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RESEARCH PAPER

Coordination of Order Acceptance, Scheduling, and Pricing Decisions in Unrelated Parallel Machine Scheduling

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ABSTRACT
We study the order acceptance, scheduling, and pricing problem (OASP) in a parallel machine environment. Each order is characterized by due date, release date, deadline, controllable processing time, sequence-dependent setup time, and price in MTO system. An MILP formulation is used to maximize the net profit. Then, under a joint optimization approach, the pricing decisions are set for the unrelated parallel machine environment. The results show that the proposed model can solve the scheduling decision problems based on different levels of products' prices. Thus, the model solves these two categories of decisions, simultaneously. Moreover, the changes in accepted orders in pricing levels can be analyzed regarding their dependency on price elasticity of items for future research.

KEYWORDS *Order acceptance, Scheduling, Pricing, Make-to-order(MTO), Unrelated parallel machine, Optimization*.

1. Introduction

Order acceptance and scheduling (OAS) are generally handled by different departments in actual factories. In addition, the main decisions made by the sales and production departments are set independently. On the other hand, it is known that these parallel decisions are so effective in minimizing the overall costs and, also, maximizing revenues. For this reason, the problem of synchronizing these individualized decisions is vital for actual cases. By this viewpoint, the firms should ask themselves *"how should these two departments coordinate their efforts to maximize the firm's profit?"*

The main aim of production planning is to minimize the total costs of production [1], [2]. However, providing a holistic view based on marketing and production planning processes enables us to maximize the firm's profit using both potentials of cost reductions (by scheduling decisions) and revenue optimizing (by pricing decisions).

Regarding the literature, the main trends in production planning and scheduling concentrate on finding solutions to the above problems in a distinct way. In addition, pricing is the only factor that matters for marketing decisions and is based on products' costs and expenses [3]. Thus, there is a great deal of effort in coordinating the decisions of scheduling and pricing.

Charnsirisakskul et al. carried out the first study in this literature on inventory, order acceptance, scheduling, and price decisions [4]. In their study, the objective is to maximize total net profit by considering a single price model and multiple pricing models. They compared the benefit of the flexibility to customized price with the benefits of the lead time and inventory flexibilities. Chen and Hall [5] considered three problems that require pricing and scheduling decisions. They examined the potentials for improving profitability through the coordination of pricing and production decisions. They considered the coordination of pricing and scheduling decisions with linear price-dependent demand.

Moreover, under such conditions, assuming that controllable processing times allow us to optimize the time and related costs regarding the best level of pricing levels and profits. Herein, we model an order acceptance, scheduling, and pricing (OASP) problem in a parallel machine environment. Each order is characterized by due date, release date, deadline, controllable processing time, sequence-dependent setup time and price in a make-to-order (MTO) system. The current study presents a mixed integer linear programming (MILP) formulation to maximize the net profit. Then, under the joint optimization

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approach, the pricing decisions are set for unrelated parallel machine environment. The results show that the basic developed problem can solve the scheduling decisions based on different levels of products' prices. Thus, the problem solves these two categories of decisions simultaneously.
The paper is organized as follows. In Section 2, the relevant literature on order acceptance and scheduling problems regarding aspects of pricing decision-making. is reviewed. Section 3 deals with model building. In Section 4, some special cases of the problem are discussed and the solutions presented. Finally, Section 5 provides concluding remarks and future research propositions.

2. Literature Review

The OAS problem has attracted significant attention from academy and business. Various OAS problems with variant characteristics have been studied over the last two decades. Talla Nobibon and Leus [6] studied a generation of the OAS problem with weighted-tardiness penalties. They considered two mixed integer formulations and two branch-and-bound (B&B) algorithms to find the optimal solution.
Oguz et al. [7] studied the OAS problem in a single machine environment. In their study, the orders were defined by their due dates, release dates, processing times, deadlines, sequence-dependent setup time, and revenues. The objective was to maximize the net profit. They presented an MILP formulation that could be solved optimally for instances with up to 10 jobs within a one-hour time limit. For solving a large-scale problem, they presented three heuristic algorithms. Emami et al. [8] proposed an MILP model for OAS problem in an unrelated parallel machine environment. They developed a Benders decomposition approach to solve it.
The first study in the literature that combines all aspects of inventory, order acceptance, scheduling, and pricing decisions was done by Charnsirisakskul et al. [4]. They proposed a model for maximizing the total profit under single and multiple pricing models. They compared the benefits of the flexible pricing customized with those of the lead time and inventory flexibilities.
Moreover, considering the pricing point of view, the problem of order acceptance and scheduling can be considered with pricing called OASP. An OASP model should consider an applicable price-dependent demand function, which can show the relation of pricing and its effect on order acceptance. Regarding the literature, different demand curves can be used in a joint pricing and production planning model by Chan et al. [9]. One of the most frequently used demand forms is linear price-dependent demand, which shows that setting higher prices results in less willingness to ordering. As one of the main related research studies, Chen and Hall [5] considered the coordination of pricing and scheduling decisions with linear price-dependent demand. They considered four solution approaches:
a) An uncoordinated approach where pricing and scheduling decisions are made independently;
b) A partially coordinated approach that uses only general information about scheduling, which a marketing department typically knows;
c) A simple heuristic approach for solving the coordinated problem;
d) Optimal algorithm for solving the coordinated problem.
The main managerial insight is that there is a significant benefit to even partial or heuristic coordination, especially when demand is sensitive to price, profit margins are small, work-in-process holding costs or processing times are large, due dates are tightly constraining, or when there are many choices for prices.
In an OASP problem, the flexibility of processing times provides effective conditions to fulfill demands variation with real constraints of production. Scheduling problems with controllable processing times have gained importance in scheduling research since the pioneering works of G. [10]. Li et al. [11] considered the identical parallel machine scheduling problem to minimize the makespan with controllable processing times, in which the processing times are linear decreasing functions of the consumed resource. In addition to the mentioned studies, there are some who addressed the parallel processors with fuzzy processing times. Balin [12] addressed parallel machine scheduling problems with fuzzy processing times in which a robust GA approach embedded in a simulation model is proposed to minimize the maximum completion. Ventura and Kim [13] considered parallel machines scheduling problem where jobs have uncommon due dates and may require, besides machines, certain additional limited resources for their handling and processing with the goal of minimizing the total absolute deviation of job completion times. Aktürk et al. [14] considered non-identical

parallel machining where processing times of the jobs are only compressible at a certain manufacturing cost, which is a convex function of the compression on the processing time. They introduced alternative match-up scheduling problems for finding schedules on the efficient frontier of time/cost tradeoff.

Many papers use an integer, linear, or MILP model to solve the OAS problem. When the problem size is large, the researchers present a heuristic algorithm to find an optimal solution. For example, Slotnick and Morton [15] applied a B&B algorithm and high-quality heuristic to solve the OAS problem. Rom and Slotnick [16] presented a genetic algorithm for the OAS problem. Slotnick and Morton [17] presented a model that considers a pool of order and used B&B algorithm for the model.

Therefore, OASP model is formulated using a MILP formulation for unrelated parallel machines with the objective of maximizing total net profit. The problem is based on the model of Charnsirisakskul et al. [4] from a scheduling viewpoint and the model of Chen and Hall [5] for the case of coordination of scheduling and pricing. Moreover, the test problem is set by an extended version of Emami et al. [8], where the controllable process time is considered for real cases in MTO systems. The next Section describes the model and its constraints.

3. The Model

In this section, OASP model using an MILP formulation for unrelated parallel machines with the objective of maximizing total net profit is formulated. The problem is formulated as follows: there is a set of n independent orders $N=\{1,2,..,n\}$ to be processed on M unrelated parallel machines. The linear demand function $k_i = \alpha_i - \beta_i e_i$ is considered, where α and β are positive constants and $\leq \frac{\alpha}{\beta}$.

Assumptions, parameters and decision variables

The assumptions of OASP are described below:

- All data are known at the beginning of the planning horizon.
- All the orders are non-preemptive and available for processing at time zero.
- Each machine (order) can process only one order (machine) at a time.
- Each order will be delivered immediately after completion; hence, there is no holding cost.
- The setup time for each order on each machine is sequence dependent.
- No order operation preemption is allowed.
- All machines are unrelated with different speeds, and each order could be processed by a free machine.
- The processing times and release dates of each order on each machine are different.

The parameters of the model are introduced as follows:

p_{im}	Processing time of job i on machine m
p'_{im}	Crash (minimum allowable) processing time of order i on machine m
p''_{im}	Expansion (maximum allowable) processing time of order i on machine m
C'_{im}	Compression unit cost of order i on machine m
C''_{im}	Expansion unit cost of order i on machine m
d_i	Due date of order i
r_i	Release date of order i
s_{ijm}	Sequence-dependent setup time on machine m for order i that precedes order j
w_i	Unit tardiness penalty cost
α_i	Primary market volume of order i
β_i	Demand price sensitivity of order i
cap_i	Capacity of order i
G	An arbitrary big positive number

The decision variables of the model are introduced as follows:

L_{im}	1 if order i is the last order on machine m; 0 otherwise
C_{im}	Completion time of order i
T_i	Tardiness of order i
e_i	The price of order i
A_{im}	Compression amount of order i on machine m
$A^{"}_{im}$	Expansion amount of order i on machine m
x_{im}	1 if order i is accepted; 0 otherwise i∈n.
E_{im}	1 if order i is processed on machine m; 0 otherwise $i \in N$, $m=1,\dots,M$
y_{ijm}	1 if order i immediately precedes order j on machine m; 0 otherwise $i,j \in N$, $i \neq j$, $m=1,\dots,M$
k_i	An integer variable for order accepted.

The mathematical model
In this section, the MILP model is defined as follows:

MILP:

$$maxz = \sum_{i=1}^{n}\left(\frac{\alpha_i - k_i}{\beta_i}x_i - w_i T_i\right) - \sum_{m=1}^{M}\sum_{n=1}^{N}\left(c'_{im}A_{im} + c^{"}_{im}A'_{im}\right)$$

$s.t.$

$$\sum_{m=1}^{M} E_{im} = x_i \qquad \forall\ i = 1,2,\dots,n \qquad (1)$$

$$\sum_{i=0}^{n} L_{im} = 1 \qquad \forall m = 1,\dots,M \qquad (2)$$

$$\sum_{j=1}^{n} y_{ijm} = E_{im} - L_{im} \qquad \forall\ i = 1,\dots,n, i \neq j\ \ \&\ \forall m = 1,\dots,M \qquad (3)$$

$$C_i + (s_{ijm} + p_{jm})y_{ijm} - A_{jm} + A'_{jm} + G(y_{ijm} - 1) \leq C_j \qquad \forall\ i = 0,\dots,n, j = 1,\dots,n, i \neq j, \forall m = 1,\dots,M \qquad (4)$$

$$(r_j + p_{jm} + s_{ijm})y_{ijm} - A_{jm} + A'_{jm} \leq C_j \qquad \forall\ i = 0,\dots,n, j = 1,\dots,n, i \neq j, \forall m = 1,\dots,M \qquad (5)$$

$$T_i \geq C_i - d_i \qquad \forall\ i = 1,\dots,n \qquad (6)$$

$$(p_{im} - p'_{im})E_{im} \geq A_{im} \qquad \forall\ i = 1,\dots,n \quad , m = 1,2,\dots,M \qquad (7)$$

$$(p^{"}_{im} - p_{im})E_{im} \geq A'_{im} \qquad \forall\ i = 1,\dots,n \quad , m = 1,2,\dots,M \qquad (8)$$

$$E_{0m} = 1 \qquad \forall m = 1,\dots,M \qquad (9)$$

$$k_i \leq cap_i . x_i \qquad \forall i = 1,\dots,n \qquad (10)$$

$$L_{im}, E_{im}, x_i \in \{0,1\} \qquad \forall\ i = 0,\dots,n,\ \ \forall m = 1,\dots,M \qquad (11)$$

$$y_{ijm} \in \{0,1\} \qquad \forall\ i = 0,\dots,n, j = 1,\dots,n, i \neq j\ \ \&\ \ \forall m\ = 1,\dots,M \qquad (12)$$

$$T_i, C_i, A_{im}, A'_{im} \geq 0 \qquad \forall\ i = 0,\dots,n \qquad (13)$$

The objective was formulated to maximize the total net profit over the planning horizon. Constraint set (1) requires that for an order to be accepted, it must be assigned to a machine. Constraint set (2) defines the last order on each machine.

Constraint set (3) makes it obligatory to deal with the fact that if an order is processed on machine m, it must precede only one job and it should be succeeded by only one job. Constraint sets (4) and (5) are added to the model in order to adjust the completion time of the orders on each machine. Constraint set (6) represents the tardiness of each order. Constraints (7) and (8) define the limit of the amount of compression and expansion of each job on each machine. Constraint set (9) defines the dummy order 0 correctly. Constraint set (10) defines the capacity of orders. It has been added to the model due to the non-linearity of the objective function. Constraints sets (11), (12), and (13) define the value ranges of the variables.

4. Computational Studies

In this section, the result of the computational experiment is investigated.

Data generation

In order to generate data, similar to Potts and Van Wassenhove [18], two predefined parameters are used: the due date range, R, and the tardiness factor, τ. In this study, the values chosen for τ were 0.3 and 0.7; the same values were applied for R as well. Therefore, problem instances could cover a wide range of cases. The following problem parameters include integer numbers, which were generated randomly from a uniform distribution in the following intervals: release date r_i in $[0, \tau P_T]$ where P_T is the total processing time of all orders, processing time p_{im} in $[1,20]$, sequence-dependent setup time s_{ijm} in $[1,10]$, and the tardiness penalty costs (w_i) selected from the discrete uniform distribution in the range [1, 10], as used in Talla Nobibon and Leus [6]. The generation of the release date is similar to the study of Akturk and Ozdemir [19]. The setup times are generated using discrete uniform distribution, which is also consistent with the existing scheduling literature by Rubin and Ragatz [20] and Tan and Narasimhan [21]. Moreover, due dates are generated from $p_a\left[1-\tau-\frac{R}{2}, 1-\tau+\frac{R}{2}\right]$, where $p_a = \sum_{i=1}^{n}\sum_{m=1}^{M}\frac{p_{im}}{M^2}$. The capacity of orders is defined as a fixed number equal to 100.

Results

This section shows the results of sample problems that are solved regarding the structure of data generation based on different values of R and τ on different machines and orders. Table 1 presents the results of price setting and the relevant revenue and profit for accepted orders. It can be seen that the orders with high prices are not accepted and the problem attempts to synchronize the marginal profit of acceptance or rejection of items based on both aspects of cost and revenue. For example, in this case, $30n, 6m, 0.7R, 0.3\tau$ order with number 3 and price of 35.68 is accepted; however, Order 5 with price of 21.01 is not accepted. According to Table 2, it is interpreted that considering the problem with 20n, 6m in the absence of pricing policy leads us to choose Case 4 with 15 numbers of acceptance and the least total cost. However, considering pricing assumptions under profit maximization problem, the best case is Case 1 with 18 chosen orders. Based on the comparison of this case and $30n, 6m, 0.7R, 0.3\tau$, it can be seen that accepting fewer items would be desirable for a production planner because producing fewer items results is lower total costs. The charts of results are given. The concave charts show that we have high marginal profits.

Tab. 1. Order sets

$10n, 6m, 0.3R, 0.3\tau$

Order	1	2	3	4	5	6	7	8	9	10
K/100	10	10	10	10	10	10	10	10	10	10
Price	26	15.71	14.29	13	10	16.66	13.75	13.33	15	14.44
Revenue	260	157.1	142.9	130	100	166.6	137.5	133.3	150	144.4

$10n, 6m, 0.3R, 0.7\tau$

Order	1	2	3	4	5	6	7	8	9	10
K/100	10	10	10	10	10	10	10	10	10	10
Price	26	18.57	18.33	10	13	21.67	15	12.22	16.25	16.25
Revenue	260	185.7	183.3	100	130	216.7	150	122.2	162.5	162.5

$10n, 6m, 0.7R, 0.3\tau$

Order	1	2	3	4	5	6	7	8	9	10
K/100	10	10	10	10	10	0	0	0	0	0
Price	17.14	16.25	16.25	10	12.22	22.22.	21	21	24.44	22.22
Revenue	171.43	162.5	162.5	100	122.22	0	0	0	0	0

$10n, 6m, 0.7R, 0.7\tau$

Order	1	2	3	4	5	6	7	8	9	10
K/100	0	0	10	0	0	0	10	0	0	0
Price	24.44	36.67	18.57	26.25	31.43	24.44	14.29	22	23.33	33.33
Revenue	0	0	185.7	0	0	0	142.9	0	0	0

$20n, 6m, 0.3R, 0.3\tau$

Order	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
K/100	10	0	10	10	10	10	10	10	10	10	10	10	10	0	10	10	10	10	10	10
Price	17.14	27.50	15.71	14.44	13.75	10	10	12	14.44	13.33	17.14	17.14	21.67	12.50	15	14.44	16.67	18.33	18.57	12
Revenue	171.4	0	157.1	144.4	137.5	100	100	120	144.4	133.3	171.4	171.4	216.7	0	150	144.4	166.7	183.3	185.7	120

$20n, 6m, 0.3R, 0.7\tau$

Order	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
K/100	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Price	15.71	12.50	14.29	15	22	10	11	13	13.33	13.33	17.14	14.29	18.33	15	16.25	13.33	21.67	16.67	18.57	13
Revenue	157.1	125	142.9	150	220	100	110	130	133.3	133.3	171.4	142.9	183.3	150	162.5	133.3	216.7	166.7	185.7	130

$20n, 6m, 0.7R, 0.3\tau$

Order	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
K/100	10	10	10	10	10	10	10	10	10	10	0	10	10	0	10	10	10	10	10	0
price	17.14	13.75	18.57	12.5	22	11	11	13	14.44	12.22	35	22	12.5	26.25	13.75	14.44	18.33	16.67	17.14	20
Revenue	171.43	137.5	185.71	125	220	110	110	130	144.44	122.22	0	220	125	0	137.5	144.44	183.3	166.7	171.4	0

$20n, 6m, 0.7R, 0.7\tau$

Order	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
K/100	10	10	10	0	10	10	10	10	0	10	10	10	10	10	10	0	10	0	10	0
price	12	14.44	20	25	26	13	12	26	35	10	17.14	18.57	16.67	15	16.25	33.33	12.50	24.44	15.71	21
Revenue	120	144.4	200	0	260	130	120	260	0	100	171.4	185.7	166.7	150	162.5	0	125	0	157.1	0

$30n, 6m, 0.3R, 0.3\tau$

Order	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	21	22	23	24	25	26	27	28	29	30										

K/100	10	0	10	10	10	10	10	10	0	0	10	0	10	10	10	0	0	10	10	0
	10	10	10	10	10	0	10	0	0	0										
Price	20.07	30.58	16.72	13.10	12.36	13.05	12.96	13.66	25.80	24.13	18.62	34.85	19	14.74	17.31	25.88	35.47	18.57	20.27	22.02
	19.59	18.85	12.59	17	15.43	34.11	11.28	36.44	35.62	24.16										
Revenue	200.7	0	167.24	131	123.6	130.5	129.6	136.6	0	0	186.2	0	190	147.4	173.1	0	0	185.7	202.7	0
	195.9	188.5	125.9	170	154.3	0	112.8	0	0	0										

$30n, 6m, 0.3R, 0.7\tau$

Order	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	21	22	23	24	25	26	27	28	29	30										
K/100	18	18	13	12	14	0	15	14	12	17	20	14	11	17	0	15	11	13	13	20
	20	11	13	16	20	12	12	19	14	19										
Price	4.63	4.17	12.86	8.06	8.65	26.09	7.56	6.30	9.83	6.90	0	11.09	19	6.70	26.63	8.23	17.73	13.51	14.03	0
	3.01	15.42	9.45	10.82	3.56	16.24	11.28	7.29	13.94	1.21										
Revenue	83.37	75.06	167.24	96.76	121.10	0	113.3	88.26	117.9	117.2	0	155.2	208.9	113.8	0	123.5	195	175	182.40	0
	60.26	169.66	122.79	173.06	71.21	194.93	135.32	138.48	195.15	22.95										

$30n, 6m, 0.7R, 0.3\tau$

Order	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	21	22	23	24	25	26	27	28	29	30										
K/100	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	10	10	0	0										
Price	28.84	20.98	35.68	18.89	21.01	26.79	22.04	24.74	32.8	26.07	26.4	30.79	26.45	32.5	30.3	17.97	15.93	20.33	24.72	31.49
	26.22	25.86	23.14	25.31	28.4	29.27	18.78	18.52	22.68	18.84										
Revenue	0	0	0	188.9	210.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	187.8	185.2	0	0										

$30n, 6m, 0.7R, 0.7\tau$

Order	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	21	22	23	24	25	26	27	28	29	30										
K/100	17	0	12	12	0	0	0	0	0	0	14	16	12	0	0	11	0	18	15	0
	0	18	12	17	11	11	14	13	16	0										
Price	4.63	31.97	12.86	8.06	27.19	24.91	23.75	21.01	27.03	22.99	9.31	7.92	15.54	26.79	29.29	11.76	35.47	3.38	9.35	25.32
	31.64	3.43	10.49	6.18	11.87	16.24	6.77	18.22	10.84	27.78										
Revenue	78.74	0	154.38	96.76	0	0	0	0	0	0	130.37	126.7	186.5	0	0	129.4	0	60.78	140.3	0
	0	61.69	125.93	105.07	130.56	178.68	94.72	236.88	173.47	0										

Tab. 2. The results

Sample	Total revenue	Total cost	Total profit (OF)	Average of price	Number of items	Production capacity ratio	Average of K (K/100)	Number of accepted order
$10n, 6m, 0.3R, 0.3\tau$	1261.8	1211.47	50.33	15.218	100/1000	0.1	10	10/10
$10n, 6m, 0.3R, 0.7\tau$	1672.9	1647.43	25.47	16.729	100/1000	0.1	10	10/10
$10n, 6m, 0.7R, 0.3\tau$	718.65	684.98	33.67	16.052	50/1000	0.05	5	5/10
$10n, 6m, 0.7R, 0.7\tau$	328.6	281.24	47.36	25.47	20/1000	0.02	2	2/10
$20n, 6m, 0.3R, 0.3\tau$	2717.7	2472.91	244.79	15.58	180/4000	0.045	18	18/20
$20n, 6m, 0.3R, 0.7\tau$	3044.1	2911.57	132.53	15.22	200/4000	0.05	20	20/20
$20n, 6m, 0.7R, 0.3\tau$	2604.64	2364.18	240.46	17.08	170/4000	0.042	17	17/20
$20n, 6m, 0.7R, 0.7\tau$	2452.8	2239.51	213.29	19.20	150/4000	0.037	15	15/20
$30n, 6m, 0.3R, 0.3\tau$	3051.74	2784.97	266.77	21.14	190/9000	0.02	19	19/30
$30n, 6m, 0.3R, 0.7\tau$	3417.8	3126.39	255.41	10.13	280/9000	0.03	28	28/30
$30n, 6m, 0.7R, 0.3\tau$	772	578.36	193.64	25.08	40/9000	0.004	4	4/30
$30n, 6m, 0.7R, 0.7\tau$	2210.93	2038.84	172.09	17.39	170/9000	0.018	17	17/30

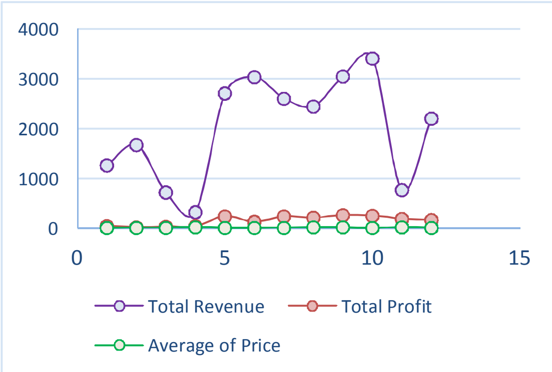
5. Conclusions and Future Researches

This study was successfully implemented to maximize total net profit and reduce orders cost depending on the amount of compression/expansion on unrelated parallel machines environment in which orders' processing times are controllable. An MILP model for the considered problem was presented and solved via GAMS software. The output data showed the coordination of order acceptance, scheduling, and pricing.

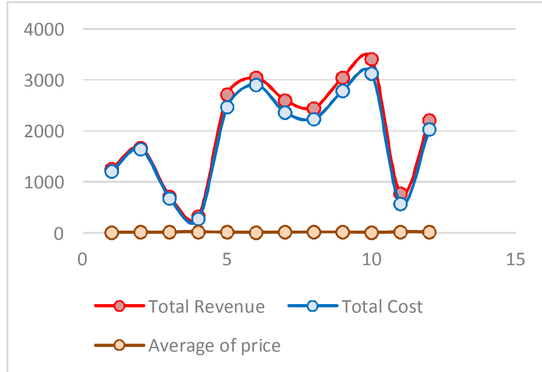
The results showed that problem in all of the cases for 10, 20, 30 orders was sensitive to simultaneous decision-making in pricing and order acceptance.

The results showed that problem in all of the cases for 10, 20, 30 orders was sensitive to simultaneous decision-making in pricing and order acceptance. The results indicate that considering high prices would be desirable for some cases where, in different items, the problem prefers moderate prices with more orders (Fig.1). Thus, the problem should be essentially considered with such a profit maximization objective. Moreover, the changes in accepted orders with respect to price should be analyzed more in comparison to the assumed price elasticity of items.

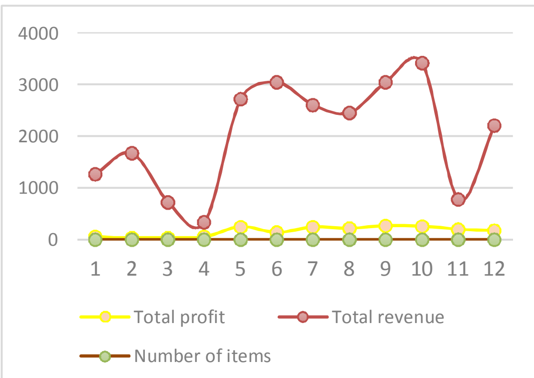
This problem based on job shop environment should be considered for future research. Solving the MILP problem with heuristic and exact algorithms such as GA and Branch-and-Price can be another interesting research for the future.



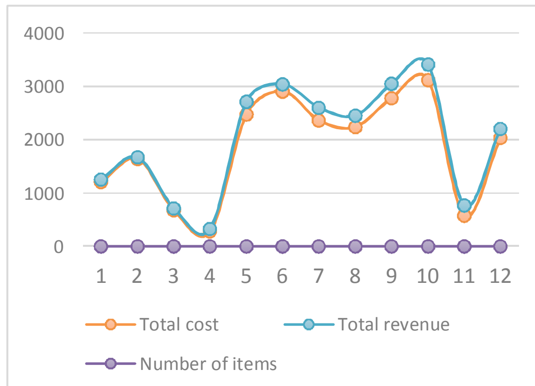
a) Total profit and total revenue with respect to average of price



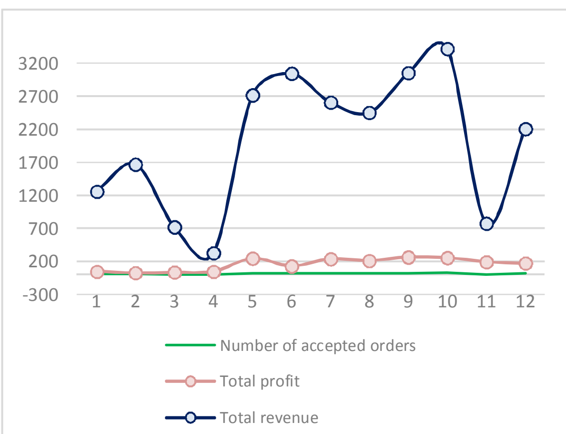
b) Total revenue and total cost with respect to average of price



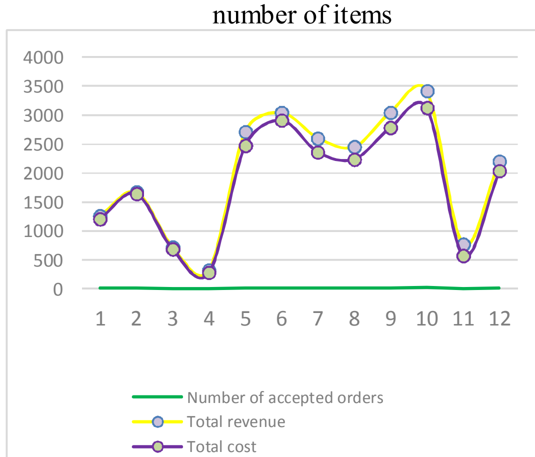
c) Total profit and total revenue with respect to number of items



d) Total cost and total revenue with respect to number of items



e) Total revenue and total profit with respect to number of accepted orders



f) Total revenue and total cost with respect to accepted orders

Fig. 1. The changes of revenue, profit, and total cost with respect to average price, number accepted orders, and items

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