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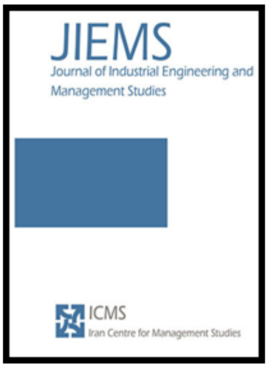

Presenting a bi-objective integrated production planning model considering constraints on order acceptance, production and customer delivery using meta-heuristic algorithms

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Abstract

In this study, the problem of simultaneous determination of order acceptance, scheduling and batch delivery considering sequence-dependent setup and capacity constraint has been presented. This problem is a combination of the three problems of order acceptance, scheduling and batch delivery. The most important innovation of this research is the simultaneous optimization of profits and the total weighted earliness and tardiness as two conflicting objectives in the problem of combining order, scheduling and batch delivery. Another innovation of this research is the use of multi-objective Grey Wolf Optimization (GWO) algorithm, which has not been used in studies of this field so far. It has also been shown that the multi-objective Grey Wolf Optimization algorithm is comparable to the exact solution methods. The second part of the numerical results compares the results of the ε-constraint method, NSGA-II and the multi-objective Grey Wolf Optimization algorithm. The results of this section show that by increasing the scale of the problem, the efficiency of the multi- objective Grey Wolf Optimization algorithm is better displayed, and in general, this method has a significant advantage relative to NSGA-II and ε-constraint in terms of DM, SNS and NPS indicators. Also, the solving time of this method is very shorter than that of the ε-constraint. Therefore, from a managerial point of view, a tool called the multi-objective Grey Wolf Optimization algorithm can be used as an efficient tool for supply and production managers, which is able to provide several optimal solutions with different profits, earliness and tardiness.

Keywords: production planning; scheduling; order acceptance; production; customer delivery; profit increase.

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1. Introduction

Production planning is generally carried out in three long-term, mid-term and short-term time horizons. Scheduling involves decisions related to production planning in the short-term time horizon that allocate production capacity to production goals (Kück and Freitag, 2021). Production scheduling at factories is the allocation of production orders for components to

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resources on the different production lines (Satyro et al. 2021). Due to a variety of domain-specific constraints, computer-aided scheduling of the production at factories is a difficult task. Different types of production methods, such as single item manufacturing, batch production, mass production, continuous production etc (Okpoti and Jeong, 2021). Its output is the precise determination of what product, when, and on what machine will be processed. In other words, the scheduling problem determines the exact start and end time of all tasks and their sequence on each machine. This classic problem has been of great interest to researchers over the past decades due to its many applications in manufacturing and service units (Mokhtari, 2015). In this study, the objective of the problem is to determine the order basket and the optimal sequence of jobs, assigning jobs to batches and delivering batches to customers so that the organization's profit is maximized. Each order can be sent to the customer immediately after processing, meaning that a batch can only include one job. In this case, the delivery cost increases significantly. It can also stay in the system to be sent along with the next job or jobs. In this case, its maintenance cost and flow time increase (Ou et al, 2015). Therefore, the approach of the problem of selection and scheduling and batch delivery is creating a balance between the cost of maintaining the order in the system until the completion of the batch (maintenance, delay, etc.) and the delivery costs dependent on batch-size. Sometimes the sequence of jobs can be changed so that two or more jobs are placed in a sequence and sent in a single batch.

The basic assumption in this problem is that there is not enough capacity to process all the orders received, and the producer has to choose from a number of demands. There are two main approaches to order acceptance and scheduling: In the first approach, the production system is penalized for not accepting each order, so the objective function in these problems will be to minimize the total cost and increase the organization's profit. The innovation of this research is the simultaneous optimization of profits and the total weighted earliness and tardiness as two conflicting objectives in the combined problem of order, scheduling and batch delivery. In general, four cost categories can be identified in this production system: production cost, sequence-dependent setup cost, maintenance cost, and batch delivery cost that depends on the number of batches sent and is independent of the number of orders inside the batch. Decision making on the delivery of products to customers, which is a short-term process, is one of the most important decisions of any production set along with the issues of supply and production. One of the delivery approaches is batch delivery. The delivery process is always done after the production process, so the delivery policies are always affected by the production schedule. On the other hand, in cases where it is required to comply with the due date set by the customer, it is necessary that the production schedule be coordinated with the delivery requirements. Therefore, the production and delivery decisions are completely interdependent and it is better to investigate these two problems simultaneously and as integrated. Considering the scheduling problem in production and the approach of batch delivery in the delivery problem, the integrated problem will include the simultaneous determination of scheduling and batch delivery. The approach of the problem of scheduling and batch delivery is creating a balance between the cost of maintaining the order in the system until the completion of the batch (maintenance, delay, etc.) and the delivery costs dependent on batch-size. Sometimes the sequence of jobs can be changed so that two or more jobs are placed in a sequence and sent in a single batch to minimize the maintenance costs in the inventory system. One of the important assumptions that exist in most studies in the field of scheduling and batch delivery is that only products that belong to a customer can be included in a batch.

The basic assumption in this problem is that there is not enough capacity to process all the orders received, and the producer has to choose from a number of demands. There are two main approaches to scheduling and order acceptance: In the first approach, the production system is penalized for not accepting each order, so the objective function in these problems will be to minimize the total cost. In the second approach, the production system earns income by accepting each order, so the objective function in these problems is to make more profit, which is obtained from the difference between income and costs. The main idea of this research is to present an integrated problem in order to simultaneously determine the accepted orders for production and determine the sequence of production and delivery of orders to the customers with batch delivery approach. In the problem under study, a number of orders are sent to the production system by several customers. The manufacturer wants to accept the best orders for production according to the available capacity and considering the income of each order and costs (including the production cost of each order, the maintenance cost of each order, sequence-dependent setup cost and delivery cost). The sequence of production, product allocation to batches, and delivery time of batches must be determined simultaneously.

According to the studies conducted so far, the integrated approach of production scheduling, batch delivery and order acceptance has not been investigated. In this study, the problem of simultaneous determination of order acceptance, scheduling and batch delivery considering capacity constraint and sequence-dependent setup has been presented. This problem is a combination of the three problems of order acceptance, scheduling and batch delivery. The most important innovation of this research is the simultaneous optimization of profits and the total weighted earliness and tardiness as two conflicting objectives in the problem of combining order, scheduling and batch delivery. Another innovation of this research is the use of multi-objective Grey Wolf Optimization algorithm, which has not been used in studies of this field so far. This algorithm was presented by Mirjalili et al. (2014) simulates the grey wolf pack hunting mechanism, including searching prey, tracking, encircling and then attacking. The Grey Wolf Optimizer is meta-heuristic evolutionary optimization algorithm.

The main research question is as follows: 1- How can the factory profit be increased according to batch delivery with the addition of the order acceptance approach? 2- How can the factory minimize the total weighted earliness and tardiness in the delivery of different orders?

According to the previous studies on the problem of order acceptance and scheduling (Iranpoor et al., 2014), adding the batch delivery problem to the above study, adding the order acceptance problem to the problem of scheduling and batch delivery (Jiang et al., 2017), providing an integrated model to examine the problem of simultaneous scheduling and batch delivery (Lu et al., 2011) with the addition of the order acceptance approach, examining the benefits of an integrated view of the problem using exact and meta-heuristic solutions, analyzing the problem, and achieving useful management results are considered as the innovations of this research. Reminder of the paper includes following issues: In the second and third sections, a review of the literature and mathematical model are presented respectively. The solution methods, in Section 4, and the numerical results, are presented in Section 5. Finally, the conclusion is presented in Section 6.

2. Literature review

Scheduling problems with processing set restriction are presented with topics such as scheduling with processing set restriction, eligibility constraint as well as machines eligibility (Leung, 2015). Yumei et al. (2010) considered the problem of scheduling n independent tasks on m parallel machines with processing set restriction. Their objective was to minimize the maximum completion time. Low (2012) developed an algorithm for solving parallel machines scheduling problem with processing set restriction and the objective function of maximum completion time. In this problem, the processing time of all tasks was equal to one.

He showed that when the number of available machines of this algorithm for each task is constrained to a fixed number, it will have the solving time of $O\ (n2 + mn)$. Chung Lan Lee (2016) considered the parallel machines scheduling problem with tasks of the same length, so that each task can only be processed on a specific subset of machines. He presented effective methods for solving problems with the objective functions of minimizing the total tardiness, minimum delays, total completion time, number of delayed tasks, and maximum completion time.

Jiang et al (2017), studied the order acceptance and scheduling problem with batch delivery in a supply chain consisting of a manufacturer and a customer, in which the manufacturer could reject some of the orders sent by the customer and process other orders in parallel machines and then deliver them to the customer in batches. The objective was to minimize the total weighted maximum flow time of accepted orders and the total cost of order rejection and delivery. So to solve the model, they created two approximate algorithms for this NP-hard problem.

Wang and Wang (2018), examined the order acceptance and scheduling problem in a two-machine flow shop environment and developed a bee colony meta-heuristic algorithm to solve the problem. The objective function of the problem was to maximize profits, which was obtained from the difference between income from accepted orders and the total weighted delay penalty.

Ramyar et al (2020), a bi-objective model is developed to deal with a supply chain including multiple suppliers, multiple manufacturers, and multiple customers, addressing a multi-site, multi-period, multi-product aggregate production planning (APP) problem. This bi-objective model aims to minimize the total cost of supply chain including inventory costs, manufacturing costs, work force costs, hiring, and firing costs, and maximize the minimum of suppliers' and producers' reliability by the considering probabilistic lead times, to improve the performance of the system and achieve a more reliable production plan.

Ayough and Khorshidvand (2019) presented a model for implementing a cellular manufacturing system. They main objective was minimizing the costs regarding a limited number of cells. Considering dynamic production times and uncertainty demands in designing cells were their main contributions. The quality of the two algorithms has been compared. The Simulated Annealing (SA) and Particle Swarm Optimization (PSO) algorithms have been used to solve their problem.

Dametew et al (2019), This study is conducted to developed innovative production planning and control strategies to manufacturing industries so as to improve production performance and competitiveness of basic metal sectors Though the study was conducted through field observation and questioner used as primary data and literature review on research articles, books, and electronic-sources which used as secondary data. While the questioner and filed observation data collection were done from two selected Ethiopian basic metal industries. Since the collected data were employed by both using descriptive and empirical analysis. Waste in the production process, poor plant layout systems, defective products, improper material requirement planning, deficiency on control and monitoring systems, insufficient inventory control, poor workflow strategies, null warehouse management systems, problems in information systems and information management strategies were investigated as the main challenges of developing the nation basic metal industries.

Ayough et al. (2020) presented a new job rotation scheduling and line-cell conversion problems. They investigated the effect of rotation frequency on flow time of a Seru system. Invasive weed optimization (IWO) has been used to solve their problem. Presenting improved IWO equipped with shake enforcement was their main contribution. The results show nonlinear behavior of flow time versus number of rotation periods. Also ability of presented method to generate clusters of equivalent solutions was shown.

Tirkolaee et al. (2020) presented a new production planning bi-objective model in manufacturing organization. Their main purposes were simultaneously minimizing the total cost of the production system and total energy consumption. The ε-constraint has been used to solve the proposed mathematical model exactly. The interactive fuzzy solution technique and a self-adaptive artificial fish swarm algorithm (SAAFSA) have been used to solve their problem. The results demonstrate the high efficiency of the proposed method in comparison with CPLEX solver in different problem instances.

Mgbemena et al (2020), this paper presented a tactical review approach to production constraints modeling. It discussed the theory of constraints (TOC) as a thinking process and continuous improvement strategy to curtail constraints in other to constantly increase the performance and efficiency of a system. It also x-rayed the working process of implementing the TOC concept which consists of five steps called "Process of On-Going Improvement". Furthermore, it talked about constraints programming and constraints-based models which were explained to some details. Finally, production constraints model formulation procedures for linear programming and non-linear programming scenarios were extensively discussed with reference to published literature as instances of production constraints modeling were also cited.

In reviewing the literature, some studies have examined the scheduling and batch delivery problem. Numerous studies have focused on order acceptance and scheduling problem. But so far, the three problems of scheduling, batch delivery, and order acceptance have not been studied simultaneously in a single framework. Therefore, the observed research gap is:

Due to the fact that the order acceptance and scheduling problem has been investigated, but batch delivery has not yet been considered in the concepts of production planning, which is the missing link in the chain of production to supply. Considering order selection for production and adding order acceptance problem to the scheduling and batch delivery problem has not been done in studies. An integrated model for simultaneous investigation of scheduling and batch delivery, with the addition of order acceptance approach has not been provided so far. According to the studies conducted, the integrated approach of production scheduling, batch delivery and order acceptance has not been done so far. In this study, the problem of simultaneous determination of order acceptance, scheduling and batch delivery with capacity constraint and sequence-dependent setup has been presented. This problem is a combination of the three problems of order acceptance, scheduling and batch delivery. The most important innovation of this research is the simultaneous optimization of profits and the total weighted earliness and tardiness as two conflicting objectives in the problem of combining order, scheduling and batch delivery. In this research, there are innovations in terms of presenting the model and solution method which will fill the identified research gap.

3. Mathematical model of the research

In this research, by presenting a mathematical model in Marun Petrochemical Complex, according to the number of orders received for production, the selection of the order is done and regarding the received order, production planning is done in such a way as to maximize the organization's profit. In this study, the problem of designing a simultaneous scheduling, order acceptance and delivery model is considered regarding the capacity constraint, sequence-dependent setup and batch delivery approach, which this model is based on mixed integer linear programming (MILP).

3.1. Problem assumptions

- Orders are received from customers (each order can include several goods that are produced).
- Each order can be sent directly to the customer after the production or after all orders of the customer are completed.
- In the short-term time period of T, the manufacturer wishes to select orders from the orders received that will maximize profits due to time constraint, system costs and earnings per order.
- Orders have a specific due date, and the company is penalized for earliness and tardiness from this due date.
- Only one order can be processed at each moment time and no order can be accepted in the decision-making system.
- Work interruption is not allowed.
- Prior to processing each order, setup is required which its duration is sequence-dependent.
- The manufacturer is obliged to deliver orders to customers by the end of the period at the latest.
- Delivery of orders is done by the batch delivery approach.
- Batches have no capacity constraints.
- One or more orders are delivered to the customer each time.
- System costs include:
- Cost of production (processing)
- Cost of maintenance (the maintenance time is the difference between the time each order is delivered to the customer and its completion time)
- Cost of setup (it is considered as a multiple of setup time)
- Cost of delivery (depends on the number of batches formed)

The following indicators, parameters and variables are used in the model to describe the above model:

3.2. Sets

I	Set of order $i \in I$
J	Set of customer $j \in J$
K	Set of batch $k \in K$

3.3. Parameters

T	Time horizon
PC_i	Cost of producing order *i*
$SC_{ii'}$	Cost of setting up order i', if order i is before it
HC_i	Maintenance cost of order *i*
R_i	Sales revenue of order *i*
P_i	Processing time of order *i*
DC_j	Cost of each delivery to customer *j*
O_{ij}	Equals to one if the order *i* belongs to customer *j*; otherwise it is zero
$ST_{ii'}$	Time of setting up order i', if order *i* is before it
due_i	Due date of order *i* from production stage to delivery stage
We_i	Earliness penalty in delivery of order *i*

Wl_i	Tardiness penalty in delivery of order *i*

3.4. Variables

s_i	Start time of order *i*
c_i	Completion time of order *i*
del_i	Delivery time of order *i*
c'_k	Completion time of batch *k*
α_j	Number of batches delivered to customer *j*
x_i	Equals to one if the order *i* is accepted; otherwise it is zero
z_{ik}	Equals to one if the order *i* is allocated to batch *k*; otherwise it is zero
z_{jk}	Equals to one if the batch *k* is allocated to customer *j*; otherwise it is zero
$y_{ii'}$	Equals to one if the order *i'* is processed after the order *i*; otherwise it is zero
Tar_i	Tardiness in delivery of order *i*
Erl_i	Earliness in delivery of order *i*

The mathematical model of the problem is presented below:

$$\text{Max Z1} = \sum_i (R_i - PC_i)\, x_i - \sum_i \sum_{i'} SC_{ii'}\, y_{ii'} - \sum_i (del_i - c_i)\, HC_i - \sum_j DC_j\, \alpha_j \quad (1)$$

$$\text{Min Z2} = \sum_i We_i\, Erl_i + \sum_i Wl_i\, Tar_i \quad (2)$$

Subject to

$$c_i \le T x_i \qquad \forall\, \boldsymbol{i} \quad (3)$$

$$c_i = s_i + P_i \qquad \forall\, \boldsymbol{i} \quad (4)$$

$$s_{i'} \ge c_i + ST_{ii'} y_{ii'} - M(1 - y_{ii'}) \qquad \forall\, \boldsymbol{i}, \forall\, \boldsymbol{i'} \quad (5)$$

$$\sum_i \sum_{i'} y_{ii'} = \sum_i x_i - 1 \quad (6)$$

$$\sum_{i'} y_{i'i} \le x_i \qquad \forall\, \boldsymbol{i} \quad (7)$$

$$\sum_{i'} y_{ii'} \le x_i \qquad \forall\, \boldsymbol{i} \quad (8)$$

$$\sum_k z_{ik} = x_i \qquad \forall\, \boldsymbol{i} \quad (9)$$

$$\sum_j z_{jk} = 1 \qquad \forall\, \boldsymbol{k} \quad (10)$$

$$\sum_i z_{ik}\, O_{ij} \le M\, z_{jk} \qquad \forall\, \boldsymbol{j}, \forall\, \boldsymbol{k} \quad (11)$$

$$\sum_i z_{ik}\, O_{ij} \ge -M\, z_{jk} \qquad \forall\, \boldsymbol{j}, \forall\, \boldsymbol{k} \quad (12)$$

$$c'_k \ge c_i - M(1 - z_{ik}) \qquad \forall\, \boldsymbol{i}, \forall\, \boldsymbol{k} \quad (13)$$

$$del_i \ge c'_k - M(1 - z_{ik}) \qquad \forall\, \boldsymbol{i}, \forall\, \boldsymbol{k} \quad (14)$$

$$\alpha_j = \sum_k z_{jk} \qquad \forall\, \boldsymbol{J} \quad (15)$$

$$Tar_i \geq del_i - due_i \qquad \forall\, \boldsymbol{i} \qquad (16)$$

$$Erl_i \geq due_i - due_i \qquad \forall\, \boldsymbol{i} \qquad (17)$$

$$\begin{gathered} c_i\,, \quad s_i\,, \quad c'_k \geq 0 \\ x_i\,, \quad z_{ik}\,, \quad z_{jk}\,, \quad y_{ii'} \in \{0\,,1\} \\ \alpha_j \in Integer \end{gathered} \qquad \forall\, \boldsymbol{i}\,, \forall \boldsymbol{j}, \forall\, \boldsymbol{k}\,, \forall\, \boldsymbol{i'} \qquad (18)$$

First objective function1 (1) is to maximize the company's profit from the production of different orders. According to this relation, the profit is obtained from the difference in sales income and costs (maintenance, setup, production and delivery).
Second objective function (2) is to minimize the total weighted earliness and tardiness in the delivery of different orders.
Constraint (3) shows that if order i is accepted ($x_i = 1$), the order completion time must be before the end of the time horizon *T*. If order *i* is not accepted ($x_i = 0$), the completion time has no meaning and is considered zero. Constraint (4) shows that if the order i is accepted, the time to complete the order i is equal to the start time plus its processing time and if the order *i* is not accepted ($x_i = 0$) the start time is equal to the end time and is assumed to be zero same as the previous constraint. Constraint (5) shows that if the order i' is processed after the order i ($y_{ii'} = 1$), the start time of order i′ is at least equal to the completion time of order i plus the setup time of order i' and if order i′ is not processed after order *i* ($y_{ii'} = 0$), the constraint will be canceled. Constraint (6) states that the number of times the setup is performed is equal to the number of orders received except for the first task in which the setup is not performed. Constraint (7) indicates that if order i is accepted ($x_i = 1$), it certainly has a place in the production sequence, and if the order i is not accepted ($x_i = 0$), it has no place in the production sequence. Constraint (8) indicates that if order $i'$is accepted ($x_i = 1$), it certainly has a place in the production sequence, and if the order $i'$is not accepted ($x_i = 0$), it has no place in the production sequence. Constraint (9) shows that if order i is accepted ($x_i = 1$), it must be allocated to a batch such as *k* and if order i is not accepted ($x_i = 0$), it has no place in any delivery batch. Constraint (10) shows that each batch such as *k* can only contain the orders of one customer such as *j*. Constraints (11 and 12) state that only if batch *k* belongs to customer *j*, the orders such as *i* belonging to customer *j* can be allocated to batch *k*, and vice versa if orders such as *i* belonging to customer *j* are in batch *k*, then batch *k* will belong to customer *j*. Constraint (13) shows that the completion time of the batch *k* is at least equal to the time of completion of the last task inside the batch (provided that the batch k contains the order *i*). Constraint (14) shows that the delivery time of order i is at least equal to the completion time of batch *k*. (provided that the batch *k* contains the order *i)*. Constraint (15) represents the total number of batches delivered to customer *j*. Constraint (16) calculates the tardiness in delivery of each order. This tardiness is the amount of positive difference of the completion time of the order from its due date. Constraint (17) shows the earliness in order delivery. This earliness is the amount of positive difference of the due time from the completion time of the order. Constraint (18) shows the types of variables.

4. Solution methods

4.1. ε-constraint Method

One of the exact methods for obtaining Pareto optimal solutions is the ε-constraint method, which was first proposed by Aljedan (Goli et al. 2019). The main advantage of this method over other multi-objective optimization methods is its use for non-convex solution spaces because methods such as weighted sum of objectives lose their efficiency in non-convex

spaces (Tirkolaee et al. 2020). Computational time of an algorithm is an important feature for its evaluation (Babaee Tirkolaee et al. 2019). Since one of the main weaknesses of algorithms based on exact search, including ε-constraint method, is their large computational time, it is obvious that using a meta-heuristic algorithm reduces the time significantly (Tirkolaee et al. 2019).
In this method, one of the objectives is optimized, provided that the highest acceptable limit is defined for other objectives in the form of constraints. Following mathematical display is for a two-objective problem:

$$\begin{aligned} &\text{Min } f_1(x) \\ &\text{Subject to} \\ &f_2(x) \le \varepsilon_2 \\ &x \in S \end{aligned} \tag{19}$$

By changing the right-side values of the new constraints ε_i, the Pareto front of the problem will be obtained. One of the major problems of the ε-constraint method is its high volume of calculations, because for each of the objective functions converted to a constraint (*p-1*), several different values of ε_i must be tested. One of the most common approaches to implementing the ε-constraint method is to first obtain the maximum and minimum of each of the objective functions without considering other objective functions in $x \in S$ space. Then, using the values obtained from the previous step, the interval related to each of the objective functions is calculated. If the maximum and minimum values of the objective functions are called f_i^{max} and f_i^{min}, respectively, then the interval of each of them is calculated as follows:

$$r_i = f_i^{max} - f_i^{min} \tag{20}$$

The r_i interval is divided into q_i intervals. Then for ε_i in relation (3-15), q_i+1 different values can be calculated from the following formula.

$$\varepsilon_i^k = f_i^{max} - \frac{r_i}{q_i} \times k \qquad k = 0,1, \dots, q_i \tag{21}$$

In the above relation, k represents the number of the new point related to ε_i. With the help of ε-constraint method, the above multi-objective optimization problem can be reduced to $\prod_{i=2}^{p}(q_i+1)$ single-objective optimization sub-problems. Each sub-problem has a solution space S, given that it will be further constrained by inequalities related to objective functions $f_2,\dots,f_p$. Each sub-problem leads to a candidate solution to the considered multi-objective optimization problem or the Pareto optimal front. Some sub-problems create infeasible space. Finally, after obtaining the Pareto optimal front, the decision maker can choose and use the most appropriate solution in his opinion.

4.2. Multi-objective Grey Wolf Optimization algorithm

The Grey Wolf Optimization algorithm is a nature-inspired meta-heuristic algorithm that mimics the behavior of gray wolves and their leadership hierarchy and hunting method. The Grey Wolf Optimization algorithm was proposed by Mirjalili et al. based on their pack hunting (Mirjalili et al, 2014). The gray wolf is a member of the Canadian wolf family. Gray wolves are at the top of the food chain and prefer to live in packs. On average, their packs include 5-12 wolves. Interestingly, they have a much stricter social hierarchy. The alpha wolf is also called the leading wolf in the pack, because its orders must be followed by the pack.

Alphas are basically responsible for making decisions about hunting, sleeping places, moving time, and so on. The second level of ranking of gray wolves is beta; betas are wolves under the command of alpha that help alpha in decision making and other activities. Beta wolf is probably the best candidate to become an Alpha and plays the role of a deputy for Alpha and a supervisor for the pack. The lowest rank of the gray wolf is the omega. Omega wolves play the role of victims for other members of the pack. They are the last wolves to be allowed to eat. If the wolf is not alpha, beta, or omega, it is called obedient (or delta). Delta wolves obey the alpha and beta and rule the Omega. For mathematical modeling of the wolves' social hierarchy when designing a GWO, the most appropriate solution is called the α wolf.
As a result, the second and third best solutions are called β and δ wolves, respectively. The remaining solutions are assumed to be ω. So in the GWO algorithm, optimization is led by α, β and δ, and ω wolves follow these three categories. Gray wolves encircle the prey while hunting. For mathematical modeling of the encircling behavior, relations (22) and (23) are proposed.

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_P}(t) - \vec{X}(t)\right| \tag{22}$$

$$\vec{X}(t+1) = X_P(t) - \vec{A}.\vec{D} \tag{23}$$

That t indicates the iteration of the flow, A and C are the vector coefficients, $\overrightarrow{X}_P$ is the position vector of the prey, and X indicates the position vector of a gray wolf. Vectors A and C are calculated, according to relations (24) and (25):

$$\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a} \tag{24}$$

$$\vec{C} = 2.\overrightarrow{r_2} \tag{25}$$

Where elements $\vec{a}$ are linearly reduced from 2 to 0 along the iteration path, r_1 and r_2 are random vectors in the range [0, 1].
Gray wolves have the ability to detect prey and encircle them. Hunting is usually guided by alpha. Beta and delta may also sometimes be involved in hunting. Therefore, in an exact search space, there are no solutions for the optimal position (prey). To mathematically simulate the hunting behavior of gray wolves, it is assumed that alpha (best candidate solution), beta, and delta are aware of the potential position of the prey. So, the first three best solutions are saved here and the other search agents (omegas) are forced to update their position according to the position of the best search agents. This operation is performed according to relations (26) to (28).

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}\right|, \qquad \overrightarrow{D_\beta} = \left|\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}\right|, \quad \overrightarrow{D_\delta} = \left|\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}\right|, \tag{26}$$

$$\vec{X}_1 = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\left(\vec{D}_\alpha\right), \qquad \vec{X}_2 = \overrightarrow{X_\beta} - \overrightarrow{A_1}.\left(\vec{D}_\beta\right), \quad \vec{X}_3 = \overrightarrow{X_\delta} - \overrightarrow{A_1}.\left(\vec{D}_\delta\right), \tag{27}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{28}$$

In short, in the GWO algorithm, the search process begins with the creation of a random population of gray wolves (candidate solutions). During the iteration period, alpha, beta, and delta wolves estimate the probable position of the prey. Each candidate solution updates its distance with prey. The parameter a is reduced from 2 to 0 to enhance the process of detection and attack to the prey. When $|A| > 1$, the candidate solutions become divergent, and when $|A| < 1$, the candidate solutions become convergent.

In the MOGWO algorithm, the overall structure of the GWO Grey Wolf Optimization algorithm is implemented. The only difference is that in each of the iterations, the unknown solutions are separated as proposed in Section 4-3. The pseudo-code of the MOGWO algorithm is shown in Figure 1.

```
Initialize the grey wolf population Xi (i = 1, 2,..., n)
Initialize a, A, and C
Calculate the fitness of each search agent
Xα=the best search agent
Xβ=the second best search agent
Xδ=the third best search agent
while (t < Max number of iterations)
for each search agent
Update the position of the current search agent by equation (44-46)
end for
Update a, A, and C
Calculate the fitness of all search agents
Do Fast Non-dominated Sorting
Update Xα, Xβ, and Xδ
t=t+1
end while
return Xα
```

Figure 1. The pseudo-code of the MOGWO algorithm

4.3. Non-dominated sorting

To rank a set of solutions and place them on different fronts in terms of the degree of non-dominance, first the following two parameters are calculated for each of the solutions; n_p is the number of solutions that have dominated the solution p, and S_p is the set of solutions that have been dominated by the solution p.
All the solutions that have $n_p = 0$take the first rank and are placed on the first front. Then, for each solution p with the first rank, each member *(q)* of the S_p set is visited and its n_q is reduced by one unit. By doing this, if $n_q = 0$, then the solution q takes the second rank and is placed on the second front. In the same way, the next fronts will be formed. In the following, fast non-dominated sorting method is presented in the form of a figure and pseudo-code. Figure 2 shows the process of sorting the non-dominated solutions of a population of solutions in the MOGWO meta-heuristic algorithm.

Fast Non-dominated Sorting(P)

for each $p \in P$

$S_p = 0$

$n_p = 0$

for each $q \in P$

if $(p \prec q)$ *then* *If p dominates q*

$S_p = S_p \cup \{q\}$ *Add q to the set of solutions dominated by p*

else if $(q \prec p)$ *then*

$n_p = n_p + 1$ *Increment the domination counter of p*

if $n_p = 0$ *then* *p belongs to the first front*

$r_p = 1$ *rank of solutions in the first front*

$F_1 = F_1 \cup \{p\}$

i=1 *Initialize the front counter*

while $F_i \neq \emptyset$

$Q = \emptyset$ *Used to store the members of the next front*

for each $p \in F_i$

for each $q \in S_p$

$n_q = n_q - 1$

if $n_q = 0$ *then* *q belongs to the next front*

$r_q = i + 1$

Figure 2. Pseudo-code of the fast non-dominated sorting procedure

4.4. Encoding the problem in MOGWO algorithm

In order to use the MOGWO algorithm for optimizing the research mathematical model, it is necessary to choose a suitable coding system to adapt the algorithm to the mathematical model. Therefore, a continuous encoding system with numbers between 0 and 1 has been selected for this purpose. Each wolf in the MOGWO algorithm is represented as a vector with values between 0 and 1. By sorting the numbers of this vector, the sequence of production of orders is determined. As a result, proper assignment to the batches and delivery is done as soon as all the batches are ready, and finally a feasible solution to the problem can be designed. An example of problem encoding is given in Table 1.

Table 1. An example of problem encoding

0.348	0.967	0.168	0.379	0.721

According to this example, orders start being produced from 2, then 5, then 4, then 1, and finally 3, respectively, and are placed in the first empty batch to be delivered to customers. This structure can comply with all the conditions and constraints of the mathematical model and provide an efficient feasible solution.

4.5.Non-dominated sorting genetic algorithm

The non-dominated sorting genetic algorithm (NSGA-II) is regarded as one of the most efficient and well-known multi-objective optimization algorithms proposed by Deb et al. (2001). This algorithm can converge with the optimal Pareto set and extend the solutions to the whole collection (Ghasemi et al. 2020). This method uses a non-dominant classification mechanism to ensure proper convergence. In addition, NSGA-II uses density estimation and comparative congestion operators to cut solutions with poor distributions, aiming to obtain good solutions (Deb et al., 2001). The basic information for implementing the proposed NSGA-II algorithm includes initial population size, probability of mutation operator, probability of intersection operator, and the number of algorithm iterations. It should be noted that the adjusted values of these parameters were obtained by using the Taguchi method.

4.6. Evaluation indicators of multi-objective methods

In this section, quantitative and qualitative indicators that are often used to compare the performance of meta-heuristic algorithms are introduced.

4.6.1. MID indicator

Using this indicator, distance between the resulting non-dominated solutions and the ideal point is obtained. The smaller the value of this indicator, the higher the priority of the algorithm will be. This indicator is calculated using the following relation (Ghasemi and Khalili-Damghani, 2021):

$$MID = \frac{\sum_{i=1}^{n} \sqrt{\left(\frac{f1_i - f1_{best}}{f1_{total}^{max} - f1_{total}^{min}}\right)^2 + \left(\frac{f2_i - f2_{best}}{f2_{total}^{max} - f2_{total}^{min}}\right)^2}}{n} \tag{28}$$

In the above relation, $f1_{total}^{max}$ is defined as the largest value among the non-dominated solutions. Also, $f1_{total}^{min}$ is considered as the smallest value among the non-dominated solutions obtained from the algorithm.

4.6.2. SNS indicator

This indicator, also known as the spread indicator, is used to calculate the diversity of Pareto solutions. The larger the value of this indicator, the higher the priority of the algorithm will be. The value of this indicator is calculated using the following relation:

$$SNS = \sqrt{\frac{\sum_{i=1}^{n}(MID - C_i)^2}{n-1}} \tag{29}$$

In the above relation, n represents the number of non-dominated solutions and also the value of C_i is calculated using the following relation:

$$C_i = \sqrt{{f_{i1}}^2 + {f_{i2}}^2} \tag{30}$$

In the above relation, f_{1i} and f_{2i} are the values of the first and second objective functions, respectively, for the non-dominated solution i.

4.6.3. Max-spread indicator

This indicator is used to calculate the spread of the Pareto optimal front solutions obtained from the algorithm. The larger the value of this indicator, the higher the priority of the algorithm will be (Ghasemi, and Talebi Brijani, 2014). The value of this indicator is calculated using the following relation:

$$DM = \sqrt{\sum_{i=1}^{I}(Min\, f_i - Max\, f_i)^2} \tag{31}$$

In the above relation, Min f_i indicates the minimum value of the objective function among all the non-dominated solutions obtained from the algorithm and Max f_i also indicates the maximum value of the objective function among all the non- dominated solutions obtained from the algorithm.

4.6.4. NPS indicator

This indicator is used to calculate the number of non- dominated solutions obtained by the algorithm. The larger the NPS indicator, the higher the priority of the algorithm will be.

5. Numerical results

5.1. Validation of mathematical model

In order to validate the mathematical model, a numerical problem has been designed and optimized with the introduced solution methods. The data considered in this study are considered as numerical examples. Therefore, the data are assumed to be artificial. Analysis of the results of this example shows the validity of the designed mathematical model. In this numerical example, 5 orders are considered for delivery to two customers. These orders are placed into three batches. The time horizon used is equal to 20 time units. The production cost of each order, the maintenance cost of each order, the income from the production of each order, the processing time of each order and the delivery time of each order are presented in Table 2.

Table 2. Data of validation problem

Parameter	Order 1	Order 2	Order 3	Order 4	Order 5
PC_i	20	15	10	30	25
HC_i	2	1.5	3	1	2
R_i	100	50	70	80	75
P_i	3	6	4	5	3
Due_i	24	18	15	10	2

Also, the cost of delivery to the customer 1 is 25 monetary units and delivery cost to the customer 2 is 20 monetary units. The first customer receives orders 1, 2 and 3, and the second customer receives orders 4 and 5. Also, the setup times for each order are presented in Table 3, depending on what order was placed in the previous step.

Table 3. Setup times of validation problem

	Order 1	Order 2	Order 3	Order 4	Order 5
Order 5	-	5	5	2.5	5
Order 5	2.5	-	7.5	5	5
Order 5	5	5	-	2.5	7.5
Order 5	2.5	2.5	5	-	7.5
Order 5	5	2.5	5	2.5	-

In Table 3, the numbers of each column indicate the setup time of an order if the previous order is in its row number. For example, the setup time of order 2 is 5 time units if order 1 is before it and vice versa, the setup time of order 1 is 2.5 if order 2 is before it. In this case, the weight of earliness in the setup of orders is equal to 0.5 and the weight of tardiness is equal to 0.5.

In the first step of validating the mathematical model, each of the objectives is optimized independently. GAMS software is used for this purpose. Each time an objective is optimized independently, the value of each of the objective functions is reported. This helps to clarify the conflict between objectives. The results of this optimization are presented in Table 4.

Table 4. Results of independent optimization of the objectives

Earliness and tardiness total weighted	Profit total amount	`
5.0	197.5	**first objective optimization**
0.5	175.0	**second objective optimization**

As can be seen in Table 4, when the first objective is optimized, the total amount of profit is 197.5. However, if the second objective is optimized, the total amount of profit will be 175. So it turns out that if the second objective function is optimized, which is the total weighted earliness and tardiness, maximum possible value for the company's profit (197.5) can't be obtained. This is also true for the second objective. The best total weighted earliness and tardiness is equal to 0.5, but when the first objective is optimized, the second objective value is 5 and is far from its best value. So, each of the objectives cannot take the other objective to their ideal level and as a result, they are in conflict with each other. Therefore, considering profit and total weighted earliness and tardiness as two independent objectives in the mathematical model is correct and valid.

The second step compares the validation of the Pareto solutions obtained by the ε-constraint (EPS) method and the multi-objective gray wolf (MOGWO) algorithm. Table 5 presents the Pareto solutions of EPS method, and Table 6 presents the Pareto solutions of MOGWO algorithm.

Table 5. Pareto solutions of ε-constraint method

Answer number	Profit total amount	Earliness and tardiness total weighted
1	197.5	5
2	195.7	4.55
3	193.9	4.1
4	192.1	3.65
5	190.3	3.2
6	188.5	2.75
7	186.7	2.3
8	184.45	1.85
9	181.3	1.4
10	178.15	0.95
11	175	0.5

Table 6. Parto solutions of multi-objective Grey Wolf Optimization algorithm

Answer number	Profit total amount	Earliness and tardiness total weighted
1	197.5	5
2	196.4	4.7
3	195.2	4.5
4	193.4	4.2
5	192.9	3.7
6	191.3	3.4
7	189.6	3.06
8	186.2	2.8
9	184.1	2.1
10	182.3	1.7
11	180.7	1.5
12	179.1	1.3
13	177.3	1.01
14	176.4	0.73
15	175	0.5

As can be seen in Table 5 and Table 6, the ε-constraint method found 11 Pareto solutions, while the multi-objective Grey Wolf Optimization algorithm found 15 Pareto solutions. The best total amount of profit is 197.5 and the best total weighted earliness and tardiness is 0.5 in both methods. Also, the values of each of the objectives are between the minimum and maximum specified in Table 4. In other words, in both methods, the total amount of profit is between 197.5 and 175, and the total weighted earliness and tardiness is between 0.5 and 5. Therefore, the results obtained from these two methods are approved and valid. In Figure 2, the Pareto fronts of these two methods are compared.

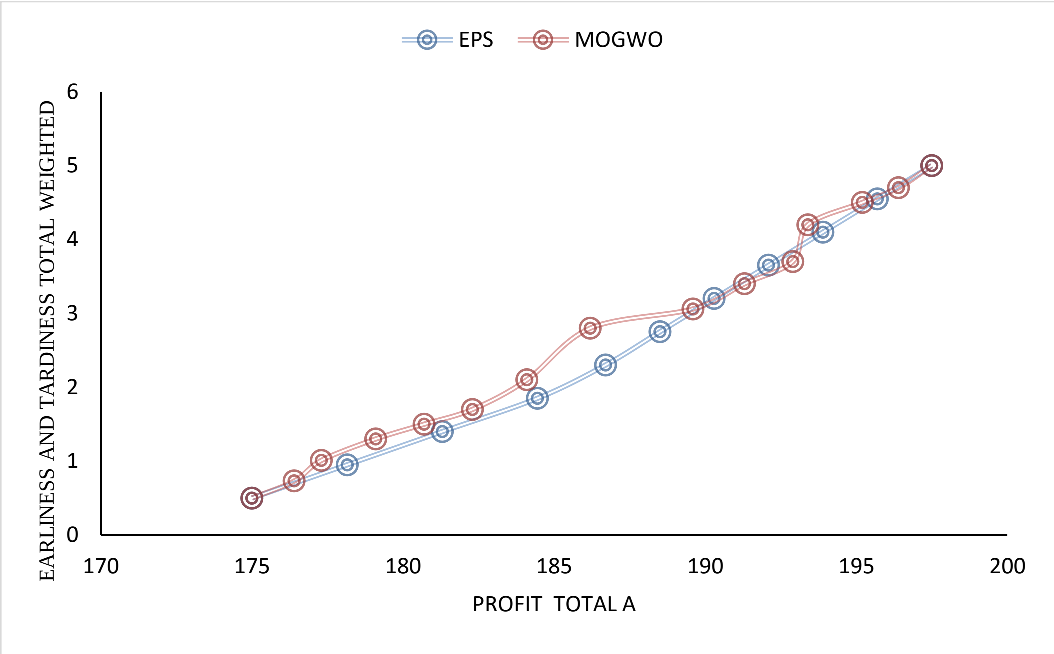

Figure 4. Pareto front of EPS and MOGWO methods

As can be seen in Figure 4, the spread of solutions is different in these two methods. In some cases, the MOGWO algorithm provided higher points than the EPS method. This is because the EPS method is an exact solution method, but the MOGWO algorithm is an approximate algorithm, so there is a small difference in their values. To better compare the two methods on the designed problem, the SNS, DM, MID, and NPS indicators were calculated for the Pareto solutions of EPS and MOGWO and presented in Table 7.

Table 7. Values of evaluation indicators of multi-objective methods

	SNS	DM	MID	NPS
ε-constraint method	187.11	22.94	0.636	11
multi-objective gray wolf algorithm	168.02	22.97	0.647	15

As can be seen in Table 7, the multi-objective Grey Wolf Optimization algorithm has a value equal to the ε-constraint method in terms of MID indicator. In terms of SNS and MID indicators, there is a small difference between the two methods. In terms of NPS indicator, Grey Wolf Optimization algorithm is better. Therefore, the multi-objective Grey Wolf Optimization algorithm has the necessary validity to be compared with the EPS method which is an exact solution method.

5.2. Performance evaluation of multi-objective Grey Wolf Optimization algorithm

5.2.1. Adjusting the parameters of MOGWO algorithm by Taguchi method

Taguchi was a Japanese engineer who introduced revolutionary ideas and measures to the field of total quality. His work in designing experiments, which Japan has been doing since the early 1950s, has provided powerful methods for designing new products and processes. In these methods, experiments are performed to identify design parameters that minimize the effect of turbulence (factors such as temperature, pressure, or human error affecting performance). Taguchi method has made it possible to provide vital information with much less experiments. The result is that products and processes are created for resistance against turbulence. The loss function is another important idea that Taguchi expressed and has had a great impact on quality-related thoughts and activities. This idea has replaced the traditional view that products are acceptable if they meet specification limits. Such a view implies that there is a limit to which extent the product becomes unacceptable due to its inability to achieve such specifications. Taguchi argued that the deviation in the product, even within the specified limits, causes "loss to society" during the life of the product; and that the more the product goes further away from its intended value, the greater the decline in its performance will be. Taguchi believed that the loss is proportional to the squared deviation from the intended value. The product that reaches the customer will cause loss if it can't work well. This loss is reflected by the customer in the costs of repair and replacement and by the manufacturer in the costs of warranty, loss of credit of the company and loss of job and market. To minimize this loss, quality improvement must continue until the ideal objective is achieved, which is no longer the technical specifications. Improvement activity should never be stopped.

In order to design experiments in the MOGWO algorithm, 3 different levels are first defined for its parameters. Then the predefined experiments are implemented in this algorithm. The suggested values for the parameters of this algorithm are according to Table 8.

Table 8. Parameters and their levels for MOGWO algorithm

parameter	Amount of each level		
	Level 1	Level 2	Level 3
Maximum number of Iterations (Max iter)	50	100	200
Number of search agent (N_S)	50	100	150
Change position rate (PR)	0.2	03	05

Then, various experiments are created by Taguchi L9 design and the MOGWO algorithm is implemented for each of them. The results are presented in Table 9.

Table 9. Variable solution values in Taguchi technique for MOGWO

NO.	Algorithm parameters			MID
	Max_iter	N_S	PR	
1	1	1	1	0.697
2	1	2	2	0.712
3	1	3	3	0.682
4	2	1	2	0.663
5	2	2	3	0.702
6	2	3	1	0.681
7	3	1	3	0.647
8	3	2	1	0.739
9	3	3	2	0.739

Now, by presenting these outputs to MINITAB software, the S / N diagram is presented in Figure 5.

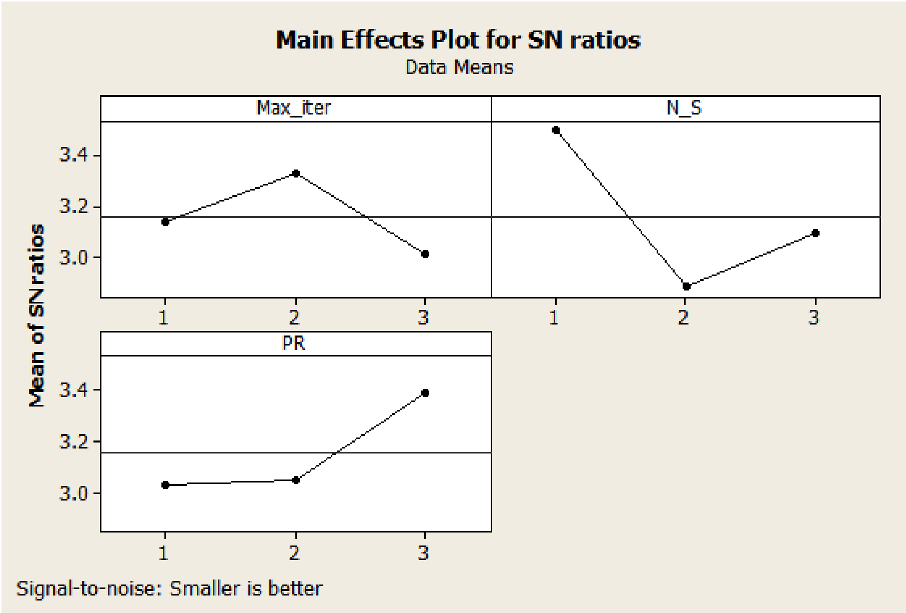

Figure 5. Minitab output for Taguchi method in MOGWO algorithm

Now, based on the output presented in the diagram above, the best value of each parameter is specified and other examples are implemented with these values of the algorithm parameters. Table 10 shows the optimal value of the parameters.

Table 10. Optimal value of variables in MOGWO

Parameter	Optimal value
Maximum number of Iterations (Max iter)	200
Number of search agent (N_S)	100
Change position rate (PR)	0.2

5.2.2. Investigating the efficiency of solution methods based on different numerical examples

In this section, the numerical results obtained from solving different numerical examples are presented in order to show the efficiency of the proposed solution methods.
Since the ε-constraint method has a longer resolution time than the multi- objective Grey Wolf Optimization algorithm, it is necessary to use another meta-heuristic algorithm to complete the evaluation of the solution methods. Therefore, in this regard, multi-objective genetic algorithm (NSGA-II) is used to complete comparisons between solving methods and comparing multi-objective Grey Wolf Optimization algorithm with conventional methods in meta-heuristic algorithms.
In this regard, 10 numerical examples have been created in medium and large scale. The scale of these problems is presented in Table 11. The values of the parameters in these numerical examples are created using a continuous uniform distribution that the lower and upper limits of the random values of each parameter are presented in Table 12.

Table 11. Scale of designed numerical problems

Scale	Issue number	Number of orders	Number of customers	Number of categories
Medium	Pr1	10	4	2
	Pr2	15	6	5
	Pr3	20	8	8
	Pr4	25	10	11
	Pr5	30	12	14
Large	Pr6	35	14	17
	Pr7	40	16	21
	Pr8	45	18	24
	Pr9	50	20	27
	Pr10	60	30	30

Table 12. Lower and upper limits of mathematical model parameters

Parameter	Low limit	Upper limit
Producing cost each order	10	30
Maintaining cost each order	1	3
Production Proceeds each order	50	100
Processing time each order	3	6
Delivery time	5	25
Preparation time	2	8

In the next step, the designed numerical problems are optimized by the ε-constraint method, NSGA-II and the multi-objective Grey Wolf Optimization algorithm and each of the SNS, MID, MD, NPS indicators is calculated. The results of the ε-constraint method are shown in Table 13, the results of the multi-objective Grey Wolf Optimization algorithm are presented in Table 14 and the results of the NSGA-II algorithm are presented in Table 15.

Table 13. Solution results by ε-constraint method

Problem	MID	DM	SNS	NPS	Time
Pr1	0.689	23.756	192.605	12	9.16
Pr2	0.729	26.055	199.225	12	34.12
Pr3	0.757	27.003	208.443	13	162.58
Pr4	0.787	28.488	210.997	15	348.16
Pr5	0.865	28.808	218.734	17	990.6
Pr6	0.876	29.914	230.140	17	1452.32
Pr7	0.932	31.613	246.497	20	2891.81
Pr8	0.962	34.685	256.876	20	3600
Pr9	-	-	-	-	-
Pr10	-	-	-	-	-
Medium	0.824609	28.790379	220.439648	15.75	1186.094

Table 14. Solution results by multi-objective Grey Wolf Optimization algorithm

Problem	MID	DM	SNS	NPS	Time
Pr1	0.711	22.921	183.587	17	12.34
Pr2	0.767	24.365	187.149	20	15.19
Pr3	0.773	24.433	202.386	32	24.47
Pr4	0.817	25.990	197.756	37	31.59
Pr5	0.912	26.903	198.438	42	40.11
Pr6	0.802	31.901	239.963	56	56.93
Pr7	0.839	32.313	252.866	73	71.29
Pr8	0.892	36.001	275.743	89	83.19
Pr9	0.905	39.505	289.333	100	102.66
Pr10	0.931	40.585	304.449	100	121.31
Medium	0.834959	30.49178	233.1671	56.6	55.908

Table 15. Solution results by NSGA-II algorithm

Problem	MID	DM	SNS	NPS	Time
Pr1	0.771	21.954	172.580	15	21.101
Pr2	0.829	23.510	181.035	19	30.323
Pr3	0.815	23.835	201.408	29	29.148
Pr4	0.889	23.636	191.540	36	61.960
Pr5	0.922	26.191	195.834	41	59.548
Pr6	0.825	30.183	235.248	45	64.634
Pr7	0.855	30.421	237.053	59	90.925
Pr8	0.949	33.093	259.594	63	153.329
Pr9	0.978	37.107	271.746	70	214.712
Pr10	0.987	37.365	284.533	79	236.617
Medium	0.882215	28.72937	223.0569	45.6	96.22959

As can be seen in Table 13, Epsilon constraint method has not been able to solve problems 9 and 10. In other words, the ability of this method for solving mathematical models decreases by increase in the scale of the problem. However, due to its heuristic nature, the multi-objective Grey Wolf Optimization algorithm has solved all the problems in a reasonable and logical time. In the following, the results of each of the indicators are analyzed separately.

Figure 6 compares the results based on the MID indicator. The average of this indicator is 0.824 for the ε-constraint method and is 0.834for the multi-objective Grey Wolf Optimization algorithm. In the first five problems, the value of MID was smaller in the ε-constraint method, so this method performed better than the multi-objective Grey Wolf Optimization algorithm. However, with the introduction of large-scale problems, the efficiency of this method has decreased and it has provided poorer results in terms of MID indicator. In total, the two methods have provided very close results in terms of this indicator. Comparing metacognitive methods in terms of MID index, it can be seen that the multi-objective genetic algorithm has provided more values than the multi-objective Grey Wolf Optimization algorithm, which shows the weakness of this algorithm against the multi-objective Grey Wolf Optimization algorithm.

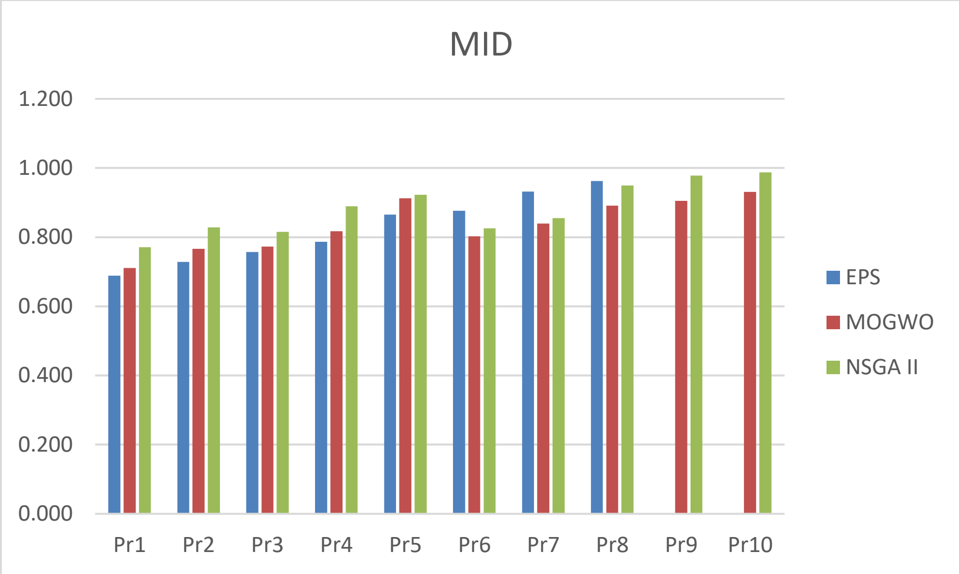

Figure 6. Comparison of solution methods based on MID indicator

Figure 7 shows the comparison of methods based on DM indicator. The average of this indicator is 28.79 for the ε-constraint method, 28.72 for the NSGA-II algorithm and is 30.49 for the multi-objective Grey Wolf Optimization algorithm. Since the larger the DM indicator, the better the multi-objective method, the multi-objective Grey Wolf Optimization algorithm has generally performed better than the ε-constraint method and NSGA-II based on DM indicator. It should be noted that in medium-scale problems, the ε-constraint method has provided higher DM than multi-objective Grey Wolf Optimization algorithm, but overall it has not been superior to the meta-heuristic method.

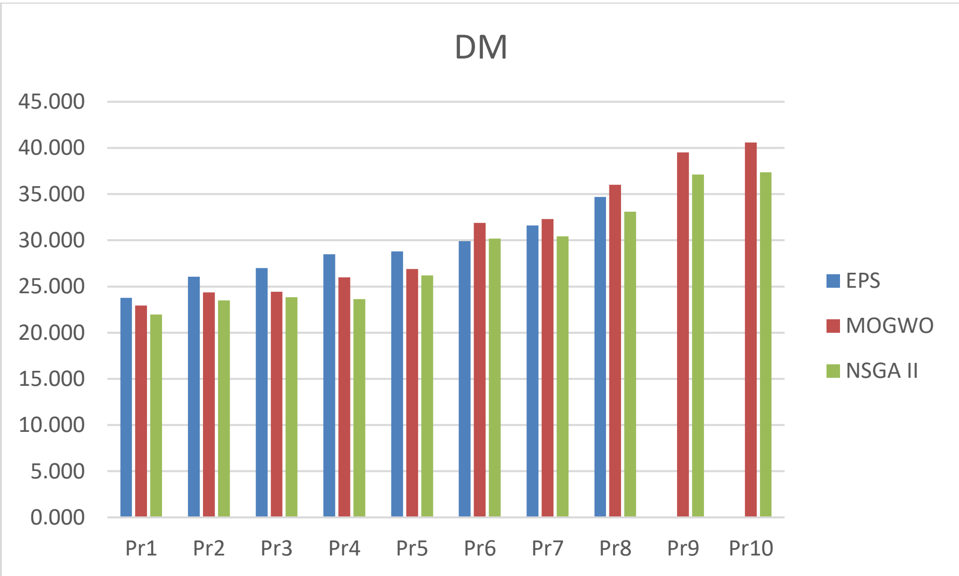

Figure 7. Comparison of solution methods based on DM indicator

Figure 8 compares the solution methods based on SNS indicator. The average of this indicator is 220.43 for the ε-constraint method, 223.05 for the NSGA-II algorithm and is 233.16 for the multi- Grey Wolf Optimization algorithm. In this indicator, similar to the previous indicators, the advantage in medium-scale problems is with the ε-constraint method, but due to the weakness of this method in large scale, the multi-objective Grey Wolf

Optimization algorithm has a significant advantage over the ε-constraint method. Also, a comparison of the meta-heuristic algorithms used shows that the NSGA-II algorithm has always achieved a lower level of SNS, indicating the weakness of this algorithm against multi-objective gray wolves.

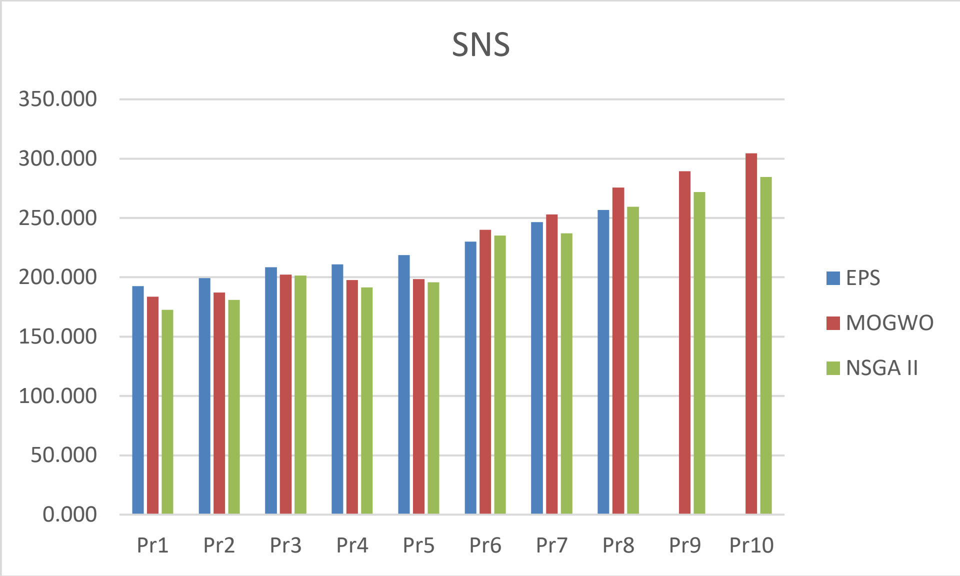

Figure 8. Comparison of solution methods based on SNS indicator

In Figure 9, comparisons are made based on NPS indicator. As can be seen in this figure, the Grey Wolf Optimization algorithm and NSGA-II have a significant advantage over the ε-constraint method in all problems. The reason for this is that the multi-objective Grey Wolf Optimization algorithm is based on searching for the solution space, and it can provide far more Pareto solutions than the ε-constraint method. Comparisons also show that by increasing the dimensions of the problem, the Grey Wolf Optimization algorithm can provide a higher number of Pareto responses than NSGA-II algorithm.

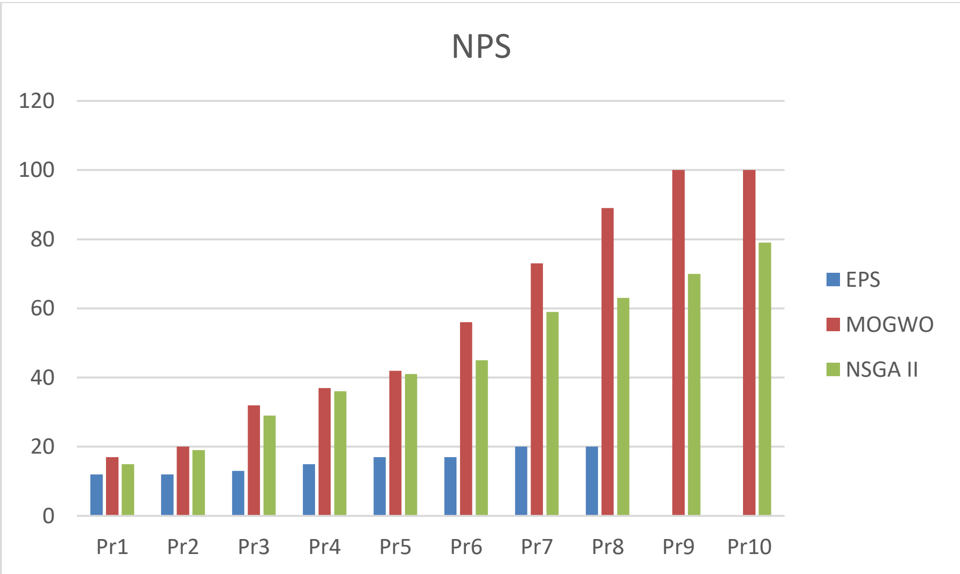

Figure 9. Comparison of solution methods based on NPS indicator

The last comparison of the solution methods is based on their solving time, which is presented in Figure 10. Accordingly, the solving time of the ε-constraint method has been greatly increased by increasing the scale of the problem. But, the solving time of multi-objective Grey Wolf Optimization algorithm and NSGA-II algorithm have not been greatly increased. The average solving time is 1186 seconds for the ε-constraint method, is about 96.22 seconds for NSGA-II algorithm and is about 56 seconds for the multi-objective Grey Wolf Optimization algorithm, which shows a significant difference in solving time of three methods.

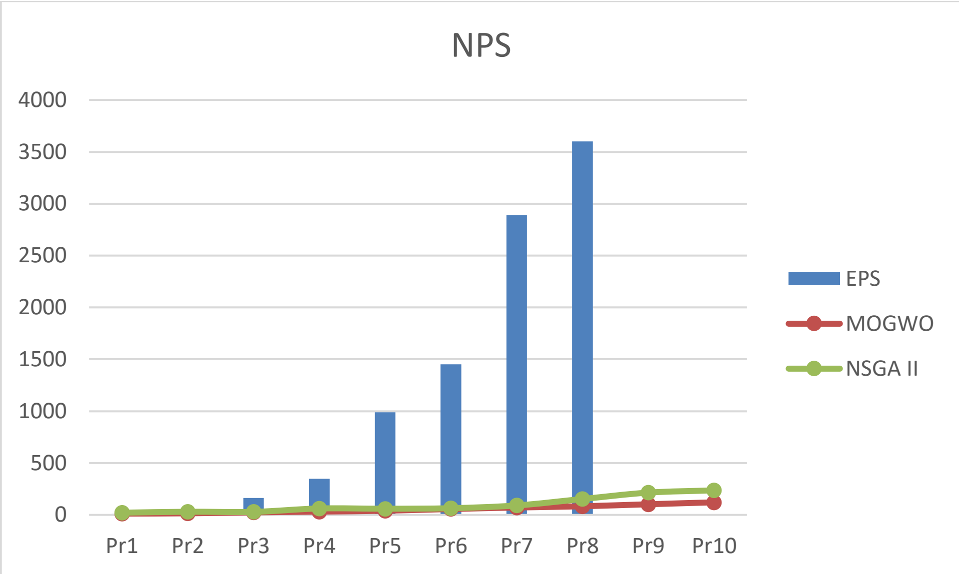

Figure 10. Comparison of solution methods based on solving time

It can be concluded that the multi-objective Grey Wolf Optimization algorithm can create very high quality and well-spread Pareto solutions at the Pareto front by spending much shorter time compared to ε-constraint method, which shows the efficiency of this meta-heuristic solution method. Also, comparing this algorithm with the multi-objective genetic algorithm (NSGA-II), which is one of the most well-known meta-heuristic algorithms, shows the efficiency and superiority of the multi-objective Grey Wolf Optimization algorithm. This indicates the efficiency of the multi- objective grey wolf cross-breeding method among all the methods used.

5.3. Sensitivity analysis of the model

Given the importance of adjusting the basic parameters of the model, it is necessary to examine the sensitivity of the input parameters to the model and to apply the appropriate policies in order to improve the scheduling situation of the case study. After examining the various parameters of the mathematical model, it becomes clear that the production time parameter is effective in both the value of the first objective function and the value of the second objective function, so it will have a significant effect on Pareto front. Therefore, it is necessary to carefully examine the fluctuations of this parameter on Pareto front. So, the validation problem is reviewed. The values provided for processing time are fluctuated between -20% up to +20% and the set of Pareto solutions is extracted. The results of the study and comparison of Pareto solutions with the corresponding parameter changes are presented in Table 16 and Figure 11.

Table 16. Pareto solutions in terms of variations in processing time of orders

0.0%		-10%		-20%		10%		20%	
197.5	5	197.5	4.85	189.7	2.75	181.23	1.54	197.5	5.35
195.7	4.55	195.7	4.4	188.68	2.495	180.607	1.451	195.7	4.9
193.9	4.1	193.9	3.95	187.66	2.24	179.984	1.362	193.9	4.45
192.1	3.65	192.1	3.5	186.64	1.985	179.361	1.273	192.1	4
190.3	3.2	190.3	3.05	185.62	1.73	178.738	1.184	190.3	3.55
188.5	2.75	188.5	2.6	185.62	1.475	178.115	1.095	188.5	3.1
186.7	2.3	186.7	2.15	182.14	1.22	177.21	1.006	186.7	2.65
184.45	1.85	184.45	1.7	180.469	0.965	176.869	0.917	184.45	2.2
181.3	1.4	181.3	1.25	178.57	0.71	176.246	0.828	181.15	1.75
178.15	0.95	178.15	0.8	176.785	0.455	175.623	0.739	178.15	1.3
175	0.5	175	0.35	175	0.2	175	0.65	175	0.85

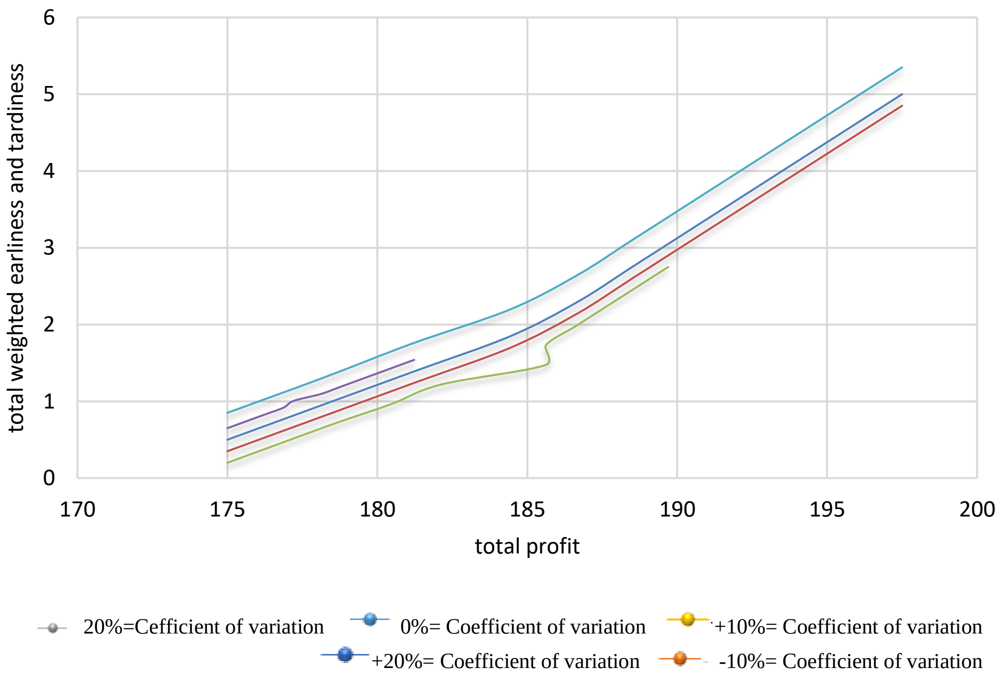

Figure 11. Comparison of Pareto front in terms of variations in order time parameter

According to Figure 11, when the order processing time is reduced by 20% (coefficient of variation = -20%), the lowest Pareto front is obtained and the when the coefficient of variation is +20%, the highest Pareto front is obtained. This means that increasing the amount of processing time can significantly increase the value of the second objective function, but its effect on increasing the first objective function is very small.

6. Conclusion

In this study, the problem of simultaneous determination of order acceptance, scheduling and batch delivery considering sequence-dependent setup and capacity constraint has been presented. Due to the novelty of this problem, a new horizon will be made available to researchers for further studies. This problem is a combination of the three problems of order acceptance, scheduling and batch delivery. Given the complexity of this new problem, some of the assumptions and conditions that are usually considered by researchers in separate study of these three problems were ignored in this study, which is the basis for defining new studies in this field.

Due to the applicability of the proposed mathematical model, the positive results can be used for various industries such as restaurants, dairy industry, drug delivery and medical equipment, etc. According to the results of sensitivity analysis, managers are advised to consider reducing processing time more than before. The reason for this is the effect of this factor on earliness and tardiness in the delivery of different orders. Therefore, managers are suggested to use higher skilled workers, machines with superior technology, higher quality raw materials, etc. to reduce processing time.

The superiority of our research over previous research includes the following: 1- The simultaneous optimization of profits and the total weighted earliness and tardiness as two conflicting objectives in the problem of combining order, scheduling and batch delivery2- The use of multi-objective Grey Wolf Optimization algorithm, which has not been used in studies of this field so far. 3- Providing an integrated model to examine the problem of simultaneous scheduling and batch delivery with the addition of the order acceptance approach, examining the benefits of an integrated view of the problem using exact and meta-heuristic solutions are considered as the innovations of this research 4- According to the previous studies on the problem of order acceptance and scheduling, adding the batch delivery problem to the above study, adding the order acceptance problem to the problem of scheduling and batch delivery 5- Analyzing the problem, and achieving useful management results are considered as the innovations of this research.

The results of the validation of the mathematical model show that the objectives studied cannot be summed up because the optimization of one of them cannot obtain the ideal value for the other objective. It has also been shown that the multi-objective Grey Wolf Optimization algorithm is comparable to the exact solution methods. The second part of the numerical results compares the results of the ε-constraint method, NSGA-II algorithm and the multi-objective Grey Wolf Optimization algorithm. The results of this section show that by increasing the scale of the problem, the efficiency of the multi- objective Grey Wolf Optimization algorithm is better displayed, and in general, this method has a significant advantage relative to NSGA-II algorithm and ε-constraint in terms of DM, SNS and NPS indicators. Also, the solving time of this method is very shorter than that of the ε-constraint. Therefore, from a managerial point of view, a tool called the multi-objective Grey Wolf Optimization algorithm can be used as an efficient tool for supply and production managers, which is able to provide several optimal solutions with different profits, earliness and tardiness.

Suggestions for future studies are as follows:

1- It is recommended to study uncertainty in different parameters and to use the approaches of possibilistic programming, chance constrained programming and robust optimization in order to deal with all kinds of uncertainty.
2- Considering other goals such as minimizing costs and minimizing environmental impacts.
3- Considering other levels in the problem such as distributors, suppliers, etc.
4- Estimate the required demand with approaches such as Fuzzy Inference System and simulation.

Research limitations are as follows:

1- Due to the lack of information about the type of machines and how the machines are arranged in this study, these two factors have been omitted.

2- Due to lack of information about the amount of budget intended, this factor is ignored.

References

Ayough, A., and Khorshidvand, B., (2019). "Designing a manufacturing cell system by assigning workforce", *Journal of Industrial Engineering and Management*, Vol. 12, No. 1, pp. 13-26.

Ayough, A., Hosseinzadeh, M., and Motameni, A., (2020). "Job rotation scheduling in the Seru system: shake enforced invasive weed optimization approach", *Assembly Automation*.

Babaee Tirkolaee, E., Goli, A., Pahlevan, M., and Malekalipour Kordestanizadeh, R., (2019). "A robust bi-objective multi-trip periodic capacitated arc routing problem for urban waste collection using a multi-objective invasive weed optimization", *Waste Management & Research*, Vol. 37, No. 11, pp. 1089-1101.

Chen, Z.L., (1996). "Scheduling and common due date assignment with earliness-tardiness penalties and batch delivery costs", *European Journal of Operational Research*, Vol. 93, No. 1, pp. 49-60.

Dametew, A. W., Ketaw, D., and Frank, E., (2019). "Production planning and control strategies used as a gear train for the death and birth of manufacturing industries", *Journal of Optimization in Industrial Engineering*, Vol. 12, No. 2, pp. 21-32.

Ghasemi, P., and Khalili-Damghani, K., (2021). "A robust simulation-optimization approach for pre-disaster multi-period location–allocation–inventory planning", *Mathematics and computers in simulation*, Vol. 179, pp. 69-95.

Ghasemi, P., and Talebi Brijani, E., (2014). "An integrated FAHP-PROMETHEE approach for Selecting the best Flexible Manufacturing system", *European Online Journal of Natural and Social Sciences*, Vol. 3, No. 4, pp-1137.

Ghasemi, P., Khalili-Damghani, K., Hafezalkotob, A., and Raissi, S., (2020). "Stochastic optimization model for distribution and evacuation planning (A case study of Tehran earthquake)", *Socio-Economic Planning Sciences*, Vol. 71, 100745.

Goli, A., Tirkolaee, E.B., Malmir, B., Bian, G.B., and Sangaiah, A.K., (2019). "A multi-objective invasive weed optimization algorithm for robust aggregate production planning under uncertain seasonal demand", *Computing*, Vol. 101, No. 6, pp. 499-529.

Iranpoor, M., Ghomi, S.F., and Zandieh, M., (2014). "Order acceptance and due-date quotation in low machine rates", *Applied Mathematical Modelling*, Vol. 38, No. (7-8), pp. 2063-2072.

Jiang, D., Tan, J., and Li, B., (2017). "Order acceptance and scheduling with batch delivery", *Computers & Industrial Engineering*, Vol. 107, pp. 100-104.

Kück, M., and Freitag, M., (2021). "Forecasting of customer demands for production planning by local k-nearest neighbor models", *International Journal of Production Economics*, Vol. 231, 107837.

Lu, L., Ng, C.T., and Zhang, L., (2011). "Optimal algorithms for single-machine scheduling with rejection to minimize the makespan", *International Journal of Production Economics*, Vol. 130, No. 2, pp. 153-158.

Mgbemena, C.O., Chinwuko, E., and Ifowodo, H.F., (2020). "Production Constraints Modelling: A Tactical Review Approach", *Journal of Optimization in Industrial Engineering*, Vol. 13, No. 1, pp. 19-27.

Mirjalili, S., Mirjalili, S.M., and Lewis, A., (2014). "Grey wolf optimizer", *Advances in engineering software*, Vol. 69, pp. 46-61.

Mokhtari, H., (2015). "A nature inspired intelligent water drops evolutionary algorithm for parallel processor scheduling with rejection", *Applied Soft Computing*, Vol. 26, pp. 166-179.

Okpoti, E.S., and Jeong, I.J., (2021). "A reactive decentralized coordination algorithm for event-driven production planning and control: A cyber-physical production system prototype case study", *Journal of Manufacturing Systems*, Vol. 58, pp. 143-158.

Ou, J., Zhong, X., and Wang, G., (2015). "An improved heuristic for parallel machine scheduling with rejection", *European Journal of Operational Research*, Vol. 241, No. 3, pp. 653-661.

Ramyar, M., Mehdizadeh, E., and Hadji Molana, S.M., (2020). "A new bi-objective mathematical model to optimize reliability and cost of aggregate production planning system in a paper and wood company", *Journal of Optimization in Industrial Engineering*, Vol. 13, No. 1, pp. 81-98.

Satyro, W.C., de Mesquita Spinola, M., de Almeida, C.M., Giannetti, B.F., Sacomano, J.B., Contador, J.C., and Contador, J.L., (2021). "Sustainable industries: Production planning and control as an ally to implement strategy", *Journal of Cleaner Production*, Vol. 281, 124781.

Tirkolaee, E.B., Goli, A., and Weber, G.W., (2019, May). "Multi-objective aggregate production planning model considering overtime and outsourcing options under fuzzy seasonal demand", In: *International Scientific-Technical Conference MANUFACTURING* (pp. 81-96). Springer, Cham.

Tirkolaee, E.B., Goli, A., and Weber, G.W., (2020). "Fuzzy mathematical programming and self-adaptive artificial fish swarm algorithm for just-in-time energy-aware flow shop scheduling problem with outsourcing option", *IEEE transactions on fuzzy systems*, Vol. 28, No. 11, pp. 2772-2783.

Tirkolaee, E.B., Mardani, A., Dashtian, Z., Soltani, M., and Weber, G.W., (2020). "A novel hybrid method using fuzzy decision making and multi-objective programming for sustainable-reliable supplier selection in two-echelon supply chain design", Journal of Cleaner Production, Vol. 250, 119517.

Wang, B., and Wang, H., (2018). "Multiobjective order acceptance and scheduling on unrelated parallel machines with machine eligibility constraints", *Mathematical Problems in Engineering*.

Yang, B., and Geunes, J., (2007). "A single resource scheduling problem with job-selection flexibility, tardiness costs and controllable processing times", *Computers & Industrial Engineering*, Vol. 53, No. 3, pp. 420-432.

Yin, Y., Cheng, T.C.E., Hsu, C.J., and Wu, C.C., (2013). "Single-machine batch delivery scheduling with an assignable common due window", *Omega*, Vol. 41, No. 2, pp. 216-225.

Yin, Y., Ye, D., and Zhang, G., (2014). "Single machine batch scheduling to minimize the sum of total flow time and batch delivery cost with an unavailability interval", *Information Sciences*, Vol. 274, pp. 310-322.

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