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EDITED BY:
Roberto Mosca
Flavio Tonelli
Riccardo Melioli

University of Genoa
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Author Index

s.tang.2002@cranfield.ac.uk

Terzi Sergio
sergio.terzi@unibg.it

Troblová Petra
ptroblov@kpv.zcu.cz

Ublova Marina
ublova@kpv.zcu.cz

Ulrych Zdenek
ulrychz@kpv.zcu.cz

Vanderhaeghen Dominik
vanderhaeghen@iwi.uni-sb.de

Visintin Filippo
filippo.visintin@siti.de.unifi.it

Werth Dirk
werth@iwi.uni-sb.de

Zang Sven
zang@iwi.uni-sb.de

Zangl Fabrice
zangl@iwi.uni-sb.de

Zeman Lukáš
lukasekzeman@seznam.cz

Ziemann Jörg
ziemann@iwi.uni-sb.de

Zoppoli Vincenzo

Zorzini Marta
marta.zorzini@polimi.it

Zraly Martin
martin.zraly@fs.cvut.cz

Table Of Contents

RE-PRINTING FROM MITIP 2004 EDITION

MASTER PRODUCTION SCHEDULE GENERATION IN A MULTI-ITEM SINGLE-MACHINE CAPACITED MANUFACTURING SYSTEM WITH SEQUENCE-DEPENDENT SETUP TIMES AND COSTS

Francesco Frattini, Maria Elena Nenni, Angelo Rossi, Massimiliano M. Schiraldi

FRANCESCO FRATTINI
DPGI - "Federico II" University of Naples
Piazzale Tecchio 80, 80125 Naples - Italy

MARIA ELENA NENNI
DPGI - "Federico II" University of Naples
Piazzale Tecchio 80, 80125 Naples – Italy
mnenni@unina.it

ANGELO ROSSI
DPGI - "Federico II" University of Naples
Piazzale Tecchio 80, 80125 Naples – Italy
angrossi@unina.it

MASSIMILIANO M. SCHIRALDI
DIM - "Tor Vergata" University of Rome
Via del Politecnico 1, 00133 Rome – Italy
schiraldi@ing.uniroma2.it

Abstract: **In this paper we address the problem of generating the Master Production Schedule in a Multi-Item Single-Machine Capacited manufacturing system, with sequence-dependent setup times and costs. For each time bucket in the MPS, deliveries of finite products are defined in terms of due dates and quantities to be shipped. Production capacity is finite, though it is possible to exploit a limited extra-capacity on the basis of availability of work-force overtime, which anyway implies additional production costs. Backlogging is not allowed, while a maximum earliness for each job is defined for each product. In the proposed approach, two sub-problems are identified: a Sequencing Problem which aims to determine the available production capacity for each period, and a Capacited Lot-Sizing Problem which aims to determine the production quantity for each product in each period. The former is modelled as a dynamic Asymmetric Travelling Salesman Problem which complies with sequence- dependent set-up costs and a rolling horizon and a genetic algorithm searches for sub-optimal schedules. We demonstrated the proposed heuristic effectiveness through a validation campaign performed in the Unilever S.p.A. manufacturing plant in Pozzilli, Italy.**

Index Terms: **scheduling and lot-sizing, genetic algorithm, master production schedule, capacited manufacturing system**

I. INTRODUCTION

In production systems with batch processing, sequence-dependent setup times and capacity constraints, it is of major importance to effectively solve scheduling and lot-sizing problems. Lots of enterprises, specifically in capital-intensive industries, which produce a large variety of products, must face this kind of problem which, if not appropriately approached, may cause late deliveries with serious impacts on costs. Scheduling and lot-sizing problems have been analyzed in different ways, depending on product structure types (Single Level, Serial, Assembly, General system), on production capacity characteristics (Uncapacited, Capacited Single-Stage, Capacited Multi-Stage) and on time modeling (Small Bucket, Large Bucket)[1]. For a large number of these instances – which cannot be optimally solved in a polynomial time, various heuristics and meta-heuristics have been developed during years [2],[3],[4].

The current best survey about lot sizing and scheduling problem is by Drexl and Kimms (1997). More recent integration is by Jans and Degraeve (2004) that have particularly focussed on dynamic lot sizing. But to the best of our knowledge, however, we now present an original contribution on capacitated Single-Machine lot sizing and scheduling sequence-dependent setup times and costs.

II. PROBLEM MODELING

Consider a *single-stage, multi-item* manufacturing production system, which has to produce *N* different items over a finite time horizon, which is composed by *T* periods of the same length, i.e. weeks; for each of these periods, a *demanded quantity* is specified; the demand must be satisfied within the end of the period and no backlog is allowed**.** Manufacturing time for each item batch is little with respect to period duration**.** However, it is possible to anticipate production of each item up to a certain number of periods: managers may decide, from time to time, to start the production of a certain item well in advance, though in accordance to storage constraints. The maximum anticipation is anyway little with respect to time horizon length, thus additional storage costs may be negligible.

Changeover implies a production capacity loss, which is directly proportional to setup times; these latter, anyway, depend on the sequence of the different items to be manufactured. Production capacity is finite and fixed for each period; however, there is the possibility to exploit overtime to recover some additional production capacity. A maximum overtime limit is anyway fixed for each period. Each time overtime is exploited, a fixed cost is bore due to the fact that standard time limit has been passed, and a variable cost is bore in dependence to overtime duration. Let us assume that raw materials and components stocks will be always available for production, thus no stock-out may occur in the upstream supply chain.

Master Production Schedule formulation in such a context is not a simple issue. The aim is to reach a solution in which production costs are minimum and no late deliveries are present.

To this extent, let us now introduce the following parameters:

T	:	Number of periods in time horizon
N	:	Number of produced items
A_i	:	Maximum number of periods the start of production of item *i* may be anticipated, with respect delivery date
LT_t	:	Planning operating time in period *t*
LT_t^{ex}	:	Unplanned overtime amount in period *t*
ct_i	:	cicle time for product *i* manufacturing
s_{ij}	:	Setup time to changeover from item *i* to item *j*
c_{ij}	:	Setup cost to changeover from item *i* to item *j*
c^{ex}	:	Overtime fixed cost
p_i^{ex}	:	Increase in production cost due to overtime, for a single *I* item
d_{it}	:	Demanded quantity of item *i* in period *t*

Along with the following **decision variables**

q_{ti}	:	Item *i* quantity to be produced in period *t*, in regular time
q_{ti}^{ex}	:	Item *i* quantity to be produced in period *t*, in overtime
x_{t^*ti}	:	Binary variable: x_{t^*ti} = 1 if the demanded quantity d_{it} is satisfied in period *t* in regular time
$x_{t^*ti}^{ex}$	:	Binary variable: $x_{t^*ti}^{ex}$ = 1 if the demanded quantity d_{it} is satisfied in period *t* in overtime
y_{ijt}	:	Binary variable: y_{ijt} = 1 if setup s_{ij} is performed in period *t*
y_t^{ex}	:	Binary variable: y_t^{ex} = 1 if in period *t* overtime is exploited

Master Production Schedule formulation problem may now be solved through the following **integer programming** formulation:

$$\text{Min} \sum_{t=1}^{T}\left(c^{ex} y_t^{ex} + \sum_{i=1}^{N} p_i^{ex} q_{t^*i}^{ex} \right) + \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j=1}^{N} c_{ij} y_{ijt} \quad (1)$$

subject to:

$$\sum_{t^*=\{t-A_i,1\}}^{t} x_{t^*ti} = \{0,1\} \qquad \forall i = 1,\dots,N \;,\; \forall t = 1,\dots,T \quad (2)$$

$$q_{t^*i} = \sum_{t=t^*}^{\{t^*+A_i,T\}} x_{t^*ti} d_{it} \qquad \forall i = 1,\dots,N \;,\; \forall t^* = 1,\dots,T \quad (3)$$

$$q_{t^*i}^{ex} = \sum_{t=t^*}^{\{t^*+A_i,T\}} x_{t^*ti}^{ex} d_{it} \qquad \forall i = 1,\dots,N \;,\; \forall t^* = 1,\dots,T \quad (4)$$

$$\sum_{i=1}^{N} ct_i \left(q_{t^*i} + q_{t^*i}^{ex} \right) + \sum_{i=1}^{N}\sum_{j=1}^{N} s_{ij} y_{ijt^*} \le LT_{t^*} + \qquad \forall t^* = 1,\dots,T \quad (5)$$

$$\sum_{i} y_{ijt} = 1 \qquad \forall t = 1,\dots,T \;, \quad \forall i \in I = \{i : q_{ti} \neq 0\} \cup \{i : q_{ti}^{ex} \neq \quad (6)$$

$$\sum_{j} y_{ijt} = 1 \qquad \forall j \in J = \{j : q_{tj} \neq 0\} \cup \{j : q_{tj}^{ex} \neq 0\} \quad (7)$$

No enclosed cycles in t $\qquad \forall t = 1,\dots,T \quad (8)$

$$x_{t^*ti}, x_{t^*ti}^{ex}, y_{ijt}, y_t^{ex} = \{0,1\} \qquad \forall i, j, t^*, t \quad (9)$$

The objective function (1) aims to minimization of setup costs and overtime costs; constraint (2) impose demand satisaction (equation yields 0 if $d_{it} = 0$, otherwise yields 1; it guarantees that in within period t - A_i and t, a production order will be launched to satisfy the demand $d_{it} \neq 0$. Note that $\{t - A_i, 1\}$ equals to $t - A_i$ if $t - A_i > 1$, otherwise equals to 1: this because the demanded quantity d_{it} , starting from period $t = A_i + 1$ may be anticipated at maximum by A_i periods, while the demanded quantity d_{it} with $t < A_i + 1$ may be only anticipated by $t - 1$ periods. Constraints (3) and (4) tie production batches q_{t^*i} and $q_{t^*i}^{ex}$ of item i to regular time and overtime in period t^*; these quantities clearly are influenced by orders related to period t^* up to t^*+ A_i . Note that $\{t^* + A_i, T\}$ equals to $t^* + A_i$ if $t^* + A_i < T$, otherwise equals to T. Indeed, starting from period $t^* = T - A_i + 1$, the produced quantities q_{t^*i} and $q_{t^*i}^{ex}$ do not depend any more on the demanded quantity of $A_i + 1$ periods, but only on that of $T - t^*$ periods.

Constraint (5) verifies that production orders launched for a period t and the related loss of production capacity due to changeovers do not violate the loading time constraint for that period.

Constraints (6), (7) and (8) are used to avoid inefficient solution, rejecting MPS in which a single item may be scheduled more that one time in a single period, and avoiding the generation of enclosed cycles.

III. PROBLEM SOLVING

Such a problem belongs to NP-hard class problems, thus usually cannot be solved with complete enumerative algorithms because – even leaving out the complexity coming from sequence-dependent setup times – that will require the evaluation of a number of MPS equals to

$$\prod_{i=1}^{N}\prod_{t=1}^{T} \{A_i + 1, t\}^{X_{it}} \quad (11)$$

where X_{it} represent a binary variable which equals to 1 if d_{it} > 0, 0 otherwise.

Thus, in this sequence-dependence context, the search for the best Master Production Schedule may be modeled in two phases:

A lot-sizing problem in each period t;

A sequencing problem in each period t modeled through the Asymmetric Travelling Salesman Problem.

The first step in the procedure resides in the solution of a Large-Bucket, Single-Machine, Multi-Item, Single-Stage, Capacited Lot-Sizing Problem, for which the following mixed integer programming formulation may be suitable:

$$\min \sum_{t=1}^{T}\left(c^{ex} y_t^{ex} + \sum_{i=1}^{N} p_i^{ex} q_{t^*i}^{ex} \right) + \sum_{t=1}^{T} \bar{c} y_t \qquad (1$$

subject to:

$$\sum_{t^*=\{t-A_i,1\}}^{t} x_{t^*ti} = \{0,1\} \qquad \forall i = 1,\dots,N \;,\; \forall t = 1,\dots,T \qquad (2$$

$$q_{t^*i} = \sum_{t=t^*}^{\{t^*+A_i,T\}} x_{t^*ti} d_{it} \qquad \forall i = 1,\dots,N \;,\; \forall t^* = 1,\dots,T \qquad (3$$

$$q_{t^*i}^{ex} = \sum_{t=t^*}^{\{t^*+A_i,T\}} x_{t^*ti}^{ex} d_{it} \qquad \forall i = 1,\dots,N \;,\; \forall t^* = 1,\dots,T \qquad (4$$

$$\sum_{i=1}^{N} u_{t^*i} q_{t^*i} + \sum_{i=1}^{N} u_{t^*i}^{ex} q_{t^*i}^{ex} \le C_{t^*} + C_{t^*}^{ex} \qquad \forall t^* = 1,\dots,T \qquad (1$$

$$x_{t^*ti}, y_t^{ex} = \{0,1\} \qquad \forall i, j, t^*, t \qquad (9$$

$$y_t \in N_0 \qquad \forall t = 1,\dots,T \qquad (1$$

Where y_t stands for the changeover number in period *t* while $\bar{c}$ stands for the average cost of a single setup. This problem represents a sub-problem of the previously described general problem, in which production capacity losses originating from setup stops are not considered.

The second step of the procedure resides in solving a sequencing problem for each period *t*, that is to find theitem sequence to be manufactured in order to reduce setup times. It is possible to demostrate that this problem – in its general form – can be lead back to an Asymmetric Traveling Salesman Problem[5],[6].

Indeed, let us consider a complete graph $G = (V, A)$ in which the set $V = \{0,1,\dots,n\}$ represents the *n* operations to be performed, on top of a "dummy" activity (node 0) at the beginning and at the end of the sequence. To the arcs ingoing and outgoing from node 0 a null cost $c_{0j} = c_{i0} = 0 \;\; \forall i, j \in V - \{0\}$ is assigned, while to all the other arcs the cost c_{ij} is assigned, where c_{ij} equals to the setup time between operation *i* and *j*; due to the fact that the optimal solution of the Traveling Salesman Problem is represented by a closed path which touch each node only one time, though minimizing the path cost; this represents the optimal solution even for the sequencing problem, because the path cost results from the sum of setup times. The sequencing problem, indeed, result of NP-hard class, being referable to a NP-hard problem. In the present case, a formulation of the problem may be the following:

$$\min \sum_{t=1}^{T} \sum_{i=0}^{N} \sum_{j=0}^{N} s_{ij} y_{ijt} \qquad (14)$$

Subject to:

$$\sum_{i \in K_t} y_{ijt} = 1 \qquad \forall j \in K_t \;,\; K_t = \{0\} \cup \{k : q_{kt} \ne 0\} \cup \{k : q_{kt}^{ex} \ne 0\} \;, \forall t = 1,\dots,T \qquad (15)$$

$$\sum_{j \in K_t} y_{ijt} = 1 \qquad \forall i \in K_t \;,\; K_t = \{0\} \cup \{k : q_{kt} \ne 0\} \cup \{k : q_{kt}^{ex} \ne 0\} \;, \forall t = 1,\dots,T \qquad (16)$$

No enclosed cycles $\qquad \forall t = 1,\dots,T \qquad$ *(8)*

$$y_{ijt} = \{0,1\} \qquad \forall i, j \in K_t \;,\; K_t = \{0\} \cup \{k : q_{kt} \ne 0\} \cup \{k : q_{kt}^{ex} \ne 0\} \;, \forall t = 1,\dots,T \qquad (17)$$

The set K_t contains the indexes of the items that should be produced during period *t* plus a dummy node 0 with the following characteristics: $s_{j0} = 0$ e $s_{0j} = s_{mj} \;\; \forall j \in K_t \;,\; K_t = \{0\} \cup \{k : q_{kt} \ne 0\} \cup \{k : q_{kt}^{ex} \ne 0\}$ where *m* equals to the index of the last item scheduled for production on the previous period *t* –1. The sequencing procedure will dynamically advance from one period to the other (index *m*) because the TSP problem will be solved *T* times starting from the first period to the last one within time horizon.

Here, the search for the sub-optimal scheduling solution is implemented through a genetic algorithm [7] which works with the following hypotheses:

- if $d_{it} \ne 0$ for item *i* in period *t*, the demanded quantity will be directly translated in a production order in period *t* or in the previous periods, up to period *t-A$_i$*. All the information regarding the demanded quantity in period *t* are contained in the vector ($x_{t-A_i,t,i}$, $x_{t-A_i-1,t,i}$,..., $x_{t-1,t,i}$, $x_{t,t,i}$), which shows all null values if $d_{it} = 0$ or it shows only one "1" if $d_{it} \ne 0$,that is $\sum_{i=1}^{N} \sum_{t^*=\{t-A_i,1\}}^{t} x_{t^*ti} = \{0,1\}$.

- For each MPS, in each period, batch size are known; thus it is possible to find a sequencing procedure in order to find the real loading time – without the losses for setups – and to verify the compliancy with the period capacity constraint. The production sequence is found through Simulated Annealing procedure;
- Fitness function (objective function) of the genetic algorithm is the following:
-

$$F = \sum_{t=1}^{T}\sum_{i=1}^{N} p_i^{ex} q_{ti}^{ex} + \sum_{t=1}^{T} Penalty1 \cdot w_t + \sum_{t=1}^{T} Penalty2 \cdot y_t^{ex} + \sum_{t=1}^{T} Penalty3 \cdot \left| \sum_{i=0}^{N}\sum_{j=0}^{N} \left(y_{ijt} + y_{ijt}^{ex} \right) - \overline{y} \right|$$

- where the first element represents the additional cost, on top of q_{ti}^{ex}, due to the exploitation of overtime; the second element decreases the target function by a value *penalty1* for each period in which the global capacity constraint has been violated $\sum_{i=1}^{N} ct_i \left(q_{t*i} + q_{t*i}^{ex} \right) + \sum_{i=1}^{N}\sum_{j=1}^{N} s_{ij} y_{ijt*} \le LT_{t*} + LT_{t*}^{ex}$; the third element applies the *penalty2* in each period in which overtime has been exploited; Last, the fourth element applies *penalty3* on the basis of the difference between the number of setup in period *t* and a benchmarking value $\overline{y}$, wished and estimated by managers.
- "Roulette-wheel Selection", with reproduction through single point crossover single-point and elitism.
- Scaling through the operation of transformation $g(x) = a \cdot f(x) + b$. The parameters suggested in [8] have been adopted, with *a* and *b* depending on $f_{\max}$, $f_{\min}$, e f_{avg} (maximum, minimum and average fitness values, unscaled, adopted by individuals of current population, and *h* related to the expected frequency with which the best genotype can be selected for repreduction.
- Instead of implementing a mutation at the end of each single reproduction, this will be performed only at the end of each entire reproduction cycle (whose dimension will be chosen with regards to the convergence of the algorithm) and will influence the entire population. This choice is to avoide the increase in computational complexity coming from the iteration of the procedure which calculates lot size, sequence and penalties among all periods. This, anyway, push towards the choice of a higher mutation probability value, with respect to those commonly present in literature, in order to guarantee an adequate genetic mix and to avoid a too much fast convergence.

IV. MODEL VALIDATION

Model validation has been performed on the bottling and packaging manufacturing lines of a fabric conditioner production in Unilever S.p.A. industrial plant in Pozzilli (Italy). The genetic algorithm has been used to verify the differences – in terms of changeovers – between a production strategy in which no earliness is admissible and a production strategy in which a maximum anticipation (of one period, thus A_i=1) is possible for each item to be produced in MPS. The examined instance was composed by *n* = 14 items, *T* = 23 periods. Twelve different tests have been performed, using the following parameters: population dimension = 30; number of epochs = 500; number of generations per epoch = 50; scaling factor *h* = 1,5; mutation probability = 0,9; moreover, $p_i = p_i^{ex}$ (that is, no additional cost for overtime was included); *Penalty1* = 100000; *Penalty2* = 100000; *Penalty3* = 250; $\overline{y} = 3$ when overtime was exploited, $\overline{y} = 5$ when only regular production capacity was used.

Table1 shows the data related to changeovers, divided in setup for "different item" and for "same item, different size/format"; befor the model implementation, there was an average of 6 setup for item change and 132 setup for size/format change during *T*.

Here, values are expressed in terms of expected value $\overline{x} = \sum_{i=1}^{n} x_i$, Mean Absolute Deviation $MAD = \frac{\sum_{i=1}^{n} \left| x_i - \overline{x} \right|}{n}$, Mean Deviation from the optimal solution $MDO = \frac{\sum_{i=1}^{n} \left(x_i - x_{opt} \right)}{n}$, Mean Deviation from the best found solution $MXD = \max\{ x_i - x_{opt} \}$ [9].

Table 1

	x_{opt}	$\bar{x}$	*MAD*	*MDO*	*MXD*
Setup for different item	1	1,91	0,82	0,91	2
Decrease % in Setup for different item	83,33	68,05	7,63	15,27	33,33
Setup for different size/format	95	99,41	2,51	4,41	10
Decrease % in Setup for different size/format	28,03	24,68	1,90	3,34	7,58

Each test takes 50 minutes on a Personal Computer with AMD Athlon™XP 1700+ 1,46GHz chip, 256Mb RAM and Microsoft® WindowsXP Professional operative system.

V. CONCLUSION

In this article a model for solving sequencing and lot-sizing problems has been presented, suitable for generating Master production Scheduling in manufacturing systems with batch production and capacity constraints. The maximum admissible earliness, in launching production orders, directly influence the computational complexity. The solution is reached through a Genetic Algorithm, and the model has been validated on a complicated industrial case; despite low computational complexity and the reach of a solution in reasonable times, the model has demonstrated its effectiveness significantly reducing the setup number. However, more tests will be performed in order to optimally calibrate the algorithms parameter and to find the optimal trade-off between computational speed and solution quality; for instance, a second series of 12 test performed with a higher number of generations for each epoch (200), after having evaluated 65.000 MPS instances, returned no significant differences in solution quality (evaluated through Student's t-test), despite an important reduction of computational time (-49%).

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