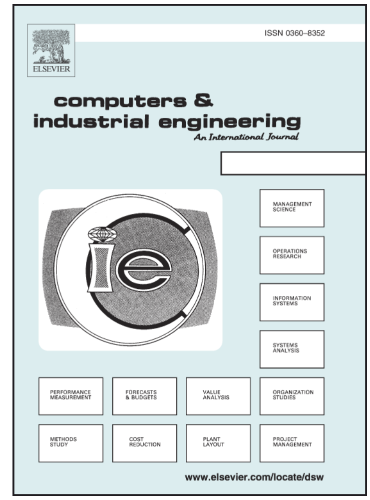
Accepted Manuscript




# Multi-stage multi-product multi-period production planning with sequence-dependent setups in closed-loop supply chain

S. Torkaman, S.M.T Fatemi Ghomi, B. Karimi

PII: S0360-8352(17)30457-6
DOI: https://doi.org/10.1016/j.cie.2017.09.040
Reference: CAIE 4926

To appear in: *Computers & Industrial Engineering*

Received Date: 27 March 2016
Revised Date: 12 March 2017
Accepted Date: 23 September 2017

Please cite this article as: Torkaman, S., Fatemi Ghomi, S.M.T, Karimi, B., Multi-stage multi-product multi-period production planning with sequence-dependent setups in closed-loop supply chain, *Computers & Industrial Engineering* (2017), doi: https://doi.org/10.1016/j.cie.2017.09.040

# Multi-stage multi-product multi-period production planning with sequence-dependent setups in closed-loop supply chain

S.Torkaman [a,b], S.M.T Fatemi Ghomi [a,c*], B.Karimi [a,d]

[a] Department of Industrial Engineering, Amirkabir University of Technology, 424 Hafez Avenue,1591634311 Tehran, Iran

[b] E-mail address: s.torkaman@aut.ac.ir

[c] Corresponding author. Tel.: (+9821) 64545381, Fax: (+9821) 66954569, E-mail address: fatemi@aut.ac.ir

[d] Tel.: (+9821) 64545374, E-mail address: b.karimi@aut.ac.ir

# Multi-stage multi-product multi-period production planning with sequence-dependent setups in closed-loop supply chain

**Abstract**

This paper studies multi-stage multi-product multi-period capacitated production planning problem with sequence dependent setups in closed-loop supply chain. In this problem, manufacturing and remanufacturing of each product is regarded consequently, and in addition to the setup for changing products, a setup while changing the processes is needed. To formulate the problem, a mixed-integer programming (MIP) model is presented. Four MIP-based heuristic named non-permutation and permutation heuristics, using rolling horizon are utilized to solve this model. Moreover, a simulated annealing algorithm using a heuristic to provide initial solution is developed to solve the problem. To calibrate the parameters of the proposed simulated annealing algorithm, Taguchi method is applied. The numerical results indicate the efficiency of the proposed meta-heuristic algorithm against MIP-based heuristic algorithms.

**Keywords** Production planning, Closed-loop supply chain, Sequence dependent setup, Rolling horizon, Simulated Annealing algorithm, Flow shop.

## 1. Introduction

The management of return flows has been increasingly paid attention by researchers during last two decades. Contrary to traditional supply chain where the products flow from manufacturers to customers, in closed-loop supply chain, the manufacturers often collect the used products from the customers and reprocess them for a higher profit or reduce the negative environmental effects.

In published literature in the field of closed-loop supply chain, numerous studies have been made and a large number of models have been developed. Stindt and Sahamie (2014) classified the quantitative studies of closed-loop supply chain in four groups of network design, production planning, product returns management, and forecasting. In closed loop supply chain there are different options for recovery such as reuse, repair, remanufacturing, refurbishing, retrieval and recycling; in which remanufacturing that transforms the defective products into an as-good-as new condition is attractive in terms of environmental concerns, legislation and economics (Stindt & Sahamie, 2014). Ilgin and Gupta (2010) categorized the studies in the field of remanufacturing into six groups of forecasting, production planning and scheduling, capacity planning, inventory management, and uncertainty effect.

Production planning in hybrid systems which includes manufacturing and remanufacturing is an important issue in closed-loop supply chain, the purpose of which is the optimum usage of production resources to produce the products according to the demand in the planning horizon. In these problems, remanufacturing is used as well as manufacturing to satisfy demands.

Production planning has been paid attention by researchers since early twentieth century. It was first studied by Wagner and Whitin (1958); they solved a single-stage, single-product, multi-period uncapacitated production planning using a forward dynamic programming. Research in the field of production planning is vast and contains numerous topics; one of the most complex of them is lot sizing. Bahl et al. (1987) classified the lot sizing problems into four categories according to the number of levels and resource capacity. Karimi et al. (2003) classified the lot sizing problems into the capacitated lot sizing problem (CLSP), the economic lot scheduling problem (ELSP), the discrete lot sizing and scheduling problem (DLSP), the continuous setup lot sizing problem (CSLP), the proportional lot sizing and scheduling problem (PLSP) and the general lot sizing and scheduling problem (GLSP), all of which are NP-hard in case of capacity constraint. Production planning or specifically lot sizing with remanufacturing is the focus of the current study.

Lot sizing in hybrid systems including manufacturing and remanufacturing is considered in many studies of closed-loop supply chain. First, Richter and Weber (2001) developed reverse Wagner-Whitin model for hybrid lot sizing problem, and proved that in the case of constant cost and demand, the optimal policy is starting remanufacturing before exchanging to manufacturing process. Yang et al. (2005) considered an uncapacitated problem with concave cost functions, and cited that even in the case of constant costs, the problem would be NP-hard. This problem is modelled as a network flow type formulation, and a polynomial time heuristic has been utilized to solve it. Teunter et al.(2006) considered two schemes for setup cost: a common setup cost for manufacturing and remanufacturing for single production line; or different setup cost for dedicated lines. In case of common production line, an exact polynomial time dynamic programming algorithm is presented. For both cases, heuristic methods as extensions of Silver-Meal method, Least Unit Cost method, and Part Period Balancing method have been proposed. Li et al. (2006) studied a multi-product problem with demand substitution, in which a higher quality product can satisfy the demand of a lower quality one, in case of large amounts of returned products, a dynamic programming method has been proposed to obtain a near optimal solution. Pan et al. (2009) investigated the problem with disposal of returned products. This problem has been analysed under different scenarios and solved using dynamic programming algorithm. Pineyro and Viera (2010) and Z.-H.Zhang et al. (2012) studied the problem with different demands for new and remanufactured products. Zhang et al. (2011) considered the startup cost in the first period among periods with positive production, Genetic algorithm is developed to solve the problem. Corominas et al. (2012) focused on overtime, lost demands and the variety of returned products. The proportion of returned products is a nonlinear function of their paid price. To solve the problem, the objective function and constraints have been linearized via piecewise functions. Chen and Abrishami (2014) assumed separate demand for new and remanufactured products and developed a Lagrangian decomposition based method to solve the problem. Li et al. (2014) developed a robust tabu search algorithm to solve the problem and evaluated it using 6480 benchmark instances. Baki et al. (2014) proposed a new MIP formulation for the problem with better bound when integrality constraints are relaxed. They developed a dynamic programming based heuristic with some improvement schemes to solve the problem. Lee et al. (2015) studied a capacity and lot sizing problem and developed two linear programming relaxation based heuristics to solve it. Sifaleras and Konstantaras (2015) proposed general variable neighbourhood search (GVNS) algorithm to solve the problem. Parsopoulos et al. ( 2015) introduced some modification in the problem formulation and developed a modified differential evolution (DE) algorithm to solve the problem. Jing et al. (2016) considered the problem with backorder and multiple factories to produce new products, remanufactured products, or both. They presented three models to consider different cases and proposed an approach based on self-adaptive genetic algorithm with population division (SAGA-PD) to solve the problem.

The existing uncertainties in closed-loop supply chain which are due to the amount and quality of returned products, the reprocessing time, effective yield and customer demand, incur the planning complexity (Stindt & Sahamie, 2014). Some of these uncertainties especially uncertain quantity and quality of returned products are considered in lot sizing with remanufacturing. Li et al. (2013) considered the stochastic and price-sensitive amount and the uncertain quality of returned products. Kenne et al. (2012) regarded two machines for manufacturing and remanufacturing with stochastic failures and repairs. Mukhopadhyay and Ma (2009) considered the uncertainty of demand and returned products' quality. Shi et al. (2010), Wei et al. (2011) , Naeem et al. (2013) and Hilger et al. (2015) considered the uncertainty of the amount of returned products and demand. Dong et al. (2011) focused on uncertainty of returned products' quality, the time of returning, and reprocessing time. They regarded inspection, recovery, and assembly operations for remanufacturing. Macedo et al. (2016) considered the uncertain demand, return rate and setup cost due to quality of returned products. They used a two-stage stochastic programming model to deal with the uncertainties.

One of the most common complexities in lot sizing problems is setup time, which is usually associated with changing tools and cleaning machines. Sequence-dependent setup time is one of the most complex setups where the setup time of current product depends on the previous scheduled product. Sequence-dependent setup time in lot sizing problem for single machine has been considered by many researchers; Gupta and Magnusson (2005) developed a heuristic method to solve the lot sizing problem with sequence dependent setups and proposed a procedure to achieve a lower bound for the problem. Almada-Lobo et al. (2007) proposed two linear mixed-integer programming (MIP) models for CLSP with sequence dependent setup time and cost, and developed a five-step heuristic approach to solve the problem. Kovács et al. (2009) presented a new approach to model the CLSP with sequence dependent setup time; in which they introduced a binary variable to indicate whether a product is produced or not, and consider prespecified efficient sequences. Almada-Lobo and James (2010) proposed a neighbourhood search algorithm to solve the CLSP with sequence-dependent setup time. Menezes et al. (2011) studied the problem with non-triangular setups and solved some examples using CPLEX software. James and Almada-Lobo (2011) considered the CLSP with sequence-dependent setup in systems with parallel machines. They proposed an iterative neighbourhood search heuristic based on MIP formulation to solve the problem.

The multi-stage production system with complex setups in lot sizing problem has been studied in recent years. Mohammadi et al. (2010) proposed a multi-product, multi-period lot sizing problem with sequence dependent setups and setup carry-over in a flow shop. To formulate the problem, for each machine and each period, $N$ (the number of products) setups are considered, and artificial setups from one product to the same one are permitted. They used a rolling-horizon and fix-and-relax heuristics to solve the problem. Mohammadi et al. (2011) proposed a genetic algorithm to solve the lot-sizing problem with sequence dependent setups in permutation flow shop. Ramezanian et al. (2013) considered a flow shop system and modelled the problem more efficiently than Mohammadi et al. (2010) and Mohammadi et al. (2011) using starting and completion time of production. They solved the problem using rolling horizon framework in permutation cases. Mohammadi (2010) and Mohammadi and Jafari (2011) considered the problem in flexible flow shops and developed MIP-based iterative approaches to solve the problem. Ramezanian et al. (2013) considered the problem with uncertain processing times and demand and developed a hybrid simulated annealing (SA) algorithm to solve it. Ramezanian et al. (2016) studied the problem in flexible flow shop environment and used rolling horizon heuristic and particle swarm optimization algorithm (PSO) to solve the problem. Urrutia et al. (2014) and Wolosewicz et al. (2015) considered the job shop systems and assumed that schedule of processing products are predetermined. Although the sequence dependent setups have been considered in many lot sizing studies, none of them consider remanufacturing.

Considering the real characteristics such as multi-stage production system and complex setups like sequence dependent setup and setup carry-over makes the lot sizing problem more complex in terms of modelling and solving, but multi-stage production system with complex setups is not considered in the previous studies of closed loop supply chain. Therefore, the motivation for this study is developing a more comprehensive model considering the multi stage system with complex setups including sequence dependent setup and setup carry-over, and remanufacturing in order to implement in complicated industries such as auto car factory.

To the best knowledge of our literature review, the conducted studies of lot sizing in closed loop supply chain considered a single stage production system with simple setups. Therefore, the main contribution of the current study is considering a multi-stage lot sizing problem with sequence dependent setups and setup carry-over in closed loop supply chain, in which it is required to determine the scheduling and sequencing of processes beside products. The preservation of setup over idle period is also considered in this study. A mixed integer programming is introduced to formulate the problem and the problem is solved by rolling horizon heuristic methods and a SA algorithm. Moreover, Taguchi method is applied to calibrate the SA parameters.

The paper is organized as follows. Section 2 gives the problem assumptions and the MIP model to formulate the problem. Heuristic methods, SA and Taguchi methods are introduced in section 3. Section 4 includes computational results; and eventually, section 5 is devoted to the conclusions and suggestions for further researches.

## 2. Problem assumptions and formulation

### *2.1. Assumptions*

The following assumptions are made for the problem under study:

- Both manufacturing and remanufacturing processes are performed on the same line, and a product change as well as an alteration in the process need a setup.
- Shortage is not permitted.
- The setup times are dependent on the sequence of products and processes, and the setup costs are also sequence dependent and proportional to the setup times.
- Setup carry-over from one time period to the next is possible.
- The setup time from product $i$ to product $j$ is always smaller than or equal to the summation of setup times from product $i$ to product $k$ and from product $k$ to product $j$, which is referred as triangular inequality.
- The production system is a flow line, and there is one machine in each stage with limited time capacity.

- Processing at a stage could only be started if a sufficient amount of the required components from the previous stage are available; which is called vertical interaction.
- In the beginning of planning horizon, machines are set up for a specific process of a specific product.
- The final products obtained from both manufacturing and remanufacturing processes have similar qualities and are named service products, which are utilized to satisfy demands.
- The inventories of intermediate products from manufacturing and remanufacturing are stored separately.
- The returned products are available in the beginning of each period.
- Returned products have different quality levels. The remanufacturing time and cost depend on these quality levels.
- Defective products of manufacturing are used for remanufacturing, as well as returned products.
- The initial inventories are all zero.
- When machine setup for product $j$ finishes, the machine is ready to perform the first process of product $j$.

*2.2. Mathematical model*

Our modelling approach is similar to Ramezanian et al. (2013) and the following notations are used in the model formulation:

Indices:

| | |
|---|---|
| $i, i', j, j', n$ | Product type indices |
| $l, k, k', q, q'$ | Process type indices, $l = 1$ implies manufacturing, and $l = 2$ refers to remanufacturing |
| $m$ | Index of production stage |
| $t$ | Index of planning period |
| $l'$ | Index of quality level of returned products |

Parameters:

| | |
|---|---|
| $T$ | Planning horizon (the number of planning periods) |
| $N$ | Number of products |
| $M$ | Number of production stages |
| $L$ | Number of quality levels of returned products |
| $b_{j,m}$ | Capacity of machine $m$ required to manufacture a unit of product $j$ |
| $b'_{l',j,m}$ | Required capacity for remanufacturing a unit of product $j$ with quality level $l'$ in stage $m$ |
| $C_{m,t}$ | Capacity of machine $m$ in period $t$ |
| $d_{j,t}$ | Demand for product $j$ at the end of period $t$ |
| $h_{j,m}$ | Holding cost per unit of new product $j$ in stage $m$ |
| $h'_{l',j,m}$ | Holding cost per unit of remanufactured product $j$ with quality level $l'$ in |

| | |
|---|---|
| | stage $m$ |
| $hs_j$ | Holding cost per unit of service product $j$ |
| $hr_{l',j}$ | Holding cost per unit of returned product. $j$ .with quality level $l'$ |
| $p_{j,\mathrm{m,t}}$ | Manufacturing cost per unit of product $j$ in stage $m$ and period $t$ |
| $p'_{l',j,\mathrm{m,t}}$ | Remanufacturing cost per unit of product $j$ with quality level $l'$ in stage $m$ and period $t$ |
| $S_{i,j,m}$ | Sequence-dependent setup time when switching from product $i$ to product $j$ in stage $m$ . If $i \neq j$ , $S_{i,j,m} \geq 0$; Otherwise, $S_{i,j,m} = 0$ |
| $W_{i,j,m}$ | Sequence-dependent setup cost when switching from product $i$ to product $j$ in stage $m$ . If $i \neq j$ , $W_{i,j,m} \geq 0$; Otherwise, $W_{i,j,m} = 0$ |
| $\alpha r_{l',j}$ | A fraction of new product $j$ which is defective and retains quality level $l'$ |
| $u_{l',j,t}$ | The amount of returned product $j$ with quality level $l'$ in period $t$ |
| $r_{l,k,j,m}$ | Sequence-dependent setup time when switching from process $l$ of product $j$ to process $k$ in stage $m$ . If $l \neq k$ , $r_{l,k,j,m} \geq 0$;Otherwise, $r_{l,k,j,m} = 0$ |
| $c_{l,k,j,m}$ | Sequence-dependent setup cost when switching from process $l$ of product $j$ to process $k$ in stage $m$ . If $l \neq k$ , $c_{l,k,j,m} \geq 0$; Otherwise, $c_{l,k,j,m} = 0$ |
| $j_0$ | Machines are set up to produce product $j_0$ in the beginning of planning horizon |
| $l_0$ | Machines are set up to perform process $l_0$ in the beginning of planning horizon |
| $bigM$ | A large real number |

Continuous decision variables:

| | |
|---|---|
| $I_{j,m,t}$ | Inventory of new product $j$ in stage $m$ at the end of period $t$ |
| $I'_{l',j,m,t}$ | Inventory of remanufactured product $j$ with quality level $l'$ in stage $m$ at the end of period $t$ |
| $Is_{j,t}$ | Inventory of service product $j$ at the end of period $t$ |
| $Ir_{l',j,t}$ | Inventory of returned product $j$ with quality level $l'$ at the end of period $t$ |
| $x_{j,m,t}$ | Manufacturing amount of product $j$ in stage $m$ and period $t$ |
| $x'_{l',j,m,t}$ | Remanufacturing amount of product $j$ with quality level $l'$ in stage $m$ and period $t$ |
| $so_{j,m,t}$ | Manufacturing starting time for product $j$ on machine $m$ in period $t$ |
| $co_{j,m,t}$ | Manufacturing completion time for product $j$ on machine $m$ in period $t$ |
| $so'_{j,m,t}$ | Remanufacturing starting time for product $j$ on machine $m$ in period $t$ |
| $co'_{j,m,t}$ | Remanufacturing completion time for product $j$ on machine $m$ in period $t$ |
| $\delta_{m,t}$ | 0, if exactly one product is produced in stage $m$ and period $t$ ; non-negative value, otherwise. |
| $\delta'_{j,m,t}$ | 0, if exactly one process of product $j$ is performed in stage $m$ and period $t$ ; non-negative value, otherwise. |

Binary decision variables:

| | |
|---|---|
| $y_{i,j,m,t}$ | 1, if the setup changes from product $i$ to product $j$ in stage $m$ and period $t$; 0, otherwise. |
| $z_{l,k,j,m,t}$ | 1, if the setup changes from process $l$ to process $k$ of product $j$ in stage $m$ and period $t$; 0, otherwise. |
| $v_{l,j,m,t}$ | 1, if process $l$ of the product $j$ is performed in stage $m$ and period $t$; 0, otherwise. |
| $y'_{i,j,m,t}$ | 1, if product $i$ is processed last in period $t-1$ and product $j$ is processed first in period $t$ and stage $m$; 0, otherwise. |
| $z'_{l,k,j,m,t}$ | 1, if setup for product $j$ is carried from period $t-1$ to period $t$ in stage $m$, and process $l$ is the last process of product $j$ in period $t-1$, and process $k$ is the first process of product $j$ in period $t$ and stage $m$; 0, otherwise. |
| $T_{j,\mathrm{m},t}$ | 1, if manufacturing or remanufacturing of product $j$ is performed in stage $m$ and period $t$; 0, otherwise. |
| $w_{m,t}$ | 1, if at least one product is produced in stage $m$ and period $t$; 0, otherwise. |
| $\alpha_{j,m,t}$ | 1, if product $j$ is the first product in stage $m$ and period $t$; 0, otherwise. |
| $\beta_{j,m,t}$ | 1, if product $j$ is the last product in stage $m$ and period $t$; 0, otherwise. |
| $\alpha'_{l,j,m,t}$ | 1, if process $l$ is the first process of product $j$ in stage $m$ and period $t$; 0, otherwise. |
| $\beta'_{l,j,m,t}$ | 1, if process $l$ is the last process of product $j$ in stage $m$ and period $t$; 0, otherwise. |

It should be mentioned that although $y'_{i,j,m,t}$, $z'_{l,k,j,m,t}$, $T_{j,\mathrm{m},t}$ and $w_{m,t}$ are defined as binary variables, they can be relaxed as $0 \le y'_{i,j,m,t} \le 1$, $0 \le z'_{l,k,j,m,t} \le 1$, $0 \le T_{j,\mathrm{m},t} \le 1$ and $0 \le w_{m,t} \le 1$ during solving. It means that, even if they are considered as continuous variables, the value of them would be either one or zero due to structure of the presented MIP model. Therefore, it is not necessary to restrict them to be integer.
With respect to the above-mentioned assumptions and notations, the MIP model would be as follows:

Objective function:

$$
\begin{aligned}
Min\ & \sum_{j=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T} p_{j,m,t}.x_{j,m,t} + \sum_{l'=1}^{L}\sum_{j=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T} p'_{l',j,m,t}.x'_{l',j,m,t} + \sum_{j=1}^{N}\sum_{m=1}^{M-1}\sum_{t=1}^{T} h_{j,m}.I_{j,m,t} + \\
& \sum_{l'=1}^{L}\sum_{j=1}^{N}\sum_{m=1}^{M-1}\sum_{t=1}^{T} \mathrm{h}'_{l',j,m}.I'_{l',j,m,t} + \sum_{l'=1}^{L}\sum_{j=1}^{N}\sum_{t=1}^{T} hr_{l',j,t}.Ir_{l',j,t} + \sum_{j=1}^{N}\sum_{t=1}^{T} hs_{j,t}.Is_{j,t} + \\
& \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T} w_{i,j,m}.(y_{i,j,m,t} + y'_{i,j,m,t}) + \sum_{l=1}^{2}\sum_{k=1}^{2}\sum_{j=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T} c_{l,k,j,m}.(z_{l,k,j,m,t} + z'_{l,k,j,m,t})
\end{aligned}
\tag{1}
$$

Equation (1) represents the objective function which minimizes the sum of the setup costs, holding costs, and costs of manufacturing and remanufacturing.

Inventory balance constraints:

$$Ir_{l',j,t} = Ir_{l',j,t-1} + u_{l',j,t} + \alpha r_{l',j} .x_{j,M,t-1} - x'_{l',j,1,t} ;\; l' = 1,...,L; j = 1,...,N; t = 1,...,T \quad (2)$$

$$Is_{j,t-1} + (1 - \sum_{l'}^{L} \alpha r_{l',j}). x_{j,M,t} + \sum_{l'}^{L} x'_{l',j,M,t} - Is_{j,t} = d_{j,t} ;\; j = 1,...,N; t = 1,...,T \quad (3)$$

$$I_{j,m,t-1} + x_{j,m,t} = I_{j,m,t} + x_{j,m+1,t} ;\; j = 1,...,N ; m = 1,...,M-1; t = 1,...,T \quad (4)$$

$$I'_{l',j,m,t-1} + x'_{l',j,m,t} = I'_{l',j,m,t} + x'_{l',j,m+1,t} ;\; j = 1,...,N ; m = 1,...,M-1; t = 1,...,T \quad (5)$$

Equation (2) indicates the production of remanufactured products from returned products and defective products. Equation (3) guarantees the demand for products in each period. Equations (4) and (5) indicate the inventory balance constraint for new products and remanufactured products in intermediate stages, respectively.

Setup-forcing constraints:

$$x_{j,m,t} \le bigM .v_{1,j,m,t} ;\; j = 1,...,N ; m = 1,...,M ; t = 1,...,T \quad (6)$$

$$\sum_{l'}^{L} x_{l',j,m,t} \le bigM .v_{2,j,m,t} ;\; j = 1,...,N ; m = 1,...,M ; t = 1,...,T \quad (7)$$

Equations (6) and (7) determine whether processing new manufactured products and remanufactured products are performed, respectively.

Capacity constraints:

$$co_{j,m,t} \le C_{m,t} ;\; j = 1,...,N ; m = 1,...,M ; t = 1,...,T \quad (8)$$

$$co'_{j,m,t} \le C_{m,t} ;\; j = 1,...,N ; m = 1,...,M ; t = 1,...,T \quad (9)$$

Equations (8) and (9) show the capacity constraint of each machine in each period.

Calculating completion time:

$$co_{j,m,t} = so_{j,m,t} + b_{j,m} .x_{j,m,t} ;\; j = 1,...,N ; m = 1,...,M ; t = 1,...,T \quad (10)$$

$$co'_{j,m,t} = so'_{j,m,t} + \sum_{l'=1}^{L} b'_{l',j,m} .x'_{l',j,m,t} ;\; j = 1,...,N ; m = 1,...,M ; t = 1,...,T \quad (11)$$

Equations (10) and (11) indicate the relation between the starting time and the completion time of new products and remanufactured products, respectively.

Scheduling production of products:

$$so_{j,m,t} \ge co_{j,m-1,t} ;\; j = 1,...,N ; m = 2,...,M ; t = 1,...,T \quad (12)$$

$$so'_{j,m,t} \ge co'_{j,m-1,t} ;\; j = 1,...,N ; m = 2,...,M ; t = 1,...,T \quad (13)$$

$$so_{j,m,t} \ge co_{i,m,t} + S_{i,j,m} .y_{i,j,m,t} - bigM (1 - y_{i,j,m,t}) - bigM (1 - \alpha'_{1,j,m,t}); \quad (14)$$
$$i = 1,...,N ; j = 1,...,N ; i \ne j ; m = 2,...,M ; t = 1,...,T$$

$$so_{j,m,t} \geq co'_{i,m,t} + S_{i,j,m}.y_{i,j,m,t} - bigM(1 - y_{i,j,m,t}) - bigM(1 - \alpha'_{1,j,m,t}); \quad i = 1,...,N;\ j = 1,...,N;\ i \neq j;\ m = 2,...,M;\ t = 1,...,T \tag{15}$$

$$so'_{j,m,t} \geq co_{i,m,t} + S_{i,j,m}.y_{i,j,m,t} - bigM(1 - y_{i,j,m,t}) - bigM(1 - \alpha'_{2,j,m,t}); \quad i = 1,...,N;\ j = 1,...,N;\ i \neq j;\ m = 2,...,M;\ t = 1,...,T \tag{16}$$

$$so'_{j,m,t} \geq co'_{i,m,t} + S_{i,j,m}.y_{i,j,m,t} - bigM(1 - y_{i,j,m,t}) - bigM(1 - \alpha'_{2,j,m,t}); \quad i = 1,...,N;\ j = 1,...,N;\ i \neq j;\ m = 2,...,M;\ t = 1,...,T \tag{17}$$

$$so_{j,m,t} \geq co'_{j,m,t} - bigM(1 - z_{2,1,j,m,t}) + r_{2,1,j,m}.z_{2,1,j,m,t};\ j = 1,...,N;\ m = 1,...,M;\ t = 1,...,T \tag{18}$$

$$so'_{j,m,t} \geq co_{j,m,t} - bigM(1 - z_{1,2,j,m,t}) + r_{1,2,j,m}.z_{1,2,j,m,t};\ j = 1,...,N;\ m = 1,...,M;\ t = 1,...,T \tag{19}$$

Equations (12) and (13) represent that the processing of product $j$ in stage $m$ could begin if only the processing of this product has finished in stage $m-1$. Equations (14)-(17) represent that if processing of product $j$ is planned after product $i$ on machine $m$, the first process of product $j$ could only begin if the processing of product $i$ has finished on this machine, and the setup for product $j$ has been performed. Equations (18) and (19) indicate that the last process of product $j$ on machine $m$, could only begin if the first process of product $j$ has been completed on this machine, and setup for the last process has been performed.

Sequencing the products:

$$\sum_{i=1}^{N} \sum_{j=1, i\neq j}^{N} y_{i,j,m,t} \geq \sum_{j=1}^{N} T_{j,m,t} - 1;\ m = 1,...,M;\ t = 1,...,T \tag{20}$$

$$\sum_{l=1}^{2} \sum_{k=1, l\neq k}^{2} z_{l,k,j,m,t} \geq \sum_{l=1}^{2} v_{l,j,m,t} - 1;\ j = 1,...,N;\ m = 1,...,M;\ t = 1,...,T \tag{21}$$

$$\sum_{l=1}^{2} v_{l,j,m,t} \leq 2T_{j,m,t};\ j = 1,...,N;\ m = 1,...,M;\ t = 1,...,T \tag{22}$$

$$\sum_{i=1, i\neq j}^{N} y_{i,j,m,t} \leq T_{j,m,t};\ j = 1,...,N;\ m = 1,...,M;\ t = 1,...,T \tag{23}$$

$$\sum_{i=1, i\neq j}^{N} y_{j,i,m,t} \leq T_{j,m,t};\ j = 1,...,N;\ m = 1,...,M;\ t = 1,...,T \tag{24}$$

Equations (20) and (21) indicate that changing products and processes require setup. Equation (22) implies that if at least one process of product $j$ is performed, $T_{j,m,t}$ would be 1. Equations (23) and (24) indicate that product $j$ can only be within a sequence of products if it is produced in stage $m$ and period $t$.

Set up carry-over of products:

$$\sum_{j=1}^{N} T_{j,m,t} \leq bigM.w_{m,t};\ m = 1,...,M;\ t = 1,...,T \tag{25}$$

$$\sum_{j=1}^{N} T_{j,m,t} - 1 \le (N-1).\delta_{m,t}\ ; m = 1,...,M\ ; t = 1,...,T \quad (26)$$

$$\sum_{j=1}^{N} \alpha_{j,m,t} = w_{m,t}\ ; m = 1,...,M\ ; t = 1,...,T \quad (27)$$

$$\sum_{j=1}^{N} \beta_{j,m,t} = w_{m,t}\ ; m = 1,...,M\ ; t = 1,...,T \quad (28)$$

$$\alpha_{j,m,t} \le T_{j,m,t} - \sum_{i=1}^{N} y_{i,j,m,t}\ ; j = 1,..., \mathrm{N}; m = 1,...,M\ ; t = 1,...,T \quad (29)$$

$$\beta_{j,m,t} \le T_{j,m,t} - \sum_{i=1}^{N} y_{j,i,m,t}\ ; j = 1,...,N\ ; m = 1,...,M\ ; t = 1,...,T \quad (30)$$

$$\alpha_{j,m,t} + \beta_{j,m,t} \le 2 - \delta_{m,t}\ ; j = 1,...,N\ ; m = 1,...,M\ ; t = 1,...,T \quad (31)$$

$$\sum_{j=1}^{N} y'_{j_0,\mathrm{j},m,1} = 1; m = 1,...,M \quad (32)$$

$$\sum_{i=1}^{N} y'_{\mathrm{i},j,m,t} \ge \alpha_{j,m,t}\ ; j = 1,...,N\ ; m = 1,...,M\ ; t = 1,...,T \quad (33)$$

$$\sum_{j=1}^{N} y'_{\mathrm{i},j,m,t} \ge \beta_{i,m,t-1}; i = 1,...,N\ ; m = 1,...,M\ ; t = 1,...,T \quad (34)$$

$$\sum_{i=1}^{N} \sum_{j=1}^{N} y'_{\mathrm{i,j},m,t} = 1; m = 1,...,M\ ; t = 1,...,T \quad (35)$$

$$\sum_{j'=1}^{N} y'_{j',j,m,t-1} + \sum_{i=1, i\ne j}^{N} y_{i,j,m,t-1} = \sum_{n=1}^{N} y'_{j,n,m,t} + \sum_{i'=1, i'\ne j}^{N} y_{j,i',m,t-1}; j = 1,...,N\ ; m = 1,...,M\ ; t = 2,...,T \quad (36)$$

Equation (25) states that in case of producing at least one product, $w_{m,t}$ should be one. According to Equations (27) and (28), even if $w_{m,t}$ is relaxed as $0 \le w_{m,t} \le 1$, it would be either one or zero; since $w_{m,t}$ equals the summation of several binary variables, it retains an integer value, on the other hand, since it is defined as $0 \le w_{m,t} \le 1$, it cannot be of a value more than 1. Equation (26) states that if more than one product is produced within a period, $\delta_{m,t}$ should be positive. Equations (27) and (28) indicate that if production is performed in one stage and one period, only one product can be the first or last produced product. According to Equations (29) and (30), if a product is not the first or last product, the corresponding $\alpha$ or $\beta$ would be zero, respectively. Equation (31) states that if only one product is produced in a period, $\delta$ would be zero. Equations (32) indicate that machines are setup in the beginning of the planning horizon for product $j_0$. Regarding Equations (33) and (34), if product $j$ is the first product in stage $m$ and period $t$, and product $i$ is the last product in stage $m$ and period $t-1$, the $y'_{i,j,m,t}$ variable would equal 1. Equation (35) claims that the setup for exactly one product is carried over from period $t-1$ to period $t$. Equation (36) guarantees the preservation of setup related to products over idle period.

Set up carry-over of processes:

$$\sum_{l=1}^{2} z'_{l_0,l,j_0,m,1} = y'_{j_0,j_0,m,1}; m = 1,\dots,M \tag{37}$$

$$\sum_{l=1}^{2} \alpha'_{l,j,m,t} = T_{j,m,t}; \ j = 1,\dots,\mathrm{N}; m = 1,\dots,M; t = 1,\dots,T \tag{38}$$

$$\sum_{l=1}^{2} \beta'_{l,j,m,t} = T_{j,m,t}; \ j = 1,\dots,\mathrm{N}; m = 1,\dots,M; t = 1,\dots,T \tag{39}$$

$$\sum_{l=1}^{2} v_{l,j,m,t} - 1 \le \delta'_{j,m,t}; \ j = 1,\dots,\mathrm{N}; m = 1,\dots,M; t = 1,\dots,T \tag{40}$$

$$\alpha'_{l,j,m,t} + \beta'_{l,j,m,t} \le 2 - \delta'_{j,m,t}; l = 1,2; \ j = 1,\dots,N; m = 1,\dots,M; t = 1,\dots,T \tag{41}$$

$$\alpha'_{l,j,m,t} \le v_{l,j,m,t} - z_{k,l,j,m,t}; l = 1,2; k = 1,2; l \ne k; \ j = 1,\dots,N; m = 1,\dots,M; t = 1,\dots,T \tag{42}$$

$$\beta'_{l,j,m,t} \le v_{l,j,m,t} - z_{l,k,j,m,t}; l = 1,2; k = 1,2; l \ne k; \ j = 1,\dots,N; m = 1,\dots,M; t = 1,\dots,T \tag{43}$$

$$\sum_{k=1}^{2} z'_{k,l,j,m,t} + bigM.(1 - y'_{j,j,m,t}) \ge \alpha'_{l,j,m,t}; l = 1,2; \ j = 1,\dots,N; m = 1,\dots,M; t = 1,\dots,T \tag{44}$$

$$\sum_{l=1}^{2} z'_{k,l,j,m,t} + bigM.(1 - y'_{j,j,m,t}) \ge \beta'_{k,j,m,t-1}; k = 1,2; \ j = 1,\dots,N; m = 1,\dots,M; t = 1,\dots,T \tag{45}$$

$$\begin{gathered} so_{j,m,t} \ge \sum_{i=1}^{N} S_{i,j,m}.y'_{i,j,m,t} + \sum_{l=1}^{L} r_{l,1,j,m}.z'_{l,1,j,m,t} - bigM(1 - \alpha'_{1,j,m,t}); \\ j = 1,\dots,N; m = 1,\dots,M; t = 1,\dots,T \end{gathered} \tag{46}$$

$$\begin{gathered} so'_{j,m,t} \ge \sum_{i=1}^{N} S_{i,j,m}.y'_{i,j,m,t} + \sum_{l=1}^{L} r_{l,2,j,m}.z'_{l,2,j,m,t} - bigM(1 - \alpha'_{2,j,m,t}); \\ j = 1,\dots,N; m = 1,\dots,M; t = 1,\dots,T \end{gathered} \tag{47}$$

$$\sum_{l=1}^{2}\sum_{k=1}^{2} z'_{\mathrm{k,l},j,m,t} = y'_{\mathrm{j,j},m,t}; \ j = 1,\dots,N; m = 1,\dots,M; t = 1,\dots,T \tag{48}$$

$$\begin{gathered} \sum_{k=1}^{2} z'_{k,l,j,m,t-1} - bigM(1 - y'_{j,j,m,t-1}) + z_{q,l,j,m,t-1} \le \sum_{q'=1}^{2} z'_{l,q',j,m,t} + bigM(1 - y'_{j,j,m,t}) + z_{l,k',j,m,t-1}; \\ l = 1,2; q = 1,2; k' = 1,2; q \ne l; l \ne k'; \ j = 1,\dots,N; m = 1,\dots,M; t = 2,\dots,T \end{gathered} \tag{49}$$

Equations (37) indicate that machines are setup in the beginning of the planning horizon for process $l_0$ of product $j_0$. Similarly to $w_{m,t}$, if $T_{j,m,t}$ is relaxed as continuous variable between zero and one, it retains the value zero or one, according to Equations (38) and (39). Additionally, according to these equations, only one of the processes of a produced product in one period and in a specific stage could be the first or last process. Equation (40) states that if both processes of manufacturing and remanufacturing are performed in one period, $\delta'_{j,m,t}$ should be positive. Equation (41) indicates that if exactly one of the processes is performed, $\delta'$ would be zero. Equations (42) and (43) show that if a process is not the first or last process of produced product $j$, the corresponding $\alpha'$ and $\beta'$ would be zero. Equations (44) and (45) state that if the setup for product $j$ is carried over from period $t-1$ to period $t$, and process $l$ is the first process of product $j$ in stage $m$ and period $t$, and process $k$ is the last process of product $j$ at the end of period $t-1$ in stage $m$, the $z'_{k,l,j,m,t}$ variable would equal 1. Equations (46) and (47) show that processing the first process of each product in each period is only possible after applying setups. Equation (48) shows that carrying of setup for processes of product is only performed under the condition of carrying product $j$ setup. Equation (49) guarantees preservation of the setup related to processes over idle $j$ period if setup related to products was preserved.

Problem variables:

$$I_{j,m,t}, I'_{l',j,m,t}, Is_{j,t}, Ir_{l',j,t}, y'_{i,j,m,t}, z'_{l,k,j,m,t}, T_{j,\mathrm{m},t}, x_{j,m,t},\\ x'_{l',j,m,t}, so_{j,m,t}, co_{j,m,t}, so'_{j,m,t}, co'_{j,m,t}, \delta_{m,t}, \delta'_{j,\mathrm{m},t}, w_{m,t} \geq 0 \tag{50}$$

$$y_{i,j,m,t}, z_{l,k,j,m,t}, v_{l,j,m,t}, \alpha_{j,m,t}, \beta_{j,m,t}, \alpha'_{l,j,m,t}, \beta'_{l,j,m,t} \in \{0,1\} \tag{51}$$

Equations (50) and (51) indicate the continuous and binary variables of the problem, respectively.

### *2.3. Restricted models*

Solution space of the original problem includes permutation and non-permutation sequences. In permutation sequences, the sequence of products and processes is the same in all stages at a period, while in non-permutation sequences, the sequence is not the same necessarily. To obtain simplified models to develop heuristic methods two restricted models are proposed using elimination of non-permutation sequences of solution space. Note that the solution of these simplified models is an upper bound on the original problem.

#### *2.3.1. The first restricted model*

In this model, the sequence of products and processes in all stages at a period is the same, so all the variables related to sequence are independent of stages ,i.e., $y'_{i,j,m,t}$, $z'_{l,k,j,m,t}$, $T_{j,\mathrm{m},t}$, $\delta_{m,t}$, $\delta'_{j,m,t}$, $w_{m,t}$, $y_{i,j,m,t}$, $z_{l,k,j,m,t}$, $v_{l,j,m,t}$, $\alpha_{j,m,t}$, $\beta_{j,m,t}$, $\alpha'_{l,j,m,t}$ and $\beta'_{l,j,m,t}$ are reduced to $y'_{i,j,t}$, $z'_{l,k,j,t}$, $T_{j,t}$, $\delta_t$, $\delta'_{j,t}$, $w_t$, $y_{i,j,t}$, $z_{l,k,j,t}$, $v_{l,j,t}$, $\alpha_{j,t}$, $\beta_{j,t}$, $\alpha'_{l,j,t}$ and $\beta'_{l,j,t}$, respectively; other variables and parameters are similar to those of the original model.

#### *2.3.2. The second restricted model*

In this model, in addition to the same sequence of products and processes in all stages, the lot sizes of manufactured and remanufactured products are similar and independent of stages, i.e., besides the variables mentioned in the first restricted model, $x_{j,m,t}$ and $x'_{l',j,m,t}$ are also reduced to $x_{j,t}$ and $x'_{l',j,t}$. Since the lot sizes of each manufactured or remanufactured product at different stages are the same, there is no intermediate inventory, therefore the variables $I_{j,m,t}$, $I'_{l',j,m,t}$ and Equations (4) and (5) are eliminated. The remaining variables and parameters are similar to those of the original model.

## 3. The proposed solution methods

### *3.1. Rolling horizon procedure*

In production planning problems, when there is not sufficient reliable data about parameters such as demands of future periods, the rolling horizon method is highly applicable. In this case, the decision is made for the first period, and after the passage of each period, the model is executed again using updated data. Moreover, rolling horizon approach has been utilized to solve multi-period production planning problems with known parameters (Mohammadi et al., 2010). In this case, to overcome computational infeasibility in large MIP problems, solving the original problem is replaced with several smaller problems which could be solved efficiently. In this iterative procedure, the planning horizon is divided into three separate sections which are as mentioned below for step k (Mercé & Fontan, 2003):

- The beginning section which consists of k-1 first periods. In this section, all or some of the decisions are made and frozen according to the previous iterations, with respect to a freezing strategy.
- The central section includes kth period in which the problem is entirely considered.
- The ending section includes final periods (from period k+1 to period T). In this section, the model is simplified according to a simplification strategy.
  This iterative method is represented in Figure 1.

**Fig. 1** Rolling horizon method (Mohammadi et al., 2010)

At the end of step k, each of these three mentioned sections rolls to the next period and step k+1 would be executed. When there is no other ending section, the algorithm will stop. The final step- step T- defines all of the decision variables in the planning horizon.

#### *3.1.1. Rolling horizon heuristic methods*

Based on the approach mentioned in section 3.1, four heuristic algorithms are proposed to solve the problem.

#### *3.1.2. First heuristic method (H1)*

In this method, the original problem is considered and three sections of the algorithm would be as below:

- Beginning section: only binary variables related to the periods of this section are frozen.
- Central section: this section consists of one period in which the problem is entirely considered.
- Ending section: all of the binary variables related to the periods of this section are relaxed between zero and one. Besides, Equations 14-19, 44-47 and 49 are ignored for the periods of this section.

*3.1.3. Second heuristic method (H2)*

This method is similar to H1 but in the beginning section all of the variables, including continuous and binary variables, are frozen.

*3.1.4. Third heuristic method (H3)*

Pay attention to the fact that the time required to solve the MIP problems would exponentially increase with increase in the number of binary variables, two previously mentioned algorithms would not be efficient for large size problems. Therefore, in order to reduce the number of binary variables to solve the problems, the third heuristic algorithm has been developed based on the first permutation model, and the three sections of the algorithm are similar with those of the first heuristic method (H1).

*3.1.5. Forth heuristic method (H4)*

This method is similar to the third heuristic method, but is developed based on the second permutation model and is more simplified.

*3.2. Simulated annealing algorithm*

Meta-Heuristic methods are efficient approaches to solve MIP problems, all of which apply an intelligent random search in the solution space of the problem to obtain an approximately optimal solution. Jans and Degraeve (2007) scrutinized the application of meta-heuristic algorithms in lot sizing problems. Simulated annealing (SA) was first introduced by Metropolis et al. (1953) and has been applied in a wide range of optimization problems.

SA starts the search in solution space with an initial solution. In each step, a new solution is created in the neighbourhood of the current solution, and would be compared with it. If new solution is better than the current solution, it would be accepted; otherwise, the acceptance of new solution would be performed according to the acceptance probability which obeys Boltzmann distribution. Escaping from local optimum solution through accepting less qualified solutions is the main idea in SA. With the increase of difference between objective values and algorithm temperature reduction, the acceptance probability decreases. SA algorithm temperature would be reduced from a relatively high temperature to a temperature near zero according to a cooling schedule, and as it reaches a specific temperature, the algorithm will stop (Kirkpatrick et al., 1983).

The proposed SA is based on the second permutation model. The binary variables of the problem are extracted from the solution representation. Substituting obtained binary variables, the problem would transform into a linear programming and the solution for continuous section would be achieved. In this section, the main characteristics of simulated annealing algorithm are introduced. To calibrate parameters of the proposed algorithm, Taguchi method is utilized.

*3.2.1. Solution representation*

The solution of problem with $N$ products, $M$ machines and $T$ periods would be considered as a $(2, 2NT)$ matrix; which is independent of M, since the sequence on all machines is assumed the same. The first row would represent the sequence of products and processes; while the second row indicates whether the processes of a product in each period have been executed. For product $j$ , $2j-1$ and $2j$ imply manufacturing and remanufacturing, respectively. The value 1 in the second row represents the execution of the corresponding process; while otherwise, it indicates that it is not executed. Figure 2 demonstrates the solution for a problem with $N=3$, $M=2$, $T=2$, $L_0=1$ and $j_0=1$. Corresponding non-zero binary variables with first part (period) of Figure 2 are brought in Table 1.

**Fig. 2** Solution representation of problem with N=3, M=2, T=2

**Table 1.** Corresponding non-zero binary variables with first part of Fig.2

| | | | | | |
|---|---|---|---|---|---|
| $y'_{111}$ | $Z_{1111}$ | $T_{1,1}$ | $T_{2,1}$ | $T_{3,1}$ | $y_{1,2,1}$ |
| $y_{2,3,1}$ | $v_{1,1,1}$ | $v_{1,2,1}$ | $v_{1,3,1}$ | $\alpha_{1,1}$ | $\beta_{3,1}$ |
| $\alpha'_{1,1,1}$ | $\alpha'_{1,2,1}$ | $\alpha'_{1,3,1}$ | $\beta'_{1,1,1}$ | $\beta'_{1,2,1}$ | $\beta'_{1,3,1}$ |

*3.2.2. Initial solution*

There are various methods to generate an initial solution to start simulated annealing algorithm. In this paper, $M$ solutions have been generated by developing the procedure proposed by Mohammadi et al. (2011) and the best of them would be selected as the initial solution. In fact, the first row of the solution is obtained from this heuristic method, and the second row is a vector with the length of $2NT$ , all elements of which equal 1.

**Creating *M* solutions with heuristic method**

This method should be repeated for $M$ times. The products are arranged in a decreasing order according to $\overline{W}_{j,m}=\sum_{i=1}^{N} W_{i,j,m}$ ; $j=1,...,N$ . Afterwards, the product with the highest $\overline{W}_{j,m}$ among non-located products would be put into a location where the summation of setup costs of products would be minimal. This procedure continues up to the point that all of the products be specified a location. After determining the sequence of products, the setup costs for the processes of each product would be compared. For instance, if the value $c_{1,2,j,m}$ is lower than $c_{2,1,j,m}$, primarily manufacturing and then remanufacturing of product $j$ would be executed. In this method, the sequence of products in different periods would be equal.

*3.2.3. Neighbourhood search scheme*

In every temperature level, it is required that an appropriate search method be used to search the neighbourhood of the current solution. According to the structure of the represented solution, two neighbourhood search methods for sequencing and production decisions are applied as below:

**First method**

In this method which is utilized to improve the sequence of products and processes, period $t$ is first randomly selected. Thereafter, a $(l, j, t)$ and a $(k, i, t)$ are randomly chosen, and would be swapped in a column form.

**Second method**

This method is applied to determine decisions about execution of manufacturing and remanufacturing of products. A $(l, j, t)$ would be randomly chosen. If the value of the selected array is 1, it would change to zero, and vice versa.

In each temperature, neighbourhood search would be repeated for $2N$ times. If the number of accepted solutions in any temperature exceeds a specific value, the search in that temperature would stop. The first and the second methods would be applied with specific probabilities P and 1-P, respectively.

*3.2.4. Cooling schedule*

Temperature would gradually decrease through the progress of the algorithm from a high value
$(\mathrm{T_i})$ to a temperature near zero with a specific pattern which is defined as bellow:

$$T_i = \alpha \times T_{i-1} \tag{52}$$

where $\alpha \in (0,1)$ is a constant value.

*3.2.5. Termination criterion*

If $\mathrm{T} < \mathrm{T_f}$, or the specific number of accepted solutions in several consecutive temperatures equals zero, the SA algorithm will stop.

*3.2.6. Attitude of encountering constraints*

In the proposed model, manufacturing and remanufacturing of each product are planned to be performed consecutively. To create a feasible solution, it is required that the arrays corresponding to manufacturing and remanufacturing of each product be consecutive in each solution. Regarding the act of first neighbourhood search method, this order might not be obeyed. Consequently, to create a feasible solution a repair procedure has been applied to modify the obtained solution. In this approach for each array, if the array relates to the manufacturing (remanufacturing) process of a product, the array corresponding to the remanufacturing (manufacturing) process of the same product would be located right after that, and the rest arrays between these two arrays, would move to the right. To encounter the demand and capacity constraints, a penalty attitude has been considered. In this regard, Equations (3), (8) and (9) are replaced with Equations (53), (54) and (55), respectively.

$$1-(Is_{j,t-1}+(1-\sum_{l'}^{L}\alpha r_{l',j}).\,x_{j,t}+\sum_{l'}^{L}x'_{l'j,t}-Is_{j,t})/d_{j,t} \le dr_{j,t}; \tag{53}$$
$$j=1,\ldots,N;\, t=1,\ldots,T$$

$$(co_{j,m,t}/C_{m,t})-1 \le vr_{j,m,t};\quad j=1,...,N;m=1,...,M;t=1,...,T \tag{54}$$

$$(co'_{j,m,t}/C_{m,t})-1 \le vr'_{j,m,t};\ j=1,...,N;m=1,...,M;t=1,...,T \tag{55}$$

where $dr_{j,t}$ is a positive variable which indicates the violation of the demand constraint and $vr_{j,m,t}$ and $vr'_{j,m,t}$ are positive variables to demonstrate violation of the capacity constraints.

By considering significant penalty in objective function for violation of demand and capacity constraints as mentioned in Equation (56), algorithm will lead toward finding feasible solutions.

$$bigM*\sum_{j=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T}\left(vr_{j,m,t}+vr'_{j,m,t}\right)+bigM*\sum_{j=1}^{N}\sum_{t=1}^{T}\left(dr_{j,t}\right) \tag{56}$$

where $bigM$ indicates the penalty cost per unit of constraint violation.

### *3.2.7. Parameter calibration*

Design of parameters of meta-heuristic algorithms is a fundamentally factor on the efficiency of the algorithm, since an inappropriate selection of algorithm parameters would lead to its weak performance. In this paper, Taguchi method has been applied to calibrate the proposed algorithm parameters. Orthogonal arrays in Taguchi method permit the analysis of numerous factors with a small number of experiments. In this method, performance measure called signal-to-noise (S/N) ratio is maximized to obtain the optimum level of factors. The term 'signal' represents the desirable value (response variable) and 'noise' represents the undesirable value (standard deviation). The S/N ratio indicates the mean-square deviation present in the response variable (Taguchi et al., 2000). Taguchi method acts as mentioned below, to calibrate the parameters (Wu & Hamada, 2011):

- For each experiment, S/N ratio is calculated.
- For factors which have a significant impact on S/N ratio, the level that maximizes the S/N ratio is optimum.
- For factors which do not have a noticeable impact on S/N ratio but affect response variable mean, the best level retains the best objective function.
- For factors which affect neither S/N ratio, nor the response variable mean, a level with the lowest calculation time would be selected.

The utilized response variable in this paper is Relative Percentage Deviation (RPD) which is preferred to be minimized and defined as below:

$$RPD_i=\left(\frac{OF_i-OF_{\min}}{OF_{\min}}\right)\times 100 \tag{57}$$

where $\mathrm{OF}_{\min}$ is the best found objective value for a specific problem, and $\mathrm{OF}_i$ is the obtained objective value for i$^{th}$ trial. Since the lower values of response variable are preferred, S/N ratio is defined as below:

$$S/N=-10\log\left(\frac{1}{n}\sum_{i=1}^{n}RPD_i^2\right) \tag{58}$$

where n is the number of replications.

By recognizing the effective parameters on the efficiency of simulated annealing algorithm, calibration of following parameters are considered:

- Cooling rate : two levels (0.95, 0.975)
- Initial temperature: three levels (75, 100, 125)
- Final temperature: three levels ($0.05T_i$, $0.075T_i$, $0.1T_i$)
- Number of neighborhood search: three levels (20, 35, 50)
- Probability of neighborhood search change: (0.4, 0.5, 0.6)
- Number of accepted solutions in each temperature to stop the search: three levels (6, 8, 10)

According to the considered levels and factors, the full factorial experiment design for mentioned six factors requires $3^5 \times 2^1 = 486$ experiments. But, regarding statistical theories, it is not necessary to perform all the experiments. Therefore, fractional replicated designs are used in this study. To select proper orthogonal array, it is needed to calculate the degree of freedom. In the current study, 1 degree of freedom for total mean, 1 degree of freedom for the factor with 2 levels and 2 degrees of freedom for each factor with three levels (2×5=10) are required. Thus, the sum of required degree of freedom would be 1+1+2×5=12. Hence, the appropriate array must have at least 12 rows. The selected orthogonal array should be able to incorporate the factor level combinations in the experiment. Therefore, orthogonal array L18 ($2^1 * 3^7$) is appropriate to implement in this study. Orthogonal arrays layout for parameter design can be seen in study conducted by Wu and Wu (2000).

Since there are five factors with 3 levels in the current study, according to Taguchi experimental design procedure, two columns could be remained empty. For each experiment of orthogonal array L18, each of the problems given in Table 2 has been created using parameters introduced in Table 3, and has been solved for 5 times. Thus, a total number of 18×5×5= 450 problems have been solved.

**Table 2.** The size of problems used in calibration of parameters

| | | | | |
|---|---|---|---|---|
| 3×3×3 | 5×5×5 | 7×7×7 | 10×10×10 | 15×15×15 |

**Table 3.** The parameters of the problem

| |
|---|
| $d_{j,t} \sim U(0,180)$, $u_{l',j,t} \sim U(0,90/L)$, $b_{j,m} \sim U(1.5,2)$, $b'_{l',j,m} \sim (0.4+(l'-1)p) \times U(1.5,2)$, $h_{j,m} \sim U(0.2,0.4)$, $h'_{l',j,m} \sim U(0.15,0.3)$, $hr_{l',j} \sim U(0.1,0.2)$, $hs_j \sim U(0.4,0.8)$, $p_{j,m,t} \sim U(1.5,2)$, $p'_{l',j,m} \sim (0.4+(l'-1)p) \times U(1.5,2)$, $W_{i,j,m} \sim U(35,70)$, $S_{i,j,m} \sim U(35,70)$, $r_{l,k,j,m} \sim U(5,10)$, $c_{l,k,j,m} \sim U(5,10)$, $\alpha r_{l',j} \sim U(0.01,0.02)$, $C_{m,t} \sim U(a_m,b_m)$; $p=(0.6-0.4)/(L-1)$, $a_m = 300N + 200(m-1)$, $b_m = 300N + 300(m-1)$ |

S/N ratio and RPD mean value for SA are demonstrated in Figure 3 and Figure 4, respectively.

**Fig.3** The mean of S/N ratio at each level of the SA parameters

**Fig. 4** The mean of RPD at each level of the SA parameters

According to these figures, Table 4 gives the best levels of factors for this algorithm.

**Table 4.** Best levels of the factors for proposed SA

| Parameter | The optimum level |
|---|---|
| Cooling rate (α) | 0.975 |
| Initial temperature ($T_i$) | 100 |

| | |
|---|---|
| Final temperature ($T_f$) | $0.05T_i$ |
| Number of neighborhood search (NS length) | 50 |
| Probability of neighborhood search change (P) | 0.6 |
| The number of accepted solutions in each temperature to stop searching in that temperature (NA) | 8 |

## 4. Numerical experiments

To evaluate the efficiency of proposed SA to solve the considered problem, computational experiments have been conducted. To compare the performance of heuristic methods and SA about solution quality and solution time, 24 problems with sizes from $N \times M \times T = 3\times3\times3$ to $N \times M \times T = 15\times15\times15$ are solved. The number of quality level is considered as 3 in all instances. The proposed model and MIP-based heuristics are coded by GAMS IDE (ver. 24.1.3) software, using CPLEX solver, and SA is coded by MATLAB 2013. The required parameters of the problem have been obtained by Uniform distributions and are as given in Table 3. All of the problems have been executed on a PC with a Core i5 2.53 GHz CPU and a 4GB RAM.

To obtain trustworthy solutions, each problem has been solved for 5 times with proposed SA method and the best results have been reported. The computational results including objective value and solution time obtained by algorithms for all instances have been cited in Table 5. Moreover, the objective values of algorithms are compared with the exact solutions for small instances.

**Table 5.** Computational results for proposed algorithms

| Problem size (N.M.T) | Exact solution | | H1 | | H2 | | H3 | | H4 | | SA | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | obj | CPU time | obj | CPU time | obj | CPU time | obj | CPU time | obj | CPU time | obj | CPU time |
| 3×3×3 | 4821.00 | 386.56 | 4821.00 (0%) | 251.26 | 4948.26 (2.64%) | 8.54 | 4866.93 (0.95%) | 11.57 | 4871.86 (1.06%) | 10.9 | 4871.86 (1.06%) | 9.037 |
| 3×4×3 | 5062.20 | 411.67 | 5062.20 (0%) | 267.59 | 5338.72 (5.46%) | 10.86 | 5133.7 (1.41%) | 12.07 | 5143.41 (1.60%) | 11.46 | 5137.14 (1.48%) | 10.96 |
| 3×3×4 | 4986.55 | 487.15 | 4986.55 (0%) | 342.87 | 5199.08 (4.26%) | 11.04 | 5003.47 (0.34%) | 13.66 | 5003.96 (0.35%) | 11.87 | 5003.96 (0.35%) | 12.68 |
| 3×3×4 | 4754.19 | 466.55 | 4754.19 (0%) | 306.99 | 5033.23 (5.87%) | 10.68 | 4769.28 (0.32%) | 18.33 | 4770.46 (0.34%) | 12.96 | 4787.43 (0.70%) | 16.96 |
| 4×4×4 | 8997.38 | 7200* | 9204.28 (2.3%) | 5504.56 | 9389.92 (4.36%) | 92.44 | 9008.34 (0.12%) | 133.39 | 9008.39 (0.12%) | 133.18 | 9008.39 (0.12%) | 25.27 |
| 3×5×3 | 6648.47 | 1284.63 | 6648.47 (0%) | 1258.45 | 6999.45 (5.28%) | 14.92 | 6702.75 (0.82%) | 22.02 | 6723.23 (1.13%) | 14.95 | 6768.17 (1.80%) | 15.43 |
| 3×3×5 | 6991.35 | 538.50 | 6991.35 (0%) | 383.05 | 7093.84 (1.47%) | 11.05 | 7036.81 (0.65%) | 16.38 | 7064.26 (1.04%) | 13.27 | 7064.26 (1.04%) | 17.13 |
| 3×3×5 | 6886.54 | 690.99 | 6886.54 (0%) | 570.56 | 7240.04 (5.13%) | 11.7 | 6918.17 (0.46%) | 24.11 | 6920.7 (0.50%) | 20.25 | 6920.7 (0.50%) | 22.57 |
| 5×5×5 | 17289.3 | 7200* | 18082.6 (4.59%) | 7200* | 18362.71 (6.21%) | 2898.97 | 17437.3 (0.86%) | 414.82 | 17447.04 (0.91%) | 126.05 | 17433.09 (0.83%) | 46.43 |
| 7×5×5 | - | - | - | - | 29348.98 | 7200* | 28535.81 | 5771.53 | 28489.51 | 5770.2 | 27935.43 | 76.01 |
| 5×7×5 | - | - | - | | 29654.28 | 3382.73 | 28711.11 | 1740.73 | 28777.21 | 424.45 | 28643.25 | 90.36 |
| 5×5×7 | - | - | - | - | 31048.24 | 3288.28 | 29958.18 | 5117.56 | 29711.00 | 3736.67 | 29853.43 | 57.72 |
| 7×7×7 | - | - | - | - | - | - | 50347.99 | 6190.10 | 50371.95 | 6184.2 | 50308.88 | 123.08 |
| 10×5×5 | - | - | - | - | - | - | 39834.49 | 5773.66 | 40048.4 | 5773.28 | 39868.76 | 83.1 |
| 5×10×5 | - | - | - | - | - | - | 40329.29 | 4595.03 | 40344.79 | 2952.71 | 39926.76 | 111.99 |
| 5×5×10 | - | - | - | - | - | - | 37233.20 | 5222.82 | 36968.74 | 5105.58 | 37160.67 | 66.88 |
| 10×7×7 | - | - | - | - | - | - | 87320.8 | 6194.2 | 82673.58 | 6189.16 | 78533.52 | 252.05 |
| 7×10×7 | - | - | - | - | - | - | 84602.45 | 6192.68 | 80626.737 | 6187.24 | 77125.21 | 214.27 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 7×7×10 | - | - | - | - | - | - | 90129.12 | 6521.13 | 78420.77 | 6493.79 | 77116.97 | 210.31 |
| 10×10×10 | - | - | - | - | - | - | - | - | 180446.58 | 7029.7 | 154987.73 | 987.19 |
| 15×10×10 | - | - | - | - | - | - | - | - | - | - | 236655.62 | 3204.66 |
| 10×15×10 | - | - | - | - | - | - | - | - | - | - | 235696.05 | 2926.89 |
| 10×10×15 | - | - | - | - | - | - | - | - | - | - | 224360.18 | 1613.1 |
| 15×15×15 | - | - | - | - | - | - | - | - | - | - | 498560.03 | 7200* |

Note: The percentage values inside the parentheses are the difference between the objective values of algorithms against the exact solutions.

Regarding the obtained results, it can be noticed that as the problem size increases, there is no possibility to solve the problems with sizes higher than 5×5×5 exactly in 7200 seconds. Heuristic algorithms also lose their efficiency with increase in the problem size, in a way that solving problems with sizes higher than 5×5×5 would not be possible with H1 in 7200 seconds. H2–by freezing all of the variables– is able to solve more problems with sizes up to 5×5×7. H3 which is based on the first restricted model solves problems with sizes up to 7×7×10 by reducing the binary variables of the original problem. H4 which is based on the second restricted model, with more simplification than H3 is able to solve problems with sizes up to 10×10×10.

The quality of solutions obtained from H1 is better than others, because it performs based on original problem without any simplification. H2 does not have acceptable quality in comparison with other algorithms; because the continuous variables are freezed in addition to binary variables in the beginning section of this algorithm, and the heuristic capability to find the better solution would be decreased. The solutions obtained from H3 are better than those of H4. H4 is based on the second restricted model and lot sizes are similar in all stages in this algorithm; but H3 is based on the first restricted model and is capable of finding better solution due to possibility of determining different lot sizes in different stages. As the size of problems increases, H4 acts better; since the second restricted model has smaller solution space than that of the first restricted model, and exploring its solution space is performed more efficiently in large instances within a specific computational time. SA has lower computational time in comparison with heuristic methods and can solve all of the problems in reasonable time. The quality of solution obtained from SA is close to H3 and H4; however, as the problem size increases, this algorithm would have a better quality than others. Since SA algorithm is faster than H3 and H4 and has the appropriate search mechanism, it is able to explore the solution space more efficiently within a specific computational time, as the problem size increases. Hence, simulated annealing algorithm is preferable in solving the problem under study.

## 5. Conclusion

This paper studied the complex setups including sequence dependent setups and setup carry-over, and flow shop system in lot sizing problem with remanufacturing for the first time. A mixed-integer programming model was proposed to formulate the problem. Since the problem is NP-hard, four heuristic methods based on rolling horizon approach, and a simulated annealing algorithm were proposed to solve the problem. Two restricted models were introduced to develop methods to solve large size problems. The two first heuristic algorithms including H1 and H2 were based on the original model, but the third and fourth heuristics called H3 and H4 were based on the first permutation and second permutation models, respectively. The simulated annealing (SA) was also based on the second permutation model and uses a heuristic method to obtain the initial solution. To calibrate the parameters of the proposed SA, Taguchi method was applied, and computational experiments were conducted to evaluate and compare the developed heuristic methods and SA algorithm. According to the numerical experiments, the problems with sizes higher than 5×5×5 could not be solved exactly in 7200 seconds. H1 is not possible to solve the problems with sizes higher than 5×5×5 in 7200 seconds. H2 is able to solve problems with sizes up to 5×5×7. H3 solves the problems with sizes up to 7×7×10 and H4 is able to solve problems with sizes up to 10×10×10. The quality of H1 solutions is better than other heuristics, and H2 has the worst quality among others. H3 performs better than H4; but as the size of problems increases, H4 acts better. SA is faster in comparison with heuristic methods and can solve all of the problems in reasonable time. The quality of SA solution is close to H3 and H4; however, SA performs better for large instances. Therefore, SA algorithm is suggested to solve the problem under study.

This study could be implemented in complicated industries such as car factories. Remanufacturing is important from an economic point of view; additionally it could be reduce the usage of raw material and is interesting environmentally. Performing remanufacturing using returned products is possible by improving reverse logistic and using incentive policies such as refunds to gather returned products. It should be noted that these activities have their own special considerations and may cause additional costs which should be concerned.

The issue of uncertainties in remanufacturing such as the quality, amount of returned products, and processing time could be a development to the current study. Additionally, modelling and solving this problem as a multi-objective problem, considering scheduling objectives such as minimizing the maximum completion time (makespan) besides the cost minimization, is suggested for further research.

## References


Almada-Lobo, B. and James, R.J. (2010). Neighbourhood search meta-heuristics for capacitated lot-sizing with sequence-dependent setups. International Journal of Production Research, 48(3), 861-878.

Almada-Lobo, B., Klabjan, D., Antónia carravilla, M. and Oliveira, J.F. (2007). Single machine multi-product capacitated lot sizing with sequence-dependent setups. International Journal of Production Research, 45(20), 4873-4894.

Bahl, H.C., Ritzman, L.P. and Gupta, J.N. (1987). OR Practice—Determining Lot Sizes and Resource Requirements: A Review. Operations Research, 35(3), 329-345.

Baki, M.F., Chaouch, B.A. and Abdul-Kader, W. (2014). A heuristic solution procedure for the dynamic lot sizing problem with remanufacturing and product recovery. Computers & Operations Research, 43, 225-236.

Chen, M. and Abrishami, P. (2014). A mathematical model for production planning in hybrid manufacturing-remanufacturing systems. The International Journal of Advanced Manufacturing Technology, 71(5-8), 1187-1196.

Corominas, A., Lusa, A. and Olivella, J. (2012). A manufacturing and remanufacturing aggregate planning model considering a non-linear supply function of recovered products. Production Planning & Control, 23(2-3), 194-204.

Dong, M., Lu, S. and Han, S. (2011). Production planning for hybrid remanufacturing and manufacturing system with component recovery. In: Advances in Electrical Engineering and Electrical Machines (pp. 511-518): Springer.

Gómez Urrutia, E.D., Aggoune, R. and Dauzère-Pérès, S. (2014). Solving the integrated lot-sizing and job-shop scheduling problem. International Journal of Production Research, 52(17), 5236-5254.

Gupta, D. and Magnusson, T. (2005). The capacitated lot-sizing and scheduling problem with sequence-dependent setup costs and setup times. Computers & Operations Research, 32(4), 727-747.

Hilger, T., Sahling, F. and Tempelmeier, H. (2015). Capacitated dynamic production and remanufacturing planning under demand and return uncertainty. OR Spectrum, 1-28.

Ilgin, M.A. and Gupta, S.M. (2010). Environmentally conscious manufacturing and product recovery (ECMPRO): a review of the state of the art. Journal of environmental management, 91(3), 563-591.

James, R.J. and Almada-Lobo, B. (2011). Single and parallel machine capacitated lotsizing and scheduling: New iterative MIP-based neighborhood search heuristics. Computers & Operations Research, 38(12), 1816-1825.

Jans, R. and Degraeve, Z. (2007). Meta-heuristics for dynamic lot sizing: A review and comparison of solution approaches. European Journal of Operational Research, 177(3), 1855-1875.

Jing, Y., Li, W., Wang, X. and Deng, L. (2016). Production planning with remanufacturing and back-ordering in a cooperative multi-factory environment. International Journal of Computer Integrated Manufacturing, 29(6), 692-708.

Karimi, B., Fatemi Ghomi, S.M.T. and Wilson, J. (2003). The capacitated lot sizing problem: a review of models and algorithms. Omega, 31(5), 365-378.

Kenne, J.-P., Dejax, P. and Gharbi, A. (2012). Production planning of a hybrid manufacturing–remanufacturing system under uncertainty within a closed-loop supply chain. International Journal of Production Economics, 135(1), 81-93.

Kirkpatrick, S., Gelatt, C.D. and Vecchi, M.P. (1983). Optimization by simmulated annealing. science, 220(4598), 671-680.

Kovács, A., Brown, K.N. and Tarim, S.A. (2009). An efficient MIP model for the capacitated lot-sizing and scheduling problem with sequence-dependent setups. International Journal of Production Economics, 118(1), 282-291.

Lee, C.-W., Doh, H.-H. and Lee, D.-H. (2015). Capacity and production planning for a hybrid system with manufacturing and remanufacturing facilities. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 229(9), 1645-1653.

Li, X., Baki, F., Tian, P. and Chaouch, B.A. (2014). A robust block-chain based tabu search algorithm for the dynamic lot sizing problem with product returns and remanufacturing. Omega, 42(1), 75-87.

Li, X., Li, Y. and Saghafian, S. (2013). A hybrid manufacturing/remanufacturing system with random remanufacturing yield and market-driven product acquisition. Engineering Management, IEEE Transactions on, 60(2), 424-437.

Li, Y., Chen, J. and Cai, X. (2006). Uncapacitated production planning with multiple product types, returned product remanufacturing, and demand substitution. OR Spectrum, 28(1), 101-125.

Macedo, P.B., Alem, D., Santos, M., Junior, M.L. and Moreno, A. (2016). Hybrid manufacturing and remanufacturing lot-sizing problem with stochastic demand, return, and setup costs. The International Journal of Advanced Manufacturing Technology, 82(5-8), 1241-1257.

Menezes, A.A., Clark, A. and Almada-Lobo, B. (2011). Capacitated lot-sizing and scheduling with sequence-dependent, period-overlapping and non-triangular setups. Journal of Scheduling, 14(2), 209-219.

Mercé, C. and Fontan, G. (2003). MIP-based heuristics for capacitated lotsizing problems. International Journal of Production Economics, 85(1), 97-111.

Metropolis, N., Rosenbluth, A.W., Rosenbluth, M.N., Teller, A.H. & Teller, E. (1953). Equation of state calculations by fast computing machines. The journal of chemical physics, 21(6), 1087-1092.

Mohammadi, M. (2010). Integrating lotsizing, loading, and scheduling decisions in flexible flow shops. The International Journal of Advanced Manufacturing Technology, 50(9-12), 1165-1174.

Mohammadi,M.,Fatemi Ghomi,S.M.T.,and Jafari, N. (2011). A genetic algorithm for simultaneous lotsizing and sequencing of the permutation flow shops with sequence-

dependent setups. International Journal of Computer Integrated Manufacturing, 24(1), 87-93.
Mohammadi, M., Fatemi Ghomi, S.M.T., Karimi, B. and Torabi, S.A. (2010). Rolling-horizon and fix-and-relax heuristics for the multi-product multi-level capacitated lotsizing problem with sequence-dependent setups. Journal of Intelligent Manufacturing, 21(4), 501-510.
Mohammadi, M. and Jafari, N. (2011). A new mathematical model for integrating lot sizing, loading, and scheduling decisions in flexible flow shops. The International Journal of Advanced Manufacturing Technology, 55(5-8), 709-721.
Mukhopadhyay, S.K. and Ma, H. (2009). Joint procurement and production decisions in remanufacturing under quality and demand uncertainty. International Journal of Production Economics, 120(1), 5-17.
Naeem, M.A., Dias, D.J., Tibrewal, R., Chang, P.-C. and Tiwari, M.K. (2013). Production planning optimization for manufacturing and remanufacturing system in stochastic environment. Journal of Intelligent Manufacturing, 24(4), 717-728.
Pan, Z., Tang, J. and Liu, O. (2009). Capacitated dynamic lot sizing problems in closed-loop supply chain. European Journal of Operational Research, 198(3), 810-821.
Parsopoulos, K.E., Konstantaras, I. and Skouri, K. (2015). Metaheuristic optimization for the single-item dynamic lot sizing problem with returns and remanufacturing. Computers & Industrial Engineering, 83, 307-315.
Pineyro, P. and Viera, O. (2010). The economic lot-sizing problem with remanufacturing and one-way substitution. International Journal of Production Economics, 124(2), 482-488.
Ramezanian, R. and Saidi-Mehrabad, M. (2013). Hybrid simulated annealing and MIP-based heuristics for stochastic lot-sizing and scheduling problem in capacitated multi-stage production system. Applied Mathematical Modelling, 37(7), 5134-5147.
Ramezanian, R., Saidi-Mehrabad, M. and Teimoury, E. (2013). A mathematical model for integrating lot-sizing and scheduling problem in capacitated flow shop environments. The International Journal of Advanced Manufacturing Technology, 66(1-4), 347-361.
Ramezanian, R., Sanami, S.F. and Nikabadi, M.S. (2016). A simultaneous planning of production and scheduling operations in flexible flow shops: case study of tile industry. The International Journal of Advanced Manufacturing Technology, 1-15.
Richter, K. and Weber, J. (2001). The reverse Wagner/Whitin model with variable manufacturing and remanufacturing cost. International Journal of Production Economics, 71(1), 447-456.
Shi, J., Zhang, G., Sha, J. and Amin, S.H. (2010). Coordinating production and recycling decisions with stochastic demand and return. Journal of Systems Science and Systems Engineering, 19(4), 385-407.
Sifaleras, A. and Konstantaras, I. (2015). General variable neighborhood search for the multi-product dynamic lot sizing problem in closed-loop supply chain. Electronic Notes in Discrete Mathematics, 47(1), 69-76.
Stindt, D. and Sahamie, R. (2014). Review of research on closed loop supply chain management in the process industry. Flexible Services and Manufacturing Journal, 26(1-2), 268-293.
Taguchi, G., Chowdhury, S. and Taguchi, S. (2000). Robust engineering: McGraw-Hill Professional.
Teunter, R.H., Bayindir, Z.P. and Den Heuvel, W.V. (2006). Dynamic lot sizing with product returns and remanufacturing. International Journal of Production Research, 44(20), 4377-4400.
Wagner, H.M. and Whitin, T.M. (1958). Dynamic version of the economic lot size model. Management science, 5(1), 89-96.
Wei, C., Li, Y. and Cai, X. (2011). Robust optimal policies of production and inventory with uncertain returns and demand. International Journal of Production Economics, 134(2), 357-367.
Wolosewicz, C., Dauzère-Pérès, S. & Aggoune, R. (2015). A Lagrangian heuristic for an integrated lot-sizing and fixed scheduling problem. European Journal of Operational Research, 244(1), 3-12.

Wu, C.J. & Hamada, M.S. (2011). Experiments: planning, analysis, and optimization (Vol. 552): John Wiley & Sons.
Wu, Y. & Wu, A. (2000). Taguchi methods for robust design: American Society of Mechanical Engineers.
Yang, J., Golany, B. & Yu, G. (2005). A concave-cost production planning problem with remanufacturing options. Naval Research Logistics (NRL), 52(5), 443-458.
Zhang, J., Liu, X. & Tu, Y. (2011). A capacitated production planning problem for closed-loop supply chain with remanufacturing. The International Journal of Advanced Manufacturing Technology, 54(5-8), 757-766.
Zhang, Z.-H., Jiang, H. & Pan, X. (2012). A Lagrangian relaxation based approach for the capacitated lot sizing problem in closed-loop supply chain. International Journal of Production Economics, 140(1), 249-255.

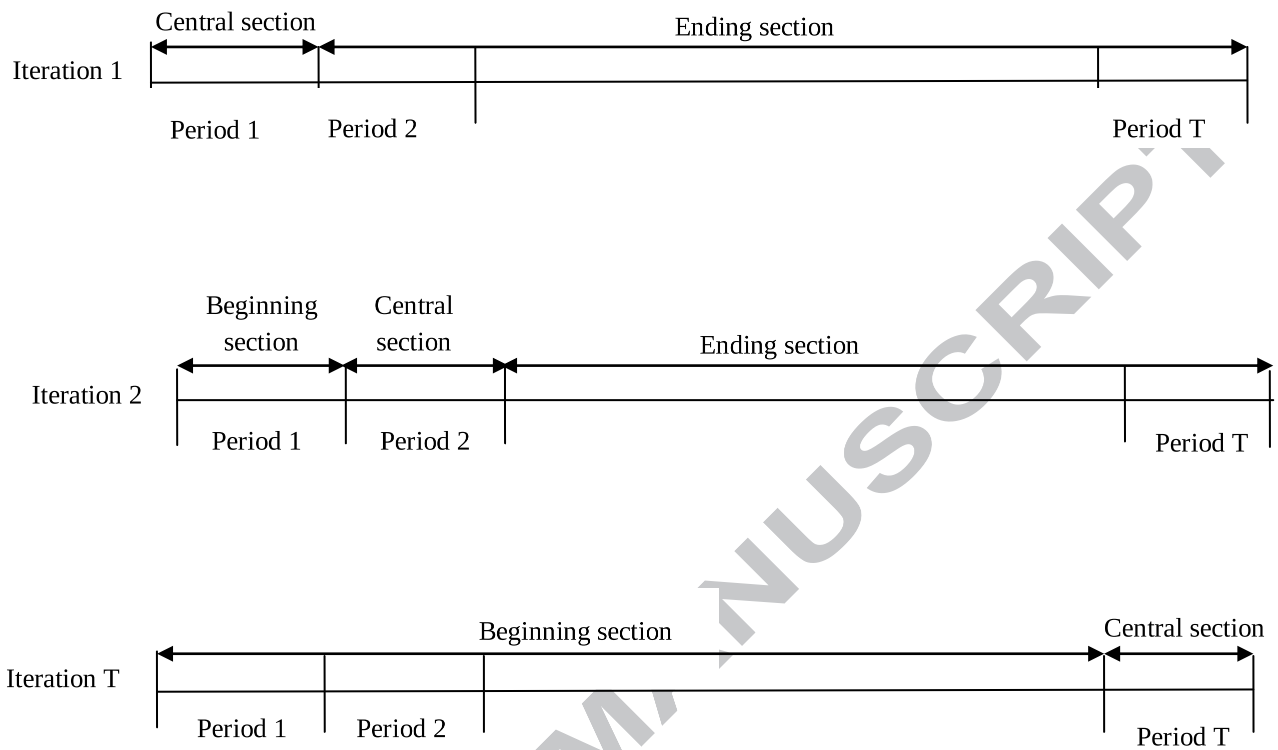



**Fig. 1** Rolling horizon method (Mohammadi et al., 2010)

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 4 | 3 | 5 | 6 | 2 | 1 | 6 | 5 | 4 | 3 |
| 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 |

**Fig. 2** Solution representation of problem with N=3, M=2, T=2

ACCEPTED MANUSCRIPT

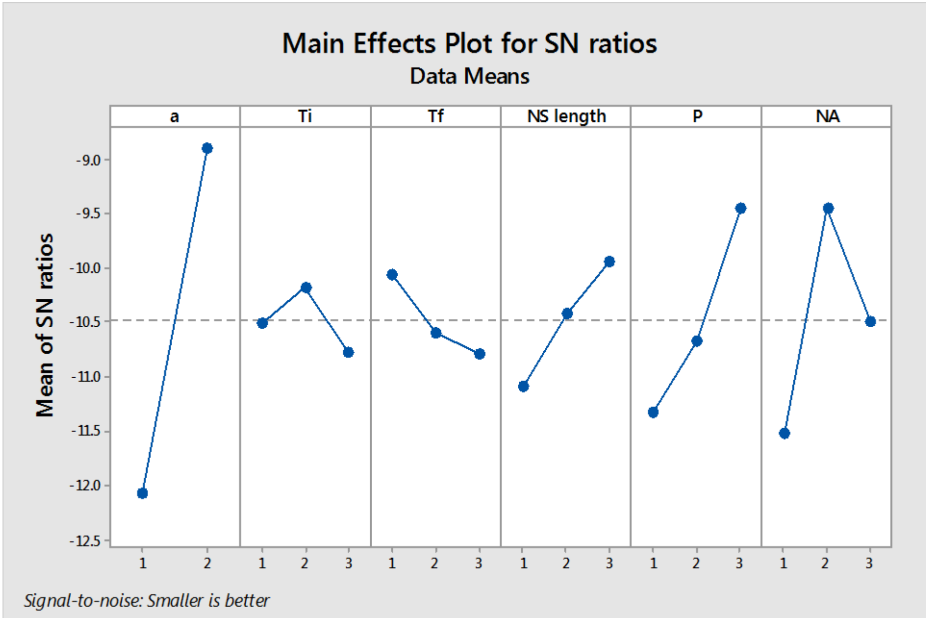



**Fig.3** The mean of S/N ratio at each level of the SA parameters

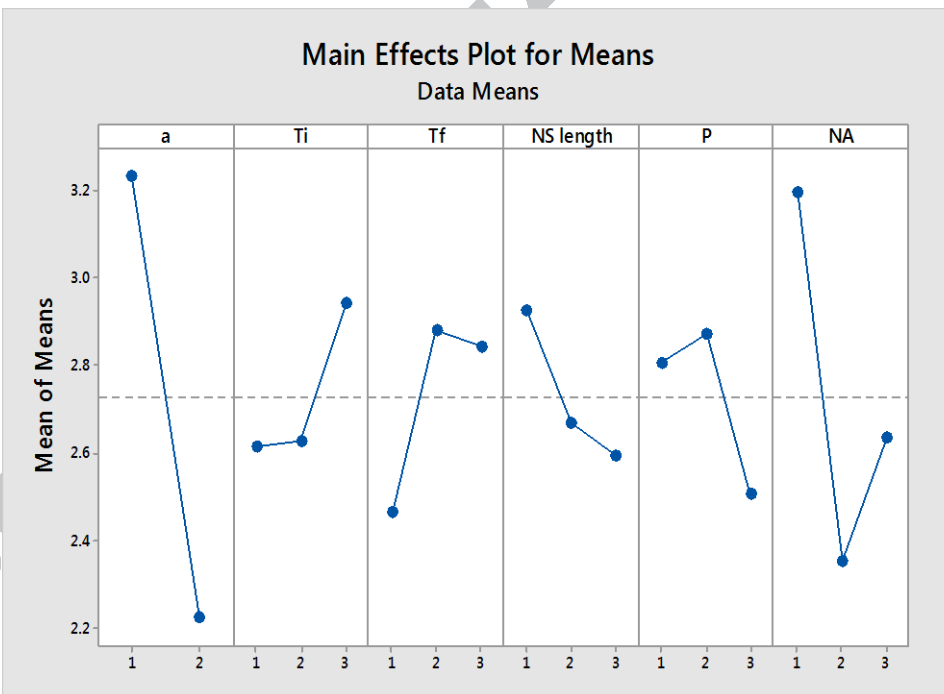



**Fig.4** The mean of RPD at each level of the SA parameters

**Research highlights**

- A multi-stage lot sizing problem with remanufacturing is modeled.
- Sequence dependent setups and setup carry-over in a flow shop are considered.
- A mixed integer programming is introduced to formulate the problem.
- Rolling horizon heuristics and a SA algorithm are proposed to solve the model.
- For large size problems SA algorithm would have better solutions than heuristics.