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Multi-objective scheduling and assembly line balancing with resource constraint and cost uncertainty: A "box" set robust optimization

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Abstract

Assembly lines are flow-oriented production systems that are of great importance in the industrial production of standard, high-volume products and even more recently, they have become commonplace in producing low-volume custom products. The main goal of designers of these lines is to increase the efficiency of the system and therefore, the assembly line balancing to achieve an optimal system is one of the most important steps that have to be considered in the design of assembly lines. The purpose of the assembly line balancing is to assign tasks to the workstation called the station, so that prerequisite relationships, cycle times, and other assembly line constraints to be met and a number of line performance criteria to be optimized. In this study, considering the social responsibility related objective function, a mathematical model is proposed for scheduling and balancing the cost-oriented assembly line that has resource constraints with cost uncertainty. The box set robust optimization is applied and the obtained model is solved with the augmented epsilon constraint in the GAMS and some test problems and their results are presented. Finally, the cost parameter has been changed in a robust optimization approach and the obtained results have been analyzed for different costs.

Keywords: scheduling; assembly line balancing; uncertainty; augmented epsilon constraint; social responsibility; box set robust optimization.

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1. Introduction

Nowadays, a large percentage of products have at least one assembly stage. Therefore, it is necessary to pay attention to the assembly phase in production planning and scheduling. Generally, efficient production and high productivity are possible when there is saving time and cost and paying attention to quality at all stages of production. The assembly stage is also one of the stages of production where with the proper scheduling of jobs to enter the stage, the

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appropriate allocating of job and operator to the machines, considering ability and availability of machines and so on can take full advantage of available resources and time. Usually, the scheduling of workpieces manufacturing and planning for assembly operations has been studied, independently (Hosseini 2019), which does not lead to ideal results for the all-inclusive production system. Therefore, in recent research, considering these two stations simultaneously in scheduling problem is more interesting (Allahverdi and Al-Anzi 2009).
In this study, a mathematical model is proposed for scheduling and balancing the cost-oriented assembly line that has resource constraints with cost uncertainty. In the developed model, an objective function of social responsibility has been added and the uncertain cost parameter is considered. As a robust optimization approach, here, the box uncertainty set is used. Finally, the model was solved using the augmented epsilon constraint approach.
The paper is further organized as follows. In section 2, we review the related papers. Section 3 is dedicated to the problem statement and mathematical model. Section 4 is assigned to proposing the augmented epsilon constraint approach for solving the bi-objective model. Numerical results are presented in Section 5. Finally, section 5 concludes the paper and suggests some potential features for future studies.

2. Literature review

The first study on assembly scheduling issues has been conducted by Lee et al. (1993). They studied a two-station assembly flowshop scheduling problem with the objective of minimizing the makespan which in this simple problem each product is made by assembling two types of pieces. The first part of each product on the first machine and the second part on the second machine is processed, and finally, the third machine assembles the two parts into the final product. They proposed a branch and bound and approximate algorithms. Potts et al. (1995), extended the model of Lee et al. (1993) with several machines so that there were *m* machines in the first stage and one machine in the second stage and proposed a heuristic algorithm to minimize the makespan. Hariri and Potts (1997) have independently proved that the assembly flowshop problem even with two machines is an NP-Hard problem. They have considered a similar problem as a previous one and presented a branch and bound algorithm. Cheng and Wang (1999) considered minimizing the makespan in a two-machine flowshop scheduling with a specific structure and obtained optimal solutions for several specific cases. Song and John (2009) studied a two-station assembly scheduling problem with an objective of minimizing makespan, in which there are *n* jobs, each job consists of two components, and one of the two components is being made with delivery time limit. Yokoyama (2001) and Yokoyama and Santos (2005) investigated a hybrid scheduling for manufacturing systems including machining workpieces and assembly operations, and developed a branch and bound algorithm. In this study, several products of different types are ordered that make the required workpieces for these products in a flowshop and each product is produced hierarchically by assembly operations. The workpieces are assembled into the first subassembly and several more workpieces and the first subassembly are assembled into the second subassembly. This assembly operation continues until the last subassembly that is the final product is produced. Allahverdi and Al-Anzi (2009) investigated a two-station assembly scheduling problem with *m* machines in the first stage and one assembly machine in the second stage with considering setup times independent of processing times. They presented a dominant rule and three heuristic algorithms, namely hybrid Tabu Search algorithm and self-adaptive differential evolution algorithm, and a new evolutionary differential algorithm. Zhang et al. (2008) also presented a multi-objective model for assembly line balancing, where operators with different levels of experience are employed. This model assumes that each operator is capable of performing all assembly tasks and the cost of wages varies depending on the level of experience of the operators. Recently, Cantos Lopes et al. (2019) considered balancing task-station assignments and sequencing/scheduling different product models in a cyclical manner. They proposed a mixed-integer linear model to optimize the steady-state of these lines. Özcan (2019) introduced the problem of balancing and scheduling tasks in parallel assembly lines with sequence-dependent setup times. For this problem, the author proposed a binary linear mathematical programming model and a simulated annealing algorithm.

Based on the reviewed papers, it can be concluded that for the first time an objective function of social responsibility has been added to scheduling and cost-oriented assembly line balancing model as a bi-objective problem. Cost uncertainty has also been added to the study, to make the situation more realistic.

3. Problem statement and mathematical model

In this study, considering the social responsibility related objective function, a model is proposed for scheduling and balancing the cost-oriented assembly line that has resource constraints with cost uncertainty. In the base model of this research (Ramezanian et al. 2013), the objective function is to assign jobs to work centers and schedule them so that the constraints on the problem are not violated and assembly system costs are minimized. The problem allows for efficient deployment of parallel stations in situations where time to do some jobs may be longer than the cycle time. An operator at each station uses different tools and equipment to perform jobs, in which case if more than one job is assigned to a station, there is an in-station setup time between jobs that is modeled as the sequence-dependent setup time. One of the important features of the base model is the consideration of resource constraints. This means that there are a number of inline equipment that can perform various assembly jobs, and the assignment to a station is only possible if the equipment at the station is available and not deficient. There are also conditions for assigning compatible and incompatible jobs in the model (Ramezanian et al. 2013). One of the practical applications of the considered problem is boiler production process modeling (Peng and Jiang 2013). In the boiler manufacturing process, the integrated scheduling of production and assembly line are difficult problems. Other practice examples are aeronautical (Borreguero et al. 2015) and automotive (Zhou and He 2020) industries.

The following assumptions are considered in the proposed model:

- The precedence constraints and the setup time between assembly tasks are pre-determined and independent of the station in which tasks are performed.
- There is more than one equipment allowed to locate at each station.
- The processing time of each job by types of equipment that can perform them is the same and independent of the work center where the equipment is located.
- Sharing a set of tasks that are performed with a specific resource is null.
- The equipment required for each job is clear and there are no different parts for the assembly process.
- Production cost has uncertainty.

In the developed model it is determined how to allocate jobs and equipment to work centers, job scheduling, and the optimal number of parallel stations for designing a system with minimum investment and operational costs.

3.1. Model indices

$i.k$: Index of jobs.

j : Index of work centers.

e : Index of equipment.

3.2. Model parameters

t_i : time of job *i*
s_j : Maximum number of scheduling positions in work center *j*
P_{max} : Maximum number of stations per workstation
tsu_{ik} : Setup time from job *i* to job *k*
Wr_i : Wage rate of job *i*
$FC.EC_e$: Cost of equipment *e*, fixed cost per workstation, respectively
I_j : Set of assignable jobs to work center *j*
I_{ej} : Set of assignable jobs to work center *j* and processable by equipment *e*
p_{ik} : A set of all ordered pairs whose job *i* is before *k*.
PT_i : A set of all pre-*i* jobs, except pre- jobs
e_i : The first work center that job *i* can be assigned to.
l_i : The last work center that job *i* can be assigned to.
$zc^-.zc^+$: A set of pairs of jobs are compatible and incompatible, respectively

3.3. Decision variables

x_{ij} : Binary variable; equals 1 if job *i* is assigned to workstation *j* and 0 otherwise.
x_{ijps} : Binary variable; equals 1 if job *i* is assigned to workstation *j* with *p* station and to position *s* and 0 otherwise.
y_j : Binary variable; equals 1 if work center *j* is used and 0 otherwise.
z_{pj} : Binary variable; equals 1 if *p* parallel workstation is assigned to work center *j* and 0 otherwise.
w_{ij} : Binary variable; equals 1 if job *i* is assigned to the last scheduling position in workstation *j* and 0 otherwise.
N_{ikj} : Binary variable; equals 1 if job *k* is performed immediately after job *i* at work center *j* in the same cycle or next cycle and 0 otherwise.
E_{ej} : Binary variable; equals 1 if equipment *e* is at the center of work *j* and 0 otherwise.

3.4. Mathematical modeling

The proposed mathematical model is as follows.

$$Min\ F_1 = \sum_{j=1}^{m_{max}} \left(\sum_{p=1}^{p_{max}} p \cdot z_{pj} \cdot \left(\frac{c \cdot \sum_{i=1}^{n} x_{ij} t_i Wr_i}{\varepsilon + \sum_{i=1}^{n} x_{ij} t_i} \right) \right) + \sum_{j=1}^{m_{max}} \sum_{p=1}^{p_{max}} p \cdot z_{pj} \sum_{e=1}^{E} E_{ej} \cdot EC_e + \sum_{j=1}^{m_{max}} \sum_{p=1}^{p_{max}} p \cdot z_{pj} \cdot FC \tag{1}$$

$s.t$:

$$\sum_{p=1}^{p_{max}} \sum_{j=e_i}^{l_i} \sum_{s=1}^{s_j} x_{ijps} = 1 \qquad \forall\ i = 1. \dots . n \tag{2}$$

$$\sum_{p=1}^{m_{max}} x_{ij} = 1 \qquad \forall\ i = 1. \dots . n \tag{3}$$

$$\sum_{p=1}^{p_{max}} \sum_{i \in I_j} x_{ijps} \leq 1 \qquad \forall\ j; s = 1. \dots . s_j \tag{4}$$

$$\sum_{p=1}^{p_{max}} \sum_{s=1}^{s_j} x_{ijps} = x_{ij} \qquad \forall\, j; i \in I_j \tag{5}$$

$$\sum_{p=1}^{p_{max}} z_{pj} = y_j \qquad \forall\, j = 1. \dots .m_{max} \tag{6}$$

$$\sum_{p=1}^{p_{max}} \sum_{i \in I_j} x_{ijps+1} \leq \sum_{p=1}^{p_{max}} \sum_{i \in I_j} x_{ijps} \qquad \forall\, j; s = 1. \dots .s_j - 1 \tag{7}$$

$$Mz_{pj} - \sum_{s=1}^{s_j} \sum_{i = I_j} x_{ijps} \geq 0 \qquad \forall\, j = 1. \dots .p_{max} \tag{8}$$

$$\sum_{p=1}^{p_{max}} \sum_{j=e_i}^{l_i} \sum_{s=1}^{s_j} \max s_j \quad j - 1 + s \;\; x_{ijps} \;\; \leq \sum_{p=1}^{p_{max}} \sum_{j=e_k}^{l_k} \sum_{s=1}^{s_j} \max s_j \quad j - 1 + s \;\; x_{kjps} \qquad \forall\, (i.k) \in P_{ik} \tag{9}$$

$$\sum_{p=1}^{p_{max}} \sum_{j=e_i}^{l_i} \sum_{s=1}^{s_j} t_i x_{ijps} + \sum_{\forall (i.k) | (i \neq k) \wedge (i.k \in I_j)} tsu_{ik} N_{ikj} \leq c \cdot \sum_{p=1}^{p_{max}} p z_{pj} \qquad \forall\, j = 1. \dots .m_{max} \tag{10}$$

$$\sum_{p=1}^{p_{max}} \left(x_{ijps} + x_{ijps+1} \right) \leq 1 + N_{ikj} \qquad \forall\, j; s = 1. \dots .s_j - 1\, ;\, \forall (i.k) | (i \neq k) \wedge (i.k \in I_j) \wedge k \notin PT_i \tag{11}$$

$$x_{ijps} - \sum_{k \in I_j | (i \neq k) \wedge (k \notin PT_i)} x_{kjps+1} \leq \, W_{ij} \qquad \forall\, j;\; p;\; i \in I_j;\; s = 1. \dots .s_j - 1 \tag{12}$$

$$W_{ij} + \sum_{p=1}^{p_{max}} x_{kjp1} \leq 1 + N_{ikj} \qquad \forall\, j; (i.k) | (i \neq k) \wedge (i.k \in I_j) \wedge i \notin PT_k \tag{13}$$

$$\sum_{i \in I_{ej}} x_{ij} - \left\| I_{ej} \right\| E_{ej} \leq 0 \qquad \forall\, j; e = 1. \dots .NE \tag{14}$$

$$\sum_{i \in I_j} x_{ij} - \left\| I_j \right\| y_j \leq 0 \qquad \forall\, j = 1. \dots .m_{max} \tag{15}$$

$$x_{aj} - x_{bj} = 0 \qquad \forall\, j; (a.b) \in zc^{+} \tag{16}$$

$$x_{aj} + x_{bj} \leq 1 \qquad \forall\, j; (a.b) \in zc^{-} \tag{17}$$

Relation (1) represents the first objective function. The first part of this function calculates the variable cost of manpower (wages) based on the weighted average of the wage rate of jobs for the whole line, the second part is related to the variable cost of tools and required equipment, and the third part calculates the summation of fixed costs of stations. Constraints (2) and (3) make each job assigned only to one work center, a scheduling position, and a specified number of parallel stations. Constraint (4) ensures that in each work center only one job can be assigned to any scheduling position within it. Relation (5) shows that if a job is assigned to a work center, then only one scheduling position and a certain number of parallel stations can exist for that job at that work center. Constraint (6) ensures that only a certain number of parallel stations can be active for each work center. Constraint (7) indicates that at each work center, jobs must be allocated to scheduling positions in an increasing trend. Constraint (8) states that all jobs assigned to a work center must have the same number of parallel stations. Constraint (9) states the prerequisite relationship between jobs. Constraint (10) ensures that the sum of processing time and setup time between jobs in each work center is less than the expected cycle time. Relations (11)-(13) define the relationship between the model variables. Relations (14) and (15) relate to resource constraints and assigned work centers. Relations (16) and (17) also reflect, respectively the constraints of the assignment of compatible and incompatible jobs (Ramezanian et al. 2013).

The second objective function states social responsibility. According to ISO 26000, International Standard of Social Responsibility Management, community participation and development is one of the key aspects of SR. There are two main ways to calculate the SR aspect:

- Creating jobs
- Regional development

In our proposed model, setting up a workstation can lead to community participation and development. In this model, we have considered job opportunities arising from setting up a workstation (Roni et al. 2017, Zhalechian et al. 2017). Social value is calculated using the number of job opportunities created (Shaker Ardakani et al. 2020). By adding this objective function to the proposed model, the model is converted to an MODM model, which will be used in the next section to the epsilon constraint method to solve that.

$$Max\ f_2 = \left(\sum_j (JO_j).\, y_j \right) \tag{18}$$

where the used parameters of social responsibility objective function are defined as follows.

JO_j : Number of fixed jobs created per workstation

y_j : 0-1 variable; equals 1 if workstation j is set up and 0 otherwise.

4. Solving approaches

4.1. Multi-objective optimization models

Various approaches have been proposed to solve multi-objective optimization (MODM) problems, such as weighted sum method (WSM), epsilon constraint (EC), augmented epsilon constraint (AEC), goal programming (GP), lexicographic (Lex) and so on (Marler and Arora 2004). In addition to the aforementioned methods, to solve complex MODM problems or large-scale problems, meta-heuristic solving methods have also been developed, including the genetic algorithm-based Inferior Sorting (NSGAII) method (Coello et al. 2007). In any of the MODM problem-solving methods, whether exact methods such as AEC or meta-heuristic methods like NSGAII, we are looking for sets of efficient solutions that have non-dominated values and are placed on the Pareto front (Matthias 2005). In this study, the AEC method is used as an exact problem-solving method.

4.2. AEC approach

The general form of an MODM problem is as follows:

$$Min\ (\, f_1(x).\, f_2(x) \dots .\, f_n(x)) \qquad x \in X \tag{19}$$

Suppose the first objective is considered as the primary objective and other objectives are limited to the upper bound of epsilon and applied to problem constraints. Thus, the EC method will be applied and the following single-objective model will be obtained:

$$\begin{aligned} &Min\ \ f_1(x) \\ f_i(x) \le e_i \quad &i = 2.3. \dots . n \\ &x \in X \end{aligned} \tag{20}$$

in which the first objective is considered as the main objective and the second to n objectives are limited to the maximum value of e_i. It is necessary to explain, if one of the objectives is maximizing (*e.g.*, $f_k(x)$), then by definition of $f_i'(x) = f_i(x)$ and its substitution as objective k, the above general form is used again. Another solution is that the constraint for this purpose is as follows:

$$f_k(x) \ge e_k \tag{21}$$

As mentioned, in the EC method, by varying values of the epsilons, different solutions are obtained that are either efficient or at least poor efficient. With minor modifications, one can always obtain an efficient solution; this method is known as the AEC method (Mavrotas 2009). For better implementation of the AEC method, the appropriate interval of epsilons (e_i) can be obtained first with the Lex method (Aghaei et al. 2011). The AEC method must first determine the appropriate interval of epsilon variations and then obtain the Pareto front for different amounts of epsilons. The two main steps followed in the AEC method are: (*i*) determining the range of the values of the epsilons, and (*ii*) programming with the AEC model (Samadi Gazijahani et al. 2020).

4.3. Robust optimization approach

One approach to optimization under conditions of uncertainty is "robust optimization". Depending on the definition of robustness and the uncertainty type in the dataset, the methods of robust optimization are distinguished (Farughi et al. 2019). One of the methods of robust optimization is the interval method of Ben-Tal et al. (2009), which is the development of the Soyster method (Soyster 1973). Accordingly, for each of the uncertain parameter of the problem, a finite interval boundary of uncertainty is considered so that the robust solution in the most cases it is feasible for dataset to be within their corresponding intervals. In order to clarify the above method, consider the following uncertain optimization problem in which $a_{ij} \in [a_{ij}^L . a_{ij}^U]$ and $b_i \in [b_i^L . b_i^U]$ for $i = 1.2. \dots . m$.

$$\begin{aligned} &\min z = \sum_j a_{0j}\, x_j + b_0 \\ &s.t.: \\ &\sum_j a_{ij} x_j \le b_i \qquad \forall i = 1.2. \dots . m \end{aligned} \tag{22}$$

where a_{ij} and b_i are the nominal values of the dataset so that

$$\begin{aligned} &a_{ij} = a_{ij} + \xi_{ij} a_{ij} \\ &b_i = b_i + \xi_i b_i . \end{aligned} \tag{23}$$

The maximum deviations of each data from the nominal value are defined as follows:

$$\begin{aligned} &a_{ij} = \frac{a_{ij}^L + a_{ij}^U}{2}\ . a_{ij} = a_{ij} - a_{ij}^L \\ &b_i = \frac{b_i^L + b_i^U}{2}\ . b_i = b_i - b_i^L \end{aligned} \tag{24}$$

According to the above definitions, it can be easily shown that the changes in each parameter in (22) in the corresponding interval are equivalent to the change in the value of the corresponding ξ in the [-1.1]. After normalizing the uncertainty interval, model (22) can be rewritten as follows in which ξ_i and $\xi_{i.j}$ are in [-1.1].

$$
\begin{aligned}
&Min\ z = \sum_j a_{0j}x_j + b_0 + \sum_j \xi_j a_{0j}x_j + \xi_0 b_0 \\
&s.t.: \\
&\sum_j a_{ij}x_j + \sum_j \xi_{ij}a_{ij}x_j \le b_i + \xi_i b_i \qquad \forall i = 1.2.\dots.m
\end{aligned}
\tag{25}
$$

After normalization, in Ben-Tal et al. (2009) in the interval method, the following model is introduced as the robust counterpart of the model (25):

$$
\begin{aligned}
&minz = \max_{\xi_j.\xi_0}\left(\sum_j a_{0j}x_j + b_0 + \sum_j \xi_j a_{0j}x_j + \xi_0 b_0\right) \\
&s.t.: \\
&\sum_j a_{ij}x_j + \Theta_i \max_{\xi_{ij}.\xi_i}\left(\sum_j \xi_{ij}a_{ij}x_j - \xi_i b_i\right) \le b_i \qquad \forall i = 1.2.\dots.m
\end{aligned}
\tag{26}
$$

where Θ_i is the uncertainty level control parameter in each constraint.

4.4. Box uncertainty set

If in the objective function and in each of the constraints of the model (26), the ξs change independently of each other in [-1, 1], then the problem will have "box" uncertainty and a robust counterpart with the following model is equivalent (Jia and Bai 2018).

$$
\begin{aligned}
&\min z \\
&s.t.: \\
&z \ge \sum_j a_{0j}\,x_j + b_0 + \psi_0\left(\sum_j a_{0j}|x_j| + b_0\right) \\
&\sum_j a_{ij}\,x_j + \psi_i \sum_j a_{ij}\,|x_j| \le b_i - \psi_i b_i \qquad \forall i = 1.2.\dots.m
\end{aligned}
\tag{27}
$$

which is linearized as follows:

$$
\begin{aligned}
&\min z \\
&s.t.: \\
&z \ge \sum_j a_{0j}\,x_j + b_0 + \psi_0\left(\sum_j a_{0j}u_j + b_0\right) \\
&\sum_j a_{ij}\,x_j + \psi_i \sum_j a_{ij}\,u_j \le b_i - \psi_i b_i \qquad \forall i = 1.2.\dots.m \\
&-u_j \le x_j \le u_j
\end{aligned}
\tag{28}
$$

$$u_j \geq 0$$

where ψ is a controller for uncertainty, and when it is zero, the model is equivalent to a definite state.

5. Numerical results

After coding the mathematical model in GAMS, and implementing the AEC method, the Pareto front is derived from two objectives as follows. As the Table 1 and Figure 1 show, the more the objective function related to social responsibility increases, we should cost more. Note that, the measurement units of the vertical and horizontal axes are the number of fixed jobs created by workstations and assembly system costs, respectively. Since, the model is multi-objective and we don't have an optimal solution and the Pareto layer is considered, the Pareto layer obtained are as follows that the decision-maker can choose a solution from it.

Table 1. Values of Object Functions

	The first objective function	The second objective function	Epsilon
1	617557.6	18.283	18.283
2	615557.6	18.401	19.574
3	477335.6	20.306	20.865
4	447335.6	22.126	22.156
5	395557.6	23.187	23.446
6	395557.6	23.187	24.737
7	357335.6	24.788	26.028
8	336335.6	27.019	27.319
9	336335.6	27.019	28.609
10	254557.6	29.9	29.9

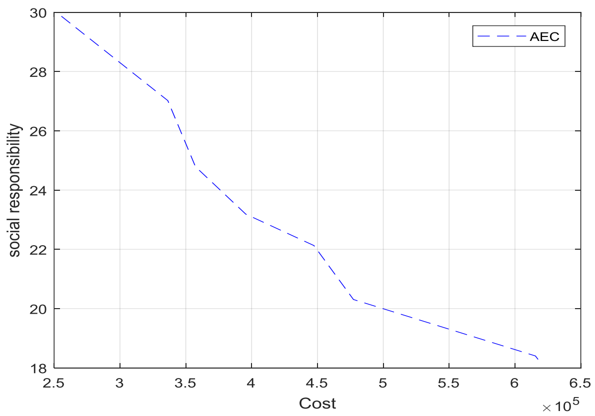

Figure 1. Relationship between the first and second objective functions

As mentioned in the proposed model, we considered the uncertain cost parameter and performed a sensitivity analysis using the Box uncertainty set. ψ is the uncertainty control action, which is when it is equal to zero it is equal to the state of a certain state. As the value increases from zero to one, the value of the cost objective function also increases as discussed in Table 2 and Figure 2. To provide more complete results, we have given different values to the parameter ψ and obtained the objective function values. As can be seen, the value of the second objective function is constant because the cost only exists in the first objective function.

Table 2. The values of the objective functions for different ψ

Ψ =0		*Ψ =0.2*		*Ψ =0.5*		*Ψ =0.7*		*Ψ =1*	
obj1	***obj2***	***obj1***	***obj2***	***obj1***	***obj2***	***obj1***	***obj2***	***obj1***	***obj2***
617557.6	18.283	621557.6	18.283	627557.6	18.283	631557.6	18.283	637557.6	18.283
615557.6	18.401	619557.6	18.401	625557.6	18.401	629557.6	18.401	635557.6	18.401
477335.6	20.306	481335.6	20.306	487335.6	20.306	491335.6	20.306	497335.6	20.306
447335.6	22.126	451335.6	22.126	457335.6	22.126	461335.6	22.126	467335.6	22.126
395557.6	23.187	399557.6	23.187	405557.6	23.187	409557.6	23.187	415557.6	23.187
395557.6	23.187	399557.6	23.187	405557.6	23.187	409557.6	23.187	415557.6	23.187
357335.6	24.788	361335.6	24.788	367335.6	24.788	371335.6	24.788	377335.6	24.788
336335.6	27.019	340335.6	27.019	346335.6	27.019	350335.6	27.019	356335.6	27.019
336335.6	27.019	340335.6	27.019	346335.6	27.019	350335.6	27.019	356335.6	27.019
254557.6	29.9	258557.6	29.9	264557.6	29.9	268557.6	29.9	274557.6	29.9

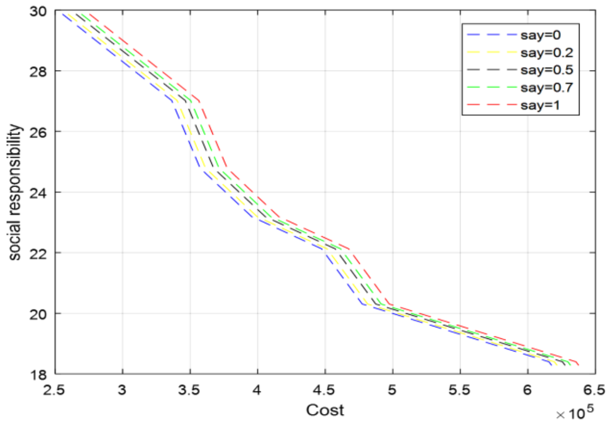

Figure 2. Diagram of Box Method

Here, several test problems have also been solved using GAMS and the obtained results are shown in Table 3. As shown, the running time increases with increasing the problem size so that in large-scale problems, using the heuristic and meta-heuristic algorithms can reduce this time (Yurtkuran et al. 2018). It is important to note, however, that in the solving of these instances, ψ is set to 1. Since, we will have a Pareto front for each example, it is not possible to report all of them and only upper and lower bound of each objective function are reported.

Table 3. Time elapsed to solve examples with different sizes

NO.	*i*j*e*p*s*	*obj1*		*obj2*		*time*
		min	*max*	*min*	*max*	
1	8*5*2*2*2	65486.31	82672.02	24.008	35.998	12(s)
2	10*5*8*3*5	112027.9	141023.7	13.69	25.333	17(s)
3	10*7*2*2*2	91618.21	110691.2	32.307	39.287	21(s)
4	12*9*3*2*2	140381.3	153789.9	41.603	51.488	39(s)
5	14*11*5*3*3	286096	314076.2	36.824	47.584	149(s)
6	20*14*5*3*3	343062.3	385607.2	72.008	81.16	406(s)
7	25*17*7*4*4	381581.8	439393.8	77.905	92.12	705(s)

6. Conclusion and future research

In this research, a multi-objective model based on an integer non-linear programming was proposed for the cost-oriented assembly line balancing where it is possible to parallelize stations, scheduling jobs and synchronize resources. In this study by adding a social responsibility objective function to a multi-objective model, and on the other hand, the uncertain cost parameter, attempts have been made to make the situation closer to the real-world. After using the box uncertainty set as a robust optimization approach, the model was solved by the augmented epsilon constraint method to obtain the Pareto layer. Also, the cost parameter of different ψs was changed using in the box set, and the obtained values of the objective functions were analyzed. In this analysis, the managers with high risk can use lower values of ψ and, on the contrary, cautious managers can use lower values for ψ. Finally, several instances as test problems were solved with different sizes. For future research, adding more objective functions, and examining model performance in the case studies and more complex examples can be pointed out. Using the metaheuristic algorithm is another direction for future research.

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