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A rolling horizon-based heuristic to solve a multi-level general lot sizing and scheduling problem with multiple machines (MLGLSP_MM) in job shop manufacturing system

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A B S T R A C T

This article addresses multi-level lot sizing and scheduling problem in capacitated, dynamic and deterministic cases of a job shop manufacturing system with sequence-dependent setup times and costs assumptions. A new mixed-integer programing (MIP) model with big bucket time approach is provided to the problem formulation. It is well known that the capacitated lot sizing and scheduling problem (CLSP) is NP-hard. The problem of this paper that it is an extent of the CLSP is even more complicated; consequently, it necessitates the use of approximated methods to solve this problem. Hence, two new mixed integer programming-based approaches with rolling horizon framework have been used to solve this model. To evaluate the performance of the proposed model and algorithms, some numerical experiments are conducted. The comparative results indicate the superiority of the second heuristic.

1. Introduction

Production planning and scheduling is one of the most challenging tasks facing managers today. For companies involved in batch or lot production, for instance, plastic injection, steel, or chemical production, planning production lot sizes for the finished products and deciding when to process them are two important problems requiring careful analysis in the production planning and scheduling. These can be termed the lot-sizing and scheduling problem. There are several lot-sizing and scheduling models being evolved under various circumstances. In most of lot-sizing and scheduling models, the production lot sizes and their schedules should be made in such a way that demand is satisfied on time and the sum of total setup costs and total holding costs and total production costs are minimized. Meyr (2002) addressed the simultaneous lot sizing and scheduling of several products on non-identical parallel production lines (heterogeneous machines). The problem solved by a heuristic, which was a hybrid algorithm by combining the local search met strategies threshold accepting (TA) and simulated annealing (SA), respectively, with dual re-optimization.

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Stauffer and Liebling (1997) described a rule-driven mathematical model for a production planning problem in an aluminum manufacturing plant characterized by milling equipment subject to wear and replacement, furnaces with limited capacities and precedence rules and timing implied by temperatures and alloy types. They applied a rolling horizon scheduling algorithm based on tabu search to solve the problem. Ferreira et al. (2010) presented a mixed integer model for the production planning of regional small-scale soft drink plants and proposed relax and fix heuristics exploring the model structure. Mateus et al. (2010) studied the lot sizing and scheduling problem in single-level manufacturing systems. In their study, the shop floor was composed of unrelated parallel machines with sequence dependent setup times. They also proposed an iterative method to build a production plan taking into account scheduling constraints due to changeover setup times. Lang and Shen (2011) considered a capacitated single-level dynamic lot-sizing problem with sequence-dependent setup costs and times, which includes product substitution options. To solve the problem, they devised a mixed integer programming based Relax-and-Fix and Fix-Optimize heuristics. Rakke et al. (2011) formulated a maritime inventory routing problem for one of the world's largest producers of liquefied natural gas (LNG). The aim of the problem was to create an annual delivery program (ADP) to fulfill the long-term contracts at minimum cost, while maximizing revenue from selling LNG in the spot market. An ADP is a complete schedule of every ship's sailing plan for the coming year.

Schemeleva et al. (2012) introduced a formulation for multi-product sequencing and lot-sizing problem, uncertainly (under uncertainties). They applied memetic algorithm to maximize the probability of producing a required quantity of items of each type for a given finite planning horizon. Surveys of various lot sizing and scheduling models can be found in the works of Karimi et al. (2003), Maravelias and Sung (2009), Karimi-Nasaband and Seyedhoseini (2013) and Stadtler and Sahling (2013). Bookbinder and H'ng (1986) applied rolling horizon approach for the production planning problem. In their paper, the rolling horizon approach implements only the earliest production decision before the model is rerun. The next production plan will again be based on M periods of future demand information, and its first lot-sizing decision will be implemented. Russell and Urban (1993) in their article, examined the effect of forecast length and accuracy in extending the planning period beyond the frozen horizon of rolling-production schedules. Ovacikt and Uzsoy (1994, 1995) presented a family of rolling horizon-based heuristics to minimize maximum lateness on single machine and parallel identical machines in the presence of sequence dependent setup times.

Dimitriadis et al. (1997) developed three rolling horizon algorithms that are formally based on the rigorous aggregated Resource-Task Network (RTN) formulation presented by Wilkinson (1996). Jian and Yuseng (1997) proposed a genetic-based rolling horizon strategy to solve a general job shop scheduling problem in dynamic environment. They introduced the rolling horizon mechanism in predictive control into the job shop scheduling problem, and use the time-based and the job-based rolling horizon scheduling approaches to meet the dynamic environment and the variation of the demand. Cowling (2003) described the scheduling problem for a steel hot rolling mill. They detailed the operation of a commercial decision support system, which provides semi-automatic schedules, comparing its operation with existing, manual planning procedures. The system features a very detailed multi objective model of the steel hot rolling process. This model is solved using a variety of bespoke local and Tabu search heuristics. Mohammadi et al. (2010) discussed the multi-product multilevel capacitated lot sizing and scheduling problem with sequence-dependent setups in the flow shop environment. Artificial setup concept, which assumes that during every planning period, N (number of products) setups occurrence is used to formulate this problem. Their modeling is an extension of the formulated model of parallel machines that proposed by Clark and Clark (2000). It is impractical to solve in reasonable computing time for non-small instances. Mishra et al. (2011) used a constrained based fast simulated annealing (CBFSA) algorithm to address the lot sizing and warehousing scheduling problem in manufacturing environment.

Mohammadi et al. (2010, 2010, 2010, 2011) proposed several heuristics for this problem in flow shop, that most of them were based on rolling horizon approach. In addition, they offered a genetic algorithm for this problem (Mohammadi et al. 2011). Mohammadi et al. (2010) and Mohammadi and Jafari (2011) proposed two exact formulations of the integrated, loading, and scheduling problem for the capacitated flexible flow shops with sequence-dependent setups. To validate the mentioned models, lower bound and mixed integer programming-based algorithms were developed. Babaei et al. (2011) considered both the backlogging and sequence-dependent setups in the capacitated lot sizing and scheduling problem in flow shop environment, they proposed an exact formulation and a lower bound for mentioned problem. Ramezanian et al. (2013) perused a multi-product multi-period lot-sizing and scheduling problem in capacitated permutation flow shop with sequence-dependent setups. They presented a mathematical model for the problem and exerted two mixed integer programming based heuristics to solve related problem. Ramezanian and Saidi-Mehrabad (2012) presented a new stochastic mixed integer programming model with big bucket time approach that deal with the lot sizing and scheduling problem of a flow shop system with capacity constraints, sequence-dependent setups, uncertain processing times and uncertain multiproduct and multi-period demand. For transforming the stochastic problem into a deterministic form, they used the chance-constrained programming (CCP) theory, and solved it by means of heuristics and hybrid simulated annealing algorithms. Meyr and Mann (2013) presented a new heuristic to the general lot sizing and scheduling Problem for Parallel production Lines (GLSPPL). Their introduced heuristic iteratively decomposes the multi-line problem into a series of single-line problems, which are easier to solve. Several researchers have focused on the rolling horizon strategy application for different field of industrial engineering, for example: production planning problem, health care management, etc. (Chand, 1983; Chand et al. 1997; Fang & Xi, 1997; Rohleder & Klassen, 2002; Thoney et al., 2002; Cho et al. 2003; Tiacci & Saetta, 2012).

With regard to the literature review, it can be concluded that in most researches in this field (lot sizing and scheduling problem) time horizon approach is small bucket and in few of researches time horizon is considered in big bucket. In addition, the big bucket ones were in flow shop production environment. Therefore, in this research with regard to the gap in literature and high usage of job shop manufacturing system the problem of job shop manufacturing system is discussed and MIP-based heuristics are presented.

The paper has the following structure. Section "Mathematical Modeling" introduces a detailed description of the problem and its underlying assumptions. Section "Development of Heuristics" provides the heuristics. Section "The Results of Numerical experiments" reports the numerical experiments and finally section "Discussions and Conclusion" is devoted to the concluding remarks and recommendations for future studies.

2. Mathematical modeling

The model presented in this paper is a multi-level general lot sizing and scheduling problem with multiple machines in job shop (MLGLSP_MM). The MLGLSP_MM is a big bucket problem for simultaneous lot sizing and scheduling for multi-level multi-product production on different machines. The model is based on the presented mathematical model of Fandel and Stammen-Hegene (2006). Hence, its assumptions are similar to that paper.

The indices, parameters and variables of the model are shown below:

Indices

i, j, k, l, n	Product or item type.
f	Indicates micro-periods of per machine in each macro-period.
β, λ	Indicates a specific micro-period of per machine in each macro-period in accordance

with the micro-period segmentation of the machine.

$m, \overline{m}$ — Machine type.

t — Macro-period

Parameters

T — planning horizon

N — Number of different products

M — Number of different machines (or different stages) available for production

a_{ji} — Production coefficient, which indicates how many units of product j are required to produce a unit of product i

B — A large number

$b_{j,m}$ — Capacity of the machine m required for the production of a unit of product j (in time units per quantity unit)

$\tilde{b}_{j,m}$ — Capacity of the machine m required as input in order to produce one unit of the shadow product j(in time units per quantity unit); also referred to as the input coefficient

$C_{m,t}$ — Available capacity of each machine m in macro-period t (in time units)

$d_{j,m}$ — External demand for product j at the end of macro-period t (in units of quantity)

$h_{j,t}$ — storage costs unit rate for product j in macro-period t

$o_{j,m}$ — Cost unit rate for maintaining the setup condition of the machine m for the product j (in money units per time unit)

$p_{j,m,t}$ — Production costs for producing one unit of product j on machine m in the macro-period t (in money units per quantity unit)

$s_{ij,m}$ — Sequence dependent setup costs for the setup of the machine m from production of product i to production of product j (in money units); for $i \neq j$, $s_{ij,m} \geq 0$ applies and for $i = j$,$s_{ij,m} = 0$

$w_{ij,m}$ — Sequence dependent setup times for the setup of the machine m from production of product i to production of product j (in time units); for $i \neq j$, $w_{ij,m} \geq 0$ applies and for $i = j, w_{ij,m} = 0$

Variables

$I_{j,0}$ — Stock of product j at the start of the planning horizon (in quantity units)

$I_{j,T}$ — Stock of product j at the end of the planning horizon (in quantity units)

$q_{j,m,f,t}$ — Production quantity of product j in the micro-period f of macro-period t on machine m (in quantity units)

$\tilde{q}_{j,m,f,t}$ — Quantity of shadow product j in the micro-period f of macro-period t on machine m (in quantity units)

$z_{j,m,f,t}$ — Binary variable, which indicates whether micro-period f of macro-period t is an idle period for machine m in which the setup condition for product j is maintained ($z_{j,m,f,t} = 1$) or not ($z_{j,m,f,t} = 0$);with $z_{j,m,f,t} = 1$ product j has the function of a shadow function

Decision variables

$x_{ij,m,f,t}$ — Binary variable, which indicates whether to set up the machine m from the production of product i to the production of product j in micro-period f of macro-period t on machine m ($x_{ij,m,f,t} = 1$) or not ($x_{ij,m,f,t} = 0$)

$y_{j,m,f,t}$ — Binary variable which indicates whether machine m is set up ($y_{j,m,f,t} = 1$) or not (

$y_{j,m,f,t}=0$) in micro-period f of macro-period t for the production of product j

Objective function:

$$\min \sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{f=1}^{3N} s_{ij,m}x_{ij,m,f,t}+\sum_{j=1}^{N}\sum_{t=1}^{T}h_{j,t}.I_{j,t}+\sum_{j=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{f=1}^{3N}\left(p_{j,m,t}.q_{j,m,f,t}+o_{j,m}\tilde{b}_{j,m}.\tilde{q}_{j,m,f,t}\right) \tag{1}$$

Subject to:

$$I_{j,t}=I_{j,t-1}+\sum_{m=1}^{M}\sum_{f=1}^{3N}q_{j,m,f,t}-\sum_{i=1}^{N}\sum_{m=1}^{M}\sum_{f=1}^{3N}a_{ji}.q_{i,m,f,t}-d_{j,t} \quad , \; j=1,\dots,N \;, t=1,\dots,T \tag{2}$$

$$\left[a_{ji}\right]\left[B.(y_{i,m,f,t}.y_{j,\bar{m},\beta,t}-1)+\left[b_{j,\bar{m}}.q_{j,\bar{m},\beta,t}+\sum_{n=1,n\neq j}^{J}\sum_{\lambda=1}^{\beta-1}\left(b_{n,\bar{m}}.q_{n,\bar{m},\lambda,t}+\sum_{k=1,k\neq n}^{J}x_{nk,\bar{m},\lambda,t}.w_{nk,\bar{m}}+\tilde{b}_{n,\bar{m}}.\tilde{q}_{\ldots}\right.\right.\right.$$

$$\left[a_{ji}\right]\left[B.\left(1-y_{i,m,f,t}\right)+\sum_{n=1,n\neq i}^{J}\sum_{\lambda=1}^{f-1}\left(b_{n,m}.q_{n,m,\lambda,t}+\sum_{k=1,k\neq n}^{J}x_{nk,m,\lambda,t}.w_{nk,m}+\tilde{b}_{n,m}.\tilde{q}_{n,m,\lambda,t}\right)\right] \tag{3}$$

$$, j=1,\dots,N \;, i\neq j \quad , m,\bar{m}=1,\dots,M \quad , f,\beta=1,\dots 3N \quad , \quad t=1,\dots,T$$

$$\sum_{j=1}^{N}\sum_{f=1}^{3N}b_{j,m}.q_{j,m,f,t}+\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\sum_{f=1}^{3N}w_{ij,m}.x_{ij,m,f,t}+\sum_{j=1}^{N}\sum_{f=1}^{3N}\tilde{b}_{j,m}.\tilde{q}_{j,m,f,t}=C_{m,t} \quad , m=1,\dots,M \;, t=1,\dots,T \tag{4}$$

$$q_{j,m,f,t}\leq \frac{C_{m,t}}{b_{j,m}}.y_{j,m,f,t} \quad , j=1,\dots,\mathrm{N}\;, m=1,\dots,M \;, t=1,\dots,T \;, f=1,\dots,3N \tag{5}$$

$$\tilde{q}_{j,m,f,t}\leq \frac{C_{m,t}}{\tilde{b}_{j,m}}.z_{j,m,f,t} \quad , j=1,\dots,\mathrm{N}\;, m=1,\dots,M \;, t=1,\dots,T \;, f=1,\dots,3\mathrm{N} \tag{6}$$

$$\sum_{f=1}^{3N}y_{j,m,f,t}\leq 1 \quad , \; j=1,\dots,N \quad , m=1,\dots,M ,\; t=1,\dots,T \tag{7}$$

$$\sum_{m=1}^{M}y_{j,m,f,t}\leq 1 \quad , \; j=1,\dots,N \quad , f=1,\dots,3N , t=1,\dots,T \tag{8}$$

$$\sum_{j=1}^{N}\left(y_{j,m,f,t}+\sum_{\substack{i=1\\ i\neq j}}^{N}x_{ij,m,f,t}+z_{j,m,f,t}\right)=1 \quad , m=1,\dots,M , t=1,\dots,T \;, f=2,\dots,3N \tag{9}$$

$$y_{j,m,(f-1),t}+x_{ij,m,(f-1),t}+z_{j,m,(f-1),t}=y_{j,m,f,t}+x_{jk,m,f,t}+z_{j,m,f,t}$$
$$, \; i,j,k=1,\dots,N \;, i\neq j \;, j\neq k \;, m=1,\dots,M \;, t=1,\dots,T \;, f=3,\dots,3N \tag{10}$$

$$y_{j,m,3N,(t-1)}+x_{ij,m,3N,(t-1)}+z_{j,m,3N,(t-1)}=y_{j,m,1,t}+x_{jk,m,1,t}+z_{i,m,1,t}$$
$$i,j,k=1,\dots,N \;, i\neq j \;, j\neq k \;, m=1,\dots,M , t=2,\dots,T \tag{11}$$

$$q_{j,m,f,t}\leq \frac{C_{m,t}}{b_{j,m}}.\left(2-y_{j,m,f,t}-y_{j,m,(f-1),t}\right) , j=1,\dots,N \;, m=1,\dots,M \;, t=1,\dots,T \;, f=2,\dots,3N \tag{12}$$

$$\tilde{q}_{j,m,f,t}\leq \frac{C_{m,t}}{\tilde{b}_{j,m}}.\left(2-z_{j,m,f,t}-z_{j,m,(f-1),t}\right) \;, j=1,\dots,N , m=1,\dots,M \;, t=1,\dots,T , f=2,\dots,3N \tag{13}$$

$$\sum_{i=1}^{J}\sum_{j=1}^{3J}x_{ij,m,1,1}\leq 1 \quad , \; m=1,\dots,M \tag{14}$$

$$I_{j,0}=I_{j,T}=0 \quad , \quad j=1,\dots,N \tag{15}$$

$$y_{j,m,f,t} \in \{0,1\} \quad , j = 1,\ldots,N \quad ,m = 1,\ldots,M \quad ,t = 1,\ldots,T \quad ,f = 1,\ldots,3N \tag{16}$$

$$x_{ij,m,f,t} \in \{0,1\} \quad , i,j = 1,\ldots,N \quad ,i \neq j \quad ,m = 1,\ldots,M \quad ,t = 1,\ldots,T \quad ,f = 1,\ldots,3N \tag{17}$$

$$z_{j,m,f,t} \in \{0,1\} \quad , j = 1,\ldots,N \quad ,m = 1,\ldots,M \quad ,t = 1,\ldots,T \quad ,f = 1,\ldots,3N \tag{18}$$

$$I_{j,t}, q_{j,m,f,t}, \tilde{q}_{j,m,f,t} \geq 0 \quad ,i,j = 1,\ldots,N \quad , m = 1,\ldots,M \quad ,t = 1,\ldots,T \quad ,f = 1,\ldots,3N \tag{19}$$

In this model, Eq. (1) represents the objective function, which minimizes the sum of the sequence-dependent setup costs, the storage costs, the production costs, and the costs of maintaining the machine's setup conditions in the planning horizon. Eq. (2) ensures the demand supply in each period. Two types of demand exist in this model: External demand for products that must be provided at the end of each macro-period, and the internal demand of the products, that is required for the production of high-level products in the product structure, must be satisfied within the macro-period. Eq. (2) ensures the demand supply in each period. The aim of Eq. (3) is to consider the vertical interaction. At the same time this enables the production of two products from successive production levels within a macro-period to minimize the products throughput times. Eq. (4) guarantees within one macro-period that product *j* is produced before product *i*, if *j* is a direct predecessor product of *i* and $i \neq j$. Eq. (4) represents the capacity constraints of machines during each macro-period. Eq. (5) indicates that setup is considered in production process. Eq. (6) indicates the duration of idle times. It obtains an upper bound for duration of idle times that.

Eq. (7) and Eq. (8) guarantee in each macro-period, at most, a lot of each product is produced. The objective of Eqs. (9)-(11) is to limit the each micro-period in each macro-period to one of the following three positions, production, set up, and idle micro-period. Eq. (12) in combination with Eq. (7) and Eq. (8) imposes this assumption to model that if a lot of a product is produced in a macro-period, the lot must be produced within a micro-period and not in two or more directly successive micro-period. Eq. (13) applies the same restriction for the machine's standstill. In the first micro-period of the first macro-period of a planning horizon the machines are artificially set up for the production of a product (Eq. 14). Eq. (15) ensures that there must not be any initial or final stock. Eqs. (16-18) define the binary variables. Non-negativity conditions are considered in Eq. (19).

3. Development of Heuristics

Rolling Horizon Approach

Rolling-horizon heuristics are usually used in dynamic lot sizing and scheduling problems, where demands are gradually revealed during the planning horizon and part types have to be allocated to machines in an on-going fashion as new orders arrive. On the other hand, a rolling-horizon approach is still suitable when all parameters are perfectly known (Beraldi et al., 2008; Araujo et al., 2007; 2008; Merece & Fonton, 2003; Clark, 2003; Clark & Clark, 2000; Mohammadi et al., 2009, 2010). In this paper, rolling-horizon heuristics have been used to overcome computational infeasibility for large MIP problems by substituting most of the binary variables and constraints with continuous variables and constraints. The method initially adopted decomposes the model into a succession of smaller MIPs, each with a more tractable number of binary variables. Each rolling-horizon method decomposes the planning horizon into three sections. For a given iteration k:

The first section (beginning section):

This section contains (k-1) period(s) from the beginning of the problem. In this section due to previous iterations of the algorithm and according to the selected freezing strategy a part or the whole decisions related to (k-1) period(s) from the beginning of the problem will be considered.

The second section (central section):

This section contains only the k^{th} period and considers the whole problem is considered.

The third section (ending section):

This section contains period k+1 to T and is simplified according to the applied simplification strategy.

In each iteration, T-period problem consisting of three sections is solved and at the end of each iteration k increases by one unit and updates according to the three sections and the new iteration starts. In the last iteration, the value of each decision variable in entire time horizon is determined. Fig. 1 demonstrates the iterative procedure.

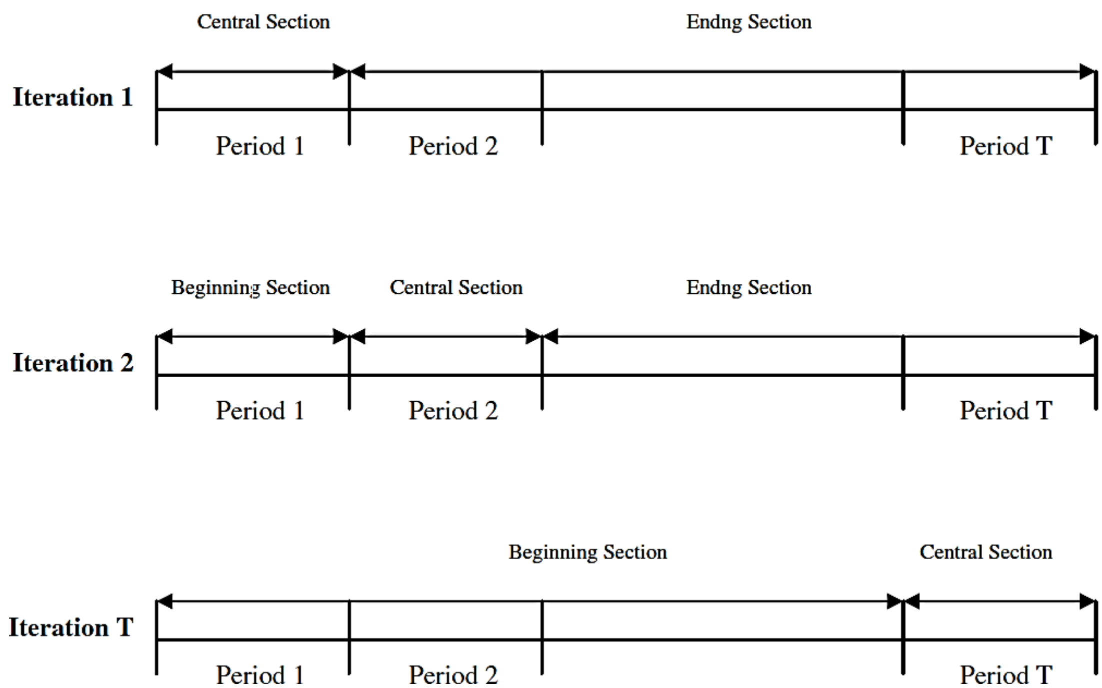

Fig. 1. The iteration procedure

Heuristic 1

Beginning section: All decisions related to the beginning section are completely frozen.

Central section: Consists of one period, the whole problem is considered.

Ending section: Binary variables are relaxed. By relaxing the binary variables in [0, 1] Eq. (3) is inefficient because after the releasing the left side of the equation will tend to a very large negative number and the right side will tend to a very large positive one.

The complexity degree of the problem has been decreased by the use of simplification methods for the ending section in the rolling horizon and also facilitates problem solving in large scale.

This solution approach divides main problem to T sub problems with solvable number of binary variables.

Heuristic 2

Beginning section: Only binary variables related to the beginning section are frozen. The heuristic central and the ending section are similar to the former heuristic (Heuristic 1). The heuristic used for sequencing of each iteration of algorithms is based on simple rules as follow:

- The studied machine should be a part of production steps
- It should comply with the production terms of the studied Machine
- The first priority are products which have lower level in the product structure
- If the output of the previous stage is more than one product with lower $\overline{S}_{j,m}$ is selected

$$\overline{S}_{j,m} = \frac{\sum_i s_{i,j,m}}{\sum_i \sum_j s_{i,j,m}} \tag{20}$$

- If the selected product is the first produced one on the studied machine the ability of executing the set up in previous period is checked

The heuristic determines the central section binary variables. Due to the first section binary variables is obtained by previous iteration of main algorithm; a linear programming model solving is adequate for other variables determination. The solved linear model is the original model that the Eq. (3) is eliminated.

4. The Results of Numerical Experiments

Computational experiments are conducted to validate and to verify the behavior and the performance of the presented heuristics employed to solve the considered integrated lot sizing and scheduling model. We try to test the performance of the heuristics in finding good quality solutions in reasonable time for the problem. For this purpose, 29 problems with different sizes from (N × M × T)=(2 × 2 × 2) to (15 × 15 × 15) are selected. The number of products, machines and periods has the most impact on problem hardness. Rolling horizon-based heuristics is coded in MATLAB R2011(a). The required parameters are produced using the following approach that implemented in the earlier works of authors.

$b_{j,m}, \tilde{b}_{j,m} \approx U(1.5,2)$, $d_{j,t} \approx U(0,180)$, $h_{j,t} \approx U(0.2,0.4)$,

$p_{j,m,t} \approx U(1.5,2)$, $w_{i,j,m} \approx U(35,70)$, $s_{i,j,m} \approx U(35,70)$,

Corresponding values of the area determined according to the shown structures in Fig. 2 (Xie and Dong, 2001 and Franca et al., 1997).

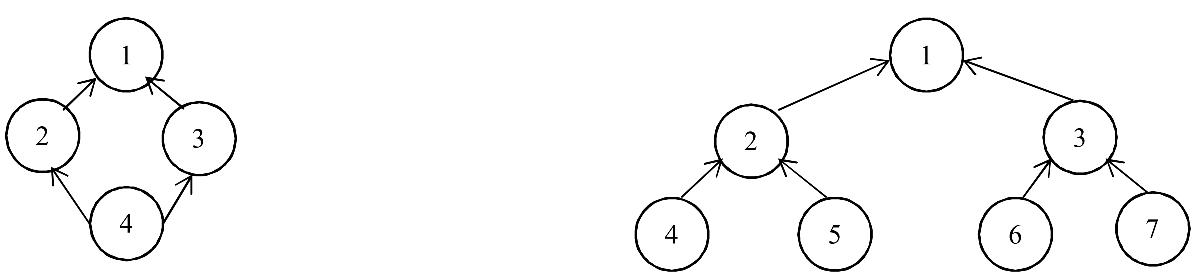

Fig. 1. General product structure for N=4, N=7

Capacity of the machine in each period $c_{m,t}$ is calculated so that, the demand of each period is satisfied according to the lot-for-lot scenarios. A personal computer with a Pentium 4 processor running at 3.4GHz is implemented to execute the lingo software and MATLAB programming language coded heuristic. Table 1 reports the comparative results for the average of CPU time and objective function value of the proposed algorithms.

Table 1
Comparison of the proposed heuristics

Problem size (N.M.T)	Heuristic 1	Heuristic 2
4.3.3	(8.5280) 1410.2109	(9.8333) 1317.6667
4.4.3	(13.1925) 2001.2013	(14.2741) 1874.3333
4.3.4	(14.3833) 1642.5853	(18.7565) 1538.6667
4.4.4	(24.1438) 2691.6378	(27.7526) 2502.3333
4.4.5	(37.8718) 2525.4322	(42.7859) 2325.3333
4.5.4	(30.8986) 2840.9781	(33.9822) 2622.3333
7.3.3	A	a
7.4.4	A	a

The values inside the brackets are the computational time in seconds and the other values are the average of the objective values of the heuristics. A Means that the software has not been generated the problem for the mentioned problem size.

Fig. 2 and Fig. 3 compare Objective function and computational time of the two heuristics. According to these figures, heuristic 1 has advantage to heuristic 2 in computational time (heuristic 1 computational time is 15.3% less than heuristic 2), but, obtained objective value by Heuristic 2 are better than heuristic 1(heuristic 2 Objective value is 7.3954% better than heuristic 1).

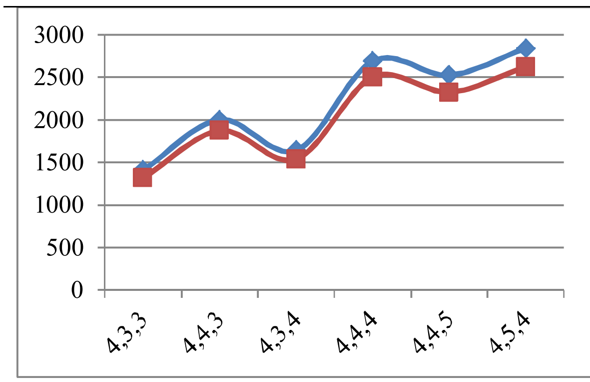

Fig. 2. The heuristics objective function comparison

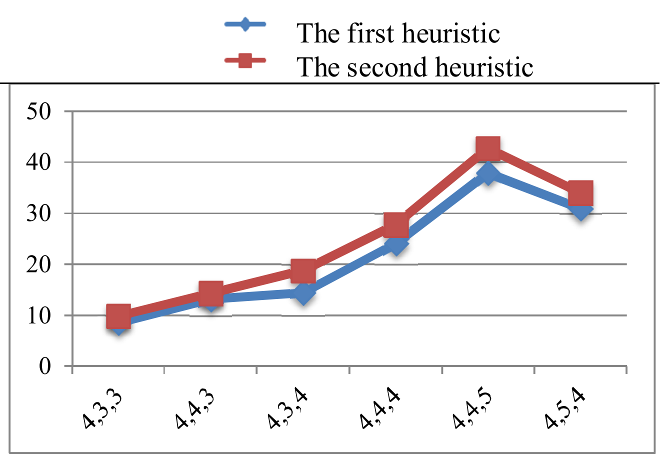

Fig. 3. The heuristics computational time comparison

The main reason to get shorter computational times at heuristic 1 over heuristic 2 can be regarded to freezing all variables and constraints of the beginning section at heuristic 1 instead of freezing only binary variables at this section (which is the case at heuristic 2). In addition, the modification made regarding the continuous variables of central section at the end of each iteration of heuristic 2 leads to better objective function value against heuristic 1.

5. Discussions and Conclusion

In this paper, we tackled the multi-level general lot sizing and scheduling problem with multiple machines in job shop (MLGLSP_MM). A formulation of the problem is provided as a mixed integer program. Assumptions such as capacity constraint, sequence-dependent setup costs and times, and the possibility of setup carryover at successive periods have been considered in the problem. Due to the complexity of the problem, to solve the problem, two MIP-based algorithms based on iterative procedures are developed. Computational experiments clearly confirmed the superiority of heuristic 2 with respect to the heuristic 1.

One straightforward area for future research is extending the assumption of the proposed model for including real conditions of production systems such as lot transportation constraints, etc. In addition, Because of the expanding role of meta-heuristic to solve complicated problem, using the various meta-heuristic can be suggested for further research.

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