A Bi-Objective Lot Sizing and Scheduling Problem Dealing with Reworking Perishable Items in a Parallel Machine System

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Abstract

Production systems generally struggle with defective products resulting from human error, machine break-down, or an imperfect production system. Reworking is one of the strategies to deal with this issue and rework planning involves the production planning and scheduling of defective items along with the master production planning. The importance of rework planning becomes more important when the products are perishable with a limited lifecycle. This research presents a linear bi-objective mathematical model to determine the production lot-sizing and scheduling as well as rework scheduling in a parallel machine system for perishable products. The optimization model aims to minimize the cost and the makespan of the production and rework processes at the same time. We test the model results on a small size problem solved using CPLEX algorithm and address the complexity of the large size problem using BAT metaheuristic algorithm. Numerical experiments and sensitivity of the results to the model varying parameters are analyzed on a sample case study with varying size.

Keywords:
Rework, Perishability, Lot sizing, Scheduling, Parallel Machines

1. Introduction

In a manufacturing environment, the main goal of planning is to fully utilize the resources to satisfy the customers' demand while gaining maximum profit over the planning horizon. The scope of planning can be categorized into three levels of time ranges: long-term, medium-term, and short-term. The long-term planning deals with facility location and allocation, tools, and process choices without paying much attention to lower level details. The medium-term focuses on forecasting production quantities or lot sizing over a finite planning horizon, and the short-term planning mainly deals with scheduling of daily operations (Hu and Hu 2016, Karimi et al. 2003). While the lot sizing problem is a medium-term production optimization problem to determine the production quantity in each period to meet the customer demand, it could also be formulated to address the multi-level planning problems where there exist inter-dependencies among items at different production levels, typically imposed by the production structure requirements (Toledo et al. 2013). Another extension to the lot sizing problem is its integration with short-term scheduling of products in a flow shop, where the lot sizing and scheduling problems are not independent and need to be integrated (Ponnambalam and Reddy 2003). Due to the machine considerations in the scheduling problems, this problem typically determines the order of operations on various machines considering the possible sequence dependent setup times and costs to reach an efficient level of resource utilization (Almada-Lobo et al. 2015). One important consideration in production and scheduling problems is that the production processes are not usually defect-free, and the defective products could be produced in any stage of in the production process. The defect could occur due to various reasons such as: human error, machine breakdowns or imperfect production system. Depending on the quality considerations and requirements, a proportion of defective items can be reworked, and sold for either the same or lower price, or scraped. Furthermore, if the original production processes consume a huge amount of power, resources and time or spread CO2 emissions or require expensive raw materials, it will be an economic and/or ecological motivation to rework defective products instead of scraping them. In addition, there could be other incentives for reworking defective items because green production processes have become increasingly popular among stakeholders, e.g. customers, suppliers, third parties, and governments. Firms have shown their environmentally friendly image by complying with the new regulations established regarding CO2 emission and disposal limitations; as a result, many companies attempt to expand their environmental image, because customers recently tend to pay a great amount of attention to it and would like to purchase such products. As a result, the reworking of defective items can result in more economical and environment- friendly production processes resulting in overall higher sales volumes and profit.

However, one concern regarding re-working of the defective items is the best time to address this task considering the production of new items, customer demand satisfaction, level of effort required to do the re-work and also the effect of keeping the defective items in inventory especially when the products are perishable as if these products are held in stock for a long time, they could be deteriorated or ruined.

In this research we aim to address the aforementioned issues in a joint lot of sizing and scheduling problem with parallel machines where the production process could produce defective perishable products. Figure 1 represents the overall process behind the model we consider developing in this study. At the first stage , raw materials move from storage to production phase where a percentage of defective items can be produced. Any manufactured item with acceptable quality can be stored in the final product inventory to be delivered to the customers. The detected defective products need to be reworked to satisfy the quality conditions. We suppose that the rework process is perfect with no disposal options. However, as the defective products stored in the work-in-process (WIP) inventory longer than their life cycle, they get deteriorated, our model aims to address the rework before this time period ends for perishing products. We introduce a mixed-integer programming (MIP) model with rework of defective perishable items to analyze a dynamic capacitated imperfect production process in integration with Lot-sizing and scheduling system. We will be optimizing two conflicting objectives which are: cost and make-span of finishing all tasks.

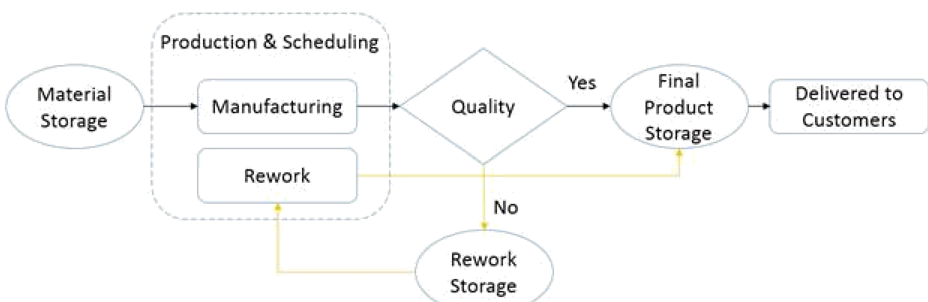

Figure 1. Production system

The remainder of this paper is organized as follows: Section 2 provides an overview about the related research on the lot sizing and scheduling problem with and without rework and perishability considerations. Section 3 provides the main assumptions, problem statement and mathematical formulation. Section 4 describes our solution method while the numerical examples settings and results are presented in Section 5 followed by the main conclusions and concluding points along with directions for future research in Section 6.

2. Literature Review

In the real world, almost all of the production systems struggle with producing the defective or low-quality items. Reworking defective items into an acceptable state can be possible in many cases. The literature and studies advocate that reworking or re-manufacturing defective items has emerged in the Lot Sizing or inventory models. Porteus Porteus (1986) considered the impact of defective items in the inventory model (the economic order quantity (EOQ)) and their relationship with quality and the lot sizes. It is shown that inspection and quality control station can be located during production process or at the end of production line in order not to interfere with its fast rate production (Hayek and Salameh 2001, Sarker et al. 2008). Moussawi Moussawi-Haidar et al. (2016) defined a model with quality screening to investigate the defective items right when production system stops, due to the quick production rate and difficulty to locate the inspection stations during the production process. In such problems, the demand is met by acceptable quality items and defective ones are reworked or salvaged at the end of the production cycle. The capacitated and dynamic production system considering in line rework, back ordering and lot sizing constraints has also been published recently (Goerler and Vo 2016). The authors demonstrate a dynamic mixed integer programing (MIP) covering the combination of described production features. One of the critical scopes in the Lot Sizing problems belongs to modeling perishable items (Onal et al. 2015, Feng et al. 2017). There exist a few studies that provide the rework assumption regarding the perishable production manufacturing cycles. Teunter and Flapper (2003) modeled a single stage production system with perishable products. The authors assume that the rework time and cost increase linearly with the holding time, so their production system switches between manufacturing to rework for decreasing the number of salvage items. The results confirm the tangible performance of the combination of lot sizing, perishability, and rework line. The critical stream is integrating the lot sizing and scheduling that can be more accurate and extensive in lot sizing modeling . Various perspectives of lot sizing and scheduling are discussed: presuming the capacitated lot sizing and scheduling (Camargo et al. 2012, Ramezanian and Saidi-Mehrabad 2013, Taghizadeh et al. 2012), Multi-level and parallel machine consideration (Tempelmeier and Buschkuhl 2008, Almeder and Almada-Lobo 2011), remarking Lead time limitation (Almeder et al. 2015), and generating the heuristic solution to solve them (Wolosewicz et al. 2015, Vahdani et al. 2017, Taghizadeh et al. 2017). Hu and Hu (2016) proposed a stochastic programming model for a lot sizing and scheduling problem to deal with the demand uncertainty in an automotive case study. Their results verify the importance of considering uncertainties to reach the optimal production planning. Over time, integrated lot sizing and scheduling problems emerge through the perishable products. For instance, a multi objective lot sizing and scheduling model for perishable products is provided solved by a hybrid NSGA-II algorithm (Amorim et al. 2011). In addition, researchers indicated the benefit of switching from batching to lot sizing decisions in perishable products, clarifying the conditions that increases the advantages of applying lot sizing versus batching Amorim et al. (2013).

Table 1. Literature review summary on lot sizing and scheduling problem

Research Study	Lot-sizing	Scheduling Rework	Perishable Products	Case Study /Simulation
Teunter and Flapper (2003)	√	√	√	Simulation
Tempelmeier and Buschkuhl (2008)	√	√		Simulation
Almeder and Almada-Lobo (2011)	√	√		Simulation
Amorim et al. (2011)	√	√	√	Case Study
Toledo et al. (2013)	√	√		Simulation
Amorim et al. (2013)	√	√	√	Case Study
Ramezanian et al. (2013)	√	√		Simulation
Almeder et al. (2015)	√	√		Simulation
Wolosewicz et al. (2015)	√	√		Simulation
Onal et al. (2015)	√		√	Simulation
Hu and Hu (2016)	√	√		Case Study
Goerler and Vo (2016)	√	√		Simulation
Moussawi-Haidar et al. (2016)	√	√		Simulation
Feng et al. (2017)	√		√	Simulation
Vahdani et al. (2017)	√	√		Simulation

Table 1 summarizes the recent and notable papers in lot sizing and scheduling models with and without consideration of reworking and perishable products. It is shown that most of the article utilize the simulation instances to analyze their model. None of these articles consider the rework process for perishable products in lot sizing and scheduling problems at the same time. Hence, our contribution is modeling a multi-objective lot sizing and scheduling problem for perishable items that can be reworked and the analysis on the model performance will be done one small and larger size problems on a sample case data.

3. Mathematical Formulation

Generally, in integrated Capacitated Lot-sizing and Scheduling Problem (CLSP), various products with known demand are produced in each period on one machine with a finite capacity. The objective is to find the optimal lot-sizes and efficient sequence of operations on each machine which minimizes the overall cost including inventory holding, setup and shortage costs. The CLSP considered in this paper consists of multiple perishable products i = 1,……, I to be scheduled on various machines m = 1,……, M and over a finite periods of time t = 1,…., T with cost and make-span minimization objectives. Regarding the crucial role of reworking, we consider reworking cost and rework holding cost in our objective function as well. Some other problem assumptions are described as follows:

- There exist parallel machines with different capacities.
- The products are perishable with limited lifetime (cycle).
- There exist defective products (imperfect product) produced by a specific rate over the production processes and they are reworkable. There is not any scrap or non-reworkable defective items. The perished defective products will not be considered for reworking and are lost.
- Reworking time/cost for each product increases linearly with the length of the time that is held in stock awaiting rework.
- Each machine can process only one job at a time, and a job can be processed on only one machine at a time.
- Machines do not fail. (there is no breakdown of machines).

The notations and formulation of our mathematical model are as follows:

Indices:

i: Product index
m: Machine index
t, t‘: Period index

Parameters:

D_{it}: Demand of product i in period t
P_{it}: Production cost of product i in period t
$RP0_{it}$: Rework fixed cost of product i in period t
RP_{it}: Rework variable cost of product i in period t
H_{it}: Inventory holding cost per unit of non-defective product i in period t
H_{it}^{R}: Inventory holding cost per unit of defective product i in period t
PR_{im}: Process time per unit of product i on machine m
PR_{im}^{R0}: Rework fixed process time per unit of product i on machine m
PR_{im}^{R}: Rework variable process time per unit of product i on machine m
C_m: Set-up cost of machine m
S_{it}: Shortage (backlogging) cost per unit of product i in period t
α_{it}: Percentage of defective product i in period t
CAP_m: Available capacity of machine m
SH: Shelf life of products (assumed to be the same for all products)

Variables:

inv_{it}: Inventory of product i in period t
$xir_{itt'}$: Quantity of product i produced in period t‘ (t‘ < t) but their rework has not been done till period t
X_{it}: Production quantity of product i in period t
Xr_{it}: Quantity of product i reworked in period t
$xr_{itt'}$: Quantity of product i that is produced in period t‘ (t‘ < t) reworked in period t
Xy_{imt}: Binary variable linking set up machine m in period t for product i to amount of product i at period

Xry_{imt} : Binary variable linking set up machine m in period t for reworkable product i to amount of product i at t
y_{imt} : Binary variable equal to 1 if (reworkable) product i processed on machine m at period t
b_{it} : Shortage quantity of product i in period t
γ_{mt} : Binary variable equal to 1 if a job is assigned to machine m in period t
C_{max} : Maximum completion time

$$Min\ f_1 :\ \sum_i \sum_i inv_{it}\, H_{it} + \sum_i \sum_t \sum_{\acute{t}} xir_{it\acute{t}} H_{it}^R + \sum_m \sum_t \gamma_{mt}\, C_m + \sum_i \sum_t S_{it}\, b_{it} + \sum_i \sum_t P_{it}\, X_{it} + \sum_i \sum_t \sum_{\acute{t}=t-SH}^{t} ((RP0_{it} + (t - \acute{t}) RP_{it}) xr_{it\acute{t}}) \quad (1)$$

$$Min\ f_2 : C_{max} \quad (2)$$

Subject to:

$$(1 - \alpha_{it}) X_{it} + inv_{i,t-1} + \sum_{\acute{t}=t-SH}^{t-1} xr_{i\acute{t}t} = inv_{it} - b_{it} + D_{it}\ , \forall i, t \quad (3)$$
$$xir_{i\acute{t}t} = x_{i\acute{t}}.\alpha_{i\acute{t}} - \sum_{t''=\acute{t}+1}^{t} xr_{i\acute{t}t''}, \forall i, t, \acute{t} = t - sh, \dots, t-1 \quad (4)$$
$$X_{it} + Xr_{it} \leq M \sum_m y_{imt}\ , \forall i, t \quad (5)$$
$$Xy_{imt} \leq X_{it}, \forall m, i, t \quad (6)$$
$$Xy_{imt} \leq M y_{imt}, \forall m, i, t \quad (7)$$
$$X_{it} - M(1 - y_{imt}) \leq Xy_{imt}, \forall m, i, t \quad (8)$$
$$Xry_{imt} \leq Xr_{it}, \forall m, i, t \quad (9)$$
$$Xry_{imt} \leq M.\, y_{imt}, \forall m, i, t \quad (10)$$
$$Xr_{it} - M(1 - y_{imt}) \leq Xry_{imt}, \forall m, i, t \quad (11)$$
$$Xr_{it} = \sum_{\acute{t}=t-sh}^{t-1} xr_{i\acute{t}t}\ , \forall i, t \quad (12)$$
$$\sum_i (Xy_{imt} PR_{im} + \sum_{\acute{t}=t-SH}^{t-1} Xry_{imt} (PR_{im}^{R0} + (t - \acute{t}) PR_{im}^{R}) \leq C_{max}\ , \forall m, t \quad (13)$$
$$\sum_i Xy_{imt} + \sum_i Xry_{imt} \leq CAP_m, \forall m, t \quad (14)$$
$$\sum_i y_{imt} \leq 1, \forall m, t \quad (15)$$
$$y_{imt} \leq \gamma_{mt}, \forall m, t \quad (16)$$
$$inv, xir_{itt'}, X_{it}, xr_{it\acute{t}}, Xy_{imt}, Xry_{imt}, b_{it}, C_{max} \geq 0, \forall i, m, t \quad (17)$$
$$y_{imt}, \gamma_{mt} \epsilon \{0,1\}, \forall m, t \quad (18)$$

The objective function in (1) minimizes the total cost related to finished and rework products inventory, machines set-up cost, shortage cost, production cost, and rework related cost. The second objective (2) aims to minimize the maximum completion time of jobs in each period. Constraint (3) is the inventory balance. Constraint (4) is an inventory related constraint for the defected and reworkable products over various periods. Constraints (5)-(8) are the logical production quantity constraints considering whether each product is chosen to be produced in each period or not. The same logical constraints are true for defective and rework products as in constraints (9)-(11). Constraint (12) presents a formulation for calculation of total reworked products over various periods and up to a specific period. Constraint (13) presents the main formulation for calculation of maximum completion time in the second objective. Constraint (14) is the machine capacity constraint for production and reworking in each period. Constraint (15) makes sure each machine can process just one product at a time and constraint (16) assures that in each period, just the utilized machines could have changeovers. Finally, constraint (17) and (18) deals with the non-negativity and binary of the variables, respectively.

4. Solution Methodology

The multi-objective model needs to be transformed to a single objective model to be handled by solution algorithms. We use the ε-constraint method introduced by Haimes et al., YV et al. (1971) which keeps only one of the attributes in the objective function and treats all the remaining as a set of inequality constraints to be satisfied. Each inequality constraint is bounded by an epsilon vector, and each vector corresponds to a point in the pareto frontier. As the magnitude of the epsilon vector changes, tradeoffs between objectives can be reached and a pareto-front can be built. Our problem formulation (based on Eq. 1 and 2)is as below:

$$Minimize\ f_1(x) \quad (19)$$
$$Subject\ to: f_2(x) \leq \epsilon \quad (20)$$

Constrains [3-18]

In addition, due to the complex nature of the joint lot-sizing and scheduling problems, as the problem size increases, the exact algorithms could lose their favorability in terms of solution time and effort. As we would like to test our proposed model performance for different problem sizes, the small problems will be solved using CPLEX solver of GAMS while the complexity of larger size problems is handled by meta-heuristic algorithms. We use BAT algorithm which is a recent meta-heuristic algorithm for global optimization. This algorithm is inspired by the echolocation behavior of microbats with varying pulse rates of emission and loudness. This algorithm is first developed by Yang (2010) . Each virtual bat flies randomly with a velocity v_i at position x_i with a varying frequency or wavelength and loudness A_i. As it searches and finds its prey, it changes frequency, loudness and pulse emission rate r. Search is intensified by a local random walk. Selection of the best continues until certain stop criteria are met. This essentially uses a frequency-tuning technique to control the dynamic behavior of a swarm of bats, and the balance between exploration and exploitation can be controlled by tuning algorithm-dependent parameters in bat algorithm. The following pseudo-code (Algorithm 1) represents the main steps of implementing the BAT algorithm.

Algorithm 1: Hybrid BAT Algorithm

Input : Population size n, Number of dimensions d, φ=1.2, $\beta = 0.5$

Output: Local Optimal

Initialize the BAT population(solution) x_i and v_i (i= 1,2,....,n)
Initialize frequencies f_i, pulse rates r_i and the loudness A_i.
Best Solution ($x_* =$ Min f(x_i))-Initial Solution. **while** $t <$ *Max number of iteration* **do**
    Average of loudness value of all Bats A^t.
    Update velocities and solution using:
    for $i = o \to n$ **do**
        $f_i = f_{min} + (f_{max} - f_{min} * rand)$
        $v_i^{t+1} = v_i^t + (x_i^t - x_*)f_i$
        $x_i^{t+1} = x_i^t + v_i^{t+1}$
        if $rand > r_i$ **then**
            Generate new solutions by adjusting frequency and
            update velocities and locations/solutions
            $f_i = f_{min} + (f_{max} - f_{min} * rand)$
            $v_i^{t+1} = v_i^t + (x_i^t - x_*)f_i$
            $x_i^{t+1} = x_i^t + v_i^{t+1}$
        else
            Generating a New Solution by flying randomly (random walk) / $x_{new} = x_* + (2 * rand(1,d) - 1) * A^t$
        end
        if $rand < A_i$, $f_T(x_{new}) < f_T(x_*)$ **then**
            Accept the new solution ($x_* = x_{new}$). Increase r_i, and reduce A_i using Constance φ=1.2, $\beta = 0.5$ as follows :
            $A_i^{t+1} = \beta A_i^t$.
            $r_i^{t+1} = r_i^0[1 - exp(-\varphi t)]$
        else
            Rank the Bats and find the current best x_*
        end
    end
end

5. Computational Study

5.1. Data

The data is adopted from Makis and Fung (1995) and slightly modified for a deteriorating production system of various product sizes with shelf life of 3 periods to be processed and scheduled on 3 machines. In each period, 5% of the produced products are defective and need reworking. 3 distributional scenarios for demand generation are considered as follows:

- **Group1:** 10 time periods with demand distribution N(200, 50).
- **Group2:** 10 time periods with demand distribution N(100, 50).
- **Group3:** 10 time periods with demand distribution N(350, 50).

To analysis the proposed model, all implementations are conducted with GAMS 28.1.0 in its default set-tings as optimizer and Java 8 software for BAT Algorithm by a personal computer with Intel Core i5 6300U CP U(2:4GHz), with 8.00 GB of RAM.

5.2. Results and Analysis

Table 2 represents various cases with different number of products and scheduling periods where each model is solved with both GAMS and BAT algorithms to compare the cost and maximum completion time in addition to the solution time. The gap for each metric is calculated using the following formulation:

$$GAP = \frac{|BAT-GAMS|}{GAMS} * 100 \quad (21)$$

Table 2. Cost and completion time GAMS, BAT algorithm comparisons, different cases, different demand groups

		I=10, T=10			I=25, T=10			I=50, T=10		
		GAMS	BAT	GAP	GAMS	BAT	GAP	GAMS	BAT	GAP
Group1	Production cost	253.09	257.16	1.61%	223.37	227.28	1.75%	411.34	415.69	1.06%
	Rework Cost	226.06	228.55	1.10%	195.10	197.72	1.35%	371.61	376.20	1.24%
	Inventory Holding Cost	23.09	23.58	2.10%	18.22	18.22	0.00%	24.01	24.28	1.11%
	Rework Inventory Holding Cost	18.06	18.62	3.10%	14.25	14.46	1.48%	18.78	19.02	1.31%
	Shortage Cost	16.09	16.55	1.01%	29.23	29.95	1.21%	38.09	39.71	2.06%
	C_{max}	1.87	1.89	1.20%	1.82	1.84	1.39%	1.98	2.01	1.20%
	Time (s)	847.76	22.14		1087.98	33.81		1398.01	31.23	
Group2	Production cost	185.91	188.76	1.53%	160.09	162.50	1.50%	202.19	205.72	1.75%
	Rework Cost	166.05	171.14	2.97%	139.82	141.66	1.31%	182.66	184.673	1.10%
	Inventory Holding Cost	19.01	19.27	1.40%	23.11	23.58	2.05%	28.09	28.57	1.71%
	Rework Inventory Holding Cost	12.77539	12.92	1.20%	15.52	16.09	3.49%	18.87	19.06	1.01%
	Shortage Cost	14.08	14.39	0.90%	12.09	12.66	4.70%	11.08	11.23	1.35%
	C_{max}	0.98	0.98	0.35%	1.86	1.90	2.09%	1.66	1.70	2.11%
	Time (s)	930.01	21.02		1190.98	41.98		1389.01	53.87	
Group3	Production cost	316.09	319.56	1.10%	375.09	378.34	0.87%	407.99	421.26	3.15%
	Rework Cost	289.33	302.70	4.42%	327.61	331.38	1.14%	368.58	372.01	0.93%
	Inventory Holding Cost	69.19	71.32	2.98%	73.09	77.31	5.46%	61.11	61.34	0.39%
	Rework Inventory Holding Cost	55.85	56.78	1.68%	59.01	60.82	3.00%	49.32	50.51	2.35%
	Shortage Cost	27.09	28.50	4.93%	28.23	30.05	6.07%	26.99	28.44936	5.13%
	C_{max}	2.01	2.11	4.87%	1.99	2.08	4.12%	2.98	3.08	3.25%
	Time	624.98	31.09		1001.08	41.98		1394.01	62.98	

The cost comparison results for all demand scenarios and different problem and scheduling periods sizes indicate the BAT algorithm is able to produce very close cost and completion time values as compared to the GAMS while it can significantly improve the solution time with no noticeable sensitivity to the number of products. As a result, we will use BAT algorithms for further sensitivity analysis on the model results. Table 3 indicates how the inventory, rework, and production cost values are sensitive to the changing costs, capacity, and process times. The rework inventory cost has the highest impact on both total rework inventory cost and rework production costs with the highest impact on rework inventory cost (as high as 145% when the rework inventory cost increases by only 5%). This implies that as the deteriorating products get closer to their end lifetime, their inventory cost as well as their processing cost could turn to serious issues which is in favor of doing the rework sooner. On the other hand, the processing times are playing an important role on inventory and production costs. If due to machine inefficiency or the labors insufficient skills the processing time increases by 10%, it can have more than 300% negative effect on the inventory holding cost which results in inventory pile-up to make sure the customer need is satisfied due to slower processing time. This could be concerning as the products could deteriorate with the pass of time.

Table 3. Algorithm sensitivity results to time and cost parameters changes, demand group 1, 10 products, 10 planning periods

	G1 - I=10, T=10			
Parameters	**Inventory Cost**	**Rework inventory cost**	**Production cost**	**rework production cost**
Setup Cost+10%	-10.54	30.72	3.43	-13.35
Setup Cost+5%	5.92	18.66	7.32	-8.54
Setup Cost-5%	6.42	-13.56	3.26	17.23
Setup Cost-10%	9.34	-30.30	5.37	32.13
Inventory Cost+10%	31.86	17.97	-1.58	-1.12
Inventory Cost-10%	99.20	66.94	-1.58	-1.12
Rework Inventory Cost+10%	31.60	66.94	-1.58	79.81
Rework Inventory Cost+5%	31.22	146.37	-1.58	53.17
Rework Inventory Cost-5%	-6.66	-24.71	-1.58	25.61
Rework Inventory Cost-10%	-10.83	-35.84	-1.58	25.61
Capacity-6%	74.01	2.67	-26.47	-22.91
Production Process time+5%	150.07	7.05	11.61	-6.87
Production Process time+10%	345.16	12.43	51.30	-1.59
Production Process time-5%	-30.61	87.54	3.41	35.65
Production Process time-10%	-56.38	125.43	-10.57	36.07
Rework Process time+10%	31.84	12.60	-1.58	-1.08
Rework Process time+5%	18.88	3.98	-1.58	-1.08
Rework Process time-5%	2.15	-7.69	-1.58	-1.08
Rework Process time-10%	-6.75	-13.6	-1.58	-1.08

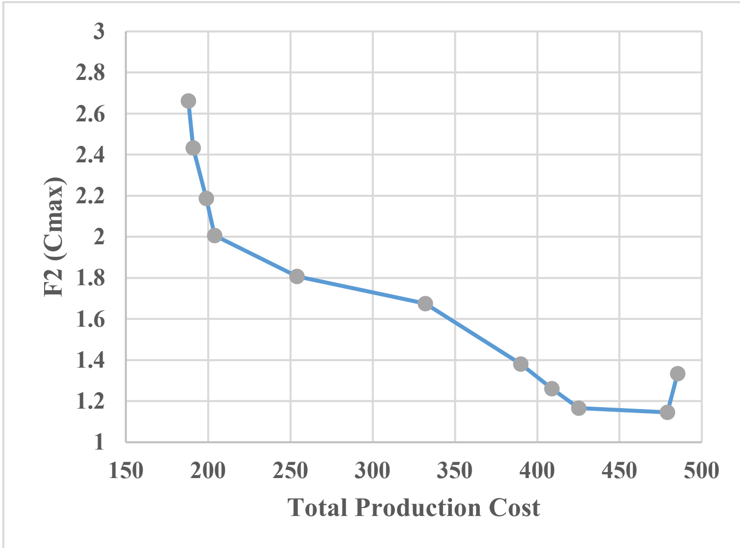

Figure 2. Pareto Frontier for the second objective versus production cost, BAT Algorithm, I=10, T=10, Group=1

Pareto Frontiers resulting from BAT algorithm for 10 items scheduled over 10 periods for demand scenarios 1 are presented in Figures 2. Pareto Frontiers presents the tradeoff between second objective value and production cost, the critical trade off point is between 1 and 1.2 for F2 with around 470 production cost. It means we can reach the appropriate time with acceptable production cost. Finally, Table 4 includes the comparative results of four models for different demand groups with 8 products to be scheduled in 8 periods where each model does not take into consideration either parallel machine or reworking while the fourth model has our model assumptions. This shows, by having parallel machines, the number of deteriorated products noticeably decreases and by doing on time reworking, the shortage cost sharply decreases but the total cost smoothly increases. In addition to reworking, our proposed model is also able to improve the maximum completion time.

Table 4. BAT algorithm results sensitivity to consideration of rework and parallel machines into the model, 8 products, 8 planning periods, different demand scenarios (G1, G2, and G3)

Problem Type	**I=8, T=8 (No Rework and M=1)**			**I=8,T=8 (Rework, M=1)**		
Scenarios	**G1**	**G2**	**G3**	**G1**	**G2**	**G3**
f2:Min C_{max}	5.98	4.87	8.19	3.64	2.88	5.11
# Products passed shelf life	6	7	8	4	2	6
Shortage cost	31.09	29.08	45.98	15.69	13.78	20.09
Total Cost	531.97	487.98	721.98	608.09	514.878	823.98
Problem Type	**I=8, T=8 (No Rework and M=3)**			**I=8,T=8 (Rework, M=3)**		
Scenarios	**G1**	**G2**	**G3**	**G1**	**G2**	**G3**
f2:Min C_{max}	4.11	3.99	5.31	1.78	0.738	2.10
# Products passed shelf life	4	4	7	1	0	3
Shortage cost	21.34	18.18	24.11	11.96	10.98	17.77
Total Cost	571.17	507.55	802.66	698.09	602.98	913.98

6. Conclusions

This research presents an optimization modeling framework for the lot-sizing and scheduling problem where the products have a limited shelf life. The bi-objective modeling approach takes into consideration parallel machines to process products in a multi-product setting. The complexity of the problem is handled by utilization of BAT algorithm as a meta-heuristic which has shown to be very efficient in producing objective values with noticeable improvement of solution time. While the process time has a noticeable effect on the inventory and production costs, the rework inventory and rework production costs are mainly affected by the rework inventory costs. In addition, the proposed model is shown to improve the maximum completion time of the products, shortage, and total costs. Based on our analysis, there exist multiple promising research directions. While we are assuming each product is processed only on one machine, application of the proposed model on cases where there exist sequence requirements in the production processes could make the modeling more challenging specially when the setups are sequence dependent. In addition, as the planning problem deals with future periods planning, the inherent demand, cost or capacity uncertainty could officially be considered in the modeling framework. Finally, machine breakdowns are another reality in the production systems which could affect the production systems performance. Consideration of machines downtime could make the problem more interesting yet more complex.

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