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Research Article

A Multi-Objective Mixed Model Two-Sided Assembly Line Sequencing Problem in a Make –to- Order Environment with Customer Order Prioritization

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Abstract

Mixed model two-sided assembly lines (MM2SAL) are applied to assemble large product models, which is produced in high-volume. So, the sequence planning of products to reduce cost and increase productivity in this kind of lines is imperative. The presented problem is tackled in two steps. In step 1, a framework is developed to select and prioritize customer orders under the finite capacity of the proposed production system. So, an Analytic Network Process (ANP) procedure is applied to sort customers' order based on 11 assessment criteria. In step 2, a mathematical model is formulated to determine the best sequence of products to minimize the total utility work cost, total idle cost, tardiness/earliness cost, and total operator error cost. After validation of the presented model using GAMS software, according to the NP-hard nature of this problem, a genetic algorithm (GA) and particle swarm optimization (PSO) are used. The performance of these algorithms are evaluated using some different test problems. The results show that the GA algorithm is better than PSO algorithm. Finally, a sign test for the two metaheuristics and GAMS is designed to display the main statistical differences among them. The results of the sign test reveal GAMS is an appropriate software for solving small-sized problems. Also, GA is better than PSO algorithm for large sized problems in terms of objective function and run time.

Keywords: Mixed model two-sided assembly line; Sequencing problem; Make-to-order; Customer order prioritization.

1. Introduction

With increasing customers' demands to generate diversity in products, firms have applied mixed-model assembly lines (MMAL) instead of single assembly lines. MMALs produce more than one product type on a similar line with smaller setup time and higher part usage rates and are able to answer customer needs in a short time (Kucukkoc & Zhang, 2016).

According to the size of products and operational requirements, assembly lines can be classified into two groups, including one-sided assembly lines and two-sided assembly lines(Özcan & Toklu, 2010). Typically, one-sided assembly lines (1SALs) utilize only one side of the assembly line to produce small-sized products, but two-sided assembly lines (2SALs) use both left and right sides of the line for handling large high-volume product models. In a 2SLs, some operations are done on one side of the line more easily than the other side. For example, mounting air filters in a truck assembly line are typically done on the left side of the line and installing air tanks are done from the right side of the line. Even so, some tasks have no preference in operation direction and can be done at either side of the line. So in this type of assembly line, the tasks are categorized into three major types: left type(L), right type(R) and either(E)(Kim, Kim, & Kim, 2000). For the first time, (Bartholdi, 1993)designed a computer-based program to balance 2SALs in a manufacturer of small utility vehicles in order to minimize the number of stations. Also, this type of assembly line has been used in more production systems such as trucks(Kim et al., 2000), motorcycles(Cortés, Onieva, & Guadix, 2010), domestic products (Baykasoglu & Dereli, 2008)and etc. Therefore, the combination of MMALs and 2SALs in production systems with large sized products leads to a decrease in setup time, number of stations and worker, worker walking, throughput time, material handling costs, tools and fixtures cost, and an increase in teamwork and flexibility (Lee, Kim, & Kim, 2001).

In more MM2SALs, 90% of assembly processes are done by humans(Zhu, Hu, Koren, & Huang, 2012).It is known that assembling different products with high volume complexity in these production systems creates a negative effect on assembly operations and work conditions of the worker, as well as leads to increase human error, delays, reduce system performance, quality of products, and productivity (Claeys, Hoedt, Soete, Van Landeghem, & Cottyn, 2015). Choice complexity is an effective factor in operation errors that is increased by product variety. The choice complexity in the MM2SALs results from the choice of the right part, tool, fixture, and assembly procedure for each module variant, which depends on cognitive skills and experience of the worker(Zhao, Hsu, Chang, & Li, 2016). Fast-Berglund, Fässberg, Hellman, Davidsson, and Stahre (2013)showed that there is a positive correlation between complexity and assembly

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errors. Also, Li, Zhou, Deng, and Fan (2011)understood that operator's errors are relevant to choice complexity by evaluation of the human factors in the piston production line. Different studies have been done in order to measure complexity and evaluate the effect of the complexity on productivity and efficiency in MMALs, such as Samy and ElMaraghy (2012); Sun and Fan (2018); Zeltzer, Limère, Van Landeghem, Aghezzaf, and Stahre (2013); Zhao et al. (2016). However, determining a rational sequence of products in MM2SALs can reduce complexity in production systems (Zhu et al., 2012).

The sequencing problem and determining the best sequence have a significant role in the efficiency of MMALs. In the literature, Mixed-model assembly line sequencing programs have been performed in order to reduce cost, increase product quality, and reduce delays. Minimization of utility work, total idle time, workload variation, the risk of line stoppage, the variation of part usage rate, line length, and throughput time are common objective functions that have been considered by researchers and reviewed byBoysen, Fliedner, and Scholl (2009). Therefore, minimizing human errors' cost due to choice complexity can be considered as a new objective function to determine sequence in MM2SALs. However, for the reason of sequence-dependent finish time of tasks in 2SLs, the sequence planning in 2SLs is more complex than 1SALs and few studies have been performed in this area(N. I. L. M. Azmi, Zainuddin, & Ahmad, 2017; N. M. Azmi, Ahmad, & Zainuddin, 2017; Chutima & Jitmetta, 2013; Chutima & Naruemitwong, 2014).For the first time,Chutima and Jitmetta (2013) presented the problem of determining the best sequence for MM2SAL and formulated a model to minimize total utility work, total setup time, and total production rate variation. The current study tries to determine a good sequence of the products in MM2SALs for minimizing total utility work cost, total idle cost, total earliness /tardiness cost, and total operators' error cost that is caused by complexity.

In real situations, firms face with limited capacity and all customers do not have the same value for them. In such a situation, firms prefer to select customers that have more value for them and sort customers with respect to their values and assign available capacity to the accepted orders to achieve more profit and optimal use of resources(Rabbani, Heidari, & Farrokhi-Asl, 2018). In the other word, before determining the sequence of products, order acceptance and prioritizing customers' order are a monumental issue for firms. Manavizadeh, Dehghani, and Rabbani (2011)presented different criteria for prioritizing customers in order to reduce costs. They used available to promise (ATP)method to determine the appropriate delivery time for customers and sorted customers using analytic hierarchy process (AHP). In the proposed problem byManavizadeh, Tavakoli, Rabbani, and Jolai (2013), customers are sorted based on three criteria, including the critical ratio of each order, the importance degree of customer, and innovation in a product. Then, the mathematical models are applied to determine the best sequence of products. In this sequence, the order with high priority is prepared sooner. Also, Rabbani, Sadri, Manavizadeh, and Rafiei (2015)applied the technique for order of preference by similarity to ideal solution (TOPSIS) approach for prioritizing customers based on 11 criteria. They classified customers into two groups, high priority, and normal priority.

Considering the aforementioned literature on MMAL sequencing, the lack of appropriate criteria for prioritizing customers, few studies in the 2SLs sequence planning, and the ignore the effects of choice complexity in the sequence planning are the primary motivations for this research. This study presents an MM2SAL sequencing problem by developing a framework based on Akyildiz, Kadaifci, and Topcu (2015) for prioritizing customers. According to this framework, first several criteria have been gathered based on literature, then customers are sorted by analytic network process (ANP).Then, a mathematical programming model is developed to achieve the best sequence of products by minimizing total utility work cost, total idle cost, total earliness /tardiness cost, and total operators' error cost that is caused by complexity choice. Also, this study considers intrinsic factors. Intrinsic factors include the operator's experience and the operator's mental deliberation thinking time. Operator's experience is defined as an operator's autonomous learning ability based on the position of the task and this factor affects operation times. Mental deliberation thinking time is applied to do cognitive activities by workers in order to increase their quality of work at the station and lead to decrease cycle time at each station. Cognitive activities contain remembering, checking, pondering, and so forth.

The highlights of this study are as follows:

- developing a new mathematical model for MM2SALs
- gathering a complete set of assessment criteria in prioritizing customers.
- prioritizing customers using Analytic Network Process (ANP) procedure and developing a framework for prioritizing customers
- determining the best sequence of products in 2SALs through a genetic algorithm and particle swarm optimization.

This study is structured as follows. In the next section, problem description and mathematical formulation are presented. The proposed metaheuristic algorithms to solve the sequencing problem are described in section 3. Section 4 is dedicated to experimental design and the results of parameters tuning for the proposed metaheuristic algorithms. Also, comparison between algorithms based on the test problems is also provided in section 4. Finally, section 5 presents the conclusion and future research on MM2SALs.

2. Problem Description

In this study, a sequence planning for MM2SALs with$M_S$mated stations is considered. Each mated station has two parallel workstations and each workstation is identified by two serial numbers, namely,$2m_S$-1 and$2m_S$for the left station and the right station, respectively. Two workers are placed in each workstation and work together on the same product without interfacing each other.

A conveyor with constant speed V moves from the center of mated stations to transfer products through the line. Mated stations are closed; that is, they have boundaries. So, workers cannot cross from the boundaries of mated stations. In MM2SALs, there are inevitable idle times because of the constraint called sequence-dependent finish time of tasks. The completion time of each worker in each workstation is the sum of total task time and the total inevitable idle time. Also, if a worker completes his/her work earlier, he/she should wait until another worker finishes his/her work. As a result, total completion time for each mated station is equal to the maximum completion time for two workers. Figure 1 shows a mated station in MM2SAL to illustrate the effect of sequence-dependent finish time of tasks.

As aforementioned, customers do not have the same value for the firm. So, acceptance or rejection of orders and prioritizing customers are an important issue for the firm faced with limited capacity. In this study, several criteria are initially gathered based on criteria in the literature and a decision framework are developed in order to select and prioritize customers. In this framework, customers are sorted by ANP. In order to show the effect of prioritizing customer in the sequencing problem, a different penalty for earliness and tardiness are considered. Also, this study considers intrinsic factors. Intrinsic factors include the operator’s experience and the operator's mental deliberation thinking time.

2.1. Assumptions

- The moving time of the workers is not considered.
- According to high volume and diversity in MM2SALs, workers and machines are versatile.
- Machine failure is not considered.
- Make to order (MTO) mode is considered to plan manufacture.
- Two workers in each mated station move together downstream to complete their tasks and they walk together upstream to next product.
- If workers cannot complete their tasks, they must walk upstream and leave unfinished task, and a utility worker completes unfinished tasks.

Generally, this study presents a framework with two steps as customer order prioritization and determining the good sequence in MM2SAL for accepted orders. Figure 2 demonstrates the structure of this framework.

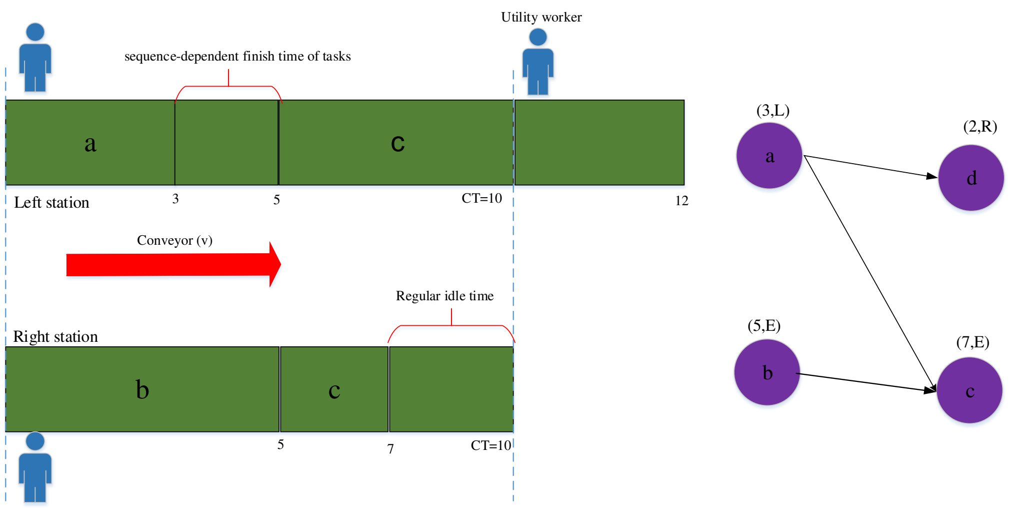

Fig .1. A MM2SAL with a mated station

2.2. Selecting and prioritizing customers

In the situation that firms encounter with capacity constraint, the demand management has a monumental role in maximizing the profit of firms. Therefore, firms should consider the efficient approach in order to select between a set of potential orders with respect to existing capacity. These potential customers’ order is considered as possible alternatives for firms that should prioritize them based on some assessment criteria. In this study, a set of assessment criteria is gathered for prioritizing potential customer orders in mixed model two-sided assembly systems. These assessment criteria are listed as follows:

- The potential profit rate per unit of time(Wang, Yang, & Lee, 1994)
- The level of potential future order with higher profit (Hung & Lee, 2010)
- The customer credit of future business opportunity(Wang et al., 1994)
- The adaptability of potential order with the current capacity (Balakrishnan, Sridharan, & Patterson, 1996)
- Innovation in order options (Manavizadeh et al., 2011)
- The determined due dates (Ball, Chen, & Zhao, 2003)

- The degree of customer astringency about preparing on time(Rabbani et al., 2015)
- Foreign/domestic or the amount of distance of customer from firm and degree of similarity between arrived and previous orders (Rabbani et al., 2015)
- Loyalty (Ball et al., 2003)
- Flexibility(Ball et al., 2003)
- The probability of changing in order options by customer(Rabbani et al., 2015)

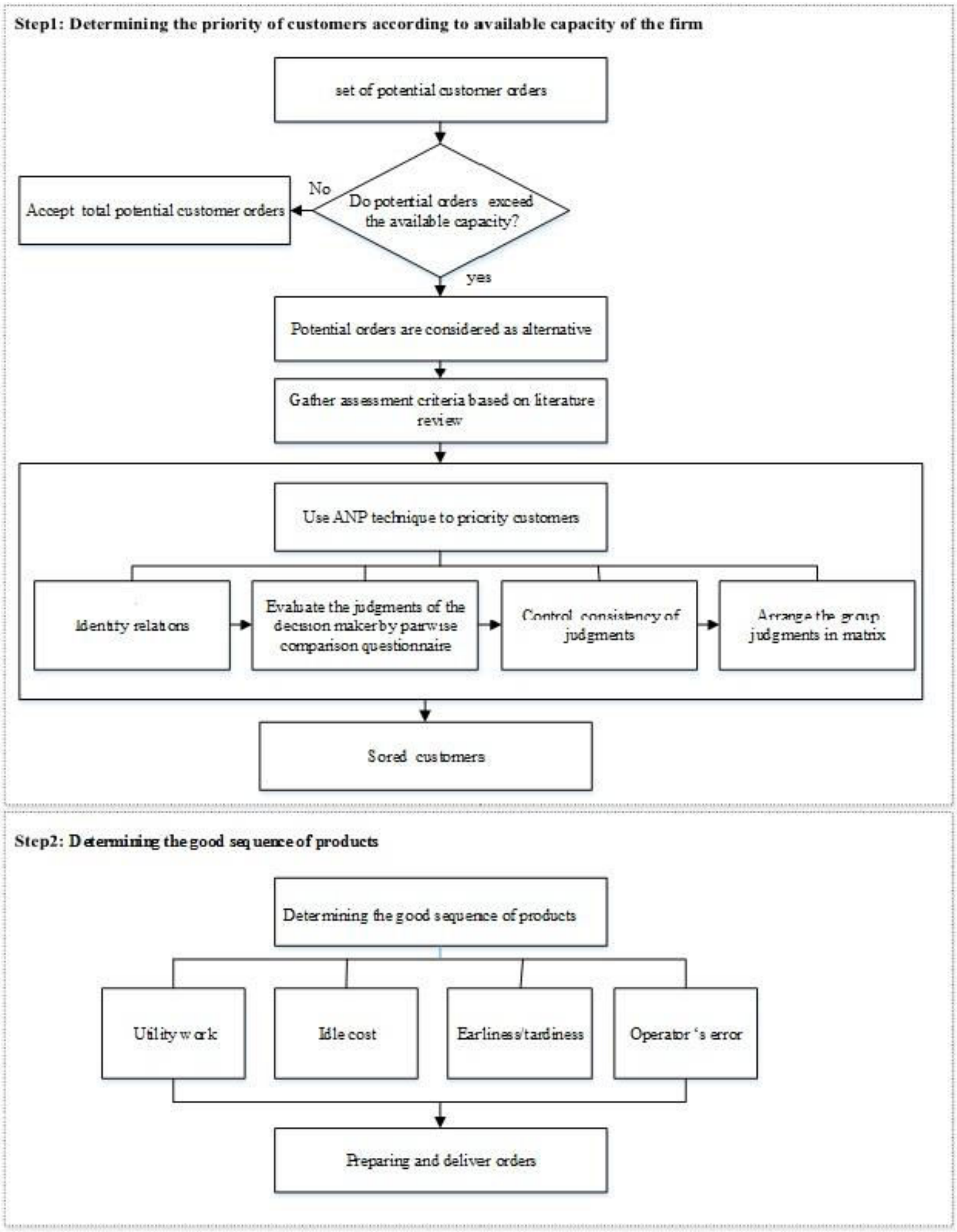

Fig. 2. Schematic view of discussed framework

After gathering assessment criteria, relations between alternatives and assessment criteria are identified by experts or managers (decision makers). It should be noted that there are dependencies between alternatives and criteria, alternatives with each other, and also criteria to together. So, Analytic Network Process(ANP) is selected as an appropriate Multi-Criteria Decision Analysis (MCDM) method to rank alternatives and criteria. ANP is a strong technique in order to solve MCDM problems and is presented by Saaty (1996)to incorporate qualitative and quantitative factors that there is interdependence between them. In the recent decade, this technique has been applied in different area and applications. Some of ANP applications are as follows: the analysis of selected issues of green supply chain management (Chand, Bhatia, & Singh, 2018), analyzing the IT problems (Koupaei, Sobhanallahi, & Horri, 2015), facility layout selection(Al-Hawari, Mumani, & Momani, 2014), and construction industry(Cakmak & Cakmak, 2014). Also, a literature review of the last ANP utilizations has been presented by Hülle, Kaspar, and Möller (2013).In this technique, relative priorities obtain from the judgment of decision-makers based on the pairwise comparisons questionnaire. So, after completing the questionnaire by managers, the consistency of judgments is controlled. If there is an inconsistency between decision-makers, they can complete the pairwise comparisons questionnaire again in order to decrease inconsistency. Then, geometric means of total paired comparisons for every question are calculated to show the aggregate group judgments. In the last step, decision makers set group judgments in an ANP software and calculate the priorities of customer orders.

2.3. Determining the sequence of products

In this step, sequence planning of MM2SAL is determined to introduce all orders that accepted in step 1. Sequencing problem of MM2SALs for the first time is presented byChutima and Naruemitwong (2014). To the best of our knowledge, few studies have been done to determine the sequence of 2SALs. In this study, in order to determine the best sequence of products four objectives are considered simultaneously. Objectives include minimizing total utility work cost, minimizing total idle cost, minimizing earliness and tardiness cost, and minimizing the operator's error cost due to choice complexity. Based on the literature, the combination of these objective functions in MM2SALs is introduced for the first time. Table 1 shows related notations of the presented problem.

Table 1

Notations of problem

Parameters	
C	Index of customer, c=1,2,..,C
K	Index of model, $k = 1, . . . , K$
M_S	Index of mated station, $m_s = 1.2. \dots . M_S$
I	Index of position, i=1,2,...,I , I=$\sum_{k=1}^{K}\sum_{c=1}^{C} d_{kc}$
$2m_s - 1.2m_s$	Index of the left and right stations, respectively
γ	Launch interval of products to the line
V	Conveyor speed (constant)
L_{ms}	The line length of mated stationm_s
DD_c	Specified due date for customer c
D_{kc}	Demand of customer c for model k
CU_{m_s}	Cost of utility worker per unit time at mated station m_s
$C^{ri}{}_{m_s}$	Cost of idle worker per unit time at mated station m_s
$CC_{k.m_s}$	Per unit cost of defective model k at mated station m
Ce_c	Earliness cost for customer c
Ct_c	Tardiness cost for customer c
$OT_{k.2n_m}.OT_{k.2n_{m-1}}$	Operation time of model k at right statin and left station, respectively
$IT_{k.2ms}.IT_{k.2ms-1}$	Inevitable idle time of model k at right statin and left station, respectively
α	operator's experience coefficient
$ne_{k.m_s}$	The number of operator's error at mated m_s station and model k
Decision variables	
$OT'_{k.2m_s}.OT'_{k.2m_s-1}$	Operation time of model k at right statin and left station, respectively by considering
$U_{i.2m_s}$, $U_{i.2m_s-1}$	Utility worker time needed at right statin and left station, respectively in sequence place i
$U_{i.m_s}$	Utility worker time needed at mated station m_s in sequence place i
$Z_{i.2m_s}$, $Z_{i.2m_s-1}$	The starting position of task on the i^{th} product in a sequence at right statin and left station, respectively
$Z_{i.m_s}$	The starting position of task on the i^{th} product in a sequence at mated station m_s
VE_c	Amount of earliness for orders of customer c
VT_c	Amount of tardiness for orders of customer c
OPT_{m_s}	total operation time at mated station m_s
FT_c	Completion time for orders of customer c
$RI_{i.m_s}$	Regular idle time at mated station $m_s$for producing product$i$
Y_{kci}	Binary variable (Y_{ikc} =1 if a copy of model k for customer c produce in sequence place i and $Y_{ikc} = 0$ otherwise)

2.3.1. Minimizing total utility work cost

For the first time, Hyun, Kim, and Kim (1998)presented minimizing total utility work time as an objective function to determine the sequence of products. When work overload is high and a regular worker cannot complete his/her work, the utility workers help him/her to complete the work. This objective reduces work overload cost, labor cost, and the risk of line stoppage. Tavakkoli-Moghaddam and Rahimi-Vahed (2006)developed it with cost coefficient and Chutima and Jitmetta (2013) extended it in a 2SAL.

$$min\, Z_1 = \sum_{m_s=1}^{M_S}\left(\sum_{i=1}^{I}\frac{CU_{m_s}\times U_{i.m_s}+Z_{(i+1).m_s}}{V}\right) \tag{1}$$

s .t.

$$Z_{(i+1).2m_s-1} = max\left[0.\,min\left(Z_{i.m_s}+V\times\sum_{k=1}^{K}\sum_{c=1}^{C}Y_{kci}\times\{OT'_{k.2m_s-1}+IT_{k.2m_s-1}\} - \gamma V\,.\,L_{m_s} - \gamma V\right)\right] \quad \forall i.m_s \tag{2}$$

$$Z_{(i+1).2m_s} = max\left[0.\,min\left(Z_{i.m_s}+V\times\sum_{k=1}^{K}\sum_{c=1}^{C}Y_{kci}\times\{OT'_{k.2m_s}+IT_{k.2m_s}\} - \gamma V\,.\,L_{m_s} - \gamma V\right)\right] \quad \forall i.m_s \tag{3}$$

$$Z_{(i+1).m_s} = max\{Z_{(i+1).2m_s}.Z_{(i+1).2m_s-1}\} \quad \forall i.m_s \tag{4}$$

$$U_{i.2m_s} = max\left[0.\frac{Z_{i.m_s}+V\times\sum_{k=1}^{K}\sum_{c=1}^{C}Y_{kci}\times\{OT'_{k.2m_s}+IT_{k.2m_s}\}-L_{m_s}}{V}\right] \quad \forall i.m_s \tag{5}$$

$$U_{i.2m_s-1} = max\left[0.\frac{Z_{i.m_s}+V\times\sum_{k=1}^{K}\sum_{c=1}^{C}Y_{kci}\times\{OT'_{k.2m_s-1}+IT_{k.2m_s-1}\}-L_{m_s}}{V}\right] \quad \forall i.m_s \tag{6}$$

$$U_{i.m_s} = U_{i.2m_s}+U_{i.2m_s-1} \quad \forall i.m_s \tag{7}$$

$$OT'_{k.2m_s} = OT_{k.2m_s}\times i^{-\alpha} \quad ;\, 0<\alpha<1 \quad \forall\, i.k.2m_s \tag{8}$$

$$OT'_{k.2m_s-1} = OT_{k.2m_s-1}\times i^{-\alpha} \quad \forall\, i.k.\,2m_s-1 \tag{9}$$

$$\sum_{k=1}^{K}\sum_{c=1}^{C}Y_{kci} = 1 \quad \forall\, i \tag{10}$$

$$\sum_{i=1}^{I}Y_{kci} = D_{kc} \quad \forall\, k.c \tag{11}$$

$$Z_{1.m_s} = 0 \quad \forall m_s \tag{12}$$

$$U_{i.2m_s}.U_{i.2m_s-1}\,.U_{i.m_s}.Z_{i.m_s} \geq 0 \quad \forall\, i.m_s \tag{13}$$

$$Y_{kci} = \{0,1\} \quad \forall\, i.k.c \tag{14}$$

Equation (1) minimizes the total cost of incomplete work i at the mated station m_s. Constraints (2) and (3) calculate the starting position for each operator at the each station (left station and right station) on the product $(i+1)$in a sequence, also the starting position in each the mated station is shown by constraint (4).Constraints (5)-(7) calculate utility work time for the product i at the right station, the left station and the mated station, respectively. Constraints (8) and (9) show the effect of the operator's experience at the operation time. Constraint(10) ensures that exactly one model and product assign to each position in the sequence. Satisfying the demand for each customer is ensured by constraint (11).$Z_{1.m_s}=0$and$Z_{i.m_s}\geq 0$ indicate mated stations are closed. Non-negativity of the variables is shown through constraint(13) and constraint (14) shows a binary variable.

2.3.2. Minimizing total operators' error

This objective function minimizes operator's error that is created by choice complexity. Choice task complexity is an extrinsic factor and an effective factor on operation errors that is generated by product variety. In MM2SALs different products with high volume are produced, so, in these production systems the probability of error increases. It is assumed that the number of errors is computed based on historical data.

$$minZ_2 = \sum_{i=1}^{I} \quad \sum_{c=1}^{C}\sum_{m_s}^{M_S}\sum_{k=1}^{K} \times \text{ne}_{km_s} \times CC_{km_s} \times Y_{kci} \tag{15}$$

s.t.

Constrains(10), (11) and (14).

2.3.3. Minimizing total idle cost

For the first time, this objective function was introduced by Sarker and Pan (1998). Manavizadeh et al. (2013)developed it with cost coefficient in mixed model assembly systems. Minimizing this objective function with cost coefficient for MM2SALs is presented in Equation (16).

$$min\ Z_3 = \sum_{i=1}^{I}\sum_{m_s=1}^{M_S} RI_{i.m_s} \times C^{ri}{}_{m_s} \tag{16}$$

s.t.

$$RI_{i.m_s} = \begin{Bmatrix} max\left[0.\gamma - \left(\frac{Z_{i.m_s}}{V} + \sum_{k=1}^{K}\sum_{c=1}^{C} Y_{kci} \times \{OT'_{k.2m_s} + IT_{k.2m_s}\} - U_{i.2m_s}\right)\right]. \\ +max\left[0.\gamma - \left(\frac{Z_{i.m_s}}{V} + \sum_{k=1}^{K}\sum_{c=1}^{C} Y_{kci} \times \{OT'_{k.2m_s-1} + IT_{k.2m_s-1}\} - U_{i.2m_s-1}\right)\right] \end{Bmatrix} \quad \forall\ i.m_s \tag{17}$$

And Constrains (2)-(14)

Constraint (17) shows the idle time at each mated station is the summation of idle time for the left station and the right station.

2.3.4. Minimizing total earliness and tardiness cost

This objective function was introduced by Rabbani et al. (2015)and tries to minimize tardiness and earliness cost for all customer to determine the sequence of products.

$$minZ_4 = \sum_{c=1}^{C} VE_c \times Ce_c + VT_c \times Ct_c \tag{18}$$

s.t.

$$VE_c = max\{0.DD_c - FT_C\} \quad \forall\ c \tag{19}$$

$$VT_c = max\{0.FT_C - DD_c\} \quad \forall\ c \tag{20}$$

$$OPT_{m_s} = max\{OT'_{k.2m_s} + IT_{k.2m_s}.OT'_{k.2m_s-1} + IT_{k.2m_s-1}\} \quad \forall\ m_s \tag{21}$$

$$FT_C = \sum_{m_s=1}^{M_S}\sum_{i=1}^{I}\sum_{k=1}^{K}(OPT_{m_s} + RI_{i.m_s}) \times Y_{kci} \quad \forall\ c \tag{22}$$

And Constrains (8),(9),(10), (11) and(14).

Constrains (19) and (20) indicate the early time and tardy time for each customer. Constrain (21) shows total operation time at each mated station considering the effect of the operator's experience. The completion time of orders for each customer is shown in constrain (22). This time is determined based on operation times and idle time. In the above model,Ce_c and Ct_c are earliness and tardiness cost, respectively. These costs are specified based on customer ranking. According to step1, if rank of

c-th customer becomes r,earliness cost and tardiness cost are calculated as:

$$Ce_c = 10 \times r \qquad \forall\, c \tag{23}$$

$$Ct_c = 2^{8-r} \qquad \forall\, c \tag{24}$$

Finally, there is a multi-objective function shown below. In this research, a weighting way is applied to the objectives based on their importance in each problem in order to solve them. Weighting to the objective functions is based on circumstances, conditions, and management goals. In some situations, the weights may equal to each other and sometimes may not. Therefore, top management decides in this respect. Therefore, the mathematical model of MM2SAL is as follows:

$$minimize\ b_1\left(\sum_{m_s=1}^{M_S}\left(\sum_{i=1}^{I}\frac{CU_{m_s}\times U_{i.m_s}+Z_{(i+1).m_s}}{V}\right)\right)+b_2\left(\sum_{i=1}^{I}\ \sum_{c=1}^{C}\sum_{m_s}^{M_S}\sum_{k=1}^{K}\times \mathrm{ne}_{km_s}\times CC_{km_s}\times Y_{kci}\right) \tag{25}$$

$$+b_3\left(\sum_{i=1}^{I}\sum_{m_s=1}^{M_S}RI_{i.m_s}\times C^{ri}{}_{m_s}\right)+b_4\left(\sum_{c=1}^{C}VE_c\times Ce_c+VT_c\times Ct_c\right)$$

s .t.

$$b_1+b_2+b_3+b_4=1 \tag{26}$$

And Constrains (2)-(14),(17), (19)-(24)

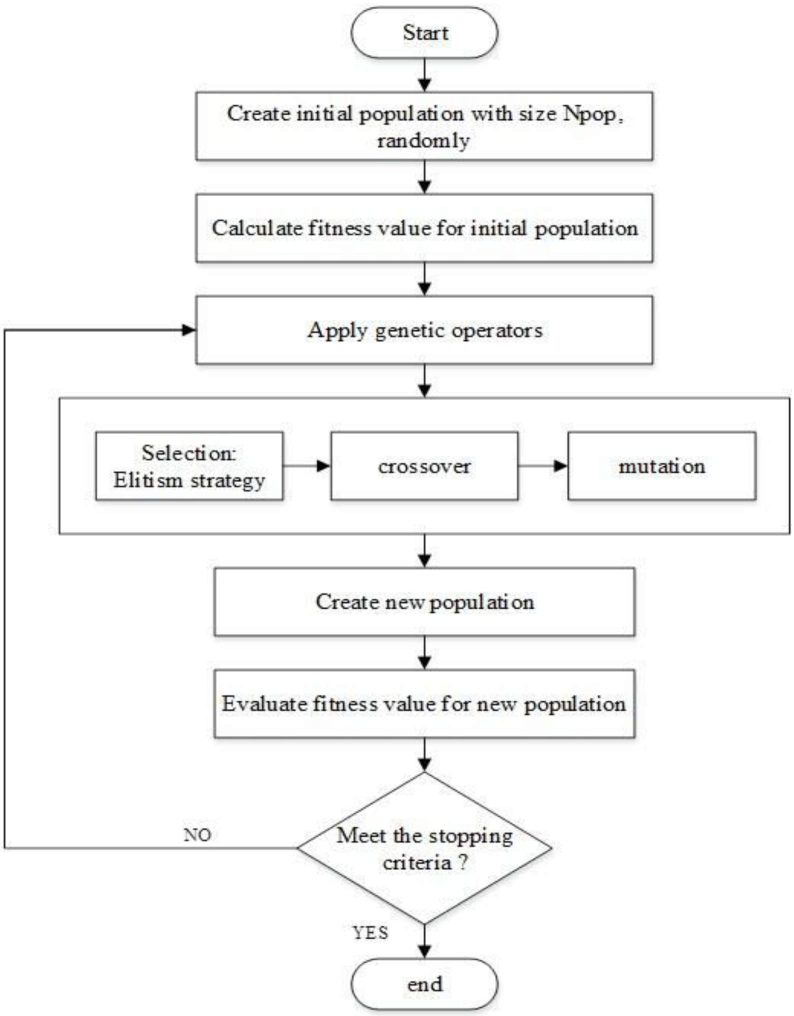

Fig .3. Flowchart of GA

3. Methodology

This study tries to determine the appropriate sequence of products in presented MM2SAL by developing a decision framework to select and prioritize between the potential customers so that total orders do not exceed available capacity of system. According to the previous researches, typically finding the best solution for the sequencing problem is difficult and this problem is categorized as an NP-hard problem(Fattahi & Askari, 2018). Some of approaches to tackle the problem are as follows: simulated annealing(McMullen & Frazier, 2000), ant colony optimization technique (Sipahi & Timor, 2010), multi-objective scatter search (Rahimi-Vahed, Rabbani, Tavakkoli-Moghaddam, Torabi, & Jolai, 2007), Pareto biogeography-based optimization (Chutima & Naruemitwong, 2014), genetic algorithms (Defersha & Mohebalizadehgashti, 2018), bi-objective genetic algorithm (Rezaeian & Zarook, 2018), and particle swarm algorithm (Bansal, 2019). In this research, a genetic algorithm (GA) and particle swarm algorithm (PSO) have been appliedfor solving the proposed problem.

3.1. Genetic algorithm

A genetic algorithm is a biological evolutionary model, successful, and suitable optimization technique to solve manufacturing optimization problems based on natural selection in unknown search space(Gen, Cheng, & Wang, 1997). The components of a genetic algorithm are a solution representation, fitness function, initial population, genetic operators (elitism, crossover, and mutation), and parameters (parameter tuning) that should be designed based on the problem. The more detailed of these components for the proposed problem has been described in the next section. Figure 3 shows the flowchart of GA.

3.1.1. Solution representation

A chromosome (individual) is a proposed solution and includes some genes that each gene indicates the features of a chromosome. Solution representation is a method for encoding position, figure, and physical attributes of solutions. So, designing an appropriate chromosome help to the success of the algorithm for solving the proposed problem. In the presented problem, the length of the chromosome is equal to the number of products in a sequence ($I = \sum_{c=1}^{C} \sum_{k}^{K} d_{kc}$). The value of every gene is shown as $[k.c]$, where k is the product model and c is the customer. The proposed chromosome is shown in Figure 4.

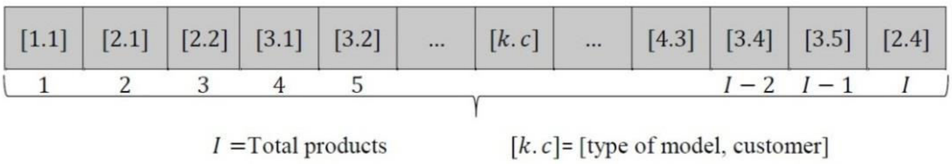

Fig. 4. An example of solution representation

3.1.2. Fitness function

The fitness function is a specific kind of objective function in order to evaluate and measure the quality of the represented solution. So in designed GA, the value of fitness function is equal to equation (25).

3.1.3. Elitism

Elitism is a selection strategy to keep and shift the good chromosome to the next generation to reproduction. So, in the next generation, the quality of solutions will not decrease.

3.1.4. Crossover

Crossover is the main operator of the genetic algorithm that has a significant effect on the performance of the algorithm in keeping genetic diversity. Crossover is the process of selecting two parent solutions and combination and sharing of their characteristics with together to produce offspring solutions. To perform crossover for the proposed problem, first, a cut point is selected randomly. Then, the first parent is copied from first to the cut point. then, the second parent is scanned and if the number gene of offspring is not yet equal to the number of it in the first parent, it is added. How to perform crossover for the proposed problem is shown in Figure 5.

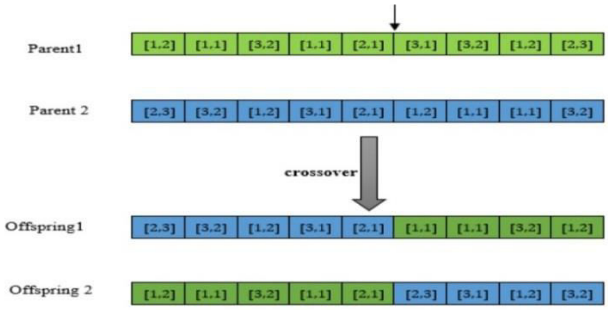

Fig. 5. An example of Crossover operator

3.1.5. Mutation

Another genetic operator is the mutation that changes an individual by selecting randomly two genes in length of chromosome and exchanges them with each other as Figure 6.

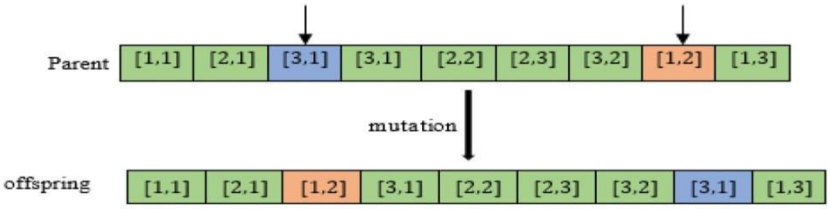

Fig. 6. An example of mutation operator

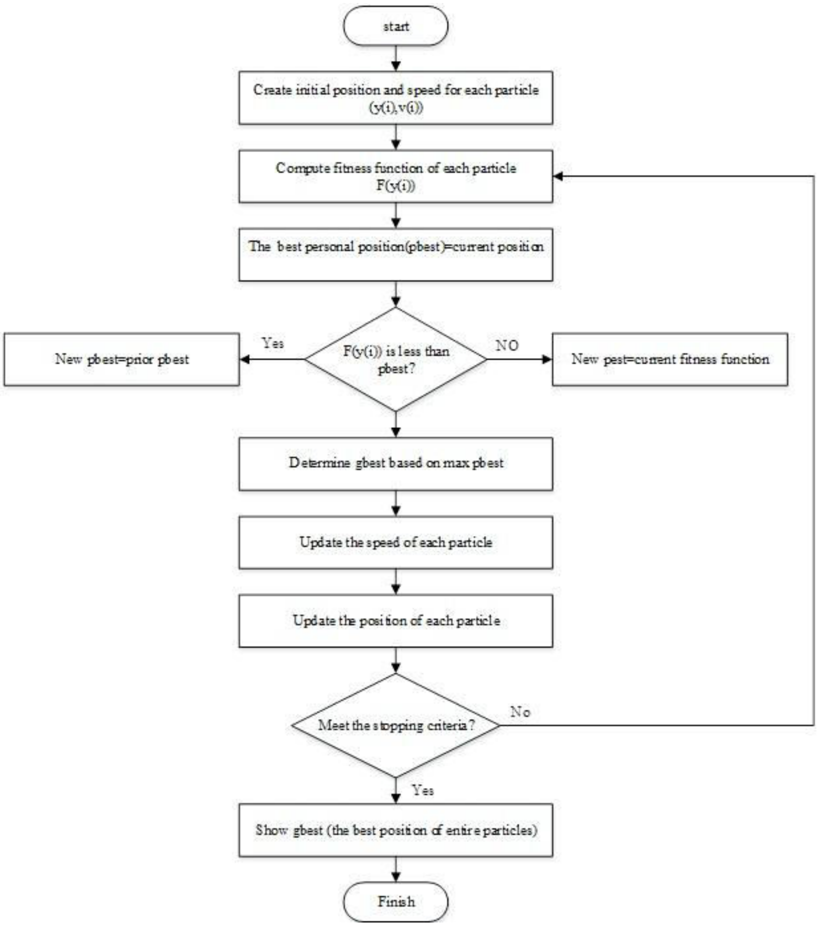

Fig. 7. Flowchart of PSO

3.2. Particle swarm optimization

Particle swarm optimization (PSO) is an evolutionary approach that was presented by Kennedy and Eberhart (1997) according to social behavior of bird flocking or fish schooling to optimize continuous non-linear functions. In PSO, every bird named a particle and the swarm is the potential solutions in every it eration like the population in the genetic algorithm. Each particle is specified with three vectors, position(y), speed (v),and best personal position($pbest$). The position vector expresses the value of decision variables for the proposed problem. The velocity vector is traveled distance by a particle in the search spacein every iteration. The best personal position vector shows the best-found position of a particle. $pbest$experienced by the best position visited by the total swarm($gbest$). In each iteration, each particle moves with a speed from the current position to the next position and can update its own position by changing the speed by using the following equations.Figure7 shows the implementation steps of this algorithm.

$$v_{id}(k+1) = w_k v_{id}(k) + c_1 r_1 [pbest_{id}(k) - y_{id}(k)] + c_2 r_2 [gbest_d(k) - y_{id}(k)] \quad (27)$$

$$y_{id}(k+1) = y_{id}(k) + v_{id}(k+1) \quad (28)$$

wherev_{id}indicates the speed of ith particle on dimension d and y_{id}indicatesthe position of the ith particle on dimension d. The $pbest_{id}$indicatesthe best personal position visited by the$i$thparticleon the dimension d, and $gbest_d$shows the global best position of theentire swarm on the dimension d. $c_1$is cognitive coefficient and c_2 is social coefficient.$r_1$andr_2 are random numbers between 0 and 1.Figure 8 displays the motion of a particle in the search space according to Equations (27) and (28).

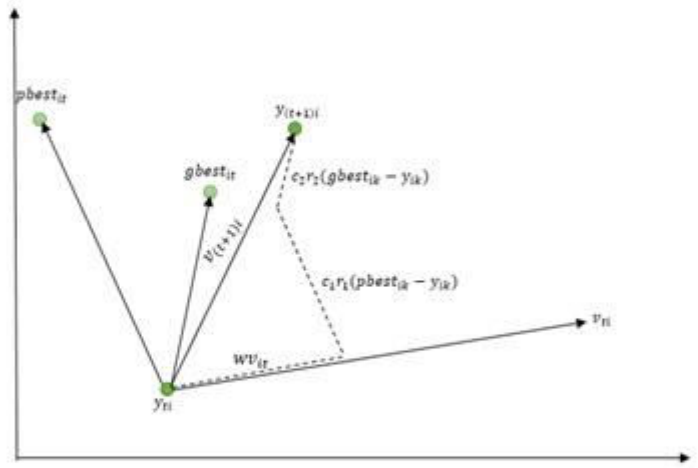

Fig. 8. The motion of a particle in the search space

4. Experimental Results

To ensure the feasibility of the presented model and to illustrate the applicability of the proposed framework, the proposed model is coded by GAMS software for small size problem first, and because the presented problem is NP-hard, then the proposed GA and PSO algorithms are coded by MATLAB R2014b for large size problems.

4.1. Parameter setting

The efficiency of the metaheuristic algorithms in exploring better solutions in less run time is largely related to their tuning parameters. So in this research, the design of experiments using Taguchi method is applied to tune the GA and PSO parameters.GA parameters include population size($npop$),mutation rate(p_m),crossover rate(p_c), and maximum number of iterations(Max $\_it$). PSO parameters are as: swarm size($npop$),maximum number of iterations(Max $\_it$), the cognitive coefficient (c_1),the stoical coefficient(c_2),and inertia weight (w). Parameter tuning for GA and PSO is performed using MINITAB software after determining the level of each parameter. The obtained results are shown in Figures 9 and 10.Table 2 summarizes tuned parameters of GA and PSO.

Table 2
Tuned parameters for GA and PSO

Algorithm	Parameters						
	$\max\_it$	$npop$	p_m	p_c	c_1	c_2	w
GA	80	75	0.15	0.65	-	-	-
PSO	80	75	-	-	1.25	1.25	0.6

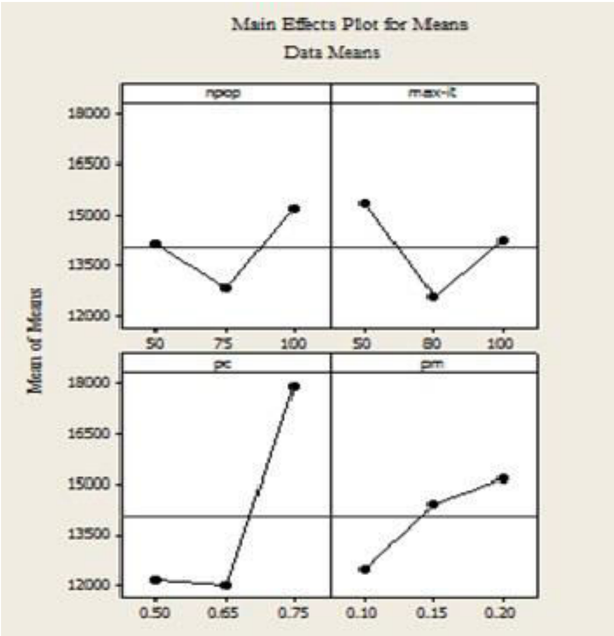

Fig. 9. Result of Taguchi design for GA parameter tuning

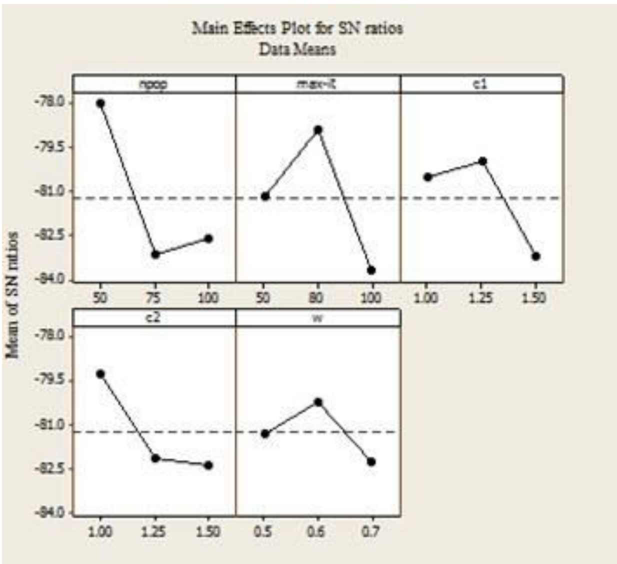

Fig. 10. Result of Taguchi design for PSO parameter tuning

4.2. Small sized problem

To ensure the model feasibility, it should be solved by an exact method. In this study, GAMS software (version 25.1 with CPLEX solver) is applied. Therefore, this subsection introduces 5 test problems carried out on small sized problems. In all problems, there are two mated stations, three customers, and three product models. Also, conveyor speed is equal to 1, the launch interval is equal to 9, and the operator's experience coefficient is -0.25. Length of mated stations, the cost of the idle worker, and the cost of the utility worker are shown in Table 3.

Operation time, inevitable idle time, the number of errors, operator's error cost in each station (left/right), demand, and due date of each customer for each defined problem are presented in Appendix A. The weight of each objective functions are: b_1 =0.3,b_2 =0.15,b_3 = 0.15,andb_4 =0.4 .Table 4indicates the computational results for GAMS on 5 test problems. In addition, the defined test problems are solved with GA and PSO algorithms and their results are displayed in Table 3. The results of GAMS software and metaheuristic algorithms are compared with each other according to the following equation and shown in Table 5. Table 5 displays that the total objective function of metaheuristic algorithms and GAMS are equal for small sized problems.

$$GAP = \frac{best\ cost\ (\text{metaheuristic algorithm }) - best\ cost\ (GAMS)}{best\ cost\ (GAMS)} \quad (29)$$

Table 3
Length of mated station and mated station's cost

Mated station	Mated station length	Cost of utility worker	Cost of idle worker
1	11	10	12
2	9	23	20

Table 4
Computational results of GAMS, GA, and PSO

	GAMS			GA			PSO		
Pr*	BC*	ET*	BS*	BC*	ET*	BS*	BC*	ET*	BS*
1	67.12	220.81	(1-1-2-3-3-1-2-2)	68.85	22.71	(1-3-2-1-3-2-1-2)	68.85	30.57	(3-2-1-3-2-1-1-2)
2	70.32	305.50	(1-2-2-3-1-1-3-3-1)	71.18	56.04	(1-3-2-2-1-1-3-3-1)	71.96	84.41	(3-2-2-1-1-1-3-1-3)
3	72.25	233.80	(2-1-1-1-3-3-1-2-2-2-3)	73.43	33.02	(2-1-2-1-3-3-3-1-2-2-1)	73.43	51.23	(1-1-1-1-3-3-2-2-2-2-3)
4	69.14	314.58	(2-2-1-1-3-2-3)	72.21	30.14	(2-2-2-1-3-1-3)	73.08	63.95	(2-2-1-1-3-2-3)
7	74.32	298.36	(1-1-1-2-3-3-3-2-2-1-3-3-2)	75.63	31.02	(1-1-2-2-1-3-3-3-2-1-3-3-2)	75.98	62.42	(1-1-1-3-3-3-3-2-1-2-3-2-2)

*Note: Problem(Pr); Best cost (BC); Exaction time (ET); Best sequence (BS).

Table 5
Comparison between GAMS software and metaheuristic algorithms

Problem	GAMS and GA	GAMS and PSO	GA and PSO
1	0.025774	0.025774	0
2	0.012229	0.023321	0.010958
3	0.0163321	0.016332	0
4	0.0444026	0.569858	0.012048
5	0.0176264	0.022335	0.004627

4.3. Large sized problem

As previously mentioned, finding the best sequence for large sizes is difficult and NP-hard. So, it must be solved by metaheuristic algorithms. In this study, GA and PSO algorithms are proposed. These metaheuristic algorithms have been coded in MATLAB R2014b and conducted on a system with Intel Core i5 PC with CPU of 2 GHz and 4.00 GB RAM.In this section, we run PSO and GA for eight test problems in large size. These problems are solved with 4 matted stations. The conveyor speed is 1, the launch interval is 9, and the operator's experience coefficient is -0.25. The mated station length, the idle cost, and the utility worker cost are shown in Table 6. Some problems (1,2,3, and 4) are solved with 5 customers and 4 product models. Operation time, inevitable idle time, the number of errors, operator's error cost, demand, and due date are shown in Appendix B. In problems 5,6,7, and 8, the number of customers is considered 6 and the number of product models is 4,4,5, and 5, respectively. Table 7 shows the computational results for GA and PSO on 8 test problems. The obtained results of the two algorithms are depicted in Figures11 and 12. As shown in these figures, the GA algorithm is better than PSO algorithm in terms of objective function and run time. As a result, the GA algorithm could be an appropriate approach for solving the proposed problem.

Table 6
Length of mated station and mated station's cost

Mated station	Mated station length	Cost of utility worker	Cost of idle worker
1	10	11	11
2	10	22	18
3	12	12	10
4	7	11	11

Table 7
Computational results of GA, and PSO

	GA			PSO		
Pr*	BC*	ET*	BS*	BC*	ET*	BS*
1	8896	22.81	(1-1-2-1-3-3-3-4-4-4-4-1-2-2-3-2-2-4-4-4-4)	10080	44.465	(1-1-2-2-3-3-3-4-4-4-4-1-1-2-3-2-2-4-4-4-4)
2	16790	55.50	(4-4-2-2-2-2-2-3-3-1-1-1-3-3-3-1-1-4-4-4-4-4-3-3)	16501	79.344	(4-4-4-4-3-3-2-2-2-3-3-2-2-1-3-3-3-1-1-1-1-4-4-4)
3	11790	33.80	(3-3-3-3-2-2-2-1-1-4-4-4-1-1-3-3-4-4-3-3-4-2-2-2)	13448	54.725	(3-3-3-3-2-2-2-1-4-4-4-4-1-1-1-3-4-3-3-3-4-2-2-2)
4	8372	25.17	(1-1-1-2-2-2-3-3-4-4-2-1-1-1-1-1)	11246	50.208	(1-1-1-2-3-4-4-3-2-2-2-1-1-1-1-1)
5	10527	30.28	(3-3-1-1-1-1-4-4-4-2-1-1-3-3-3-4-2-2-2-3-3-3-4-1-2-2-4)	12251	59.912	(1-1-1-1-3-1-4-4-1-2-1-4-3-3-3-4-2-2-2-3-3-3-4-4-2-2-3)
6	10375	29.58	(1-1-1-2-2-4-4-4-3-3-3-2-2-1-1-1-3-3)	11901	49.56	(2-1-1-1-2-4-4-3-3-3-3-2-2-1-1-1-4-3)
7	12762	35.94	(1-1-2-2-3-3-5-5-5-1-1-4-4-5-1-1-2-2-2-3-4-4-4)	13207	60.985	(1-1-2-2-3-3-1-5-5-1-1-4-4-3-4-1-2-2-2-4-4-5-5)
8	11348	32.07	(5-5-5-1-1-2-3-1-1-4-4-4-3-3-3-2-4-4-4-5-5-5-2-2-2-2-2)	13090	58.185	(5-5-5-1-1-1-1-5-3-4-4-2-2-2-3-3-2-4-4-4-5-2-2-3-2-4)

*Note: Problem(Pr); Best cost (BC); Exaction time (ET); Best sequence (BS).

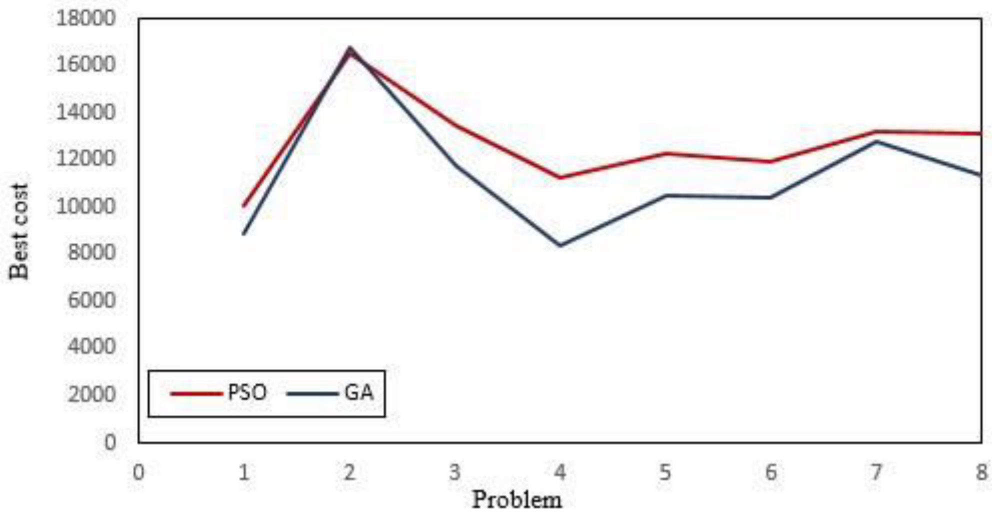

Fig. 11. Comparison between PSO and GA in terms of best cost

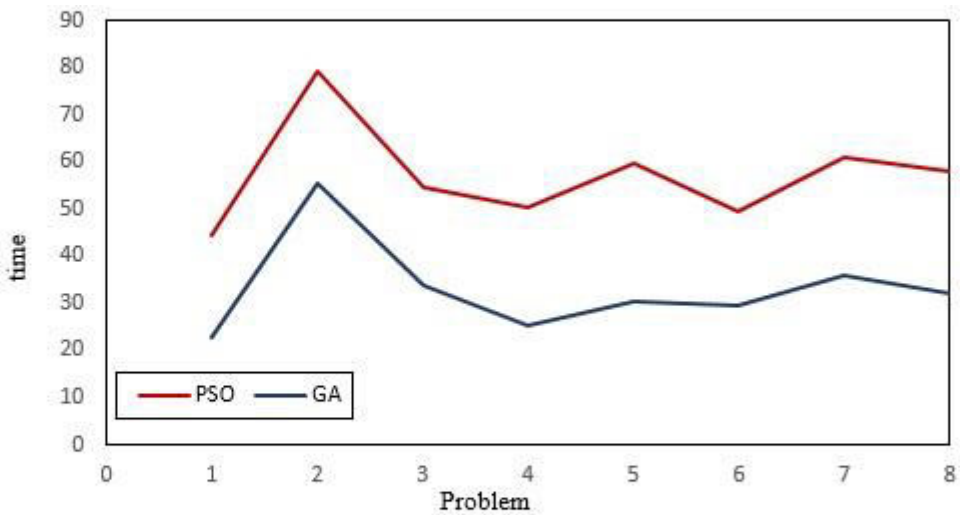

Fig. 12. Comparison between PSO and GA in terms in computational time

4.4. Comparison of GA, PSO, and GAMS

This section tries to apply a nonparametric test in order to display the main statistical differences among the GA, PSO algorithms, and GAMS. Nonparametric tests could be used to continuous data applying ranking-based transformations and tuning the input data to the test requirements(Manavizadeh et al., 2013). In this research, a sign test is applied to perform individual comparisons between optimization techniques. This test is a useful way to compare the overall performances of optimization algorithms that count the number of cases on which an algorithm is the overall winner, and it applies these counts with the form of two-tailed binomial test. Generally, in a statistical test, two hypotheses are defined: (1) H_0 or the null hypothesis and (2) H_1or the alternative hypothesis. The null hypothesis presents that there is no significant difference and the alternative hypothesis is a statement of the presence of a difference (in this study, differences between algorithms). To reject a hypothesis, a level of significance α is used for determining the level at which the hypothesis may be rejected. Under the sign test, If both algorithms compared are equivalent, as assumed under theH_0, each should win approximately $\frac{m}{2}$out of m problems. The number of wins is distributed based on a binomial distribution. For a greater number of cases, the number of wins is distributed under the H_0based on $m\left(\frac{m}{2}.\sqrt{\frac{m}{2}}\right)$, that permits to the use of the z-test: if the number of wins is at least $\left(\frac{m}{2}+1.96\sqrt{\frac{m}{2}}\right)$, then the algorithm is significantly better with $p < 0.05$.

According to(Derrac, García, Molina, & Herrera, 2011), Table 8 presents the critical number of wins needed to achieve both $\alpha = 0.05$ and $\alpha = 0.1$ levels of significance. An algorithm is significantly betterthan the other if it performs better on at least the cases given in each row of Table7. Since tied matches support the null hypothesis, they should not be discounted when using this test, but if there is an odd number of them, one should be ignored.

The proposed algorithms are compared according to the sign test and the results are given in Table 9. The null hypothesis or H_0 is presented in the second column and shows the equivalence of each algorithm. The third column shows the number of wins of the first algorithm for each comparison. Finally, the acceptance or rejection of the null hypothesis is given in the fourth and fifth columns. From Table 9, we observe that for small-sized problems, GAMS is better than GA and PSO algorithm and there is no significant difference between GA and PSO algorithms. Whiles for large sized problems, GA is better than PSO algorithm and there is a significant difference between them.

Table 8
Critical values for the two-tailed sign test at $\alpha = 0.05$ and $\alpha = 0.1$

Cases	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
$\alpha = 0.05$	5	6	7	7	8	9	9	10	10	11	12	12	13	13	14	15	15	16	17	18	18
$\alpha = 0.1$	5	6	6	7	7	8	9	9	10	14	11	12	12	13	13	14	14	15	16	16	17

Table 9
The results of the sign test

Problems	The null hypothesis	The number of wins	$\alpha = 0.05$	$\alpha = 0.1$
Small size problems	GAMS =GA	5	Reject	Reject
	GAMS=PSO	5	Reject	Reject
	GA=PSO	4	Accept	Accept
Large size problems	GA=PSO	8	Reject	Reject

5. Conclusion

Considering the fact that not all customers have the same value of profitability, it is necessary to focus on the most profitable customers and their needs. Therefore, this study provided some assessment criteria based on the literature in order to select and prioritize potential customer orders. Since there are feedback and dependence between criteria, ANP method was applied to sort customers. Next, a mathematical model was formulated to determine the best sequence of products on the two-sided assembly line. Minimizing the sum of the total utility work cost, tardiness/earliness cost, total idle cost, and total operator's error cost were considered as the objective functions of this model. The combination of these objective functions in order to determine the best sequence of products in 2SALs and MTO environment was introduced for the first time in this study. Furthermore, for each operator, factors such as operator's experience and the operator's mental deliberation thinking time are considered. The presented model was validated solving five small-sized problems using GAMS software. Then, the problem was solved using the genetic algorithm and particle swarm optimization in a large size. The performance of these algorithms was evaluated using some test problems. The results showed that the GA algorithm is better than PSO algorithm in terms of objective function and run time. Finally, a sign test for the two metaheuristics and GAMS was performed to display the main statistical differences among them. The results of this test revealed that for small-sized problems, GAMS is better than GA and PSO algorithm and there is no significant difference between GA and PSO algorithms. Whiles for large sized problems, GA is better than PSO algorithm and there is a significant difference between them.

For future research direction, interested readers can solve this problem using other tools to determine relationships among assessment criteria such as System Dynamics. Also, researchers can consider some new objectives such as maximizing the quality of products and efficiency due to choice complexity. Assign buffer to the mated station and minimizing them in MM2SALs would be a good suggestion for future research.

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Appendix A. Small sizes problems

		Operation time			Inevitable idle time		
		Model			Model		
		1	2	3	1	2	3
Problem 1							
Right station	1	7	9	6	2	1	3
	2	9	8	10	2	1	3
Left station	1	8	8	4	3	1	1
	2	7	8	6	2	2	3
Problem 2							
Right station	1	7	9	6	2	1	3
	2	9	8	12	2	3	3
Left station	2	8	8	4	3	1	1
	2	7	6	8	2	1	2
Problem 3							
Right station	1	7	10	6	2	1	3
	2	9	8	10	1	1	3
Left station	1	8	8	4	3	1	1
	2	7	6	8	2	1	3
Problem 4							
Right station	1	8	9	6	1	1	3
	2	9	8	11	2	1	4
Left station	1	9	6	4	3	2	1
	2	7	7	6	1	2	3
Problem 5							
Right station	1	8	11	6	2	3	3
	2	9	8	11	2	1	1
Left station	1	6	8	5	3	2	2
	2	7	8	7	1	1	3

Mated station	Problems 1 and 4 (The number of errors)			Problems 2 and 5 (The number of errors)			Problem 3 (The number of errors)		
	Model			Model			Model		
	1	2	3	1	2	3	1	2	3
1	4	7	3	4	7	3	4	7	3
2	2	2	4	2	5	4	2	2	4

Customer	Problem 1					Problem 2					Problem 3				
	Model (demand)			Rank	Due date	Model (demand)			Rank	Due date	Model(demand)			Rank`	Due date
	1	2	3			1	2	3			1	2	3		
1	0	2	0	2	162	1	1	2	1	160	1	1	1	3	140
2	1	0	2	3	124	1	0	1	2	120	2	2	1	2	180
3	2	1	0	1	200	2	1	0	3	209	1	1	1	1	205

Customer	Problem 4					Problem 5				
	Model (demand)			Rank	Due date	Model (demand)			Rank	Due date
	1	2	3			1	2	3		
1	0	1	0	2	152	1	2	2	1	150
2	1	1	1	3	130	0	1	1	2	132
3	1	1	1	1	180	3	1	2	3	195

Appendix B. Large sizes problems

Problem1

Operation time				
Right station	Model			
	1	2	3	4
1	7	9	6	11
2	9	8	10	9
3	5	10	7	6
4	9	6	8	11

Operation time				
Left station	Model			
	1	2	3	4
1	8	8	4	12
2	7	8	6	11
3	5	8	8	6
4	10	4	10	7

Inevitable idle time				
Right station	Model			
	1	2	3	4
1	2	1	3	1
2	2	1	3	3
3	3	1	2	2
4	2	1	3	3

Inevitable idle time				
Left station	Model			
	1	2	3	4
1	3	1	1	2
2	2	2	3	3
3	1	2	2	2
4	1	2	1	2

The number of errors				
Mated station	Model			
	1	2	3	4
1	4	7	3	2
2	2	2	4	4
3	3	4	3	5
4	3	6	6	5

Problem 2

Operation time				
Right station	Model			
	1	2	3	4
1	7	9	6	11
2	9	8	12	9
3	6	10	7	6
4	9	6	8	11

Operation time				
Left station	Model			
	1	2	3	4
1	8	8	4	12
2	7	6	8	11
3	5	8	12	4
4	10	4	10	7

Inevitable idle time				
Right station	Model			
	1	2	3	4
1	2	1	3	1
2	2	3	3	3
3	3	1	1	2
4	2	3	3	3

Inevitable idle time				
Left station	Model			
	1	2	3	4
1	3	1	1	2
2	2	1	2	3
3	1	2	2	2
4	2	2	1	2

The number of errors				
Mated station	Model			
	1	2	3	4
1	4	7	3	2
2	2	5	4	4
3	3	3	3	5
4	3	6	6	5

Problem3

Operation time				
Right station	Model			
	1	2	3	4
1	7	10	6	11
2	9	8	10	9
3	5	10	7	6
4	9	6	10	11

Operation time				
Left station	Model			
	1	2	3	4
1	8	8	4	12
2	7	6	8	13
3	5	8	10	4
4	10	4	10	7

Inevitable idle time				
Right station	Model			
	1	2	3	4
1	2	1	3	1
2	1	1	3	3
3	3	1	3	2
4	2	1	3	3

Inevitable idle time				
Left station	Model			
	1	2	3	4
1	3	1	1	2
2	2	1	3	3
3	1	2	1	2
4	1	2	1	2

The number of errors				
Mated station	Model			
	1	2	3	4
1	4	7	3	2
2	2	2	4	4
3	3	3	5	5
4	3	6	6	5

Problem 4

Operation time				
Right station	Model			
	1	2	3	4
1	7	9	6	11
2	9	8	8	9
3	5	10	7	6
4	9	4	8	11

Operation time				
Left station	Model			
	1	2	3	4
1	8	8	4	12
2	9	6	8	11
3	5	8	8	4
4	10	4	10	7

Inevitable idle time				
Right station	Model			
	1	2	3	4
1	2	1	3	1
2	2	2	3	3
3	1	1	1	2
4	2	1	3	3

Inevitable idle time				
Left station	Model			
	1	2	3	4
1	3	1	1	2
2	2	1	3	3
3	2	2	2	2
4	1	2	1	2

The number of errors				
Mated station	Model			
	1	2	3	4
1	4	7	3	2
2	5	2	4	4
3	3	3	3	5
4	3	6	6	5

Problem 1

Demand					Rank	Due date
Customer	Model					
	1	2	3	4		
1	0	2	0	1	2	162
2	1	0	2	3	4	124
3	2	1	0	0	1	200
4	1	0	0	3	3	180
5	0	2	2	1	5	183

Problem 2

Demand					Rank	Due date
Customer	Model					
	1	2	3	4		
1	1	1	1	1	2	160
2	1	0	2	2	4	120
3	2	1	1	0	1	209
4	1	1	0	3	3	180
5	0	2	3	1	5	19

Problem 3

Demand					Rank	Due date
Customer	Model					
	1	2	3	4		
1	1	1	3	1	2	140
2	1	2	2	2	4	180
3	1	2	2	2	1	200
4	0	0	1	1	3	100
5	1	1	0	0	5	120

Problem 4

Demand					Rank	Due date
Customer	Model					
	1	2	3	4		
1	2	1	0	0	2	120
2	0	0	1	1	4	110
3	2	1	0	0	1	128
4	3	1	0	0	3	100
5	1	1	1	1	5	120

Problem 5

Demand					Rank	Due date
Customer	Model					
	1	2	3	4		
1	1	1	2	1	3	110
2	2	1	1	1	2	182
3	0	1	0	1	4	120
4	1	0	2	0	1	140
5	1	2	1	2	6	200
6	2	1	2	1	5	210

Problem 6

Demand					Rank	Due date
Customer	Model					
	1	2	3	4		
1	0	0	1	1	3	90
2	2	2	1	1	2	180
3	0	0	1	0	4	65
4	1	1	1	1	1	100
5	2	1	0	0	6	80
6	1	0	1	0	5	85

Problem 7

Operation time					
Right station	Model				
	1	2	3	4	5
1	7	9	6	11	10
2	9	8	10	9	4
3	5	10	7	6	7
4	9	6	8	11	9

Operation time					
Left station	Model				
	1	2	3	4	5
1	8	8	4	12	9
2	7	6	8	11	5
3	5	8	8	4	8
4	10	4	10	7	6

Inevitable idle time					
Right station	Model				
	1	2	3	4	5
1	2	1	3	1	1
2	2	1	3	3	2
3	3	1	1	2	2
4	2	1	3	3	3

Inevitable idle time					
Left station	Model				
	1	2	3	4	5
1	3	1	1	2	1
2	2	1	3	3	1
3	1	2	2	2	1
4	1	2	1	2	2

The number of errors					
Mated station	Model				
	1	2	3	4	5
1	4	7	3	2	7
2	2	2	4	4	4
3	3	3	3	5	6
4	3	6	6	5	7

Demand							
Customer	Model					Rank	Due date
	1	2	3	4	5		
1	0	0	1	1	1	3	155
2	1	1	0	0	1	2	150
3	2	1	0	1	0	4	148
4	1	1	1	2	1	1	200
5	1	1	0	1	1	6	140
6	1	1	1	0	0	5	145

Problem 8

Operation time					
Right station	Model				
	1	2	3	4	5
1	7	9	6	11	10
2	9	8	10	9	8
3	5	10	5	6	7
4	9	6	8	11	9

Operation time					
Left station	Model				
	1	2	3	4	5
1	8	8	4	12	9
2	7	6	6	11	5
3	5	8	8	4	8
4	9	4	10	7	6

Inevitable idle time					
Right station	Model				
	1	2	3	4	5
1	2	1	3	1	1
2	2	2	3	3	2
3	3	2	1	2	2
4	2	1	3	3	3

Inevitable idle time					
Left station	Model				
	1	2	3	4	5
1	3	1	1	2	1
2	2	1	3	5	1
3	1	2	2	2	1
4	1	2	1	2	2

The number of errors					
Mated station	Model				
	1	2	3	4	5
1	4	10	3	2	7
2	2	2	4	4	4
3	3	3	5	5	6
4	3	6	6	5	7

Demand							
Customer	Model					Rank	Due date
	1	2	3	4	5		
1	1	1	0	0	0	3	120
2	1	1	1	1	1	2	185
3	0	1	0	1	1	4	170
4	1	2	1	1	1	1	200
5	1	1	1	2	2	6	180
6	0	1	1	1	1	5	150