words, we first solve the lot sizing problem for the end product and with the variables x_t^E that were found we solve the problem for the ingredients.

Considering the value of the integration we see that it depends on the characteristic of the problem. The biggest benefit is on average around 11% which is found for the problems with normal capacity, high setup costs for the end product and low production costs for the ingredients. On the other hand, considering tight capacity the benefit of the integration decreases to 3.8%. Furthermore, the results show that increasing the level of BOM flexibility the benefits of the integration decrease.

4 Conclusions

In this work, the integrated lot sizing and blending problem is studied. Three different new formulations have been proposed, and the value of the BOM flexibility is analysed, i.e., the proportion imposed for each of the ingredients can vary between a minimum and a maximum level instead of being fixed. Furthermore, the value of the integration of these two problems is also analysed compared to four different approaches that do not fully capture this integration. Our computational experiments show that, there is a significant difference in terms of the LP values and the formulation using the transportation approach found better lower bounds, especially for instances with high level of flexibility. However, the IP values are similar for all classes of instances considering the fixed time limit of 1800 seconds. The results also show that the value of BOM flexibility depends on the characteristics of the instances and this value is highest for the instances with 10 ingredients, low setup cost for the end product and high production cost of the ingredients in which the benefits of BOM flexibility reach 16.5%. Finally, we also see that there is a significant value of considering the integrated model compared to all of the other approaches analysed.

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Multi-stage stochastic capacitated lot sizing under tight service constraints

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Abstract

This work introduces a responsive multi-stage approach for stochastic capacitated lot sizing with uncertain demand in rolling horizons. For each period the decision is taken in two steps: The setup pattern is determined some periods in advance based on the distribution parameters of demand. The actual production quantities, however, are determined in the respective period, factoring in previously realized demand observations. By considering expected costs for additional production in the optimization, optimal implicit dynamic safety stocks are determined. Model extensions allow avoiding shortages in demand fulfilment completely, to determine robust plans in planning situations with limited overcapacity and to enable optimal adjustments of the predetermined setup pattern. Due to incorporating observed realizations of random variables when taking further decisions, this approach leads to both more stable production plans and less total costs in stochastic production environments.

1 Introduction and problem description

The presented planning approach aims at dealing with the problem of finding optimal decisions on both the setup pattern and the production quantities for the single level, multi period, multi product lot sizing problem with a single production resource and scarce but extendable production capacity. Backlogs are allowed and controlled either by penalizing them in the objective function or by limiting them with service-constraints. Setups on short notice are more expensive than regular ones.

Deterministic lot sizing approaches leave aside the stochasticity of input parameters like uncertain demand. Stochastic lot sizing approaches, like Helber et al. (2013) ([1]) and Tempelmeier and Hilger (2015) ([2]), however, incorporate that stochasticity. But many of those approaches are static, as they decide on both production times and production quantities before any demand is realized. Therefore, those decisions are often premature: If demand is underestimated, delivery reliability will be low, while an overestimated demand would lead to high inventory holding costs. A more promising way of incorporating stochasticity in lot sizing is to use some kind of multi-stage approach. Such an algorithm is introduced in this work, as it takes prior demand realizations into account when deciding on the production quantities for subsequent periods. Unlike static approaches, the responsive approach ensures meeting a given service level, and first results show that in many problem instances it also leads to lower total costs.

2 The responsive multi-stage algorithm

Within the proposed multi-stage planning approach the production plan is determined in rolling horizons. For each period, decisions are taken in two steps. As a first step, an initial setup pattern for the respective period is determined some periods in advance based on the distribution parameters of the demand, before demand realizations for that period are known. This ensures a certain level of predictability and stability of the production plans.

The second step is performed after the demand realization for the period has been observed. With this new demand information and updated demand forecasts, the production plan is re-optimized, while the already fixed variables are retained. This allows responding to the demand realizations and to adapt the production plans in a reasonable way. All available demand information is considered in the decision. This also ensures to accomplish a target service-level with certainty, which cannot be guaranteed in static stochastic lot sizing.

The updated plan can imply changes in the fixed setup pattern, due to cancelled setups or additional setups scheduled on short notice. Those short-termend decisions are considered particularly costy and therefore short-termed adjustments are only used to react to unexpected demand realizations if unavoidable or economically reasonable.

Figure 1 shows an example of a production plan determined with the introduced responsive multi-stage algorithm with a rolling horizon approach. It depicts the results of the optimization executed in period 2. In this example, it is assumed that the setup pattern is specified three periods in advance. In order to avoid myopic production plans, the algorithm comprises two additional periods in any optimization. So in this example, in period 2 the production plan is calculated for the periods 2 to 6. However, the setup pattern is fixed only for the periods 2 to 4 while the plan for the additional periods 5 and 6 is still alterable. Although calculated for all the periods considered, the production quantities are only fixed for the current period 2.

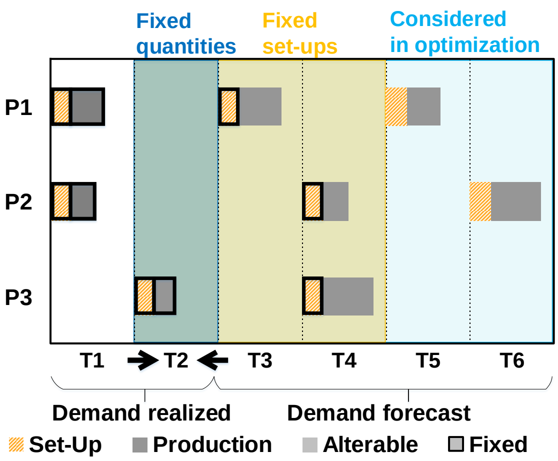

Figure 1: Exemplary plan determined with the proposed multi-stage algorithm

3 Expected costs for additional production

The objective function not only considers costs for inventory holding, setup activities and overcapacity, but also takes into account the expected costs for additional setups as a function of the production quantities and the demand information. As this additional production might as well lead to additional overcapacity, the expected overcapacity costs for the additional production are also considered. This leads to dynamic implicit safety stocks, whose levels are chosen endogenously depending on the current utilization. Those safety stocks reduce the realized total costs as well as they increase the stability of the production plans and therefore enhance the performance of the algorithm considerably.

4 Avoidance of realized backlogs

The service-constraints are implemented as cyclic waiting time constraints. Backlogs are restricted by limiting the mean waiting time of demand fulfillment in each production cycle. This formulation avoids the disadvantages of the well known service-level constraints.

Applying static stochastic lot sizing approaches, the choice of the postulated service level strongly influences the total costs in the optimal solution and therefore the deviation from the ex-post optimum. Very tight service level restrictions with few accepted backlogs lead either to extraordinary high safety stocks or to particularly dense setup patterns, resulting in high cost deviations from the ex-post optimum.

The proposed responsive algorithm, by contrast, is able to find solutions with significantly lower ex-post deviations by taking into account the expected costs for additional production as described in section 3. By considering these expected costs in every optimization run, safety stocks are produced, which reduce the probability of a violation of the target service level to an economically reasonable level. However, the violation of the service level is still accepted with low probability in the optimum in order to avoid excessive safety stocks. In case a demand realization is observed, which would lead to a violation of the postulated service level, an additional setup is carried out and the missing quantities are produced to reduce the realized backlogs to the accepted level. This approach makes stochastic lot sizing with very tight service restrictions possible. In an extreme case it is even able to deal with problem instances without any realized backlogs with moderately increased total costs.

5 Limiting allowed overcapacity

To guarantee feasibility, in the basic variant of the model an unlimited amount of allowed overcapacity is assumed. However, in reality overtime is restricted due to organizational reasons or legal requirements. Therefore, applying a robust approach is necessary in cases with limited overcapacity.

In the service-constrained model, feasibility can no longer be guaranteed. When demand realizations are particularly high, performing an additional setup and using all the available overcapacity for additional production might not be enough to limit the backlogs to the accepted level. Therefore, a feasibility robust approach is applied by introducing an additional chance constraint, which ensures feasibility in a given percentage of possible demand realizations. In order to avoid over-conservativeness, the concept of budgeted polytopes is applied to limit the total number of parameters that are allowed to take extreme values [3].

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Approximation algorithms for lot-sizing problems using sandwich functions

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Abstract

We consider single-item lot-sizing problems which are (NP-)hard because of the shape of the objective function, typically not concave. We propose polynomial time approximation algorithms based on a 'sandwich' technique, in which the objective function of the original problem is bounded from below and above by simpler cost objective functions. In fact, finding the tightest sandwich function is an optimization problem on its own, of which the result determines the obtained approximation ratio, typically depending on the problem parameters. We show that this idea can be applied to several lot-sizing problems such as the problem with batch procurement. Moreover, in case of a separable objective function where each component can be sandwiched, we provide an approach to generate multiple solutions all satisfying the approximation ratio, an interesting feature that is not common for approximation algorithms.

1 Introduction

Consider the minimization problem (P)

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & x \in F, \end{array}$$

with $f(x)$ some 'complicated' objective function and F the feasible region. Suppose that we are able to find some 'easy' function $r(x)$ and parameter $\beta > 1$ satisfying

$$r(x) \leq f(x) \leq \beta r(x) \text{ for any } x \in F.$$

Then we say that $f(x)$ is β-sandwiched by $r(x)$. Now consider the relaxed problem

$$\begin{array}{ll} \min & r(x) \\ \text{s.t.} & x \in F, \end{array}$$

and assume it can be solved efficiently with $\hat{x}$ an optimal solution. Then it is not difficult to verify that $\hat{x}$ gives a β-approximation for problem (P). We will apply this principle to several lot-sizing problems.

2 Lot-sizing with batch procurement

Consider some lot-sizing problem with a FTL cost structure with batches of size B. That is, the cost to order a quantity $x \geq 0$ is given by:

$$f(x) = K\mathbb{I}(x > 0) + \lceil x/B \rceil k + px$$

with $K \geq 0$ the setup cost, $k \geq 0$ the fixed cost per batch, $p \geq 0$ the unit ordering cost and $\mathbb{I}(\cdot)$ the indicator function. It is not difficult to verify that for $x \geq 0$ the function $f(x)$ is 2-sandwiched by the affine function

$$r(x) = \tfrac{1}{2}(K + k)\mathbb{I}(x > 0) + \tfrac{1}{2}(k + p)x.$$

However, we can find a tighter sandwich function. To this end, consider the parameterized function

$$r_\alpha(x) = (K + \alpha k)\mathbb{I}(x > 0) + ((1 - \alpha)k + p)x$$

with $0 \leq \alpha \leq 1$. If $f(x)$ is β-sandwiched by $r_\alpha(x)$, then one can verify that the conditions $\beta K + \beta\alpha k \geq K + k$ and $\beta(1-\alpha) \geq 1$ should hold. Therefore, the 'optimal' sandwich function can be found by solving the (non-linear) optimization problem

$$\min_{\alpha,\beta} \quad \beta$$

$$
\begin{aligned}
\text{s.t.} \quad & \beta K + \beta\alpha k \geq K + k, \\
& \beta(1-\beta) \geq 1, \\
& 0 \leq \alpha \leq 1,
\end{aligned}
$$

which has an optimal objective value of $\beta^* = \frac{K+2k}{K+k} < 2$ for $K > 0$. For instances such that $K \geq k$, which is a quite realistic assumption, we obtain an a posteriori performance guarantee of at most 3/2.

We can apply this result to find approximation algorithms for the following two lot-sizing problems: multi-level lot-sizing (i) with time-independent but level-dependent batch deliveries, and (ii) with time-independent but level-dependent capacities, which both can be shown to be NP-hard. By using the above sandwich function for each level i and period t and solving this relaxed problem with the $O(LT^4)$ algorithm of [2], a β-approximation algorithm with $\beta \leq 2$ can be obtained.

3 Obtaining multiple solutions in case of a separable objective function

In many cases the objective function $f(x)$ is separable and can be written as $f(x) = \sum_{i=1}^n f_i(x)$. The next proposition states that, if each function f_i can be sandwiched, then f is not sandwiched worse than any f_i. More precisely, by denoting $y^+ \equiv \max_{i=1,\ldots,n}\{y_i\}$ as the maximum value over its components for a vector $y = (y_1, \ldots, y_n)$, we have:

Proposition 1. *If each function f_i is β_i-sandwiched by some r_i, for $i = 1, \ldots, n$, then $f = \sum_{i=1}^n f_i$ is β^+-sandwiched by $r = \sum_{i=1}^n r_i$.*

As is common for approximation algorithms in general, one only obtains a single solution. This can be considered a weakness of an approximation algorithm, in case the solution is for example used as an initial solution for a meta-heuristic such as local search or simulated annealing. However, we discuss now how to use sandwich approximations to potentially obtain multiple solutions, all with the proven performance guarantee. First of all, one would intuitively expect that optimizing over functions $\alpha_i r_i(x)$ with $1 \leq \alpha_i \leq \beta_i$, provides a solution closer to the optimal one as $\alpha_i r_i(x)$ better resembles $f_i(x)$. This results into the problem (R_α):

$$
\begin{aligned}
\min \quad & \sum_{i=1}^n \alpha_i r_i(x) \\
\text{s.t.} \quad & x \in F.
\end{aligned}
$$

The next proposition shows that we do not loose much in terms of the approximation factor when solving (R_α).

Proposition 2. *An optimal solution $\hat{x}$ of (R_α) has a performance guarantee of $(\beta/\alpha)^+\alpha^+$ for problem (P).*

In fact, for a suitable choice of α_i, we can still obtain a performance guarantee of β^+, for example, if we set $\alpha_i = (1-\lambda)+\lambda\beta_i$ or $\alpha_i = \beta_i^\lambda$, where λ is a real value in $[0,1]$. As a consequence of Proposition 2, we can try different α_i values to obtain multiple solutions, all of them with a performance guarantee of β. One way to accomplish this is by solving the parametric problem (R_λ):

$$
\begin{aligned}
z(\lambda) = \quad & \min \quad \sum_{i=1}^{n}(1+\lambda\beta_i)r_i(x) \\
& \text{s.t.} \quad x \in F,
\end{aligned}
$$

for $\lambda \in [0,1]$, which boils down to performing a parametric analysis on the objective coefficients. The function $z(\lambda)$ is a piecewise linear and concave, where each piece corresponds to a solution. A complete characterization of the function can be obtained by a method introduced by [1]. In this algorithm one needs to solve problem (R_λ) at most $2m+1$ times where m is the number of line segments. This results in a running time of $O(mT)$, where T is the running time of solving problem (R_λ) for a given λ.

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Decomposition methods for a capacitated three-level lot sizing and transportation problem with a distribution structure

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Abstract

We address a three-level lot sizing and transportation problem with a distribution structure (3LSPD). We consider one production plant that produces one type of item over a discrete and finite planning horizon. The items produced are transported to warehouses and then to retailers using direct shipments. Each retailer is linked to a unique warehouse and there are no transfers between warehouses nor between retailers. The objective is to minimize the sum of the fixed production and ordering costs and of the unit variable inventory holding costs. We use decomposition methods to solve exactly a capacitated version of the problem, where the capacity constraint limits the amount of goods that can be produced by the plant in each time period. The decomposition methods include Dantzig-Wolfe decomposition and Benders decomposition. We run experiments on both a balanced and an unbalanced network (in the balanced network each warehouse serves the same number of retailers whereas in the unbalanced network 20% of the warehouses serve 80% of the retailers). We compare our results with the ones obtained by a commercial solver to analyze the strenghts and weaknesses of our methods.

1 Introduction

We address here an integrated and capacitated three-level lot sizing and transportation problem with a distribution structure (3LSPD). We consider a general manufacturing company that has one production plant (level one), several warehouses (level two) and multiple retailers (level three) facing a dynamic and known demand for one item over a discrete and finite time horizon T. The supply chain considered here has a distribution structure: the warehouses are all linked to the single plant and all retailers are linked to exactly one warehouse. When we consider the demand of a particular retailer, the flow of goods in the supply chain network is hence as follows: an item is produced at the production plant, then sent to the warehouse linked to the retailer for storage and finally sent to the retailer to satisfy its demand. The objective of the problem is to determine the optimal timing and flows of goods between the different facilities while minimizing the operational and transportation costs in the whole network (sum of the fixed setup and transportation costs and unit inventory holding costs).

The motivation to work on decomposition methods for the capacitated 3LSPD is to improve the results obtained in a previous work. In particular, we want to use our knowledge of the problem and exploit its substructures to improve the time taken to solve it.

2 Dantzig-Wolfe decomposition

Employing the idea of an echelon stock presented in Federgruen and Tzur [1], the 3LSPD can be decomposed into several independent single item uncapacitated lot sizing problems (SI-ULSP). To do so, the inventory variables typically used in lot sizing models are replaced with echelon stock variables representing the total inventory of one item at all descendents of a particular facility.

Let $G = (F, A)$ be a graph where F is the set of nodes (facilities in our problem) and A is the set of arcs. Let $P = \{p\} \subset F$ be the set containing the unique production plant, $W \subset F$ be the set of warehouses and $R \subset F$ be the set of retailers. Let $\delta(i)$ be the set of all direct successors of facility i and $\delta^w(r)$ be the warehouse linked to the retailer $r \in R$. Let d_t^r be the demand for retailer r in period t. The notion of the demand faced by any retailer is extended to the production plant by setting $d_{pt} = \sum_{r\in R} d_{rt}$, and to the warehouses by setting $d_{wt} = \sum_{r\in\delta(w)} d_{rt}$ for any warehouse w. We also introduce D_{it}, the total demand between period t and the end of the time horizon computed as $D_{it} = \sum_{k\geq t} d_{ik}$. We define hc_{it} as the unit holding cost at facility i in period t, and sc_{it} as the setup cost for facility i in period t. We further denotes C as the available capacity for production at each time period. Let x_t^i represent the production quantity in period t at the plant level and the quantity ordered from the predecessor at the warehouse and retailer level. Let y_t^i be a boolean setup variable taking value 1 iff $x_t^i > 0$. Finally, let E_{it} be the echelon stock variables. The echelon stock formulation ES is as follows:

$$\text{Min} \sum_{t \in T} \left(\sum_{i \in F} sc_{it} y_{it} + \sum_{p \in P} hc_{pt} E_{pt} + \sum_{w \in W} \left(hc_{wt} - hc_{pt} \right) E_{wt} + \sum_{r \in R} \left(hc_{rt} - hc_{\delta_w(r)t} \right) E_{rt} \right) \tag{1}$$

$$\text{s.t. } E_{i,t-1} + x_{it} = d_{it} + E_{it} \qquad \forall\, t \in T, i \in F \tag{2}$$

$$x_{it} \leq D_{it} y_{it} \qquad \forall\, t \in T, i \in F \tag{3}$$

$$x_{it} \leq \min\{D_{it}, C\} y_{it} \qquad \forall\, t \in T, i \in F \tag{4}$$

$$E_{it} \geq \sum_{j \in \delta(i)} E_{jt} \qquad \forall\, t \in T, i \in P \cup W \tag{5}$$

$$x_{it}, E_{it} \geq 0 \qquad \forall\, t \in T, i \in F \tag{6}$$

$$y_{it} \in \{0, 1\} \qquad \forall\, t \in T, i \in F. \tag{7}$$

The objective function (1) minimizes the sum of the fixed setup and transportation costs and of the unit echelon inventory holding costs. Constraints (2) are the inventory balance constraints using the echelon stock variables. Constraints (3) are the setup forcing constraints. Constraints (5) are the echelon stock constraints ensuring that the echelon stock at a specific facility is greater than the sum of the echelon stocks at all its direct successors. Constraints (4) are the production capacity constraints.

The ES formulation has the advantage of containing a SI-ULSP substructure in constraints (2)-(3). We exploit this substructure by applying a Dantzig-Wolfe decomposition to (1)-(7). We propose two different decompositions. In the first one, we keep constraints (4) and (5) in the master problem and have a SI-ULSP subproblem for each facility. In the second decomposition, we only keep constraints (5) in the master problem. We then have a single item capacitated lot sizing (SI-CLSP) subproblem for the production plant and a SI-ULSP subproblem for each of the warehouses and retailers. The idea is then to use a column generation algorithm to generate the variables of the Dantzig-Wolfe reformulation and work with these generated variables in the master problem. The columns are generated by means of a dynamic programming algorithm.

3 Benders decompostion

To apply Benders decomposition, we start from the multi-commodity formulation MC proposed by Melo and Wolsey [2] for a two-level lot sizing problem and apply it to the capacitated 3LSPD. In the following formulation, we denote by δ_{kt} the Kronecker delta that takes the value 1 if $k = t$ and 0 otherwise. If we denote by w_{kt}^{lr} the quantities produced/ordered in level l in period k to satisfy d_{rt} and by σ_{kt}^{lr} the stock in level l at the end of period k to satisfy d_{rt}, the MC formulation is as follows:

$$\text{Min} \sum_{t \in T} \left(\sum_{i \in F} sc_t^i y_t^i + \sum_{r \in R} \sum_{k \leq t} hc_k^p \sigma_{kt}^{0r} + \sum_{r \in R} \sum_{k \leq t} hc_k^{\delta_w(r)} \sigma_{kt}^{1r} + \sum_{r \in R} \sum_{k \leq t} hc_k^r \sigma_{kt}^{2r} \right) \quad (8)$$

$$\sigma_{k-1,t}^{0r} + w_{kt}^{0r} = w_{kt}^{1r} + \sigma_{kt}^{0r} \quad \forall\, t \in T, k \leq t \in T, r \in R \quad (9)$$

$$\sigma_{k-1,t}^{1r} + w_{kt}^{1r} = w_{kt}^{2r} + \sigma_{kt}^{1r} \quad \forall\, t \in T, k \leq t \in T, r \in R \quad (10)$$

$$\sigma_{k-1,t}^{2r} + w_{kt}^{2r} = \delta_{kt} d_t^r + (1 - \delta_{kt}) \sigma_{kt}^{2r} \quad \forall\, t \in T, k \leq t \in T, r \in R \quad (11)$$

$$w_{kt}^{0r} \leq d_t^r y_k^p \quad \forall\, t \in T, k \leq t \in T, r \in R \quad (12)$$

$$w_{kt}^{1r} \leq d_t^r y_k^{\delta_w(r)} \quad \forall\, t \in T, k \leq t \in T, r \in R \quad (13)$$

$$w_{kt}^{2r} \leq d_t^r y_k^r \quad \forall\, t \in T, k \leq t \in T, r \in R \quad (14)$$

$$\sum_{r \in R} \sum_{t \geq k} w_{kt}^{0r} \leq \min\{C_k, D_k^p\} y_k^p \quad \forall k \in T \quad (15)$$

$$w_{kt}^{0r}, w_{kt}^{1r}, w_{kt}^{2r}, \sigma_{kt}^{0r}, \sigma_{kt}^{1r}, \sigma_{kt}^{2r} \geq 0 \quad \forall\, t \in T, k \leq t \in T, r \in R \quad (16)$$

$$y_t^i \in \{0; 1\} \quad \forall t \in T, i \in F. \quad (17)$$

Constraints (9), (10) and (11) are the balance constraints for each commodity at the production plant, at the warehouses and at the retailers, respectively. Constraints (12), (13) and (14) are the setup forcing constraints for the production plant, the warehouses and the retailers, respectively. Constraints (15) are the capacity constraints at the production plant. In our Benders decomposition, all the constraints go in the subproblem and the master problem is composed by the traditional feasibility and optimality cuts generated in the iterations of the Benders algorithm.

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Lot-sizing models with simultaneous backlogging and lost sales

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Abstract

Whereas several lot-sizing models have considered either backlog or lost sales, none of them consider that both backlog and lost sales can happen simultaneously in case of a stock-out. We will discuss several assumptions related to the possible interaction between lost sales and backlog and present new formulations.

1 Introduction

Lot-sizing models are Mixed Integer Programming (MIP) models used to determine the optimal timing and level of production. In their most basic form, lot-sizing models consider the trade-off between setup costs and holding costs, while satisfying deterministic and dynamic demand. Oftentimes, it is assumed that demand must be completely satisfied on time. However, in practice, this demand assumption often does not hold true and companies face situations where demand cannot be satisfied on time, typically due to limited capacity. We study lot-sizing models in which demand possibly cannot be satisfied on time. We describe this inability to satisfy demand on time as a stock-out. Once faced with a stock-out, there are different situations that can arise, two of which are backlogging the unsatisfied demand and incurring lost sales.

The term backlogging is used to describe the situation in which unsatisfied demand in a specific period is satisfied by production in later periods. Researchers have studied models that consider backlogging [1, 2, 3]. However, it is usually assumed that backlogged demand is eventually all satisfied during a later period within the planning horizon, at a given cost. Once again, this is often not the case in practice. Industries are becoming more saturated and competitive and customers are willing to shop elsewhere if their demand cannot be immediately satisfied. When producers are faced with stock-outs, demand can sometimes be lost [4, 5, 6]. Within the lot-sizing literature, both backlog and lost sales have been studied separately but not jointly. Note that Absi et al. [7] also study the two cases separately.

2 Modelling combined backlogging and lost sales

In this paper, we study a capacitated multi-item lot-sizing problem which simultaneously considers the possibility of backlog and lost sales as a means of dealing with a stock-out. When faced with a stock-out, some customers will be willing to wait (leading to backlog), while other customers will not be willing to wait (leading to lost sales). The combination of these two concepts has not yet been pursued in the literature. When considering these two concepts simultaneously, one must first determine how the two interact with each other.

In combination with backlog, there are two possibilities of lost sales that are studied: a fixed-proportion and a variable-proportion version. Before defining the two versions, it is important to note that in our study, we treat each unit of demand as a separate individual customer. Customers with multiple units of demand are a more complex problem that can be an interesting extension for future research. In both the fixed and variable version, when a stock-out occurs, a minimum fixed proportion of the unsatisfied demand is lost. This fixed percentage represents the customers who are not willing to wait in case of a stock-out. For the fixed-proportion lost sales, the remaining unsatisfied demand must be backlogged and satisfied in later periods. As for the variable-proportion lost sales, the company decides whether the remaining unsatisfied demand will be lost sales or become backlog that must be satisfied in later periods.

The important idea to note is that this framework applies to situations where, in case of a stock-out, some customers are willing to wait (leading to backlog) and others are not willing to wait (leading to lost sales). The goal is to develop various mathematical optimization models for a manufacturer that will represent different relationships between backlog and lost sales. Furthermore, we will consider that the customers that are willing to wait, can have a different maximum period they are willing to wait for. This research has hence two main contributions:

1. We extend the backlog concept to model customers that have a different willingness to wait. This leads to a model that is a generalization of the basic backlogging model.

2. We propose new lot-sizing formulations, which incorporate backlog and lost sales simultaneously. This leads to a generalized model that includes both the basic model with backlog and the basic model with lost sales as a special case.

The new formulations are based on the simple plant location reformulation of the lot-sizing problem [8].

3 Computational experiments

In order to conduct computational experiments, CPLEX 12.6.3.0 is used to solve test instances for different formulations which are modelled using the OPL coding environment. We conduct our computational experiments on two datasets developed by Trigeiro et al. [9]. The datasets are adapted to fit our new formulations. We analyze the performance of the various formulations in terms of objective function value and CPU time. We also analyse the structure of the solutions, and the trade-off between backlog and lost sales. Finally, we conduct sensitivity analyses to determine the impact of changing some key parameters such as the capacity tightness, the backlog restriction, the proportion of customers choosing not to buy in case of a stock-out, and the lost sales cost. Detailed computational results will be provided during the workshop.

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Heuristics for the stochastic economic lot sizing problem with remanufacturing

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Abstract

We consider an inventory system where demand can be met by manufacturing new products and remanufacturing returned products, and address the economic lot sizing problem therein. The system faces stochastic and time-varying demands and returns over a finite planning horizon. The problem is to match supply with demand while minimizing the total expected cost which is comprised of production costs for manufacturing and remanufacturing and inventory costs for serviceable products and returns. This is a challenging problem as its deterministic counterpart is known to be NP-Hard. We introduce heuristic policies for the problem which offer different levels of flexibility with respect to production decisions and present computational methods thereof. We numerically illustrate the cost performance and the computational efficiency of the proposed heuristics.

1 Introduction

The practice of "remanufacturing" falls into the context of environment-friendly production operations. It refers to a set of value-added recovery operations, i.e. the entire process of transforming used/returned components or products into "as-good-as-new" condition (Van Der Laan and Teunter, 2006). As it has been proven to be economical and environmental-friendly, remanufacturing is well-received in practice.

Hybrid manufacturing and remanufacturing systems are common in industries producing high-value products such as automotive parts, personal computers, cameras, medical instruments, engines, tires, aviation and military equipment, and furniture (see e.g. Kelle and Silver, 1989; Van Der Laan et al., 1999; Toktay et al., 2000; Golany et al., 2001; Ferguson and Toktay, 2006). In such production systems, customer demands can be satisfied by manufacturing new products and remanufacturing returned products. This obviously necessitates a strong coordination between manufacturing and remanufacturing operations to match supply with customer demands. Nevertheless, it is often difficult to coordinate these two production sources effectively, especially in presence of fixed production costs as compared to traditional manufacturing systems. This leads to an increasing need for integrated inventory control approaches for hybrid manufacturing and remanufacturing systems.

2 Background

We consider the inventory control problem in a hybrid manufacturing remanufacturing system where period demands and returns are non-stationary and stochastic. The objective is to minimize the expected total costs which is comprised of fixed costs of manufacturing and remanufacturing and inventory costs of serviceables and returns. We refer to this problem as the stochastic economic lot-sizing problem with returns—abbreviated as SELSR.

To the best of authors' knowledge; Naeem et al. (2013), Hilger et al. (2016), and Kilic et al. (2018) are the only studies that address variants of SELSR. These studies adopt different policies in approaching the problem which can be classified by Bookbinder and Tan's (1988) well-known scheme which differentiates between static, dynamic, and static-dynamic uncertainty strategies. Hilger et al. (2016) adopt a static-uncertainty strategy where manufacturing and remanufacturing quantities in each period are determined at the beginning of the planning horizon. Naeem et al.'s (2013) stochastic dynamic program employ a dynamic uncertainty strategy as manufacturing and remanufacturing quantities are strictly state dependent. Kilic et al.'s (2018) policies follow a static-dynamic uncertainty strategy as they are characterized by fixed manufacturing ad remanufacturing schedules, while allowing flexibility in manufacturing and/or remanufacturing quantities. It is important to remark that these strategies have their advantages and disadvantages. For instance, because the cost-effectiveness of a policy improves as it effectively exploits more information in making decisions, the dynamic uncertainty strategy is the best in terms of cost performance. The static uncertainty strategy, on the other hand, offers advanced information on production quantities, and, as such, it is very suitable for systems characterized by limited flexibility. The static-dynamic uncertainty strategy eliminates the uncertainty (or the so-called nervousness) in the replenishment schedule which is known to be critical in practice (Inderfurth, 1994; Heisig, 2001), while exploiting the cost advantage of flexible production quantities.

3 Overview and Results

The aim of this paper is to present new heuristics for SELSR, based on dynamic and static-dynamic uncertainty strategies. Our contributions are outlined as follows.

First, we propose a heuristic policy following the dynamic uncertainty strategy. This heuristic is aimed at alleviating the computational burden of the optimal stochastic dynamic program of SELSR, while providing cost-effective solutions by exploiting the advantages of the dynamic uncertainty strategy. It is a stochastic adaptation of Silver and Meal's (1973) heuristic tailored for hybrid manufacturing and remanufacturing systems with stochastic demands and returns.

Second, we adopt the heuristic policies introduced by Kilic et al. (2018) which are based on the static-dynamic uncertainty strategy. The mathematical models of these policies were build on the restrictive assumption that non-stockout probabilities are sufficiently high that the effect of backorders can be neglected in cost computations. This assumption—which is only reasonable under service level constraints that require high non-stockout probabilities—enables one to safely replace the true non-linear cost function by a linear approximation, and thereby obtain a simpler mathematical model. In the current study, we relax this restrictive assumption and develop certainty equivalent MIP models of Kilic et al.'s (2018) static-dynamic policies which allow for more general measures of service quality.

Finally, we conduct a numerical study and evaluate the cost performance and the computational efficiency of the proposed dynamic and static-dynamic policies, while using Hilger et al.'s (2016) static policy as a benchmark. Our results clearly demonstrate the trade-off between the cost performance and the flexibility of the policies under consideration, and point out problem settings where a particular policy can be a better alternative to others.

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Integrated Lot Sizing, Scheduling and Cutting Stock Problem

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Abstract

In this work, we consider an integrated lot-sizing, scheduling and cutting stock problem. The cut pieces, which are generated in the cutting process, are addressed in the assembly process of final products, which consists of a lot-sizing problem. In order to model a completely cutting plan in the mathematical models proposed, we take into account constraints to model the scheduling decisions of the cutting plan, as well as, scheduling decisions related to the final products. A solution approach is proposed based on column generation procedure in a preliminary computational experiment.

1 Introduction

The idea of an integrated lot-sizing and cutting stock problem is to consider, simultaneously, the decisions related both problems so as to capture the interdependency between these decisions in order to obtain a better global solution. Most of the cutting plans described by the current models of the cutting stock problems provides a set of cutting patterns and the corresponding frequencies of the patterns. However, in some settings, it becomes necessary to determine a production plan that also indicates the optimal sequence of the cutting patterns. The inclusion of the pattern sequence in the model may be related to a specific objective function, usually related to a practical application, such as, the minimization of the knives changes, where each insertion and removal of knives takes time to be processed ([14]); the minimization of open stacks, i.e. the number of mounting compartments around the cutting machine, in which a stack remains open until the last cutting pattern that contains the piece of the stack is cut ([3, 10, 12, 15, 16, 17]; the minimization of the order spread, which refers to the number of open stacks during the cutting process ([7, 9]); orders due dates, which refers to the necessity of filling the orders before a given due date ([1, 2, 4, 13]). It is worth to mention that this sequencing problem which emerges as an extension to cutting stock problem, has been extensively addressed in lot-sizing problems. As the lot-sizing problems considers the production of several products, the sequence in which these products are produced can influence the quality, total cost, and even the feasibility of the solution. In such a case, an integrated lot-sizing and scheduling problem with sequence-dependent setups arises (see [5, 6, 8]).

2 Mathematical Model and Solution Approach

In this work, we consider an integrated lot-sizing and cutting stock problem taking into account constraints to model the scheduling decision related to the cutting and lot-sizing problem. In the cutting stock level (Level 2), the cutting patterns used to generate the cut pieces are scheduling in order to minimize the cost of waste and the changeover from one cutting pattern to other cutting pattern. These cut pieces are then addressed in the assembly process of final products (Level 3). The final products are scheduling in order to meet their demand and minimize the cost of production, inventory and changeover from one final product to other final product. For more details about integrated lot-sizing and cutting stock models see the literature review [11].

To model the scheduling decisions, we consider two approaches from the literature. The first one is based on the General Lot Sizing and Scheduling Problem with Setup Times, who considers the loss of capacity resulting from sequence-dependent setup times. The other is the asymmetric travelling salesman problem, with dependent sequences, where the setup state is carried over between periods. Both approaches are used to take into account the scheduling decisions of the cutting plan, as well as, lot-sizing of final products.

Considering the generation of a solution for this problem, we develop a column generation based heuristic which consists of applying the column generation approach to generate the matrix of cutting patterns at Level 2 and then the integer problem, considering all the generated columns is solved with an optimization package in order to obtain a feasible solution to the problem. The solutions are compared considering the different approaches to model the scheduling decisions, as well as, the impact of the scheduling decisions in the integrated problem.

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A column generation based heuristic for inventory routing with practical constraints

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Abstract

We propose a hybrid method based on the column generation technique to address basic and practical variants of the inventory routing problem (IRP). Because of the many decisions involved, the IRP variants are typically very challenging, especially when they include practical constraints. We consider a real-world rich variant of the IRP that arises in the distribution of industrial gases through a multi-period time horizon. The proposed method relies on local search heuristics combined with an interior point column generation method, to provide stabilized primal and dual solutions of the linear relaxation of problem. We verify the performance of the proposed strategy using instances created from real-world data provided by a company. The computational results indicate that the proposed combination of methods is beneficial and leads to an effective solution strategy.

1 Introduction

The inventory routing problem (IRP) has gained increased attention in the last years. It consists of inventory management decisions integrated to vehicle routing and scheduling, in a way that the supplier is in charge of deciding when, how and how much to deliver to each customer, at each time period of the planning horizon. As the result of integrating so many decisions, IRP variants can be very challenging, especially when considering practical constraints.

In this paper, we briefly describe a novel hybrid solution strategy that relies on different techniques to solve a challenging variant of the IRP. The problem characteristics are based on a real-world application in the bulk gas distribution industry under a vendor-managed inventory (VMI) system. The proposed solution strategy uses constructive and local search heuristics and the column generation (CG) algorithm. The heuristics are used to obtain feasible working shifts for delivering the product to customers, while the CG strategy seeks for the best combination of these shifts, considering the available trucks and drivers and their corresponding restrictions, such as time windows and customer compatibility. Due to the rich characteristics of the addressed variant, the heuristics are essential to make the problem tractable, while the CG is an effective way of combining the shifts.

2 Problem definition

We consider the repeated distribution of a single product to a set of n customers over a discrete and finite planning horizon of T time periods. The supplier monitors and manages the customer inventories, making several decisions simultaneously: when to deliver to each customer; how much to deliver in each visit; how to combine such deliveries into feasible routes; and which resources to use. To accomplish this, it has to determine a set of driver shifts to satisfy customer demand requirements, maximum duration and additional technical constraints. There is a set of transportation and human resources (trucks and drivers), which are located at one single base (depot). Drivers have different availabilities according to their time windows. The fleet of vehicles is heterogeneous and each vehicle can perform multiple routes in the planning horizon. Multiple production sites (sources) are available in the problem, which means that the vehicles can load the product at different points. Each source has a list of vehicles allowed to load. A fixed service time (loading/unloading) is incurred at each source and customer (safety reasons).

Each shift must start at the base, visit a subset of customers and/or sources, and then return to the base. All these visits must satisfy vehicle capacity, customer tank capacity and safety level, customer time windows, maximum driving duration, trailer usage and minimum operation quantity. Customers are divided into two classes: VMI customers and call-in customers. For each VMI customer, the company monitors its tank level and guarantees that this level never becomes lower than a given safety level. Call-in customers place orders through the planning horizon and they are mandatory. A customer can be further classified as *layover*, which means that the duration of a shift containing this customer can be extended by including a resting time for the driver. The cost of the shifts is proportional to its duration (driver costs) and includes the driving time, the idle time and the loading/unloading time.

The goal is to minimize the logistic ratio, given by the total transportation cost of the shifts divided by the total quantity delivered over the planning horizon. Holding costs are not included in this objective. The logistic ratio has a practical appeal, as it corresponds to the average cost per unit of delivered product. It captures the long-term impact of a short-term planning, given that it focuses on the efficiency of the process [2, 5, 1].

3 Solution strategy

The proposed solution strategy is based on the interaction of different components, namely: (*i*) a construction heuristic; (*ii*) local search heuristics; (*iii*) an interior point CG algorithm to solve a lot sizing based master problem (MP); and (*iv*) a black-box optimization software to solve the MP. These components are called iteratively, as follows. We first call the constructive heuristic to obtain feasible shifts, imposing a maximum number of iterations and a running time limit. Then, we feed the MP with the obtained shifts and run a few iterations of the CG algorithm, to solve the linear relaxation of the MP and generate new columns. We rely on an interior point algorithm to stabilize primal and dual solutions and thus reduce the number of iterations in the CG method [3, 4]. The subproblems used to generate new columns are solved by the construction heuristic, which guarantees short running times. There is one subproblem for each vehicle and driver.

Once the CG method terminates, we then impose integrality to the MP variables corresponding to shifts and solve the resulting problem using a black-box optimization software, also imposing a maximum running time limit. For every integer solution obtained by the optimization solver, we apply the local search heuristics on the shifts used in the solution, to identify improved shifts. If this procedure identify shifts that are not in the current MP, then we add them to the MP and the process is restarted. The overall iterative process finishes when the objective value between two consecutive iterations remains the same.

The construction heuristic used in the solution strategy determines a set of shifts to satisfy customer demand requirements and technical constraints. Each shift must start at the base, visit a subset of customers and/or sources, and then return to the basis. The heuristic computes the consumption progress of all customers through the time horizon, according to the their demand forecast. Based on this, it determines which customers must be visited and when they must be visited to maintain their tank level never below the safety level. For this, the heuristic uses two main parameters: `look_ahead`, which tells how many periods ahead we should look in order to check if a customer safety level is violated; and `longterm_multiplier`, which defines an extra penalty to avoid the inventory level of the customers to get too low on the longterm. These parameters have practical meanings and may be intuitively handled by the decision makers.

The MP used in the CG method is based on a classical lot sizing formulation that includes additional variables and constraints to link shifts with delivery and inventory decision variables. The delivery variable x_{it}^k determines how much to deliver to customer i in time period t using vehicle k. Variable I_{it} represents the inventory level at customer i at time period t. There is also a load variable l_{kt} that controls the load of vehicle k at time period t. They are all continuous variables. Related to the shifts, we have the binary variable λ_{ks} that assumes the value of 1 if, and only if, vehicle k uses shift s. In the objective function, we use an approximation for the logistic ratio, given that this measure is nonlinear. The function consists of maximizing the total amount delivered to customers (based on variable x_{it}^k) minus the total delivery costs (based on variables λ_{ks}).

4 Final remarks

The proposed solution strategy relies on different components and seeks to explore the advantages offered by each of them. Its performance was tested using instances created from real-world data provided by a company. The computational results indicate that the proposed combination of methods is indeed beneficial and leads to an effective solution strategy for the addressed practical variant of the IRP.
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Integrated lot sizing and cutting stock problems in paper industries[1]

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Abstract

In many manufacturing industries, there are the production of the objects and the cutting of the objects into smaller pieces in order to meet a specific demand. In the optimization of such productive processes, one can identify the lot sizing and the cutting stock problems. The cutting stock problem can be considered a fundamental subproblem of the production planning problem. However, in the literature, these problems are mostly dealt separately. Treating these two problems separately can increase overall costs. In this research, we deal with these problems in a coupled way, proposing an integrated model for the production and cutting of paper based on the literature, which considers setup costs and production capacity. For the solution of the proposed model, we used the column generation method, the relax-and-fix heuristic and an optimization package. Computational tests were carried out in order to analyze the methodology used in the resolution of the model.

1 Introduction

In paper industries, large reels of different lengths and types of paper, called jumbos, are produced and cut to meet a certain items demand. In the optimization of these productive processes, the lot sizing problem is related to the cutting stock problem. The objective of this research is to deal with these problems in an integrated way

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through the proposition of a model for the production and cutting of paper. This formulation is based on the model proposed by [2] and considers the costs of production, preparation and stock, material waste as well as production capacity. A methodology for solving the model was also proposed using the column generation method and a relax-and-fix heuristic.

2 Proposed model

Consider the following data and parameters: $t = 1, ..., T$ the number of the period in the planning horizon; $j = 1, ..., N_m$ the number of the cutting patterns for reels of type m; $i = 1, ..., N$ the number of the ordered item; $m = 1, ..., M$ the number of the machines which produces reels of length L_m; s_{mt} the setup cost for machine m producing a reel in period t; c_{mt} the production cost for a reel being made in machine m in period t; h_{mt} the inventory cost for a reel produced in machine m at the end of period t; σ_{it} the cost for holding final items i at the end of period t; cp_t the cost for each centimeter of paper wasted during the cutting process in period t; b_m the weight of reel produced in machine m; f_m the paper waste in setting up machine m; p_{jm} the paper waste in cutting pattern j used to cut a reel of length L_m; D_t the demand of paper in period t; C_{mt} the capacity of machine m in period t; a_{jm} the vector associated to cutting pattern j for reel of length L_m where each component a_{ijm} means the number of items i cut according to cutting pattern j for the reel of length L_m; d_t the vector of demand quantities of final items in period t and Q a big number.

Consider the following variables: x_{mt} the number of reels produced in machine m in period t; w_{mt} the number of reels produced in machine m stored at the end of period t; z_{mt} the binary variable that means if there was production or not in machine m in period t; y^j_{mt} the number of reels produced in machine m in period t which are cut using the cutting pattern j and e_t the vector of final items held at the end of period t. Therefore, the proposed integrated model is given by:

$$\min \sum_{t=1}^{T} \sum_{m=1}^{M} (c_{mt}x_{mt} + h_{mt}w_{mt} + s_{mt}z_{mt}) + \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{j=1}^{N_m} cp_t p_{jm} y^j_{mt} + \sum_{t=1}^{T} \sum_{i=1}^{N} \sigma_{it} e_{it} \quad (1)$$

$$\text{s. t.} \quad \sum_{m=1}^{M} (b_m x_{mt} + b_m w_{m,t-1} - b_m w_{mt}) = D_t, \quad t = 1, ..., T \quad (2)$$

$$\sum_{m=1}^{M} \sum_{j=1}^{N_m} a_{jm} y^j_{mt} + e_{t-1} - e_t = d_t, \quad t = 1, ..., T \quad (3)$$

$$b_m x_{mt} + f_m z_{mt} \le C_{mt}, \quad m = 1, ..., M; t = 1, ..., T \quad (4)$$

$$\sum_{j=1}^{N_m} y_{mt}^j = x_{mt} + w_{m,t-1} - w_{mt}, \quad m = 1, ..., M; t = 1, ..., T \tag{5}$$

$$x_{mt} \leq Q\, z_{mt}, \quad m = 1, ..., M; t = 1, ..., T \tag{6}$$

$$z_{mt} \in \{0, 1\}, \quad m = 1, ..., M; t = 1, ..., T \tag{7}$$

$$w_{m0} = 0, \;\; e_0 = 0, \quad m = 1, ..., M \tag{8}$$

$$x_{mt} \in \mathbb{Z}^+, \;\; w_{mt} \in \mathbb{Z}^+, \quad m = 1, ..., M; t = 1, ..., T \tag{9}$$

$$y_{mt}^j \in \mathbb{Z}^+, \;\; e_t \in \mathbb{Z}^+, \quad m = 1, ..., M; t = 1, ..., T \tag{10}$$

The model aims to minimize the costs of production, inventory and setup and the material waste in the cutting process (1), subject to the constraints of balancing stock of reels (2) and items (3), capacity constraints (4), coupling constraints (5), constraints related to the binary variables (6)-(7) and the null inicial inventories (8) and constraints associated with de non-negative and integer values of the variables (9)-(10).

3 Computational tests

The proposed integrated model, the column generation method and the relax-and-fix heuristic were implemented through the OPL/CPLEX. At first, the column generation method was applied to the model with the relaxed integrality constraints (9) - (10) until an optimal solution was found. Then, with the determined cutting patterns, the relax-and-fix heuristic was applied to the relaxed model, in order to obtain a solution for the binary variables z_{mt} (More details in [1]). Finally, to find an integer solution for the integer variables of the model, the integrated model was solved by CPLEX with the binary variables z_{mt} all set in the value found in the previous step and the cut patterns determined by the first step.

Computational tests were performed for 9 classes, with 10 randomly generated example in each class. The number of periods and items ranged from 8 to 10 and from 5 to 20 respectively. 2 machines were considered, that is, two reel lengths. In Table 1, mean values of gaps calculated at the end of all steps (Final Gap column) and the average computational time, reported in seconds, spent to solve these instances (Total Time column) are shown for each class. In the first and second columns (Class and T/N), the classes and the number of periods (T) and items (N) of each one are identified.

Note that the mean value of the final gaps was 0.22778% and the average time used to solve the instances was 30.887 seconds. The average total time spent on solving the instances ranged from 13.999 seconds, to instances with 8 periods and 5 items, to 65.225 seconds, for instances with 12 periods and 20 items.

Table 1: Mean values of the final gaps and the total time spent in the model resolution for each class of instances.

Class	T/N	Final Gap (%)	Total Time (sec.)
1	08/05	0.38475	13.999
2	08/10	0.19247	18.270
3	08/20	0.09454	32.941
4	10/05	0.42569	16.711
5	10/10	0.20788	27.727
6	10/20	0.09112	46.135
7	12/05	0.37636	22.244
8	12/10	0.19020	34.734
9	12/20	0.08702	65.225
	Average	0.22778	30.887

In order to compare the quality of the solution found by the proposed methodology, the integrated model was solved also by CPLEX with all possible cut patterns for all instances of Class 1 and Class 2. For the Class 3, CPLEX could not find a solution due to memory problems since the number of cut patterns was too large. For the Class 1, the proposed methodology found the optimal solution at 6, from the 10 instances and, for the Class 2, found 7 optimal solutions. The difference between the gaps found by both resolution forms was less than 10^{-2}%. The resolution by the CPLEX was, on average, faster, however, using the methodology adopted it was possible to solve all the instances.

4 Conclusions

The limitation presented by CPLEX evidenced the need to adopt alternative methodologies to solve the model, such as the proposal that solved all the generated instances with a good average computational time, and good solution quality.

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Stochastic lot-sizing for remanufacturing planning with lost sales and returns

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1 Introduction

We consider an uncapacitated multi-item multi-echelon lot-sizing problem within a remanufacturing system involving three production echelons: disassembly, refurbishing and reassembly. We seek to plan the production activities on this system over a multi-period horizon. We consider a stochastic environment, in which the input data of the optimization problem are subject to uncertainty.
Stochastic lot-sizing problems have been studied under several modeling and uncertainty assumptions. Multi-period single-echelon single-item stochastic lot-sizing problems have been studied in [1] and [2], taking under consideration both stochastic demand and returns quantity. Subsequently, Macedo et al. [3] and Hilger et al. [4] studied a multi-item variant of the problem taking into account both stochastic demand and returns quantity. Wang and Huang [5] and Fang et al. [6] studied multi-period multi-echelon multi-product stochastic lot-sizing problems for remanufacturing systems comprising several operations such as disassembly, recycling and reassembly. We focus in this work on a multi-echelon system with not only disassembly and reassembly operations, but also refurbishing operations. We explicitly consider uncertain input parameters and propose a multi-stage stochastic programming approach. Multi-stage stochastic integer programming approaches usually rely

on scenario trees to represent the uncertain information structure and result in the formulation of large-size mixed integer linear programs. Linear programming relaxation strengthening techniques focused on stochastic lot-sizing problems expressed on scenario trees have been studied in [7], [8], [9] and [10]. All these works have focused on single-echelon production systems and do not consider used product returns nor lost sales. In contrast, we investigate a multi-stage stochastic integer programming approach dealing with a multi-echelon multi-item stochastic lot-sizing problem with lost sales within a remanufacturing environment.

2 Mathematical formulation

We consider a multi-stage decision process corresponding to the case where the value of the uncertain parameters unfolds little by little following a discrete-time stochastic process and the production decisions are adapted progressively as more and more information is collected. This leads to the representation of the uncertainty via a scenario tree $\mathcal{T} = (\mathcal{V}, \mathcal{E})$. Each node $n \in \mathcal{V}$ corresponds to a single planning period t belonging to a single decision stage $s \in \mathcal{S}$. It represents the state of the system that can be distinguished by the information unfolded up to that period t. At any non-terminal node of the tree, there are one or several branches to indicate future possible outcomes of the random variables from the current node. The nodes of the scenario tree are indexed from 0 to $|\mathcal{V}|-1$. Each node n (except root node 0) belongs to a time period $t+1$ and has a unique predecessor node denoted a^n corresponding to the time period t. The probability associated with the state represented by the node n is ρ^n. Each non-terminal node n is a root node of a subtree $\mathcal{T}(n)$. The set $\mathcal{L}(n)$ represents the set of leaf-nodes belonging to $\mathcal{T}(n)$. The set of nodes on the path from a node n to a node μ is denoted by $\mathcal{P}(n, \mu)$.

We use the following notation for the problem formulation: I is the number of part types involved in one product, $\mathcal{I}$ represents the set of all products involved in the system, $\mathcal{I} = \{0, ..., 2I+1\}$, where $i = 0$ corresponds to returned product and $i = 2I+1$ corresponds to remanufactured product. The set of recoverable (resp. $\mathcal{I}_s$) parts provided by the disassembly (resp. refurbishing process) is denoted by $\mathcal{I}_r = \{1, ..., I\}$ (resp. $\mathcal{I}_s = \{I+1, ..., 2I\}$). $\mathcal{J} = \{0, ..., I+1\}$ is the set of production processes where $p = 0$ corresponds to the disassembly process, $p = 1, ..., I$ correspond to the refurbishing processes and $p = I+1$ corresponds to the reassembly process.

The deterministic parameter is α_i that is the number of parts i embedded in a returned/remanufactured product. The stochastic parameters are introduced as follows: r^n is the quantity of used products (returns) collected at node $n \in \mathcal{V}$, d^n is the customers demand at node $n \in \mathcal{V}$, π_i^n is the proportion of recoverable parts $i \in \mathcal{I}_r$ obtained by disassembling one unit of returned product at node $n \in \mathcal{V}$.

The cost parameters are l^n, unit lost-sales penalty cost at node $n \in \mathcal{V}$, f_p^n, the setup cost for process $p \in \mathcal{J}$ at node $n \in \mathcal{V}$, h_i^n, the unit inventory cost for part $i \in \mathcal{I}$

at node $n \in \mathcal{V}$, q_i^n, unit cost for discarding a recoverable part or a returned product $i \in \mathcal{I}_r \cup \{0\}$ at node $n \in \mathcal{V}$ and g^n, unit cost for discarding the unrecoverable parts obtained while disassembling one unit of returned product at node $n \in \mathcal{V}$.
Due to the unknown quality of the returned product, there exists an implicit flow of unrecoverable parts generated when disassembling used products. We thus introduce $g^n = \sum_{i=1}^{I} q_i^n (1 - \pi_i^n)\alpha_i$ which represents the unit cost of the parts that cannot be recovered when a returned product is disassembled. Moreover, we assume that at each stage, the realization of the random parameters happens before we have to make a decision for this stage
We propose a multi-stage stochastic integer programming model based on the uncertainty representation described above. The decision variables involved in the model are: X_p^n is the quantity of parts processed on process $p \in \mathcal{J}$ at node $n \in \mathcal{V}$, $Y_p^n \in \{0, 1\}$ is the setup variable for the process $p \in \mathcal{J}$ at node $n \in \mathcal{V}$, S_i^n is the inventory level of part $i \in \mathcal{I}$ at node $n \in \mathcal{V}$, Q_i^n: quantity of part $i \in \mathcal{I}_r \cup \{0\}$ discarded at node $n \in \mathcal{V}$, and L^n are the lost sales of remanufactured products at node $n \in \mathcal{V}$. The mixed integer linear programming model is given below.

$$Z^* = min \sum_{n \in \mathcal{V}} \rho^n \Big(\sum_{p \in \mathcal{J}} f_p^n Y_p^n + \sum_{i \in \mathcal{I}} h_i^n S_i^n + l^n L^n + \sum_{i \in \mathcal{I}_r \cup \{0\}} q_i^n Q_i^n + g^n X_0^n \Big) \tag{1}$$

$$X_p^n \leq M_p^n Y_p^n \qquad \forall p \in \mathcal{J}, \forall n \in \mathcal{V} \tag{2}$$
$$S_0^n = S_0^{a^n} + r^n - X_0^n - Q_0^n \qquad \forall n \in \mathcal{V} \tag{3}$$
$$S_i^n = S_i^{a^n} + \pi_i^n \alpha_i X_0^n - X_i^n - Q_i^n \qquad \forall i \in \mathcal{I}_r, \forall n \in \mathcal{V} \tag{4}$$
$$S_i^n = S_i^{a^n} + X_{i-I}^n - \alpha_i X_{I+1}^n \qquad \forall i \in I_s, \forall n \in \mathcal{V} \tag{5}$$
$$S_{2I+1}^n = S_{2I+1}^{a^n} + X_{I+1}^n - d^n + L^n \qquad \forall n \in \mathcal{V} \tag{6}$$
$$S_0^0 = r_0^0 - X_0^0 - Q_0^0 \tag{7}$$
$$S_i^0 = \pi_i^0 \alpha_i X_0^0 - Q_i^0 \qquad \forall i \in \mathcal{I}_r \tag{8}$$
$$S_i^0 = X_{i-I}^0 - \alpha_{i-I} X_{I+1}^0 \qquad \forall i \in \mathcal{I}_s \tag{9}$$
$$S_{2I+1}^0 = X_{I+1}^0 - d^0 + L^0 \tag{10}$$
$$S_i^n \geq 0 \qquad \forall i \in \mathcal{I}, \forall n \in \mathcal{V} \tag{11}$$
$$L^n \geq 0 \qquad \forall n \in \mathcal{V} \tag{12}$$
$$X_p^n \geq 0, Y_p^n \in \{0, 1\} \qquad \forall p \in \mathcal{J}, \forall n \in \mathcal{V} \tag{13}$$

The objective function (1) aims at minimizing the expected total cost, over all nodes of the scenario tree. This cost is the sum of the expected setup, inventory holding, lost sales and disposal cost. Constraints (2) link the production quantity variables to the setup variables. Constraints (3)-(10) are inventory balance constraints. Constraints (3) (resp. (4) and (5)) involve a term corresponding to a dependent demand X_0^n (resp. X_i^n and $\alpha_i X_{I+1}^n$) whereas Constraints (6) only involve an independent demand term d^n.

3 Contributions

We propose a branch-and-cut framework to solve the resulting large-size mixed integer linear program. The algorithm relies on a new set of valid inequalities obtained by mixing previously known path inequalities [11]. These valid inequalities increase exponentially in the number of nodes in the scenario tree. We provide an efficient cutting-plane generation strategy to identify the useful subset of this class. Our computational experiments show that the proposed method is capable of significantly decreasing the computation time needed to obtain guaranteed optimal solutions.

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A supply chain tactical planning approach for optimizing the tomato processing industry

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Abstract

This paper presents an optimization approach based on mixed integer programming model (MIP) to support tactical planning decisions in the tomato processing industry. The model considers relevant features of the agricultural and industrial activities. The first one refers to the tomato cultivation (planting/harvesting) and its transportation from the fields to processing plants. The industrial activities are related to the production (lot-sizing, scheduling & blending) and logistics (transport & inventory) management of semi-finished and final products to consumers. Some model features were inspired in the Proportional Lot-sizing and Scheduling Problems [1]. The solutions were analyzed using a set of real data. The outcomes have demonstrated that the model is able to optimize the considering decisions.

1 Introduction

The tomato processing sector is one of the most important agro-industries worldwide. Delivering the desired products to final consumers from agricultural raw materials requires much information and coordinated action among the various agents throughout the supply chain. An appropriate system of collecting data and analysis is primordial for a company to achieve a competitive advantage over the market players. Optimization can contribute to improve the quality of planning and management decisions. Basically, in this sector, there are farmers who produce tomatoes to the processing companies that manufacture final products to consumers. Logistics agents are responsible for transporting tomatoes from the growing fields to the processing plants. Into industrial environment, stock management of semi-finished and final products are crucial for costs. Managers are responsible for defining the industrial settings to produce all products. Decisions are connected and one can affect almost the whole supply chain.

2 The decisions

The activities modeled in this study were grouped in two stages based on the process and outputs. Planting, harvesting and transporting of tomatoes from regions to plants are grouped in the "agricultural stage". The second one is the "industrial stage", which can be further split in two more stages. The first industrial stage is responsible for receiving the tomatoes and transform them into concentrated tomato pulp. The second industrial stage produces final products to consumers. There are several regions to cultivate distinguished tomato varieties. All tomatoes delivered in the plants are converted into tomato juice for producing semi-finished products. They can then follow two paths, being consumed promptly to make final products or to replenish the stocks. Tomato crop is seasonal and the demand of tomato-based products is spread throughout the year, which should be met by current production or by stocks. Thus, the different types of tomato pulp must be in stock to meet the demand of different types of final products.

Semi-finished products of pulp and crush cannot be produced simultaneously in the concentrators due to their different physical characteristics of particle size, content of tomato seeds and fibers, as well as the soluble solids concentration. The equipment should always be prepared to produce a single group of a semi-finished product, i.e. pulp or crush. Suppose that a concentrator is set to produce tomato crush. Once the production begins, it is possible to obtain crush of different brix levels, according to the juice holding time in the concentrator. However, if the next production set in this equipment is from the pulp group, then immediately after the crush production it is necessary to empty it for cleaning purposes because of the tomato seeds from the crush. Additional adjustments are necessary to complete the concentrator setup, such as changing the sieves to obtain a finer particle size. The setup may take several minutes depending on the equipments capacity. Despite the long setup time required between the production changeovers, the direct costs involved are not high for this kind of operation in the company where this study took place, but the equipment idleness cost can be relevant in some situations and should be accounted for.

In contrast to the previous situation, if the concentrator is producing pulp and right after is scheduled to produce crush, this changeover is not as time consuming as the one previously described. Changing from pulp to crush does not require a cleaning operation, which is the longest task. It is enough to empty the concentrator and change its sieves. Briefly, crush production can occur soon after pulp, requiring only a few minor adjustments in the process. However, the inverse situation (from crush to pulp) presents long setup times. It is acceptable to perform at most one production changeover within a week. Therefore, the sequence dependent setup times between the productions of tomato pulp and crush are a relevant matter for the industrial team. The planning problem in the agricultural stage involves assigning tomato varieties to regions determining the cultivated area. Production lot sizing and scheduling are the problems of the first industrial stage. Blending and production mix problems are characteristics of the second industrial stage. All these are integrated in a single MIP model.

3 The mathematical model

It consists of an objective function (OF) that minimizes the main production and logistics costs, while providing an economic benefit to produce stocks of concentrated pulp (CP) in the last period of the planning horizon. The OF components are: cost of transporting tomatoes from the regions to the plants, inventory cost of CP, procurement cost of CP in the market, transportation cost of CP among plants, energy cost to produce CP in the concentrators, inventory cost of final products (FP), and the benefit of making stocks of CP that will be consumed in the period inter crops. The constraining equations are: the limit of area to cultivate tomatoes, reception capacity of each plant, equation for converting tomatoes into soluble solids to produce CP, constraints to calculate the brix of the tomato juice - these constraints are linear piecewise approximation, constraints to set the evaporation capacity of the concentrators, constraints to schedule the production of CP - these are inspired by the PLSP model [1], balance inventory equations for CP and FP, inequalities in charge of blending CP to produce FP, constraints to set the production capacity of FP, and finally, the constraints to meet the demand for PF, besides, the non-negativity and binary constraints.

4 Results

The mathematical model was implemented in the General Algebraic Modeling System (GAMS) version 24.0.2 and solved by the CPLEX 12.5 in its default settings and using three threads in a Pentium I3 processor. Extensive computational experiments were carried out using real data. The solutions were compared to the company's achievements and plans. The overall outcomes have indicated better economic results compared to the company's accomplishments. The magnitude of the economic savings and gains depended on the data set used, for an instance composed of two processing plants, three tomato regions, five types of concentrated pulp, three families of final products and planning horizon of twelve months, using forty steps for the brix curves, the savings on the total costs ranged from 5% to 30% and for the benefits of making more stocks of concentrated pulp ranged from 3% to 30%, compared to the data of the company's accomplishment.

5 Conclusions

The MIP model presented here appropriately represents and optimizes the supply chain of the processing tomato industry. The outcomes of this study are promising and encourage further research for developing decision support tools for the tomato processing industry. An obvious challenge for this kind of study is to obtain data and to outline final results because those depend on the data set used. All the model approach presented here is deterministic and a straightforward extension is to build robust or stochastic models to deal with uncertainty in the data set, since agricultural systems are naturally subjected to uncertainty. More detail about this study can be found in [2].

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A strategic production problem balancing cost and flexibility

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Abstract

In some industry, such as luxury brands, balancing cost efficiency (by specializing the plants) and ability to deal with demand uncertainty (by diversification) is a major concern. Within a partnership with a consulting company, we address this question and formulate it as a stochastic multi-item facility location problem with average value-at-risk (AV@R) constraints. While the AV@R – a risk measure widely used in finance – is still in its infancy in a supply chain context, it captures several crucial features of risk from a business perspective. On top of being an accurate modeling tool, it can be linearized when the sample space is finite, which makes it computationally appealing. Combining this property with sample average approximation, we design an efficient method to solve a two-stage relaxation of the problem by mixed integer linear programming, which can be handled by any up-to-date MIP solver. We are currently running tests on real-world data in order to compare our results with decisions taken by a client of our partner.

1 Context

The conflicting requirements of cost reduction and increase of *flexibility* (capacity to change the composition of their product mix) are especially present in the highly strategic problem of product assignment to plant met by luxury brands. By assigning product to plant, we mean giving to the plant the ability to produce the product.

Such decisions have to be taken on a regular basis (typically, each semester) in order to take into account the launch of new products or change in the distribution requirement. Generally speaking, assigning the same product to several plants increases the cost but also the flexibility since multiple plants can more easily adjust their production to match at best an uncertain demand. We propose for this problem a formalization based on our discussions with an industrial partner, Argon Consulting, a leader company in supply chain and operations consultancy. Strategic decisions are classical in production management (*e.g.*, Aghezzaf (2007) [1] addresses deterministic examples and Govindan (2017) [3] provides a literature review of stochastic models and methods), but we are not aware of previous works that match the understanding of this problem by our partner.

Moreover, a key feature of our formalization is that demand-satisfaction under uncertainty is addressed via a financial tool, the average value-at-risk, which is new in the context of production management. An average value-at-risk constraint is a stronger requirement than the more classical chance constraint. Indeed, this new constraint is sensitive to the intensity of constraint violation. Furthermore, the average value-at-risk gets an easy linear expression in the sample average approximation method. Building upon this latter property, we propose a method for solving the problem.

2 Problem formulation and model

The problem takes the form of the following stochastic program:

$$
\begin{aligned}
\min \quad & \sum_{r\in\mathcal{R}}\sum_{p\in\mathcal{P}} c_p^r y_p^r & & & \\
& \boldsymbol{s}_t^r = \boldsymbol{s}_{t-1}^r + \sum_{p\in\mathcal{P}} \boldsymbol{q}_{pt}^r - \boldsymbol{d}_t^r & & \forall t\in[T],\ \forall r\in\mathcal{R} & \text{(i)} \\
& \mathrm{AV@R}_{1-\beta}\left(\boldsymbol{s}_t^r\right) \le 0 & & \forall t\in[T],\ \forall r\in\mathcal{R} & \text{(ii)} \\
& \sum_{r\in\mathcal{R}} v_{pt}^r \boldsymbol{q}_{pt}^r \le C_p & & \forall t\in[T],\ \forall p\in\mathcal{P} & \text{(iii)} \\
& m_p^r y_p^r \le v_{pt}^r \boldsymbol{q}_{pt}^r \le M_p^r y_p^r & & \forall t\in[T],\ \forall p\in\mathcal{P},\ \forall r\in\mathcal{R} & \text{(iv)} \\
& \boldsymbol{q}_{pt}^r,\ \boldsymbol{s}_t^r \preceq \sigma\left(\left(\boldsymbol{d}_\tau^r\right)_{r\in\mathcal{R},\ \tau\in[t]}\right) & & \forall t\in[T],\ \forall p\in\mathcal{P},\ \forall r\in\mathcal{R} & \text{(v)} \\
& y_p^r \in \{0,1\} & & \forall t\in[T],\ \forall p\in\mathcal{P},\ \forall r\in\mathcal{R} & \text{(vi).}
\end{aligned}
\tag{P}
$$

where all constraint are assumed to hold almost surely. We have a set $\mathcal{P}$ of plants and a set $\mathcal{R}$ of products to be produced over T months. At time $t=0$, the products each plant will be able to produce have to be chosen (encoded by variables y_p^r). At the beginning of each month $t\in[T]$, the production level $\boldsymbol{q}_{pt}^r$ has to be decided for each plant and each product, in order to satisfy a random demand $\boldsymbol{d}_t^r$, with the help of inventory $\boldsymbol{s}_t^r$. There is a cost c_p^r of giving plant p the ability to produce product r and the total cost has to be minimized. There is no other cost (production, inventory, and logistic costs are not taken into account).

Constraint (i) models the evolution of inventory and constraint (ii) is the demand satisfaction formalized with the average value-at-risk, explained more in detail below. Negative inventory levels are allowed and are interpreted as non-satisfied demand. Constraints (iii) and (iv) are capacity constraints, with two particular features: a plant able to produce product r has to maintain a minimal production of this product over each month; the indexes t in the parameter v_{pt}^r allow to model the fact that a plant do not reach immediately its full capacity for a product r (workers need to be trained, means of production to be adapted). Constraint (v), written as a "measurability constraint", means that the values of the variables $\boldsymbol{s}_t^r, \boldsymbol{q}_{pt}^r$ can only depend on the values taken by the demand at time t and before (the planner does not know the future). Note that these decision variables are random since they depend on the realization of the demand at t and before.

Average value-at-risk. The definition of the average value-at-risk (also called conditional value-at-risk or expected shortfall measure) relies on the value-at-risk. These notions are widely used in finance and we refer the reader to the book by Föllmer and Schied (2004) [2] for further discussions. For $\alpha \in (0,1)$, the *value-at-risk* $\mathrm{V@R}_\alpha(\boldsymbol{s})$ of a random variable $\boldsymbol{s}$ is, roughly speaking, the smallest real number m such that $\boldsymbol{s} + m$ is smaller than 0 with probability lower than α. (Since such an m is not necessarily reachable, the true definition is with an infimum instead.) In other words, $\mathrm{V@R}_\alpha(\boldsymbol{s})$ is the right-side α-quantile of the distribution of $-\boldsymbol{s}$. Its *average value-at-risk* $\mathrm{AV@R}_\alpha\big(\boldsymbol{s}\big)$ is the average of $\mathrm{V@R}_\tau(\boldsymbol{s})$ over $\tau \in (0,\alpha)$: $\mathrm{AV@R}_\alpha\big(\boldsymbol{s}\big)$ is the average value of $\boldsymbol{s}$ over the α worst outcomes.

3 Method

Due to the obvious hardness of program (P), we turn to an approximate method. It consists first in relaxing the measurability constraint to get a two-stage stochastic program where the first-stage variables are still the y_p^r and where the second-stage variables are the $\boldsymbol{q}_{pt}^r$. Relaxing the measurability constraint means that once the y_p^r has been chosen, the demand over the whole horizon is supposed to be revealed. Second, we use sample average approximation (see a paper by Kleywegt *et al.*(2002) [4] for a general presentation of this method), roughly as follows.

The sample space is replaced by a finite sample space Ω of scenarios drawn uniformly at random. Each scenario is a possible realization of $(\boldsymbol{d}_1^r, \ldots, \boldsymbol{d}_T^r)_{r\in\mathcal{R}}$. With the following lemma based on results by Rockafellar and Uryasev (2002) [5], the two-stage approximation with finite sample space Ω becomes a mixed integer linear program, where the only integer variables are the binary variables y_p^r. It can then be solved by any standard MIP solver and standard results allow to control the error when using Ω in place of the original sample space.

Lemma 1. *For a random variable* $\boldsymbol{s}$ *taking its value uniformly at random in a set* $\{s_\omega \colon \omega \in \Omega\}$*, the inequality* $\mathrm{AV@R}_{1-\beta}\big(\boldsymbol{s}\big) \leq 0$ *holds if and only if the following polyhedron is nonempty:*

$$\left\{ \big(\boldsymbol{x}, m\big) \in \mathbb{R}_+^\Omega \times \mathbb{R} \colon \ \frac{1}{|\Omega|} \sum_{\omega\in\Omega} x_\omega \leq (1-\beta)m \quad \text{and} \quad x_\omega \geq m - s_\omega \text{ for all } \omega \in \Omega \right\}.$$

We are currently running tests on industrial data with 20 to 25 plants and 100 to 150 products, over an horizon of 6 months. These data have been provided by a client of our partner, together with the decisions it took. We will thus be able to compare our results with those obtained in practice by the client.

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A Lot Sizing Perspective for the Battery Storage Coordination in Power Distribution Systems

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Abstract

Smart grid innovations are changing the landscape of power distribution systems. The use of batteries to store and release energy is among these innovations, and gives the problem of defining the optimal operation of distribution systems a lot sizing character. As energy prices vary during the planning horizon, batteries can be used to store energy when the prices are low, and release energy to meet the demands when the prices are higher. This talk investigates the problem of finding the best moments to buy energy, and define their lot sizes, in order to meet the demands at each node of a distribution network, along a given horizon. The network topology, the demands at each node for each time period, the position and attributes of all batteries, the bounds for line flows, the positions where energy can be purchased, and their variable prices are assumed known. The solution should unveil the best lot sizes for buying and storing energy in the network, along a given planning period.

1 Introduction

The structure and regulation of the Brazilian electric energy sector have been changing in the last 20 years, following general guidelines of providing a fair competition environment for utilities and better choice for consumers. Among these changes is the Free Energy Market, which allows consumers with installed demand over 500 kW to chose the energy supplier; when the local utility is not the energy supplier, a regulated compensation toll is paid for the use of the network. The Free Energy Market also allows different energy prices for different times of a day. This flexibility give consumers the power to negotiate with different electric energy suppliers to benefit from the competition, according amounts, prices and delivering times for their energy needs.

Smart grid innovations come hand in hand with this new regulatory scenario, providing the technical tools that allows to profit from better prices and delivering times (Lightner & Widergren 2010). The use of batteries to store and release energy is among these innovations, and gives the problem of defining the optimal operation of distribution systems a lot sizing character (Schneider et al. 2016). As energy prices vary during the planning horizon, batteries can be used to store energy when the prices are low, and release energy to meet the demands when the prices are higher.

Studies about the benefits of batteries in distribution networks are recent, but already embraces a diversity of objectives. For instance, Santos et al. (2017) propose a mixed integer linear programming model to optimize the benefits from battery storage and distributed generation (DES) in the planning of an electric distribution network, and Levron et al. (2013) revisit the optimal power flow problem to appraise benefits from energy storage in microgrids.

This research addresses the problem of energy storage management that must unveil a policy for energy purchase and storage that minimizes the total energy cost to meet a given demand pattern in a distribution network, along a given planning horizon. The dynamical behavior of the problem arises from the time variability of energy prices and demands, and from the constraints on storage. Usually, the cost of energy increases during the periods of high demand – see Tarifa Branca[1]; therefore, at times when demands are close to their maximum values, energy costs are at their highest values, and the costs decrease as demand decreases.

2 Modelling and illustrative case study

Using the information presented in the previous section, this research proposes a network-flow mathematical optimization model to solve the problem of energy purchase and battery management in a distribution network. To have a better grasp of the problem, consider the maquette network shown in Figure 1, where variable loads during four time intervals are assigned to nodes A and C, and a storage battery able to store 10% of the maximum demand of the network is in node B; also, network losses are considered negligible.

Table 1 summarizes information about demands and energy prices considered in a illustrative study based in the maquette network. The prices were based on the daily rates practiced by the Electric Energy Trading Chamber[2]; note that the behavior of energy prices are in line with the ideas discussed in the previous section, with the highest prices in periods of high consumption of electric energy.

[1]Available in: http://www.aneel.gov.br/tarifa-branca
[2]Available in: https://www.ccee.org.br/

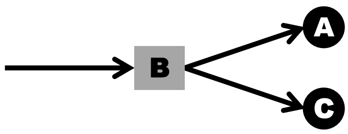

Figure 1: Configuration of the maquette network.

	Demand (MW)			
Node	t=1	t=2	t=3	t=4
A	0.2	0.2	0.3	0.1
C	0.05	0.1	0.2	0.07
Price (R$/MWh)	480	790	1230	790
Min. Constr.(MW)	0.2	0.2	0.2	0.2
Max. Constr.(MW)	0.3	0.4	0.5	0.4

Table 1: Parameters used in the maquette problem.

Equations (1)-(5) summarizes the network flow model for the problem. The loading and discharging times for the battery are assumed much smaller than the duration of the time intervals. The objective function (Equation 1) to be minimized represents the energy purchasing costs, while Equation 2 and Equation 3 controls the energy inventory balance and ensures that demands will be satisfied. Equations 4 and 5 represent the limits on energy purchases and battery operation.

$$\min \quad z = \sum_{t=1}^{n} (c_t u_t + M m_t) \tag{1}$$

$$\text{s.t.} \quad s_{t+1} = s_t + u_t + m_t \tag{2}$$

$$s_t + d_t = u_t \tag{3}$$

$$0 \le u_t \le \overline{u_t} \tag{4}$$

$$-\overline{s} \le s_t \le \overline{s} \tag{5}$$

c_t and d_t are the price and the demand in period t (in average MW), and M is the penalty paid for consumption above $\overline{u}$. The variables u_t, s_t and m_t are, respectively, the amount of energy purchased within the contract range, the amount of energy stored and the amount of energy requested above the maximum value specified in the contract for t. The maximum values of storage and purchase, in each period, are represented by $\overline{s}$ and $\overline{u_t}$. The minimum purchase amount in each period is determined by $\underline{u_t}$. The clauses of maximum and minimum purchases of energy are typical of energy contracts; the minimum value for purchase ($\underline{u_t}$) is always paid, being actually delivered or not in a given time interval; on the opposite side, there is a fine for requests of energy above the upper limit (represented by m_t).

Given the configuration represented in Figure 1 and Table 1, and setting the parameters $M = 5000$ and $\overline{s} = 0.05MW$, the optimal solution without the presence of a battery have cost $z = 1106.30$ (R$). When the possibility of storage is considered, the optimal policy is given by $S = (0.05;\ 0;\ 0;\ 0.03)$, with a cost of $z = 1092.50$ (R$). Since the value of energy stored at the end of the planning horizon is not represented in the model, the storage at the end of the horizon has the minimal value.

Considering a seven days planning horizon, with the demands shown in Figure 2, the optimal solution without storage has the value R$ 7143.9; the optimal solution with storage is R$ 6959.4 (Figure 3). Figure 3 presents the optimal policy, represented by bars, and the energy prices, represented by lines, in each period. Of course, since the the value of energy stored at the end of the horizon is not modeled, all energy stored is used before the last period of the planning horizon.

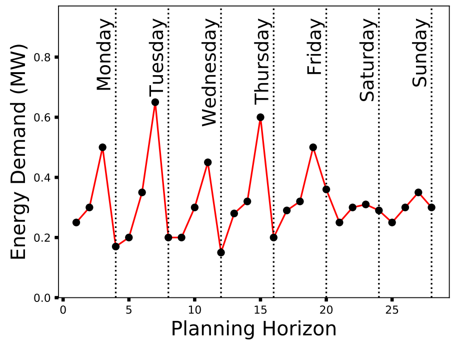

Figure 2: Demand in the planning horizon.

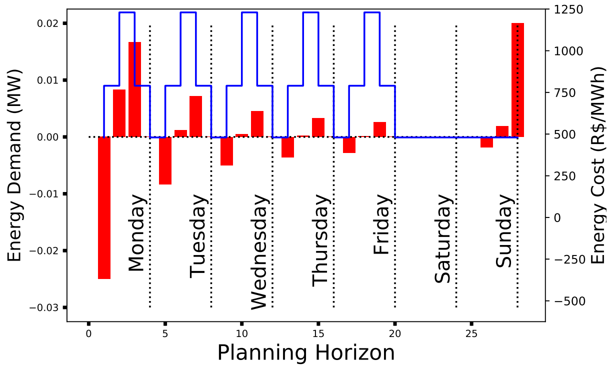

Figure 3: Battery Management Policy.

3 What is next

The next steps in this research will consider scenarios with real scale networks, and include the modeling of losses associated to energy flows in lines and battery operations. Following, the random behavior of energy demands will be investigated.

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Stochastic Lot Sizing Problem with Joint Service Level Constraints

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Abstract

In the stochastic lot-sizing problem, demand uncertainty is explicitly taken into account. In the context where the planner must ensure that a service level can be satisfied, the objective is to minimize the total expected cost whereas the decisions are subject to certain demand fulfillment criteria in which the probability of reaching a service level must be greater than or equal to a predefined value. In this research α and β service levels are considered. These service levels are usually defined for each product separately. In this research we investigate a joint service level which is defined jointly for multiple products in addition to individual service levels. Different mathematical models are proposed to approximate this problem. These approaches are piecewise linear approximation, a quantile based approach and also an approach based on a scenario set. Computational experiments and simulation are conducted to analyse the effect of a joint service level and compare the different approaches.

1 Introduction

While the standard assumption in lot sizing problems is that all the parameters are deterministic, it is inevitable that some parameters are actually uncertain in practice. To deal with the uncertainty in demand, safety stock is usually predetermined for each item under different and strict assumptions such as stationary demand, normality, which may not be realistic in the dynamic lot sizing problem. The decisions resulting

from models that do not incorporate uncertainty are known to be sub-optimal compared to the solution of the models in which the uncertainty has explicitly been taken into account [1]. Consequently, there is a need to have methods to take into account the demand uncertainty and simultaneously determine the time-dependent lot size and buffer stock decisions in the dynamic lot sizing problem. A common model to deal with such a situation is the stochastic lot sizing problem.
The stochastic lot sizing problem is an extension of the deterministic lot sizing in which the problem is to determine the production schedules and quantities to satisfy the random demand over a finite planning horizon. In the context where the planner must ensure that a service level can be satisfied, the objective is to minimize the expected total cost whereas the decisions are subject to certain demand fulfillment criteria. These criteria are usually modeled as chance constraints in which the probability of reaching a service level must be greater than or equal to a predefined value [2]. There are several service level measures that are commonly used in practice [3]. These service levels are usually defined for each product separately.

Having multi-item multi-period capacitated lot sizing problem, in this research, we consider a joint service level which is defined jointly for multiple products in addition to individual service levels when uncertainty in the demand is present. The individual service level is less strict compared to the joint service level. For example the joint service level is 95% while the individual service levels can take any value greater than or equal to 90% provided that the joint service level constraint is satisfied. Many papers studied the stochastic lot sizing problems using different strategies and service level constraints [3, 4, 5]. None of the reviewed papers consider the joint service level in a stochastic context. This research addresses this gap in the literature. Gruson *et al.* studied the joint service level in a deterministic setting [6].

Two different types of mathematical models are proposed to investigate this problem. The first one is based on probabilistic constraints and the second one is based on a scenario set. In this research, we also introduce two different types of joint service level. The first one is based on the α_p service level and the second one is based on the β service level. In all models a static strategy in which all the decision are made at the beginning of the planning horizon is considered and the production quantity decisions cannot be changed when demands are realized.

2 α_p joint service level

The first type of joint service level is based on the α service level and is defined in (1) in which w_i is a weight for each product and α_p^i is the maximum probability of stock out for product i in all planning periods. In this joint service level the weighted average of α_p^i should be less than or equal to the joint α.

$$\sum_{i \in I} w_i \alpha_p^i \leq \alpha_{joint} \tag{1}$$

Two different approaches are proposed for the stochastic lot sizing problem with individual and joint service levels.

In the first approach the model is an extension of the model presented by Tempelmeier [5] in which the α service level is modeled as a chance constraint that can be modeled as linear constraints using a quantile based approach. The joint service level is a parameter while the individual service levels for each item are decision variables in the model and must be larger than or equal to the minimal individual service level. In this formulation the choices of possible service levels for each item are pre-determined.

In the second approach, the problem is modeled as a two-stage stochastic programming model. The difference between this model and the previous one is that the uncertain demand is represented as a discrete scenario set. Following the *static* strategy, the setup and production variables are the first stage variables and they do not have any index for the different scenarios in this model.

3 β joint service level

The second version of the joint service level which is based on the β service level, is defined in (2). $E\{B_{it}\}$ is the expected amount of backorder for product i in period t. This constraint guarantees that the total expected backorder divided by total expected demand is less that a predefined percentage [7]. The joint service level (2) can also be extended to consider the value of each product.

$$\frac{\sum_{t \in T} \sum_{i \in I} E\{B_{it}\}}{\sum_{t \in T} \sum_{i \in I} D_{it}} \leq 1 - \beta \tag{2}$$

To solve this problem we use two different approaches. In the first approach we calculate the expected backorder based on the liniarization of the loss function of the normal distribution. The expected inventory and backlog in each planning period is a non-linear function of the cumulative production in each planning period. In this formulation these non-linear functions are approximated using piecewise linear functions [7]. The second approach is based on the scenario set and discretizing the demand uncertainty which is the same as the second approach for the α service level.

4 Conclusion and future directions

In this research we investigate different approaches to solve a lot sizing problem with individual and joint service level constraints. These approaches are approximations of the real problem. Each of the approaches have their own advantages and disadvantages. While the scenario-based model is sensitive to the number of scenarios, it has the advantage that it can work with any demand distribution, which is not the case in the quantile based and piecewise linear models. Preliminary calculations show that all models still remain difficult to solve. Presenting efficient algorithms to solve large size instances is the next step of this research.

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A Lagrangian heuristic for the capacitated lot sizing and scheduling problem on parallel related production lines

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Abstract

We address a lot sizing and scheduling problem based in a real world production environment where production lines share scarce production resources. Due to the lack of resources and characteristic of demands, the production lines cannot operate all simultaneously and they need to be assembled in each period respecting the capacity constraints of resources. The problem is formulated as a mixed integer programming (MIP) model and a Lagrangian based heuristic is developed to deal with the problem. A MIP based feasibility procedure is proposed to find feasible solutions. Computational tests are performed to verify the efficiency of the proposed method.

1 Introduction and problem description

The simultaneous lot sizing and scheduling problem (LSP) consists of determining the sizes and schedules of production lots in order to minimize costs, such as production, holding and setup costs. This problem has been extensively studied in the literature and several mathematical models were proposed to deal with the problem ([5], [2], [4]).

[2] introduced the general lotsizing and scheduling problem (GLSP) that treated the LSP with dynamic deterministic demand and sequence-dependent setup costs on

a single machine. The main idea of GLSP is to split each period into several micro periods with varying sizes where only one item can be produced. By determining which items will be produced in each micro period, the production lot schedules can then be automatically determined.

The CLSD model, proposed in [5], was introduced using constraints and variables from the traveling salesman problem (TSP) to model the sequencing decisions. The idea is to map the start time and end time of the production of each item in each period.

Reviews of models to represent the LSP problem can be found in [6] and a review with various extensions and solutions approaches of these models can be found in [1].

This paper addresses a lot sizing and scheduling problem inspired in a production environment where several parallel production lines share the same production resources (workers and machines). Due to a lack of these resources, these lines cannot operate all simultaneously and they need to be assembled in each production period (day). Acquiring new resources to keep all production lines running all the time is unfeasible because:

- is necessary high investments (the plant needs to be enlarged and more machines and workers are needed);
- there are not sufficient demands (in this type of industry) to maintain every line working all the time;
- high productions increase inventory levels of perishable items so that items can be deteriorated by the expiration date.

Therefore, managers need to decide which lines will be assembled in each period respecting the capacity constraints of resources and aiming to met customer demands at lower cost. The production environment is characterized by the existence of significant sequence dependent setup times and costs when there are changes between items in the same production line. The setup state preservation between periods is not considered. In the food industry, at the end of each production day, every machine needs to be cleaned, and therefore the setup state is dropped.

The addressed problem in this paper consists of to determine simultaneously: i) which production lines will be assembled in each period, ii) the sizes of the production lots, and iii) the schedules of these lots in each period. Therefore, we deal with a simultaneous lot sizing and scheduling problem on parallel production lines that are related by the production resources. We introduce the nomenclature lot sizing and scheduling problem on parallel related lines (LSPPRL) to represent this problem. The CLSDPRL model proposed to deal with LSPRLP is an extension of the CLSD model proposed in [5]. To deal with the LSPPRL we also propose a Lagrangian based heuristic. The Lagragian sub-problem can be decomposed into a lot sizing problem with decisions about assembly lines and a scheduling problem that can be decomposed by periods and production lines. A MIP based procedure is also proposed to find good solutions for the problem.

2 The Lagrangian heuristic

We propose a Lagrangian approach (LH) to solve the CLSDPRL model consisting of the dualization of the capacity constraints and the constraints that link the production variables and scheduling variables. The resulting problem can be decomposed into two sub-problems: a lot sizing problem with production lines assembly decisions and a parallel machine scheduling problem.

The lot sizing sub-problem has very simple capacity constraints and is easier-to-solve than the CLSDPRL model. The parallel machine scheduling sub-problem can be further decomposed into a set of single machine and single period sub-problems that can be solved by commercial solvers in short computational time.

The subgradient method proposed in [3] is used to solve the dual problems. It updates the Lagrangian multipliers (or dual variables) iteratively based on the dual bound (objective function value of the Lagrangian sub-problem) and the primal bound of the problem (objective function value of the original problem).

To complete our solution approach, we propose a feasibility procedure based on the mathematical formulation of the problem consisting of fixing the value of some binary variables in the value obtained by solving the lot sizing sub-problem and optimizing the resulting variables in the original problem by production line decomposition.

3 Final remarks and conclusions

We propose a set of 140 test instances to study the computational performance of the proposed approach. We compare the Lagrangian approaches with the Branch-and-Cut algorithm of a commercial powerful solver and we identify the advantages of each method. Computational tests showed that for medium and large size instances, our approach can significantly reduce the average deviations from the dual bound obtained by a powerful solver. Further studies can investigate more efficient algorithms to solve the Lagrangian sub-problems with the aim to avoid using the Branch-and-Cut algorithm.

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A single-item lot-sizing problem with a by-product and inventory bounds

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Abstract

Waste accumulation and global warming are currently hot topics. To overcome these issues, new environmental regulations have been adopted by different organizations. In this context, we propose a model for the single-item lot-sizing problem with a by-product and inventory bounds. During the production of a main product, a by-product is generated, stored in a limited capacity and transported with a fixed transportation cost. The problem is investigated for two types of the by-product inventory capacity: non-decreasing time-dependent and stationary. We first show that the problem with non-decreasing inventory bounds is NP-Hard. To solve it optimally, we propose a pseudo-polynomial dynamic programming (DP) algorithm, based on the classical decomposition into blocks of periods. For the version with a stationary capacity, a polynomial solution approach is proposed.

1 Introduction

The production process of a wide range of industrial sectors often generates collateral substances/products together with a main product, namely: **(i)** *co-products*, which have the same importance as that of the main product, and **(ii)** *by-products* or *waste-streams*, which are usually unexpected and have less economic importance than the main product. By-products are currently low-value used and often go to disposal, despite their potential for high added-value exploitation by alternative ways.

Given the considerable waste accumulation in landfills, governments around the world enforce new constraining environmental regulations. In particular, The Directive nr. 1999/31/EC of April 1999 forbids companies to dispose of by-products, like chemical liquids and gases, in landfills. Under this conjuncture, companies start to consider by-products in their supply chains, as well as, to think how to convert them into high added-value products.

Given the topicality of this issue, only a few studies coupling by-products management with production planning problems can be found in the related literature. Spengler et al. [4] propose a model jointly with a dynamic programming algorithm for the by-products re-use in the iron and steel industries. Sridhar et al. [5] address a NP-hard problem, where the function expressing the by-products production is non-linear and non-convex. Generalized lot-sizing problems dealing with collateral products are given in [1, 3]. The problem with by-products and lost sales is shown to be NP-hard [3].

Motivated by the industrial imperative to exploit the economic potential of by-products and following the former studies, we address a single-item lot-sizing problem (SILSP) with a by-product and inventory bounds. After the problem statement given in Section 2, a preliminary analytical study is conducted in Section 3. Finally, Section 4 concludes and gives short term perspectives of this work.

2 Problem statement

Consider a single-item lot-sizing problem (SILSP) with a by-product and inventory bounds (cf. Figure 1). It aims to determine, over a planning horizon of T periods, when, where and how much to produce a main product, while satisfying a periodic deterministic demand and managing the generated by-product. During this process an amount of by-products is produced with a known ratio. These by-products have a limited inventory capacity for every period. Unlike Ağralı [1] and Lu and Qi [3], no demand for the by-products is considered. All costs relating to the main product, specific to classical time-dependent lot-sizing, appear in the objective function: fixed setup, variable production, and holding costs. As far as by-products are concerned, inventory holding and fixed transportation costs are added. Transportation costs occur when produced and/or stored by-products are transported in order to empty the stock at the end of a given period. The objective function aims at minimizing the sum of the costs occurring over the entire planning horizon.

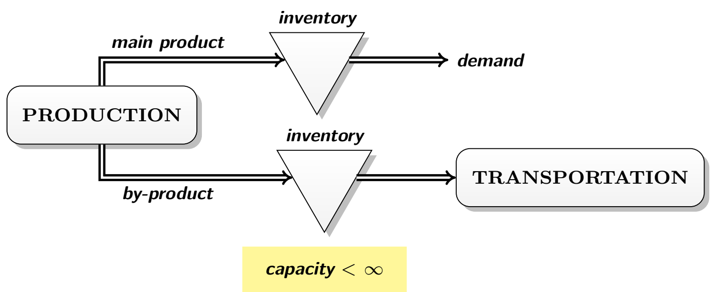

Figure 1: Single-item lot-sizing problem with a by-product and inventory bounds

3 Analytical study

Before proposing sound solution methods, let us study the complexity of the SILSP for two types of the inventory limited capacity: **(i)** non-decreasing, **(ii)** stationary over the time horizon. To do this, we use structural properties of optimal sub-plans.

Definition 1. *A period is called:*

- ***Regeneration period****: if the production quantity in this period is different from zero.*
- ***Inventory period****: if the inventory level of a type of product is zero.*
- ***Fractional transportation period****: if there is transportation but the quantity of by-products transported does not reach the capacity.*

SILSP with a by-product and non-decreasing inventory bounds

Let the inventory level of the by-product be non-decreasing. Note that, this assumption often mirrors industrial realities, since there is no reason for a company, which has invested in a warehouse or a reservoir, to not use it later. By reduction to the subset sum problem, the following theorem holds.

Theorem 1. *The SILSP with a by-product and non-decreasing inventory bounds is NP-hard.*

Property 1. *In an optimal solution of the SILSP with a by-product and non-decreasing inventory bounds, there is at most one period with production between two inventory periods.*

Property 1 can be proved by contradiction. By virtue of this property, the optimal solution can be decomposed in blocks of periods [2]. Each block is delimited by two consecutive inventory periods. The inventory levels of both, the main and by-product(s), are not necessarily equal to zero in the same time. Consequently, both incoming or outgoing flows can emerge in or out the block. The main product flows depend on the total demand of the problem, while the by-product flows are limited by the capacity.

Based on the above decomposition into blocks of periods, the corresponding dynamic programming algorithm turns out to be pseudo-polynomial. It implies that the SILSP with a non-decreasing capacity on the by-product inventory is weakly NP-hard.

SILSP with a stationary capacity on the by-product inventory

Focus now on the SILSP with a stationary capacity on the by-product inventory. The following property can be proven by contradiction:

Property 2. *In an optimal solution of the SILSP with a by-product and constant inventory bounds, there is at most one fractional transportation period between two periods where the inventory levels of both the main product and the by-product are zero.*

In the light of Property 2, the optimal solution of SILSP can be decomposed in blocks of periods, delimited by the periods in which the inventory levels of both the main product and the by-product are zero. This decomposition allows us to define a polynomial solution method based on dynamic programming, the main idea of which resides in: **(i)** find the the least expensive succession of blocks, **(ii)** in each block, calculate the cost of demand production in different fractional transportation periods.

4 Conclusion and perspectives

This paper introduces a single-item lot-sizing problem with a by-product and inventory bounds. The problem is studied for two types of the by-product inventory capacity: non-decreasing time-dependent and stationary. We show that the problem with a non-decreasing time-dependent capacity is NP-hard, and proposed a pseudo-polynomial DP algorithm. For the version with a stationary capacity, a polynomial solution approach is provided. Future research would be dedicated to highlighting at industrial scale the practical interest and the viability of the given model jointly with the DP based solution methods.

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Short abstracts

Integrated Lot Sizing and Cutting Stock Problem Applied to a Spring Industry

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Abstract

Industries in general have the need to use their resources efficiently. For companies that deal with the cutting stock problem, that is, whose production process involves cutting of raw material in the production of demanded items, minimizing the loss of raw material is a very important need. The cutting stock problem occurs in several industries, such as paper, steel, wood, springs and many others. This work deals with the analysis of a spring industry aimed at reducing inventory costs and steel losses in the bar cutting process, which is addressed as a multiperiod one dimensional cutting stock problem. A mathematical model from the literature was modified to consider demand for objects, parallel machines and stock limits. According to the exact techniques performances, heuristics will be used for results comparisons. It is expected that this study results in a tool that reduces material losses in cutting process of the studied company, and possibly in other similar industries.

Lot sizing and scheduling problem considering customers orders

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Abstract

The lotsizing and scheduling problem aims to determine the sizes of the production lots and the sequence of these lots in each period of a planning horizon, in order to minimize costs. We consider the problem where the demands are managed through customers orders, which one can be composed of several distinct items. Customers do not receive partial orders, so, the order can be rejected if there is not enough production capacity to produce all the requested items in an order. Moreover, each order must be delivered within a time window specified by the customer and items produced are perishable and may remain stored for a limited time. Preliminary tests using an integer linear optimization model, show that the quality of the solutions provided by an optimization solver is influenced by the quality of the bounds obtained within a defined time limit. Thus, the objective of the work is to develop new formulations/reformulations to improve the quality of the bounds.

Machine Flexibility in Lot Sizing Problems: Construction of Heuristics

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Abstract

This study is related to the lot sizing problem with parallel machines, which consists of determining the quantity of items to be produced (in each one of the machines), in a finite time horizon, satisfying some constraints and minimizing the production costs. In the standard lot sizing problem with parallel machines, each item can be produced on any of the machines. However, in practice, it can be very expensive to install machines that have full flexibility, especially if the products are very different. Therefore, it may be interesting to implement only a limited amount of flexibility. In the studied mathematical formulation, the investment of upgrading a machine to produce a specific product becomes a binary decision variable and there is a global budget on investment decisions. The computational results obtained with CPLEX showed that the formulation is very difficult, especially for instances with many items. Therefore, two different heuristics are proposed for this problem, in order to obtain good solutions in reasonable computational times.

The Integrated Lot-Sizing and Cutting Stock Problem Applied to a Mattress Industry

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Abstract

In an increasingly globalized and competitive market, companies need to reduce costs and waste in order to increase their productivity and differentiate themselves from others. Two fundamental processes arise in the production planning of many industries: the Lot Sizing Problem and the Cutting Stock Problem. Usually, these problems are handled separately, but by looking at them in an integrated way, it is possible to obtain more precise and better results. This work intends to investigate the integrated problem applied to a mattress manufacturing industry, aiming at reducing costs and waste in this company. An initial mathematical model is proposed and initial computational results are presented.

A Fix-and-optimize with objective function exchange applied to the production planning in pulp and paper industry.

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Abstract

The production planning in pulp and paper industry consider critical units which produces pulp, paper and energy. The units are organized in a two-stage problem with multiple papermaking machines. An alternative Fix-and-optimize heuristic was proposed to solve the problem, motivated by the difficult to treat multi-stage problems when the objective function of the problem does not directly depend on the earlier stages variables. Furthermore, partition the two-stage decision variables are difficult to synchronize and solve in sub-MIP problems. The proposed method has two phases. In the first, the method fixes sub-periods sizes and the papermaking machine incumbent solution, and change the objective function based on pulp inventory levels. In the second, the original objective function is restored, the sub-period sizes are released, and the first-stage variables are fixed to the solution obtained in the first stage. From this point, the fix-and-optimize partitions are applied.

Reformulations for the Lot Sizing Problem: an initial study

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Abstract

In this undergraduate project we study reformulations for the lot sizing problem with multiple items and capacity constraints. We have done a detailed study of some reformulations based on the shortest path and facility location problem. These formulations have been studied for several authors in the last years. In addition to the theoretical study, the mathematical models were implemented and solved by optimization packages and some computational results are presented.

Capacitated lot sizing and replanning problem for machining industry

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Abstract

This research considers an application of capacitated lot sizing problem with multi-machines and multi-items in a machining industry. In these problems, the demand for each item needs to be satisfied respecting the capacity constraint for multi-machines and multi-items. Backorders, overtime, setup time, inventory and their respective costs are allowed. Frequently, these industries are surrounded by interruptions in the machines which are inherent from productions systems and forces the production replanning. The purpose of this research is to integrate the lot sizing problem with the replanning problem that occurs due to interruptions in the machines. The replanning problem considers two causes of interruption: corrective machine maintenance and tools break down, both cases are common in the machining industry. Computational tests were performed and the optimal solution was found in few seconds.

Keywords: Lot Sizing Problem; Replanning Problem; Mixed Integer Programming.

Production planning considering cutting and scheduling aspects

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Abstract

Production planning is a concern inherent in a production process and, particularly, in production environments where materials are cut. In some industrial applications, delivering the orders on time can be far more important than reducing cut objects cost. While cutting problems usually aim to minimize the waste of raw material, scheduling problems deal with the allocation of orders of production over a time horizon, respecting the operational constraints of the process. Meeting the due dates is an objective that gained a prominent importance in companies for avoiding fines, maintaining the service level, among others. In this work, we propose a mathematical model that combines the standard objective of minimizing the number of rolls used with a scheduling term penalizing the tardiness of the cutting operations. A solution method is proposed using column generation and valid inequalities. Computational results are presented for real instances and randomly generated instances.

A new model integrated in the planning and programming of furniture production

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Abstract

In many manufacturing industries, there are the production of the objects and the cutting of the objects into smaller pieces in order to meet a specific demand. In the optimization of such productive processes, one can identify the lot sizing, schedulling and the cutting stock problems. Treating these problems separately can to make the space of solutions and interdependence between them reduced. The mathematical models proposed by researchers of the area integrate only two of the problems and do not worry about the sequence with which the cutting patterns must be executed. However, in some industrial contexts, such as furniture industry determinate a production planning that indicate a best sequence these patterns can lead to improvements in overall production costs. In this work, we propose a mixed integer mathematical model that will integrate three optimization problems present in the production process of the furniture industry.

Integrated Lot Sizing and Cutting Stock Problem with Usable Leftovers

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Abstract

This research deals with the integrated lot sizing and cutting stock problem with usable leftovers. The idea is to consider, simultaneously, the decisions related to both problems so as to capture the interdependency between these decisions in order to obtain a better global solution. Both problems appear together in many companies and are complex and very difficult to be solved. An integrated mathematical model was proposed to determine the best way to cut objects available in stock to produce demanded items in a planning horizon by minimizing the waste of raw material and the inventory costs of anticipated items and possible leftovers that can be generated to be used in the future. Some preliminary computational tests were performed and show the good performance of the proposed solution strategy.

A lot sizing and cutting stock problem in a trusses slabs industry

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Abstract

This paper addresses the problem of production planning in a trusses slabs industry. The main component of a truss slab is the joist, which is formed by a concrete base and a lattice frame. The production of these joists, of varying lengths, takes place in forms that are filled by concrete using separators, and can be interpreted as a cutting/packaging problem. The lattice frames, in turn, must be cut, also in varying lengths, to compose the joist. We propose a mathematical model to deal with the production planning of joist in a finite time horizon, with discrete periods, considering a two-level integrated lot sizing and cutting stock problem. The objective is to optimize the cutting of lattice frames and the filling of the forms, in order to meet the demand and minimize the loss of material and space, inventories costs and setup costs. A solution method is proposed and some computational results, based on practical data, are presented.

Production planning integrated to the optimization problem of the use of moulds

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Abstract

In this work, we approach the alveolar slabs production planning integrated to the optimization of the use of moulds. The production process begins with an orders portfolio, where the client's demand is specified including the deadline. Then the process manager plans weekly, deciding which and how many pieces will be produced. Following this schedule, the assembly sector conducts the preparing of moulds, placing of reinforcement, prestressing, casting of concrete and removing the mould. Based on this, we propose an initial model on Multi-Period Cutting Stock Problems (see Melega et. al [1]): we consider the production as cutting of large objects (the moulds) into smaller pieces (the slabs), in order to minimize waste of raw material (steel cable) and inventory costs, satisfying the demand and the capacity of the moulds. We intend to improve this model and apply solution methods to the studied models, like CG method. Computational results will be obtained based on real data.

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The integrated lot sizing and transportation problem

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Abstract

This work analyses the value of the machine flexibility applied to the integrated lot sizing and transportation problem. We look at this problem in the context of a network of existing plants that are (or can be) configured to make one or many different products. We consider a network of customers and specific transportation costs between each plant and customer. The decision on which plants to upgrade and to which type(s) of product has to take into account the trade-off with the transportation cost and hence the geographical dispersion of the demand.