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A Mathematical Model for an Integrated Assembly Line Regarding Learning and Fatigue Effects

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SUMMARY
In this paper, an integrated mathematical model for the balancing and sequencing problems of a mixed-model assembly line (MMAL) is developed. The proposed model minimizes the total overload and idleness times. For the sake of reality, the impact of operator's learning and fatigue issues on the optimization of the assembly line balancing and sequencing problems is considered. Furthermore, it is assumed that the Japanese mechanism is used in this assembly line to deal with the overload issue. With respect to the complexity level of the proposed model, a genetic algorithm is developed to solve the model. In order to set the parameters of the developed genetic algorithm, the well-known Taguchi method is used and the efficiency of this solution method is compared with the GAMS software using several test problems with different sizes. Finally, the sensitivity of the balancing and sequencing problems to the parameters such as station length, learning rate, and fatigue rate are analyzed and the impact of changing these parameters on the model is studied.

KEYWORDS: Mixed-model assembly line; Balancing; Sequencing; Learning and fatigue rate; Genetic algorithm.

1. Introduction

In recent years, the variation of customer demand made many manufacturers to use the Mixed-model Assembly Line (MMAL) as their main production system. Generally, the mixed-model assembly line is a type of assembly line in which several similar models of a product are assembled. In such systems, there is a basic product and by changing its features can lead to producing other similar products.

With respect to the similarity of the production processes, the resources availability is a significant issue in MMAL. Accordingly, the homogeneity level of production processes in MMAL has to be minimized.[1] On the other hand, different factors such as the cycle time, number of stations, the order of processes, and the assembly line's balance can considerably affect the utilization of this type of production lines.

The mixed-model assembly lines can be classified into paced and un-paced assembly lines based on the movement of finished parts through the stations. The earlier include assembly lines in which each work station is given the same cycle time and this cycle time determines the production rate. In contrast, in un-paced assembly lines, there is no fixed time to complete the tasks, and works are moved to the next station immediately upon the completion. Furthermore, the paced assembly lines can perform in both moving and synchronous states. While in synchronous lines, the workpieces are

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moved periodically from station to station, in moving assembly lines, the parts move continuously and workers perform some tasks while walking along with a moving conveyor.[2]

In the moving assembly lines, there are two significant issues, which include workload and learning and fatigue effects.

Workloads occur when a workpiece reaches the end of a station, while its work is not finished yet. There are two mechanisms called Japanese and American mechanisms to manage the workload issue in working assembly lines. In the Japanese mechanism, the conveyor is stopped by the operator till finishing the work. In the American mechanism, while the operator leaves the unfinished work and goes back to the upstream side of the station to work on the next piece, several extra workers finished the left work.[3] In this paper, the mixed-model moving assembly line with the Japanese mechanism is scrutinized.

The other issue in MMALs is the positive influence of learning and negative influence of fatigue on workers' efficiency. The learning effects on workers' efficiency was first studied by Wright.[4,5] Despite many researches in the assembly lines area, few researches consider the relationship between learning effects and operation time. Besides the learning effect, both physical and mental fatigues, which lead to decreasing in workers' performance level and consequently the production rate, can be regarded as another effective factor in MMALs.[6] Therefore, it is better to consider the fatigue issue and its effects on assembly lines.

In this paper, the balancing and sequencing problems of the MMALs are studied, in which the Japanese mechanism is used to handle the workload and learning and fatigue are considered as effective factors on production rate. The organization of this paper is as follows: the problem definition and model formulation are discussed in Section 3. In Section 4, the solution procedures are presented. To analyze the performance of proposed algorithms, several numerical examples are studied in Section 5. In Section 6, a sensitivity analysis for the model is performed. Finally, the conclusions and future researches suggestions are given in Section 7.

2. Literature Survey

The main concentration of this paper is on the simultaneous balancing and sequencing problems in the mixed-model assembly lines. Accordingly, the relevant works in this area are reviewed in the current section.

2.1. Assembly line balancing problem

The balancing issue in the assembly lines is studied widely by the researchers. For example, Mamun et al.,[7] focused on the parallel stations in the mixed-model assembly line balancing problem. A multi-objective model which aims to minimize the cycle time, minimize the number of workstations, and maximize the line efficiencies in the assembly line balancing problem is studied by Rabbani et al.[8] Zeynel Abidin Cil et al.,[9] evaluated the robotic mixed-model assembly line balancing problem in which both assigning tasks and robots to the stations are considered. The mixed-model assembly line balancing and worker assignment problem are studied by Ramezanian and Ezzatpanah.[10] Zheng-mei Jie et al.[11] presented a multi-objective genetic algorithm for mixed-model two-sided assembly line balancing problem with respect to minimizing the number of stations, the balance index, and the wait time, simultaneously. Zahiri et al.[12] presented a balancing model for U-shaped mixed-model assembly lines in which optimizing total costs and workload of stations are aimed. Furthermore, they considered zoning and task duplications as constraints in their study. Furthermore, Delice et al.[13] introduced a modified particle swarm optimization algorithm to solve mixed-model two-sided assembly line balancing problem. Li et al.[14] studied comprehensively two-sided assembly line balancing problems. They also developed two new decoding schemes to balance the workload in the assembly line. Also, Zhang and Kucukkoc[15] investigate the model variations for parallel two-sided assembly lines. Recently, Li et al.,[16] evaluated two-sided assembly line balancing problems with respect to the setup times in the robotic industry and proposed a meta-heuristic method to solve the developed model.

For more details in studying the assembly line balancing problems, the authors refer to Boysen et al.,[17] Kriengkorakot,[18] Sivasankaran,[19] Girwal[20] who reviewed this issue comprehensively.

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2.2. Assembly line sequencing problem

There are numerous researches that focused on sequencing problem. Sarker and Pan[21] studied the problem of minimizing the total cost of the idle and utility times incurred in sequencing problem of the mixed-model assembly line that manufactures mixed models of sheet metal cabinets. Ref. [22] presented the sequencing problem of mixed-model assembly lines, which aimed to fulfill the customer demands and minimize the total work overload. In this study, the fixed-rate launching and closed stations are considered too. Boysen et al.[1] reviewed the three major planning approaches in assembly line models including mixed-model sequencing, car sequencing, and level scheduling. Chutima and Naruemitwong[4] proposed a Pareto biogeography-based optimization approach to solve a mixed-model sequencing problem, which aimed to minimize the variance of production rate, the total sequence-dependent setup time, and the total utility work, simultaneously. Xiaobo and Ohno[23] considered the Japanese mechanism in a mixed-model assembly line with sequencing problem, which aimed to minimize the total conveyor stoppage time. Rauf et al.,[24] considered a multi-criteria model sequence problem with respect to flow time, makespan, and idle time and proposed a smart heuristic algorithm for multi-criteria optimization.

Based on Scholl and et al.,[20] a few researchers considered the learning and fatigue as effective factors in the mixed-model assembly line sequencing problem. For example, the deteriorating jobs, the learning effect, and the setup times are considered by Lee.[25]Salehi and et al.[26] considered past-sequence-dependent setup times, deteriorating jobs, and learning effects in an identical parallel machines scheduling problem. Torres et al.[27] studied the preventive maintenance events of machines and the dependence between processing time of the jobs and the deterioration of the machine in the parallel machine problems. Chutima and Naruemitwong[4] considered the learning effect in the sequencing problem of the two-sided assembly line.

Despite wide consideration of learning effect in the flow shop scheduling problems, a few researches considered this issue in mixed-model assembly balancing and sequencing.

2.3. Balancing and sequencing problem

According to the previous relevant works on the assembly line balancing and sequencing problem, there exist several researches in which balancing and sequencing problems are considered together. Zhan and Zhang[28] studied a stochastic mixed-model U-line balancing and sequencing problem and introduced a genetic algorithm to solve this problem. Kucukkoc and Zhang[29] considered balancing and sequencing problems simultaneously in a mixed-model parallel two-sided assembly line and presented an ant colony optimization algorithm to solve the proposed problem. Nie et al.[30] developed an integrated approach for flexible mixed-model assembly lines in which both balancing and sequencing problems are regarded with respect to the precedence relations and task duplications. Maurizio Faccio et al.[31] employed a supplementary flexible workforce as a balancing and sequencing hierarchical approach to deal with paced mixed-model assembly lines. Jintao Dong et al.[3]evaluated the mixed-model assembly U-line balancing and sequencing problem with respect to the stochastic task times and attempted to optimize the expectation of work overload time. Manavizadeh et al.[32] presented a new multi-objective heuristic algorithm to solve the sequencing and balancing problems in U-shaped mixed models, which aimed to optimize the cycle times, the wastages, and the work overload, simultaneously. In ref. [33], the mathematical model for integrated assembly line balancing and sequencing is developed and the length and number of stations of the assembly line for a continuous conveyor are considered. Also, Zhang et al.,[34] proposed a dragonfly algorithm-based approach to solve the balancing and sequencing problem of mixed-model U-shaped robotic assembly line.

While the application of the Japanese mechanism is significantly effective in balancing and sequencing problems of mixed-model assembly lines, all the abovementioned works studied the American mechanism in case of work overload.

To indicate the distinction of current study and previous relevant works, Table I indicates a brief review of these works, besides the features of current paper.

As shown in Table I, the main contribution of the current paper is focused on sequencing and balancing problems in mixed-model assembly lines besides the consideration of both learning and fatigue effects. Furthermore, the Japanese mechanism is regarded to handle the overloads at the stations, while to the best of authors' knowledge, no research on this issue has been published before.

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Table I. Brief review of the related literature and contributions of this study.

Author	Problems		Moving lines approaches		Effects		Assembly line					Mathematical model	Solving method		
							Straight			U shape					
	Balance	Sequences	US	Japan	Fatigue	Learning	One way	Two way	Parallel	One way	Two way		Exact	Meta-heuristic	Innovative
Mamun et al.[7]	✓								✓			✓		✓	
Ramezanian and Ezzatpanah[10]	✓						✓					✓	✓	✓	
Zheng-mei Jie et al.[11]	✓							✓						✓	
Zahiri et al.[10]	✓									✓		✓	✓		
Masoud Rabbani et al.[8]	✓									✓		✓		✓	
Yılmaz Delice et al.[13]	✓							✓						✓	
Zixiang Li et al.[14]	✓							✓						✓	✓
Zeynel Abidin Cil et al.[9]	✓						✓					✓			✓
Li et al.[16]	✓							✓				✓		✓	
Scholl et al.[20]		✓	✓				✓				✓				✓
Xiaobo and Ohno[22]		✓		✓			✓								✓
Sarker and Pan[21]		✓	✓				✓					✓	✓		
Chutima and Naruemitwong[4]		✓	✓			✓		✓						✓	
Lee[23]		✓			✓	✓									✓
Salehi et al.[24]		✓			✓	✓						✓		✓	
Torres et al.[25]		✓			✓							✓			✓
Rauf et al.[24]		✓					✓					✓		✓	
Zhan and Zhang[26]	✓	✓								✓				✓	
Kucukkoc and Zhang[27]	✓	✓						✓	✓					✓	
Jietao Dong et al.[3]	✓	✓	✓							✓		✓		✓	
Li Nie et al.[28]	✓	✓					✓					✓		✓	
Manavizadeh et al.[30]	✓	✓	✓				✓			✓		✓			✓
Maurizio Faccio et al.[29]	✓	✓					✓					✓	✓		
Defersha and Mohebalizadeh-gashti[33]	✓	✓					✓					✓		✓	
Zhang et al.[34]	✓	✓								✓		✓		✓	
This study	✓	✓		✓	✓	✓	✓					✓		✓	

3. Mathematical Model

In this paper, the simultaneous balancing and sequencing problems of mixed-model moving assembly lines with Japanese mechanism to handle the overload is aimed. It is assumed that the mixed models are fed periodically into an assembly line in which there is a conveyor with fixed speed that connects several closed workstations together. Also, a boundary is determined in each station in which working on the pieces by operators is permitted.

Because of the Japanese mechanism, it is supposed that the operator walks along the station to finish working on a workpiece, and then returns to upstream to begin working on a new workpiece. An overload occurs when working on a workpiece is not finished in time. At these times, the assembly line is stopped till finishing the work on pieces. On the other hand, the waiting time of an operator for arriving at the next workpiece is considered as idleness. Furthermore, it is assumed that working on the workpieces starts from the upstream side of stations at the first sequence of production cycles.

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When a piece is under work and the next piece arrives, the operators have to stop the conveyor, finish the current work, and then return to upstream side to begin working on the arrived next piece.

With respect to the conveyor's fixed speed (V_c) and the time of arrival of two successive workpieces (a), the constant distance between two successive sequences (w) can be simply calculated using Eq. (1):

$$w = a * V_c. \tag{1}$$

As mentioned before, the deterioration and learning effects are considered in the proposed assembly line. To consider the deterioration effect, the model proposed by Toksari et al. [35] is used. In this model, it is assumed that there is a linear relationship between the start time of job jth (ST_j) and the duration time of task on this job. Also, the log-linear curve form of the learning effect is employed to consider the learning effects in balancing and sequencing problems. Hence, the effect of deterioration and learning factors can be formulated by Eq. (2):

$$P_{jr} = \left[P_j + \beta ST_j\right] r^{\alpha} \quad j, r = 1, 2, \ldots, n, \quad \alpha \leq 0, \beta \geq 0, \tag{2}$$

where P_j is the basic task time of jth job, α and β are learning and deterioration effects, respectively, ST_j is start time of jth job and P_{jr} is the actual task time of jth job ordered in rth sequence.

3.1. Assumptions

The problem is modeled with the following assumptions:

- The assembly line includes a conveyor that is moving at a constant speed ($V_c = 1$), continuously.
- The entrance order of the workpieces to the line determines their passing order through the stations.
- The operator's walking time to return to the upstream side of station is ignorable.
- Demands for the models are exactly known.
- The Japanese mechanism is used so that the operator stops the conveyor and prevents arriving next pieces when he fails to finish working on current piece.
- The scheduling of operations is based on the earliest start time.
- The entrance of workpieces is periodic.
- A single shared station is considered for the activities present in two or more product models.

3.2. Indexes

i: Indicator for the sequences ($i \in \{1, 2, \ldots, NI\}$, $NI = \sum_m d_m$)
j: Indicator for the stations ($j \in \{1, 2, \ldots J\}$)
k: Indicator for the jobs ($k \in \{1, 2, \ldots, K\}$)
m: Indicator for the model of product ($m \in \{1, 2, \ldots, M\}$)

3.3. Parameters

d_m Demand for model m
a Time between entering two successive workpieces, minute.
L_j Length of station j
t_{km} Basic task time of the kth job of the model m
M A large number
ε A small number
α Learning rate
β Fatigue rate

$$W^m_{k_1,k_2} = \begin{cases} 1; \text{ If task } k_1 \text{ is precedence of task } k_2 \text{ in model } m \\ 0; \text{ Otherwise} \end{cases}$$

$$B^k_{m_1,m_2} = \begin{cases} 1; \text{ If task } k \text{ is common in models } m_1 \text{ and } m_2 \\ 0; \text{ Otherwise} \end{cases}$$

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```
Begin
Set W as predecessor matric,
Set i:=0, LIST:={}
Do while i< jobs number
i=i+1;
according to W set List := {s|s ∈ jobs be the predecessor of i}
while List ≠ ∅ do
begin
j=0;
select a node s in LIST;
   for j=1 to jobs number
         if W(j,s)=1 then set
            W(j,i)=1;
         end
  end
 end
end
for ip =1 to jobs number
for jp=1 to jobs number and ip<>jp
   if W(ip,jp)<>1 and W(jp,ip) <>1  then set
      W(ip,jp)=1;
      W(jp,ip)=1;
   end
end
end
set E=W;
```

Fig. 1. Pseudocode for determining matrix E.

$$F_{km} = \begin{cases} 1; \text{ If task } k \text{ belongs to Model } m \\ 0; \text{ Otherwise} \end{cases}$$

$$E^{m}_{k_1,k_2} = \begin{cases} 1; \text{ If task } k_1 \text{ can be performed in model } m \text{ before task } k_2 \\ \quad \text{according to the precedence relationship between tasks} \\ 0; \text{ Otherwise} \end{cases}$$

It should be noted that the parameter $E^{m}_{k_1,k_2}$ can be defined using the parameter $W^{m}_{k_1,k_2}$. In this manner, the topological orders of jobs should be defined first via the method described in ref. [32], and then the matrix E is determined with respect to the algorithm indicated in Fig. 1.

3.4. Variables

$$x_{im} = \begin{cases} 1; \text{ If a product of model } m \text{ is located at the } i\text{th position of the production sequence} \\ 0; \text{ Otherwise} \end{cases}$$

$$y^{i'j'}_{ij} = \begin{cases} 1; \text{ If sequence } i \text{ is present at station } j \text{ during the overtime for sequence } i' \text{ in station } j' \\ 0; \text{ Otherwise} \end{cases}$$

$$r^{i'j'}_{i} = \begin{cases} 1; \text{ If there is overtime for sequence } i' \text{ in station } j' \text{ before entering sequence } i \text{ in station 1} \\ 0; \text{ Otherwise} \end{cases}$$

$$P^{j}_{km} = \begin{cases} 1; \text{ If task } k \text{ of model } m \text{ is assigned to station } j \\ 0; \text{ Otherwise} \end{cases}$$

$$f^{m}_{k'k} = \begin{cases} 1; \text{ If task } k' \text{is performed before task } k \text{ in model } m \\ 0; \text{ Otherwise} \end{cases}$$

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$$q_j = \begin{cases} 1; \text{ If at least one task is allocated to the station } j \\ 0; \text{ Otherwise} \end{cases}$$

u_{ij}: The required time to complete the incomplete operation of the ith product at station j

ID_{ij}: Idle time of operator to arrive the ith sequence at the jth station (active and Inactive stations)

ID'_{ij}: Idle time of operator related to active stations to arrive the ith sequence at the jth station (The active station is in reverse to the inactive station of the station where at least one task is assigned)

ST_{ij}: The total stop time in the ith sequence at jth station

S_{ij}: The stop time in the ith sequence at jth station without the overtime for sequence i at station j

BT_{ij}: The start time of sequence i in station j

ET_{ij}: The end time of sequence i in station j

AT_{ij}: The arrival time of sequence i at station j

$\hat{t}^i_{km}$: The actual processing time of the task k of the model m, influenced by learning and fatigue in the ith sequence.

3.5. The nonlinear mathematical model

The nonlinear mathematical form of the proposed model is as follows:

$$\text{Min}: Z = \sum_i \sum_j u_{ij} + ID'_{ij} \tag{3}$$

$$\sum_j P^j_{km} = F_{km} \quad \forall k,m, \tag{4}$$

$$W^m_{k_1,k_2} * \sum_j j * P^j_{k_1,m} \le \sum_j j * P^j_{k_2,m} \quad \forall\, k_1, k_2 \in k \quad \& \quad \forall m, \tag{5}$$

$$B^k_{m_1,m_2} * P^j_{km_1} \le P^j_{km_2} \quad \forall m_1, m_2 \in m, \quad m_1 < m_2 \quad \& \quad \forall j, k, \tag{6}$$

$$M * \sum_k \sum_m P^j_{km} \ge \sum_k \sum_m P^{j+1}_{km} \quad \forall j, \tag{7}$$

$$\sum_m x_{im} = 1 \quad \forall\, i, \tag{8}$$

$$\sum_i x_{im} = d_m \quad \forall m, \tag{9}$$

$$AT_{i1} = (i-1)\, a + \sum_{i'<i} \sum_{j'} u_{i'j'} * r^{i'j'}_i \quad \forall\, i, \tag{10}$$

$$(i-1)\, a + \sum_{i''<i'} \sum_{j''} u_{i''j''} * r^{i''j''}_i + \sum_{j''<j'} u_{i'j''} * r^{i'j''}_i \ge \left(ET_{i'j'} - u_{i'j'}\right) + \varepsilon - M\left(1 - r^{i'j'}_i\right) \quad \forall\, i,i',j' \quad i > i', \tag{11}$$

$$(i-1)\, a + \sum_{i''<i'} \sum_{j''} u_{i''j''} * r^{i''j''}_i + \sum_{j''<j'} u_{i'j''} * r^{i'j''}_i \le \left(ET_{i'j'} - u_{i'j'}\right) + M * r^{i'j'}_i \quad \forall\, i,i',j' \quad i > i', \tag{12}$$

$$AT_{ij} = \sum_{j'<j} L_{j'} + \sum_{j'<j} ST_{ij'} + AT_{i1} \quad \forall\, i, (j > 1)\,, \tag{13}$$

$$BT_{1j} = AT_{1j} \quad \forall\, j, \tag{14}$$

$$BT_{i+1.j} = ET_{ij} + ID_{i+1,\ j} \quad \forall\, i < NI,\ \forall\, j, \tag{15}$$

$$ET_{ij} = BT_{ij} + \sum_k \sum_m \hat{t}^i_{km} * x_{i,m} * P^j_{km} \quad \forall\, i,j, \tag{16}$$

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$$S_{ij} = \sum_{i' \neq i} \sum_{j'} y_{ij}^{i'j'} * u_{i'j'} \quad \forall\, i, j, \tag{17}$$

$$ST_{ij} = S_{ij} + u_{ij} \quad \forall\, i, j, \tag{18}$$

$$u_{ij} = \max \left\{ 0, \left[\left(ET_{ij} - \left(\sum_{j' \leq j-1} ST_{ij'} + S_{ij} \right) \right) - \left(\sum_{j' \leq j} L_j + AT_{i1} \right) \right] \right\} \quad \forall i, j, \tag{19}$$

$$ET_{i'j'} - u_{i'j'} \geq AT_{ij} - M \left(1 - y_{ij}^{i'j'} \right) \quad \forall\, i, j, i', j', \tag{20}$$

$$ET_{i'j'} - u_{i'j'} \leq AT_{ij} - \varepsilon + M * y_{ij}^{i'j'} + M * h_{iji'j'}^{1} \quad \forall\, i, j, i', j', \tag{21}$$

$$ET_{i'j'} - u_{i'j'} \leq AT_{i,j+1} + M * \left(1 - y_{ij}^{i'j'} \right) - u_{i'j'} * y_{ij}^{i'j'} \quad \forall\, i, j, i', j', \tag{22}$$

$$ET_{i'j'} - u_{i'j'} \geq AT_{i,j+1} + \varepsilon - M * y_{iji'j'} - M * h_{iji'j'}^{2} - u_{i'j'} * y_{ij}^{i'j'} \quad \forall\, i, j, i', j', \tag{23}$$

$$h_{iji'j'}^{1} + h_{iji'j'}^{2} = 1 - y_{ij}^{i'j'} \quad \forall\, i, j, i', j', \tag{24}$$

$$ID_{ij} = \max \left\{ 0 \,, \left[AT_{ij} - ET_{i-1,\, j} \right] \right\} \quad \forall i > 1, j, \tag{25}$$

$$\hat{t}_{km}^{i} = \left[t_{km} + \beta \left(\sum_{j} BT_{ij} * P_{km}^{j} + \sum_{k' \neq k} \hat{t}_{k'm}^{i} * f_{k'k}^{m} \right) \right] * i^{\alpha} * x_{im} \quad \forall\, k, m, i, \tag{26}$$

$$f_{k'k}^{m} + f_{kk'}^{m} = \sum_{j} P_{km}^{j} * P_{k'm}^{j} \quad \forall\, m, k, k' \neq k, \tag{27}$$

$$f_{k'k}^{m} \leq E_{k'k}^{m} \quad \forall\, k' \neq k,\ \forall\, m, \tag{28}$$

$$ID'_{ij} \geq ID_{ij} - M \left(1 - q_j \right) \qquad \forall\, i > 1, j, \tag{29}$$

$$ID'_{ij} \leq ID_{ij} + M \left(1 - q_j \right) \qquad \forall\, i > 1, j, \tag{30}$$

$$ID'_{ij} \leq M q_j \qquad \forall\, i > 1, j, \tag{31}$$

$$\sum_{k} \sum_{m} P_{km}^{j} \leq M q_j \qquad \forall i > 1, j. \tag{32}$$

In Eq. (3), the minimization of total overload and idle time is considered as the objective function. Assignment of each task of the product model only to one station is ensured by Eq. (4). Equation (5) indicates the precedence relationships between the activities of product models. Equation (6) guarantees that tasks is common in two or more product models and should be assigned to only one station. Equation (7) indicates that there is no gap among two consecutive opened workstations. Assignment of one product to each sequence is stated by Eq. (8). Equation (9) ensures that the demands are completely met. Equation (10) indicates the arrival time of sequences at the first station. Also, the relationship between stopping conveyor at stations and the arrival time of sequences at the first station is stated by Eq. (11). Accordingly, Eqs. (12) and (13) denote the variable $r_i^{i'j'}$. The arrival time of each sequence at different stations is stated by Eq. (14). Equation (15) indicates that the start time of each station's activities depends on the arrival time of the first sequence. The start time and completion time of tasks on sequences at different stations are denoted, respectively, by Eqs. (16) and (17). Equation (18) denotes the total stoppage times of sequences in stations. The overload time of sequences in stations is calculated by Eq. (19). The variable $y_{ij}^{i'j'}$ is stated by Eqs. (20)–(24). The idle time of sequences in stations is stated by Eq. (25). The deterioration and learning effects on actual task time of product models with respect to the sequence are considered by Eq. (26). Equation (27) ensures that one of the parameters $f_{k'k}^{m}$ or $f_{kk'}^{m}$ takes the value of one if two activities are assigned to the same station. Equation (28) determines which activities can be done before the others. The idle time in stations is indicated in Eqs. (29)–(32).

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3.6. Linearization of the proposed model

The model presented in Section 3.6 is a nonlinear mathematical model. For the sake of simplicity, some changes are needed to transform the model into a linear mathematical model. These changes are explained in the current subsection.

To linearize the expression $u_{i'j'} * r_i^{i'j'}$ in Eqs. (10)–(12), $UR_{ij}^{i'j'}$ is used as an extra variable. Accordingly, Eqs. (33)–(35) should be added to the proposed model.

$$UR_{ij}^{i'j'} \leq u_{i'j'}, \tag{33}$$

$$UR_{ij}^{i'j'} \geq u_{i'j'} - M * \left(1 - r_i^{i'j'}\right), \tag{34}$$

$$UR_{ij}^{i'j'} \geq 0. \tag{35}$$

To linearize the term $\hat{t}_{km}^{i} * x_{i,m} * P_{km}^{j}$, Eqs. (36)–(41) are employed. It should be noted that Eqs. (36)–(38) are used to linearize the term $x_{i,m} * P_{km}^{j}$. Furthermore, the term $\hat{t}_{km}^{i} * xP_{km}^{ij}$ is linearized using Eqs. (39)–(41). Hence, the term $\hat{t}_{km}^{i} * x_{i,m} * P_{km}^{j}$ is replaced by a newly added variable T_{km}^{ij}.

$$x_{i\ ,m} + P_{km}^{j} \leq 1 + xP_{km,}^{ij} \tag{36}$$

$$x_{i\ ,m} + P_{km}^{j} \geq 2 * xP_{km,}^{ij} \tag{37}$$

$$xP_{km}^{ij} \in \{0, 1\}, \tag{38}$$

$$T_{km}^{ij} \leq \hat{t}_{km,}^{i} \tag{39}$$

$$T_{km}^{ij} \geq \hat{t}_{km}^{i} - M * \left(1 - xP_{km}^{ij}\right), \tag{40}$$

$$T_{km}^{ij} \geq 0. \tag{41}$$

To linearize the term $y_{ij}^{i'j'} * u_{i'j'}$, the variable is $UY_{ij}^{i'j'}$ is defined in Eqs. (15), (22), and (23). In this manner, the following equations are added to the proposed model.

$$UY_{ij}^{i'j'} \leq u_{i'j',} \tag{42}$$

$$UY_{ij}^{i'j'} \geq u_{i'j'} - M * \left(1 - y_{ij}^{i'j'}\right), \tag{43}$$

$$UY_{ij}^{i'j'} \geq 0. \tag{44}$$

The following equations are used to modify the max functions in Eqs. (19) and (25).

$$u_{ij} \leq \left(ET_{ij} - \left(\sum_{j' \leq j-1} ST_{ij'} + S_{ij}\right)\right) - \left(\sum_{j' \leq j} L_j + AT_{i1}\right) + M * n_{ij}, \tag{45}$$

$$u_{ij} \geq \left(ET_{ij} - \left(\sum_{j' \leq j-1} ST_{ij'} + S_{ij}\right)\right) - \left(\sum_{j' \leq j} L_j + AT_{i1}\right) - M * n_{ij}, \tag{46}$$

$$u_{ij} \leq M * \left(1 - n_{ij}\right), \tag{47}$$

$$\left(ET_{ij} - \left(\sum_{j' \leq j-1} ST_{ij'} + S_{ij}\right)\right) - \left(\sum_{j' \leq j} L_j + AT_{i1}\right) \leq M * \left(1 - n_{ij}\right), \tag{48}$$

$$n_{ij} \in \{0, 1\}, \tag{49}$$

$$ID_{ij} \leq AT_{ij} - ET_{i-1,\ j} + M * v_{ij}, \tag{50}$$

$$ID_{ij} \geq AT_{ij} - ET_{i-1,\ j} - M * v_{ij,} \tag{51}$$

$$ID_{ij} \leq M * \left(1 - v_{ij}\right), \tag{52}$$

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$$AT_{ij} - ET_{i-1,\ j} \leq M * \left(1 - v_{ij}\right), \tag{53}$$

$$v_{ij} \in \{0,\ 1\}\ . \tag{54}$$

The Eq. (26) is replaced by Eq. (55).

$$\hat{t}^i_{km} = \left[t_{km} * x_{im} + \beta \left(\sum_j BT_{ij} * P^j_{km} * x_{im} + \sum_{k' \neq k} \hat{t}^i_{k'm} * f^m_{k'k} * x_{im} \right) \right] * i^{\alpha}. \tag{55}$$

The terms $BT_{ij} * P^j_{km} * x_{im}$ and $\hat{t}^i_{k'm} * f^m_{k'k} * x_{im}$ are, respectively, replaced by terms $Bx\,P^{ij}_{km}$ and $T f^{im}_{k'k}$. As a consequence, Eqs. (56)–(64) are added to the model.

$$Bx\,P^{ij}_{km} \leq BT_{ij}, \tag{56}$$

$$Bx\,P^{ij}_{km} \geq BT_{ij} - M * \left(1 - x\,P^{ij}_{km}\right), \tag{57}$$

$$Bx\,P^{ij}_{km} \geq 0, \tag{58}$$

$$f^m_{k'k} + x_{im} \leq 1 + x f^{im}_{k'k}, \tag{59}$$

$$f^m_{k'k} + x_{im} \geq 2 * x f^{im}_{k'k,} \tag{60}$$

$$x f^{im}_{k'k} \in \{0,\ 1\}\ , \tag{61}$$

$$T f^{im}_{k'k} \leq \hat{t}^i_{k'm,} \tag{62}$$

$$T f^{im}_{k'k} \geq \hat{t}^i_{k'm} - M * \left(1 - x f^{im}_{k'k}\right), \tag{63}$$

$$T f^{im}_{k'k} \geq 0. \tag{64}$$

Finally, the term $DP^{jm}_{kk'}$ is used to linearize the nonlinear term $P^j_{km} * P^j_{k'm}$ in Eq. (29) via considering Eqs. (65)–(67).

$$P^j_{km} + P^j_{k'm} \leq 1 + DP^{jm}_{kk'}, \tag{65}$$

$$P^j_{km} + P^j_{k'm} \geq 2 * DP^{jm}_{kk'}, \tag{66}$$

$$DP^{jm}_{kk'} \in \{0,\ 1\}. \tag{67}$$

4. The Solution Approach

As discussed in ref. [28], the sequencing problem of assembly lines is an NP-hard problem. It is obvious that consideration of balancing problems and the sequencing problem complicates the assembly line models. Furthermore, the addition of fatigue and deterioration parameters to the model increases its complexity. As a consequence, it can be concluded that the proposed model is Np-hard as well.

Based on the complexity of the proposed model, the genetic algorithm as a well-known meta-heuristic algorithm is suggested to solve the model. The genetic algorithm, introduced by Holland[36] in 1975, is basically inspired by evolution phenomenon. In this algorithm, it is assumed that there is an initial generation in which the better members have more possibility to transfer their features to the next generations. Accordingly, the new members of each generation inherit the good features of the best members who form the parents of current generation and in this way, the evolution occurs. In order to model this phenomenon as a mathematical solution approach, the genetic algorithm starts with an initial population. In each iteration of the algorithm, the best members based on their fitness function are selected as parents. Then, a crossover operator is applied on selected parents to form a portion of next generation's members as children. Also, a mutation operator is employed to make another portion of next generation's members and retain the diversity of algorithms in searching the solution area. These steps are repeated till a stop condition occurs (in this paper, the maximum number of iterations is considered as a stop criterion).

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4.1. Solution representation

One of the main requirements of all meta-heuristic algorithms is determining a suitable solution representation, which indicates the encoding structure of the solutions. In this paper, two attributes are considered in representing each solution so that the attribute B is related to the balancing problem, while the attribute S deals with the sequencing problem.

On the other hand, the attribute S, which is determined via a set of numbers indicates the sequence of the product models with respect to its demands. For example, if there are four demands for the product model 1, three demands for the product model 2, and two demands for the product model 3, then one feasible solution of attribute S can be [2 1 1 3 2 3 1 2 1].

4.2. Crossover operation

The crossover operator is used as a recombination technique by which the genetic information of parents is employed to generate new children offspring for next generations. The crossover operator used separately for the balancing and sequencing attributes of solutions is randomly based on one-point or two-point method. Furthermore, the selection of the parents, on which the crossover operator is applied, is based on the roulette-wheel technique. Accordingly, the parents with better fitness function are more possible to be selected for applying the crossover operator.

4.3. Mutation operation

The mutation operator is used to reinforce the diversification in searching the solution area. According to the distinct attributes, two different methods are used in order to apply this operator on balancing and sequencing attributes. Similar to crossover operator, the selection of parents for mutation operator is based on the roulette-wheel technique.

4.3.1. Mutation operation for the balancing attribute. The mutation operator used for the balancing attribute is based on relocating a cell that belongs to a station. As a result, the number of stations may remain unchanged or increase or decrease one unit. Then, a gene from the selected parent–offspring is randomly determined and all subsequent genes are reordered with respect to the precedence relationships. In this way, the new child's offspring is generated.

4.3.2. Mutation operation for the sequencing attribute. The mutation operator used for the sequencing attribute is based on the swapping demands of two randomly selected product models.

5. Parameters Setting

To set the parameter of the proposed meta-heuristic algorithm, the well-known Taguchi approach is used, based on Niaki and Ershadi.[37] In this manner, three different levels are considered for each parameter and the smaller-the-better approach is used to set the Taguchi loss function. Table II indicates different levels of the proposed algorithm's parameters.

Table III indicates the values of the assembly line parameters assumed in this paper.

Furthermore, Table IV denotes the demand for products (d_m) and the duration of each activity (t_{km}). Also, the precedence relationships of activities for each product model is shown in Fig. 2.

Finally, the optimal values for the proposed genetic algorithm are indicated in Table V. It should be noted that, in order to apply the Taguchi approach, the L27 design is implemented in MINITAB 17.

6. Computational Tests

To evaluate the efficiency of the proposed model, the solution method is applied on several test problems via MATLAB (R2015) and the results are compared with well-known commercial software GAMS (24.7) with the SCIP solver. The activity time is generated randomly based on the uniform distribution between zero and the station length ($t \sim U(0, L)$)). The results achieved by both methods are indicated in Table VI. As shown in Table VI, both GAMS and the proposed genetic algorithm performed equivalently in the case of small-scale problems. But, in the case of the large-scale test problem, it can be clearly seen that the GAMs fails to solve the test problems during 10,800 s while the developed genetic algorithm achieved a good solution in a rational time.

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Table II. Different levels for the parameters of the genetic algorithm.

	Levels		
Parameter	**Low**	**Medium**	**High**
Max-It	100	150	200
nPop	10	20	25
PC	0.7	1.3	1.8
PM	0.2	0.7	1
Select pressure	5	8	15
pSingleB	0.3	0.5	0.7
pSingleS	0.3	0.5	0.7

Table III. Values of the parameters.

Parameter	V_c	a	m	L_j	α	β
Value	$1\frac{\text{m}}{\text{s}}$	3 min	2	8	−0.5	0.1

Table IV. Problem data.

	Time duration	
Activity	**Model 1**	**Model 2**
1	5	4
2	3	4
3	6	5
4	7	0
5	5	7
6	2	6
7	5	0
8	6,5	0
9	7	3
Demand	3	5

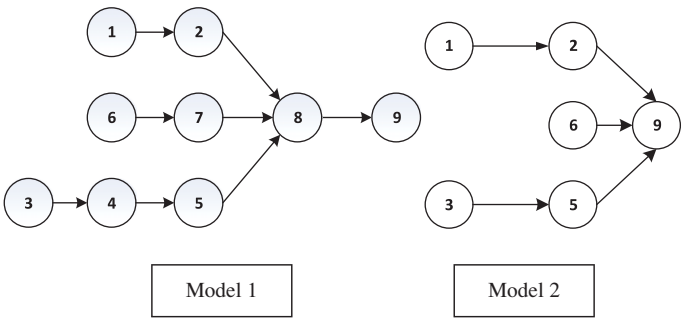


Fig. 2. The precedence network for the activities.

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Table V. Optimal levels for genetic algorithm parameters.

Parameter	Optimal level
Max-It	150
nPop	25
PC	1.8
PM	1
Select pressure	15
pSingleB	0.7
pSingleS	0.5

Table VI. A summary of the GAMS response and time and the genetic method for problems.

Row	Models demand	Activity count	Genetic			SCIP	Gap (%)	CPU time	
			Worst	Best	Average			Genetic	SCIP
1	[1-1]	4	2.2086	2.2086	2.2086	2.2086	0	0.1626	19.11
2	[1-2]	4	5.847	5.847	5.847	5.847	0	0.2476	424.22
3	[2-1]	4	5.3055	5.3055	5.3055	5.305	0	0.2750	255.16
4	[2-2]	4	10.6716	10.6716	10.6716	–	–	0.4565	–
5	[2-3]	4	10.999	10.999	10.999	–	–	0.4640	–
6	[7-5]	4	34.6875	34.6875	34.6875	–	–	1.9560	–
7	[2-3]	9	52.5261	42.2821	46.2562	–	–	256.85	–
8	[3-3]	9	51.1404	39.7050	42.0167	–	–	284.41	–
9	[4-4]	9	62.8788	45.7805	52.5051	–	–	471.431	–
10	[3-5]	9	70.9316	57.0782	62.4472	–	–	449.48	–
11	[4-7]	9	109.031	85.711	96.6455	–	–	802.18	–

7. Sensitivity Analysis of Parameters

To study the influence of the parameters on the model, a sensitivity analysis is implemented in this section with respect to changing of parameters such as the station length, learning rate, and fatigue rate.

7.1. Analysis of sensitivity to the station length

Figure 2 indicates the relationship between the changing in the station length and the objective function. Accordingly, it can be concluded that increase in station length leads to a decrease in the objective function, although this correlation is not uniform.

As seen in Fig. 3, 0 to −30% change in the station length, changes almost linearly the objective function. Also, it is obvious that with more decrease in the station length, the increase of the objective becomes sharper. In fact, when the station length is shorter than a corresponding value with respect to the maximum activity time, the overload occurs and as a consequence, the objective function increases significantly.

On the other hand, an increase in the station length, decreases the objective function. If the station length exceeds a threshold, which corresponds to the total time of all activities, the overload is prevented and consequently, the objective function decreases sharper.

7.2. Analysis of sensitivity to the learning rate

It can be seen in Fig. 4 that there is an exponential negative relationship between the learning effect and the objective function. It is clear that this relationship is due to the formulation of the learning effect ($i^{\alpha}(\alpha \leq 0)$).

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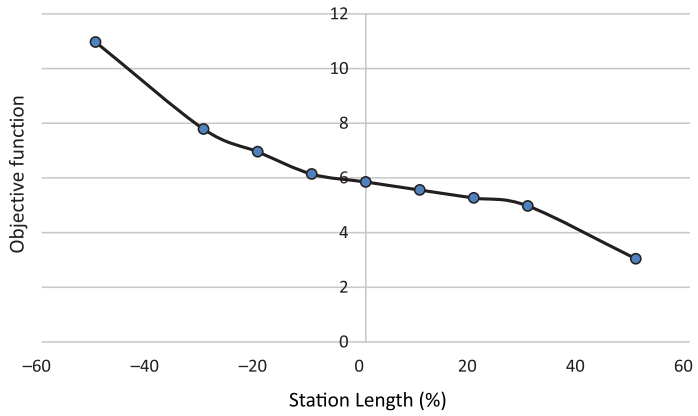


Fig. 3. Sensitivity analysis of station length.

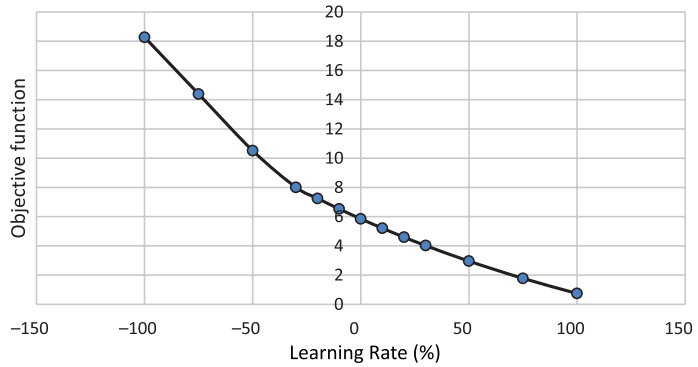


Fig. 4. Sensitivity analysis of learning rate.

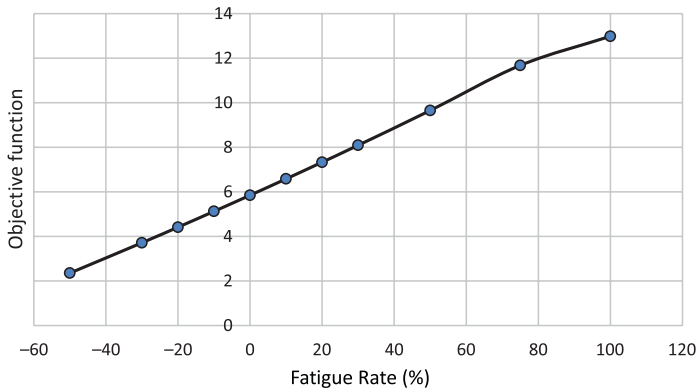


Fig. 5. Sensitivity analysis of fatigue rate.

7.3. Analysis of sensitivity to the fatigue rate

As shown in Fig. 5, there is almost a linear relationship between fatigue or deterioration rate and the objective function.

7.4. Impact of learning rate on overload and idle time

In the following, the impact of learning rate on overload and idle time is analyzed in the absence of the deterioration rate ($\beta = 0$). Accordingly, the overload and idle times are calculated based on different learning rates. In this manner, the learning rate changes from 0 to -1 ($-1 \leq \alpha \leq 0$) and the relevant overload and idle times are calculated.

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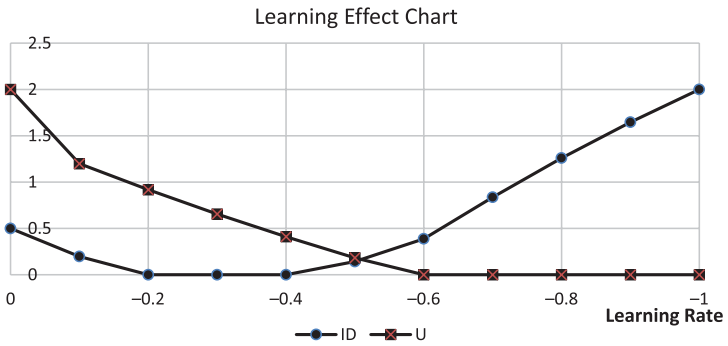


Fig. 6. Effect of learning rate on the overload and idle time.

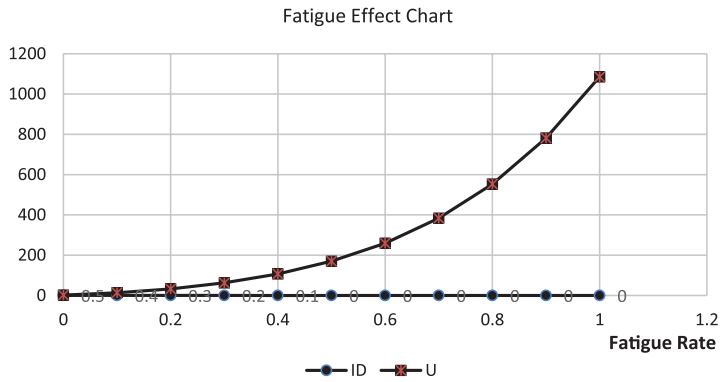


Fig. 7. Effect of fatigue rate on work overload and unemployment.

Based on Fig. 6, it can be seen that the learning rate positively affects the overload time and decrease in the learning rate, decreases the overload time. In contrast, an increase in the learning rate reduces the idle time. Of course, a threshold exists for the learning rate so that when the learning rate exceeds this threshold, an increase in idle time occurs with respect to increase in the learning rate.

7.5. Impact of fatigue rate on overload and idle time

The relationship between the deterioration or fatigue rate and overload and idle times is considered. In this manner, the impact of change in the fatigue rate on the overload and idle times are evaluated in the absence of the learning rate ($\alpha = 0$).

As shown in Fig. 7, increase in the fatigue rate from 0 to 1 results in increase in the overload time. Furthermore, when the fatigue rate is increased, the idle time is decreased smoothly.

7.6. Impact of learning and fatigue rates

Finally, the impact of presence and absence of the learning and fatigue rates on the objective function is tested.

Accordingly, $\alpha = -0.5$ and $\beta = 0.1$ are considered, respectively, for the learning and fatigue rates, which leads to the optimal objective function value of 32.4425.

To examine the absence effect of these rates on the objective function, it is assumed that there is no learning and fatigue effect ($\alpha = 0$, $\beta = 0$). In this case, the value 40.5 is calculated for the optimal objective function.

Also, with respect to the optimal values achieved in the absence of the learning and fatigue rates and replacing them in the problem with $\alpha = -0.5$ and $\beta = 0.1$ (presence of the learning and fatigue rates) leads to the optimal value of 95.2145 for the objective function. Hence, it is clear that the consideration of the learning and fatigue rates can significantly affect the objective function.

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8. Conclusions

In recent decades, fast-changing customer requirements led the industries to utilize the MMAL as flexible production lines to meet the customer demands. In this type of production line, the balancing and sequencing problems of assembly line are the two main issues.

In this paper, the balancing and sequencing problems of a mixed-model assembly line were studied in which the effects of operators' learning and fatigue issues on the balancing and sequencing of the assembly lines are considered. Accordingly, a mathematical model was proposed to formulate the mentioned problem.

To solve the proposed model and with respect to the complexity of the model, a developed genetic algorithm as a meta-heuristic algorithm was presented, and several test problems were used to evaluate the efficiency of the proposed solution method. Also, the results were compared to the values achieved by solving the problem via the commercial GAMS software.

Finally, sensitivity analysis was applied to test the impact of different parameters such as station length, learning rate, and fatigue rate on the problem.

Based on the achieved results it was concluded:

- Consideration of the learning and fatigue issues can significantly affect the balancing and sequencing problems of the assembly lines.
- The station length had a negative relationship with the total overload and idle times as the objective function and increase in the station length led to decrease in the overload and idle times and vice versa.
- Sensitivity analysis indicated that a negative relationship exists between the learning rate and total overload and idle times.
- The fatigue or deterioration rate affected the total time of overload and idleness positively so that increase in the fatigue rate increases the total overload and idle times.

One of the main goals of the current paper was considering learning and fatigue effects on the total times of overload and idleness, while the model can be improved by regarding the other objective functions and as a result, a multi-objective function can be proposed in the future researches. Furthermore, more techniques such as branch-and-bound method and Benders' decomposition method can be used to solve the proposed model.

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