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Comparison of Single Model and Multi-Model Assembly Line Balancing Solutions

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Abstract

This paper considers assembly line balancing problems (*ALB problem type 1*) with single model and mixed-model, and comparison of their solutions. The objective of the *ALB problem type 1* is to group the tasks into a minimum number of workstations for a given cycle time, which in turn maximizes balancing efficiency of the assembly line.

In the single model assembly line balancing, only one model will be assembled in the assembly line, whereas in the mixed-model assembly line balancing, more than one model will be assembled in the same assembly line. The responsiveness of a company to its customer needs necessitates the use of mixed-model assembly line balancing. If a company manufactures more than one model, then the implementation of the mixed-model assembly line balancing would help the company to meet the demand of different models simultaneously. But, this approach may end up with a loss in balancing efficiency.

Hence, in this paper an attempt has been made to compare the extent of variation between the solution of the single model assembly line balancing problem and that of the mixed-model assembly line balancing problem through a complete factorial experiment using a randomly generated set of problems. From the results of the analysis, it is found that the results of the single model assembly line balancing problem are better than those of the mixed-model assembly line balancing problem.

Keywords: Line balancing, balancing efficiency, single model, mixed-model, ANOVA

1. INTRODUCTION

The growing global competitive business world compels implementation of mass production system, which brings manifold benefits to have enhanced organizational productivity. The mass production system involving assembly operations aims to balance the assembly line such that the balancing efficiency of the assembly line is maximized. The assembly line balancing (*ALB*) problem can be classified into *ALB* problem type 1 and *ALB* problem type 2. The objective of the first type is to subdivide a given precedence network of tasks into a minimum number of workstations for a given cycle time, where the cycle time is determined based on a given production volume per shift. The objective of the second type is to minimize the cycle time for a given number of workstations. The balancing efficiency is computed using the following formula.

Balancing efficiency = [Sum of task times/ (Number of workstations x Cycle time)] x100

where, cycle time is the ratio between the effective time available per shift and the production volume per shift.

The *ALB* problem is further classified into single model assembly line balancing problem and mixed-model assembly line balancing problem. In the single model assembly line balancing, only one model will be assembled in the assembly line, whereas in the mixed-model assembly line balancing, more than one model will be assembled simultaneously in the same line. The growing global competition necessitates companies to use the mixed-model assembly line balancing, mainly to meet the demand of different models on daily basis.

The concept of the mixed- model *ALB* problem is explained using a numerical example. Consider Fig.1 and Fig.2, which are precedence networks of model 1 and model 2, respectively. The model 1contains 6 tasks and the model 2 contains 7 tasks. The mixed-model by combining the precedence networks of the model 1 and the model 2 is shown in Fig.3, which has 9 tasks.

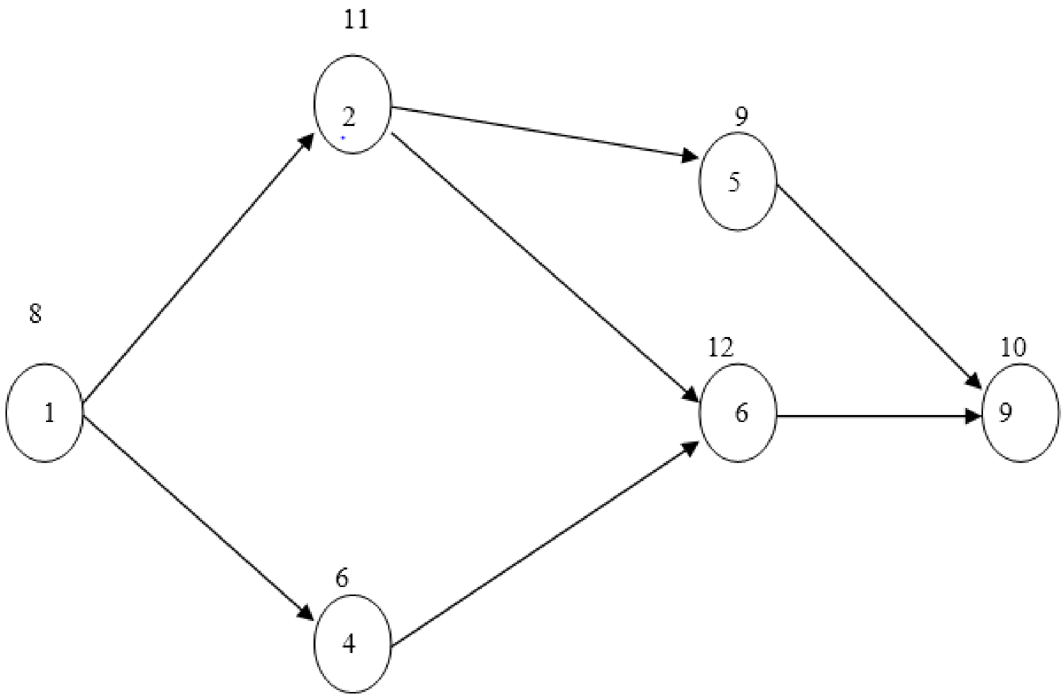


Fig.1 Precedence network of Model 1

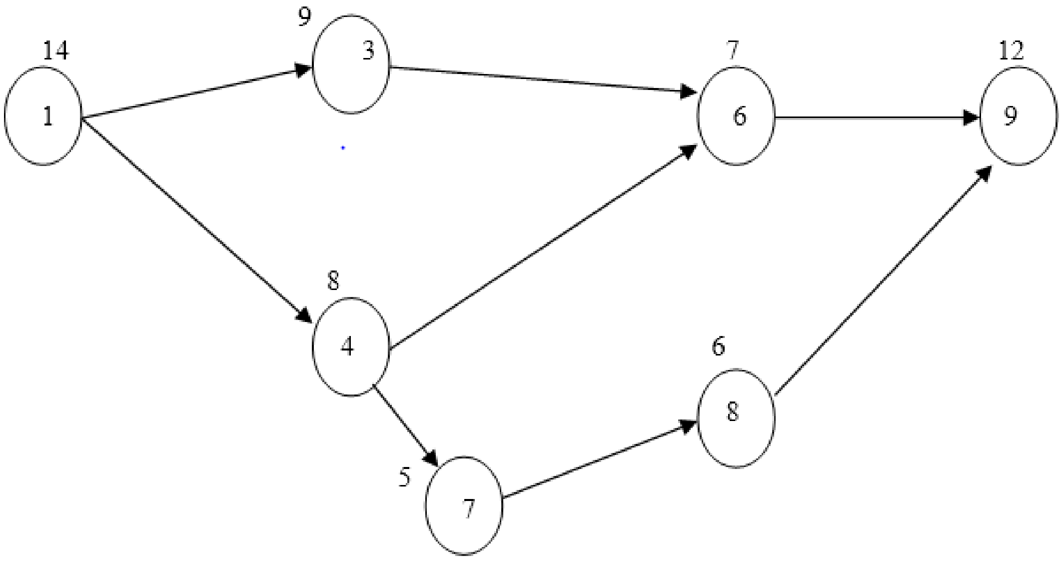


Fig.2 Precedence network of Model 2

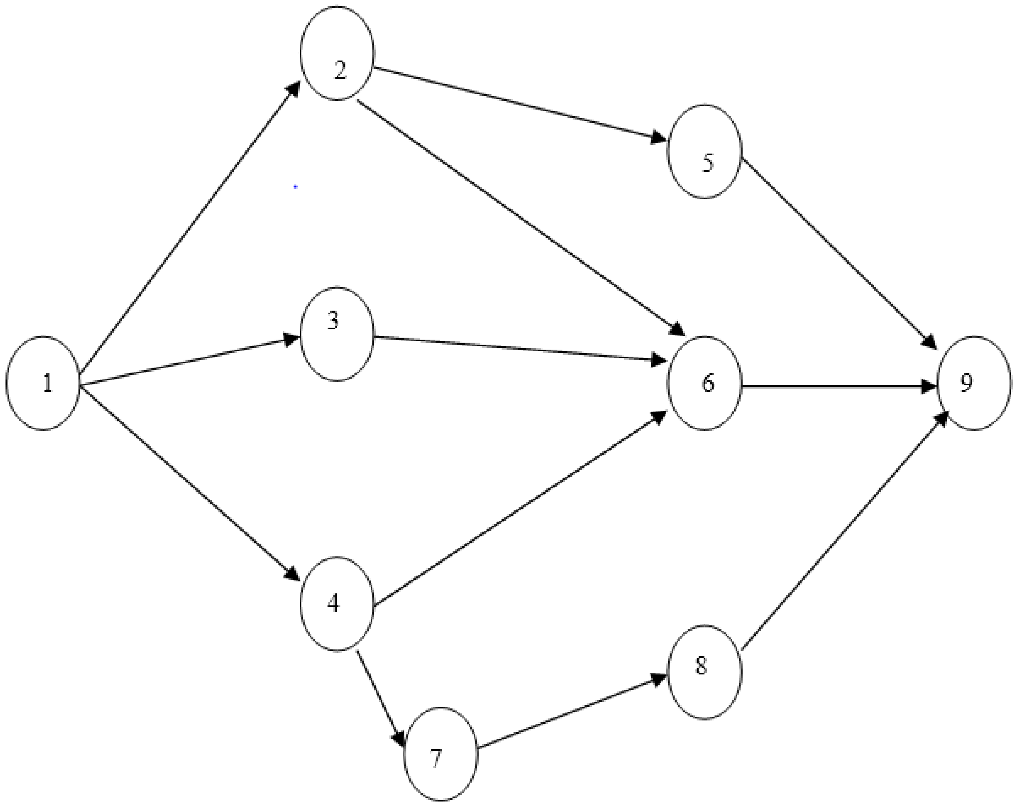


Fig.3 Mixed-model of Model 1 and Model 2

Past researchers used average task time for each task in the mixed-model, while forming workstations. In this paper, the original task times of the models are used as such without any modification in the design of the assembly line to have more perfection. Each model is given with a cycle time which is derived from its production volume per shift. The average of the cycle times of the models is assumed as the cycle time of the mixed-model assembly line balancing problem.

Though the reality warrants the use of the mixed model assembly line balancing, the authors make an hypothesis that the loss in the balancing efficiency of each model of the mixed-model assembly line balancing is more when compared to that of each of the models, if each model is solved by treating it as single model assembly line balancing problem.

Hence, in this paper, an attempt has been made to analyze the extent of differences between the solutions of the single model *ALB* problem and those of the mixed-model *ALB* problem using a randomly generated set of problems.

2. LITERATURE REVIEW

This section gives a review of literature of assembly line balancing problems. In the past, researchers used several approaches to solve the single model as well as mixed model assembly line balancing problems, which are reviewed in this section.

Thangavelu and Shetty (1971), Deckro and Rangachari (1990), Pastor (2011) and Sivasankaran and Shahabudeen (2013b) developed mathematical models for the single model assembly line balancing problem. Panneerselvam and Sankar (1993), Genikomsakis and Tourassis et al. (2012), and Mutlu and Ozgormus (2012) developed heuristics for the same problem. Rubinnovitz and Levitin (1995), Ponnambalam et al. (2000), and Sabuncuoglu et al. (2000) developed genetic algorithms to solve this problem. Simulated annealing algorithms are developed by Hong and Cho (1997), and Narayanan and Panneerselvam (2000) for the single model assembly line balancing problem.

Gokcen and Erel (1997), Gokcen and Erel (1998) and Kara et al. (2011) developed mathematical models to solve the mixed-model assembly line balancing problem. Kim and Kim (2000), Matanachai and Yano (2001), Jin and Wu (2002) , Hop (2006), Kilincci (2011), and Zhang and Han (2012) developed heuristics for the same problem. Sivasankaran and Shahabudeen (2013a) developed a genetic algorithm to solve the mixed-model assembly line balancing problem by taking original tasks times, which is unique in literature. Further many other researchers (Fattahi and Salehi, 2009, Ozcan, Cercioglu, Gokcen and Toklu 2010) attempted simulated annealing algorithm.

Though attempts have been made on the single model as well as the mixed model assembly line balancing problems in the past, a critical analysis is not carried out in terms of balancing loss while using mixed-model assembly line balancing in contrast to that of the single model assembly line balancing for a give set of problems.

Hence, in this paper, a critical analysis is carried out to compare the balancing efficiency of the models when they are solved using single model approach and mixed-model approach through a complete factorial experiment.

3. ALGORITHMS TO SOLVE SINGLE AND MIXED-MODEL ASSEMBLY LINE BALANCING PROBLEMS

In this paper, genetic algorithms are presented to solve the single model and mixed-model assembly line balancing problems.

3.1 Genetic Algorithm to Solve Single Model Assembly Line Balancing Problem

The steps of the genetic algorithm with cyclic crossover method and modified workstation formation to solve single model assembly line balancing problem are explained below. For each of the offspring that will be obtained using crossover operation, an ordered vector will be constructed, which gives a sequence of the tasks in the immediate precedence network such that their sequential assignment to workstations satisfies the immediate precedence relationships among the tasks in the network. In addition to this, while moving from current workstation to next workstation, one can try fitting different feasible tasks which fit with the unassigned cycle time and finally the task which yields the least unassigned cycle time may be assigned to the workstation. This additional step is unique to literature and it is termed as modified workstation formation.

Step 1: Input the following.

- Precedence network of the line balancing problem
- Task times
- Cycle time
- Number of generations to be done, K

Step 2: Generate the desired number of chromosomes (Population) by randomly placing the tasks as the genes of each chromosome.

Step 3: Find the ordered vector of each chromosome and find its fitness function value in terms of balancing efficiency.

Step 4: Sort the chromosomes in descending order of their fitness function values.

Step 5: Select a subpopulation from the top of the sorted list of chromosomes.

Step 6: Perform crossover operation using cyclic crossover operation (Sivasankaran and Shahabudeen 2013a) for different pairs of chromosome in the subpopulation and obtain their offspring.

Step 7: For each offspring, perform mutation for a given mutation probability.

Step 8: Design the workstations of each offspring for the given cycle time using the processing times of the tasks and the immediate predecessor(s) matrix as per its ordered vector with the following guidelines and obtain its fitness function value (balancing efficiency).

While moving from one workstation to another workstation, if there is idle time in the current workstation, then look for alternate succeeding task(s) which can best fit into the current workstation that will result with either zero idle time or least idle time in that workstation.

Step 9: Replace the chromosomes of the population with the corresponding offspring.

Step 10: Sort the chromosomes of the population in descending order as per their fitness function values.

Step 11: Increment the generation count k by 1.

Step 12: If the generation count k is less than or equal to K, then go to Step 5; otherwise, go to Step 13.

Step13: Print the chromosome at the top of the sorted population as the final solution along with its balancing efficiency.

Step 14: Stop

3.2 Genetic Algorithm to Solve Mixed-Model Assembly Line Balancing Problem

The steps of the genetic algorithm with cyclic crossover method and modified workstation formation to solve mixed-model assembly line balancing problem are explained below. As explained in the previous subsection, for each of the offspring that will be obtained using crossover operation, an ordered vector will be constructed, which gives a sequence of the tasks in the immediate precedence network such that their sequential assignment to workstations satisfies the immediate precedence relationships among the tasks in the network. In addition to this, while moving from current workstation to next workstation, one can try fitting different feasible tasks which fit with the unassigned cycle time and finally the task which yields the least unassigned cycle time may be assigned to the current workstation.

Step 1: Input the following.

- Number of models
- Precedence networks of the models of the line balancing problem
- Combined precedence network
- Task times of the models
- Cycle time of each model and average cycle time
- Number of generations to be done, K

Step 2: Generate the desired number of chromosomes (Population) by randomly placing the tasks as the genes of each chromosome.

Step 3: Find the ordered vector of each chromosome in the population.

Step 4: Assign the tasks to stations based on the combined precedence network and with the original task times of the models.

Step 5: Find the fitness function value in terms of average balancing efficiency of the models.

Step 6: Sort the chromosomes in descending order of their fitness function values.

Step 7: Select a subpopulation from the top of the sorted list of chromosomes.

Step 8: Perform crossover operation using cyclic crossover operation (Sivasankaran and Shahabudeen 2013a) for different pairs of chromosome in the subpopulation and obtain their offspring.

Step 9: For each offspring, perform mutation for a given mutation probability.

Step 10: Design the workstations of each offspring for the given cycle time using the processing times of the individual models and the immediate predecessor(s) matrix of the combined model as per the ordered vector with the following guidelines and obtain its fitness function value (Balancing efficiency).

> *While moving from one workstation to another workstation, if there is idle time in the current workstation, then look for alternate succeeding task(s) which can best fit into the current workstation that will result with either zero idle time or least idle time in that workstation.*

Step 11: Replace the chromosomes of the population with the corresponding offspring.

Step 12: Sort the chromosomes of the population in descending order as per their fitness function values.

Step 13: Increment the generation count k by 1.

Step 14: If the generation count (k) is less than or equal to K, then go to Step 7; otherwise, go to Step 15.

Step15: Print the chromosome at the top of the sorted population as the final solution along with its balancing efficiency.

Step 16: Stop

4. COMPARISON OF ASSEMBLY LINE BALANCING SOLUTIONS

In this research, two models, viz. model 1 and model 2 are considered in the mixed-model *ALB* problem. The analysis is carried out for each of the following cases by assuming 20 minutes, 25 minutes and 30 minutes as cycle times.

- Treating model 1 as well as model 2 as single model assembly line balancing problem
- Treating the models as parts of the mixed-model assembly line balancing problem.

For each model, its results by treating it as single model ALB problem and those by treating it as a part of mixed-model ALB problem are compared. Further, the average of the balancing efficiencies of the models by treating them as single model ALB problems and the average of the balancing efficiencies of the models by treating them as parts of mixed-model ALB problem are also compared.

The analysis of the results of each of these cases is carried out using a complete factorial experiment with three factors as listed below.

- Problem Size (Factor A), which is represented by the number of nodes in the network. The levels of this factor are 15 nodes, 20 nodes, 25 nodes, 30 nodes, 35 nodes and 40 nodes.
- Assembly line balancing problem type (Factor B), whose levels are Single model and Mixed- model. This is represented by *ALB* type.
- Cycle time (Factor C), whose levels are 20 minutes, 25 minutes and 30 minutes.

Under each experimental combination, two replications are carried out. The model of this ANOVA is as given below.

$$Y_{ijkl} = \mu + A_i + B_j + AB_{ij} + C_k + AC_{ik} + BC_{jk} + ABC_{ijk} + e_{ijkl}$$

where,

μ is the overall mean

Y_{ijkl} is the balancing efficiency of the l^{th} replication under the i^{th} level of the factor A, j^{th} level of the factor B and the k^{th} level of the factor C.

A_i is the effect of the i^{th} level of the factor A on the balancing efficiency

B_j is the effect of the j^{th} level of the factor B on the balancing efficiency

AB_{ij} is the effect of the i^{th} level of the factor A and the j^{th} level of the factor B on the balancing efficiency

C_k is the effect of the k^{th} level of the factor C on the balancing efficiency

AC_{ik} is the effect of the i^{th} level of the factor A and the k^{th} level of the factor C on the balancing efficiency

BC_{jk} is the effect of the j^{th} level of the factor B and the k^{th} level of the factor C on the balancing efficiency

ABC_{ijk} is the effect of the i^{th} level of the factor A, j^{th} level of the factor B and the k^{th} level of the factor C on the balancing efficiency

e_{ijkl} is the error associated with the balancing efficiency of the l^{th} replication under the i^{th} level of the factor A, j^{th} level of the factor B and the k^{th} level of the factor C.

4.1 Comparison of Balancing Efficiencies of Model 1

As per the complete factorial experiment presented earlier, the results of the balancing efficiencies of the model 1 by treating it as a single model assembly line balancing problem and as a part of the mixed model assembly line balancing problem are shown in Table 1.

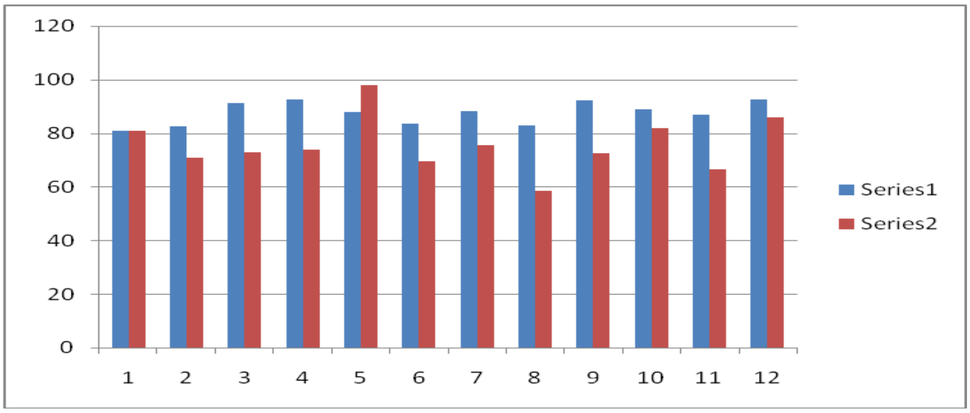
For the model 1, the balancing efficiencies of the six problems each with two replications (totally 12 problems) using the single model approach and the mixed-model approach for the cycle times of 20 minutes, 25 minutes and 30 minutes are shown in the form of bar chart in Fig.4, Fig.5 and Fig.6, respectively. The problems are numbered from 1 to 12. From Fig.4, one can verify that the balancing efficiency obtained using the single model approach and that obtained using the mixed-model approach are the same for the problem 1 (first replication of the problem with 15 nodes). Further, it is clear that for each of all other problems, the balancing efficiency obtained using the single model approach is more than that obtained using the mixed model approach, except for the problem 5 (first replication of the problem with 25 nodes). In Fig.5, for all the problems, the balancing efficiencies obtained using the single model approach are more than the respective balancing efficiencies obtained using the mixed model approach. In Fig.6, the balancing efficiencies obtained using the single model approach and those obtained using the mixed-model approach are the same for the problem 1 (first replication of the problem with 15 nodes) and the problem 12 (second replication of the problem with 40 nodes). For all other problems, the balancing efficiencies obtained using the single model approach are greater than the respective balancing efficiencies obtained using the mixed model approach.

Based on these facts, one can conclude that for any problem, the balancing efficiency obtained using the single model approach will be greater than the balancing efficiency obtained using the mixed model approach. Now, the question is whether the difference between them is statistically significant. This can be answered using a carefully designed ANOVA experiment, which is already explained.

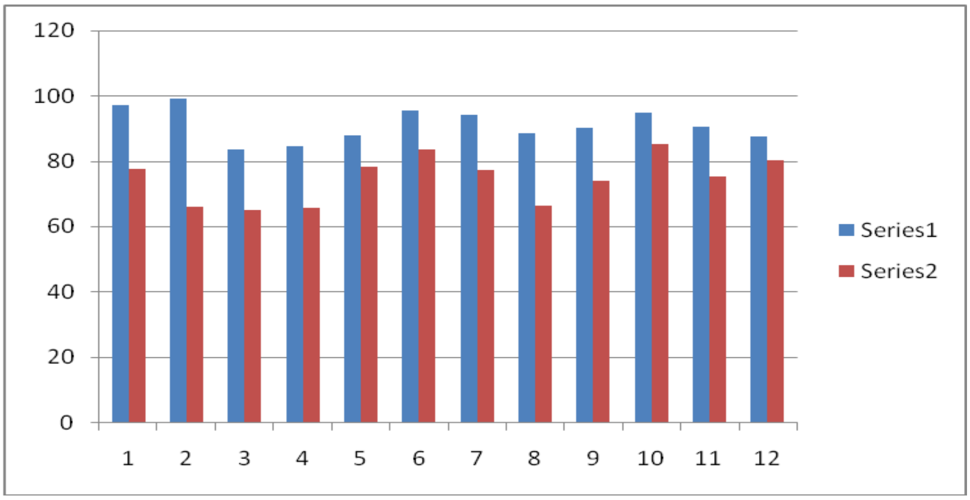
Table 1. Results of Balancing Efficiencies of Model 1

Problem size	Replication	ALB Type					
		Single Model			Mixed-model		
		Cycle Time			Cycle Time		
		20 min	25 min	30 min	20 min	25 min	30 min
15	1	80.83	97.00	80.83	80.83	77.6	80.83
	2	82.50	99.00	82.50	70.71	66.00	66.00
20	1	91.25	83.43	97.33	73.00	64.89	69.52
	2	92.50	84.57	98.67	74.00	65.78	70.40

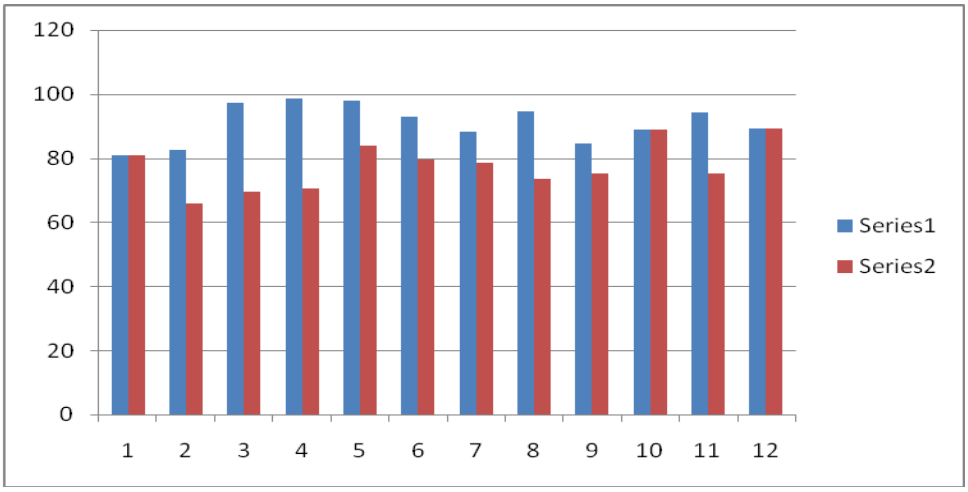
25	1	88.00	88.00	97.78	97.78	78.22	83.81
	2	83.50	95.43	92.78	69.58	83.50	79.52
30	1	88.33	94.22	88.33	75.71	77.09	78.52
	2	82.92	88.44	94.76	58.53	66.33	73.70
35	1	92.27	90.22	84.58	72.50	73.82	75.19
	2	88.75	94.67	88.75	81.92	85.20	88.75
40	1	86.92	90.40	94.17	66.47	75.33	75.33
	2	92.69	87.64	89.26	86.07	80.33	89.25



Series 1 Balancing efficiencies of Model 1 using single model approach
Series 2: Balancing efficiencies of Model 1 using mixed-model approach
Fig.4 Balancing efficiencies of Model 1 when cycle time is 20 minutes



Series 1 Balancing efficiencies of Model 1 using single model approach
Series 2: Balancing efficiencies of Model 1 using mixed-model approach
Fig.5 Balancing efficiencies of Model 1 when cycle time is 25 minutes



Series 1 Balancing efficiencies of Model 1 using single model approach
Series 2: Balancing efficiencies of Model 1 using mixed-model approach
Fig.6 Balancing efficiencies of Model 1 when cycle time is 30 minutes

For the data shown in Table 1, the results of ANOVA are shown in Table 2. From this table, it is clear that the effect of the factor B "ALB type" on the balancing efficiency is significant and the effects of all other components on the balancing efficiency are insignificant at a significance level of 0.05. Since, the number of levels for ALB type is only 2, the best "ALB type" in terms of balancing efficiency can be obtained by comparing their mean balancing efficiencies. The mean balancing efficiency through the single model assembly line balancing is 89.81% and that through the mixed-model assembly line balancing is 75.89%. From this comparison, it is evident that the model 1 when it is solved by treating it as a single model gives better balancing efficiency.

Table 2. ANOVA Results of Balancing Efficiency of Model 1

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Sum of Squares	F Ratio (calculated)	Table F value at α=0.05	Remark
Problem Size (A)	437.38	5	87.48	2.049	2.48	Insignificant
ALB Type (B)	3487.88	1	3487.88	81.703	4.12	**Significant**
AB	363.34	5	72.69	1.703	2.48	Insignificant
Cycle Time (C)	82.94	2	41.47	0.971	3.27	Insignificant
AC	439.41	10	43.94	1.029	2.11	Insignificant
BC	68.69	2	34.34	0.804	3.27	Insignificant
ABC	376.88	10	37.60	0.881	2.11	Insignificant
Error	1536.75	36	42.69			
Total	6792.27	71				

4.2 Comparison of Balancing Efficiencies of Model 2

As per the complete factorial experiment presented earlier, the results of the balancing efficiencies of the model 2 by treating it as a single model assembly line balancing problem and as a part of the mixed model assembly line balancing problem are shown in Table 3.

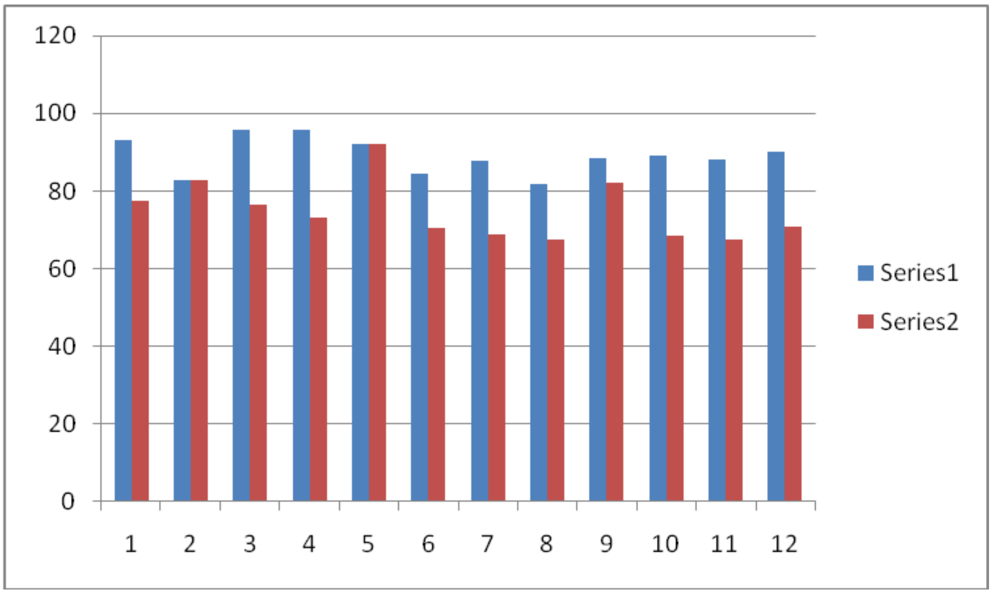
For the model 2, the balancing efficiencies of the 12 problems using the single model approach and the mixed-model approach for the cycle times of 20 minutes, 25 minutes and 30 minutes are shown in the form of bar chart in Fig.7, Fig.8 and Fig.9, respectively. From Fig.7, one can verify that the balancing efficiencies obtained using the single model approach and those obtained using the mixed-model approach are the same for the problem 2 (second replication of the problem with 15 nodes) and the problem 5 (first replication of the problem with 25 nodes). Further, it is clear that for each of all other problems, the balancing efficiency obtained using the single model approach is more than that obtained using the mixed model approach. In Fig.8, for all the problems, the balancing efficiencies obtained using the single model approach, are more than the respective balancing efficiencies obtained using the mixed model approach. In Fig.9, the balancing efficiencies obtained using the single model approach and those obtained using the mixed-model approach are the same for the problems 1 and 2, which are the first and the second replications of the problem with 15 nodes. For all other problems, the balancing efficiencies obtained using the single model approach, are greater than the respective balancing efficiencies obtained using the mixed model approach.

Based on these facts, one can conclude that for any problem, the balancing efficiency obtained using the single model approach will be greater than the balancing efficiency obtained using the mixed model approach. Now, the question is whether the difference between them is statistically significant. As stated earlier, this can be answered using a carefully designed ANOVA experiment, which is already explained.

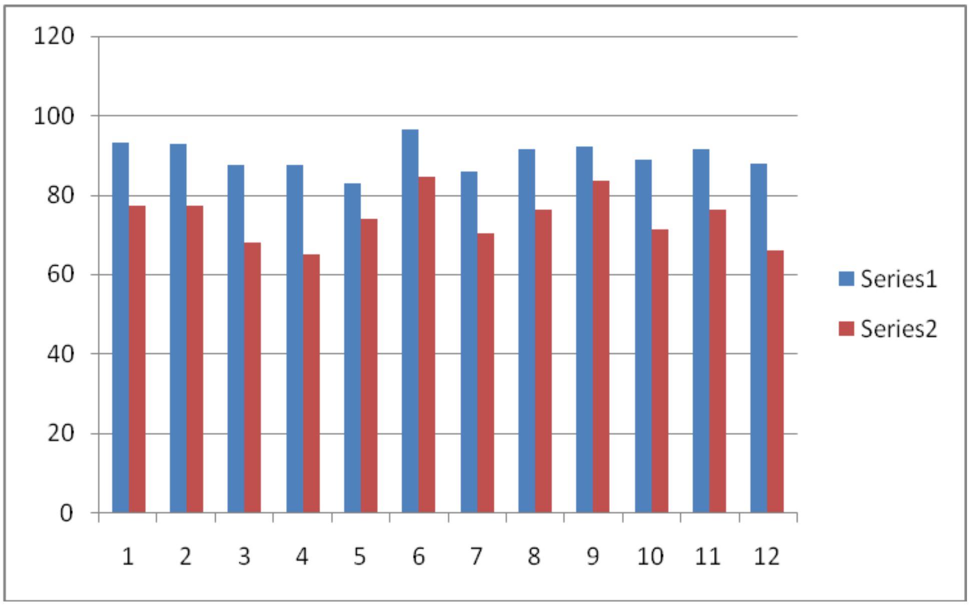
For the data shown in Table 3, the results of ANOVA are shown in Table 4. From this table, it is clear that the components of ANOVA, viz. Problem Size (A) and ALB type (AB) are significant and all other components are insignificant at a significance level of 0.05. Since, the number of levels of "ALB type" is only 2, the best ALB type in terms of balancing efficiency can be obtained by comparing their mean balancing efficiencies. The mean balancing efficiency using the single model approach is 89.72% and that using the mixed-model approach is 75.25%. From this comparison, it is evident that the model 2 when it is solved by treating it as a single model gives better balancing efficiency.

Table 3. Results of Balancing Efficiencies of Model 2

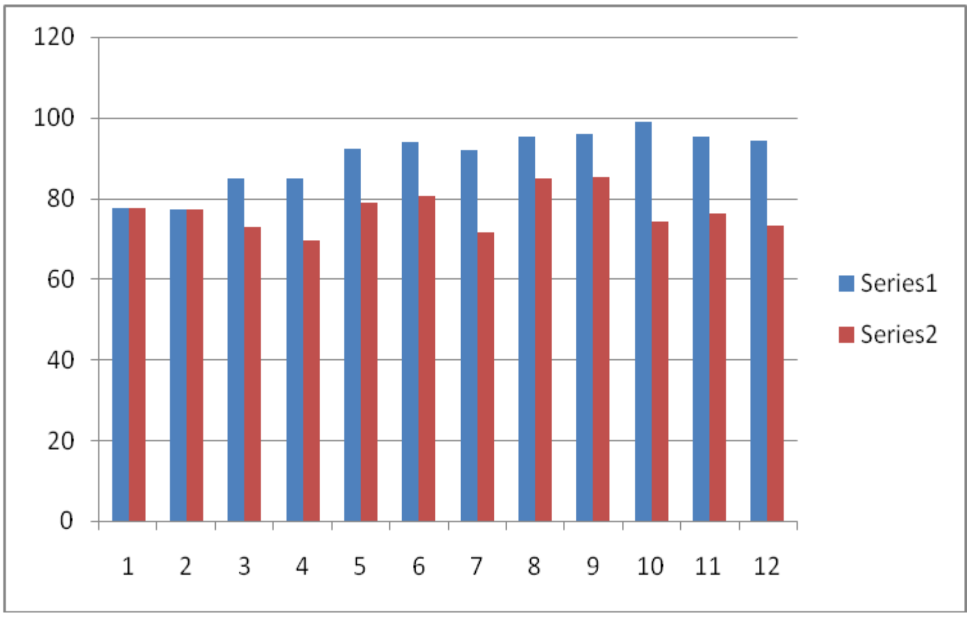
Problem size	Replication	ALB Type					
		Single Model			Mixed-model		
		Cycle Time			Cycle Time		
		20 min	25 min	30 min	20 min	25 min	30 min
15	1	93.00	93.00	77.50	77.50	77.40	77.50
	2	82.86	92.80	77.33	82.86	77.33	77.33
20	1	95.63	87.43	85.00	76.50	68.00	72.86
	2	95.63	87.43	85.00	73.00	64.89	69.52
25	1	92.22	83.00	92.22	92.22	73.78	79.05
	2	84.50	96.57	93.89	70.42	84.50	80.48
30	1	87.73	85.78	91.91	68.93	70.18	71.48
	2	81.79	91.60	95.42	67.35	76.33	84.82
35	1	88.46	92.00	95.83	82.14	83.64	85.19
	2	89.00	89.00	98.89	68.46	71.20	74.17
40	1	88.08	91.60	95.42	67.32	76.33	76.33
	2	90.00	88.00	94.26	70.77	66.00	73.33



Series 1 Balancing efficiencies of Model 2 using single model approach
Series 2: Balancing efficiencies of Model 2 using mixed-model approach
Fig.7 Balancing efficiencies of Model 2 when cycle time is 20 minutes



Series 1 Balancing efficiencies of Model 2 using single model approach
Series 2: Balancing efficiencies of Model 2 using mixed-model approach
Fig.8 Balancing efficiencies of Model 2 when cycle time is 25 minutes



Series 1 Balancing efficiencies of Model 2 using single model approach
Series 2: Balancing efficiencies of Model 2 using mixed-model approach
Fig.9 Balancing efficiencies of Model 2 when cycle time is 30 minutes

Table 4 ANOVA Results of Balancing Efficiency of Model 2

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Sum of Squares	F Ratio (calculated)	Table F value at α=0.05	Remark
Problem Size (A)	263.00	5	52.60	1.962	2.48	Insignificant
ALB Type (B)	3764.75	1	3764.75	140.42	4.12	**Significant**
AB	319.91	5	63.98	2.386	2.48	Insignificant
Cycle Time (C)	39.31	2	19.66	0.733	3.27	Insignificant
AC	609.53	10	60.95	2.273	2.11	**Significant**
BC	16.72	2	8.36	0.312	3.27	Insignificant
ABC	172.72	10	17.27	0.644	2.11	Insignificant
Error	965.22	36	26.81			
Total	6151.16	71				

4.3 Comparison of Average Balancing Efficiencies of Model 1 and Model 2

As per the complete factorial experiment presented earlier, the results of the average balancing efficiencies of the model 1 and model 2 by treating them as single model assembly line balancing problem and mixed model assembly line balancing problem are shown in Table 5.

The averages of the balancing efficiencies of model 1 and model 2 of the 12 problems using the single model approach and the mixed-model approach for the cycle times of 20 minutes, 25 minutes and 30 minutes are shown in the form of bar chart in Fig.10, Fig.11 and Fig.12, respectively. From Fig.10 and Fig.11, one can verify that for each problem, the average of the balancing efficiencies of the model 1 and the model 2 obtained using the single model approach is greater than that obtained using the mixed-model approach. In Fig.12, the same holds good except for the problem 1 (first replication of the problem with 15 nodes) for which they are same.

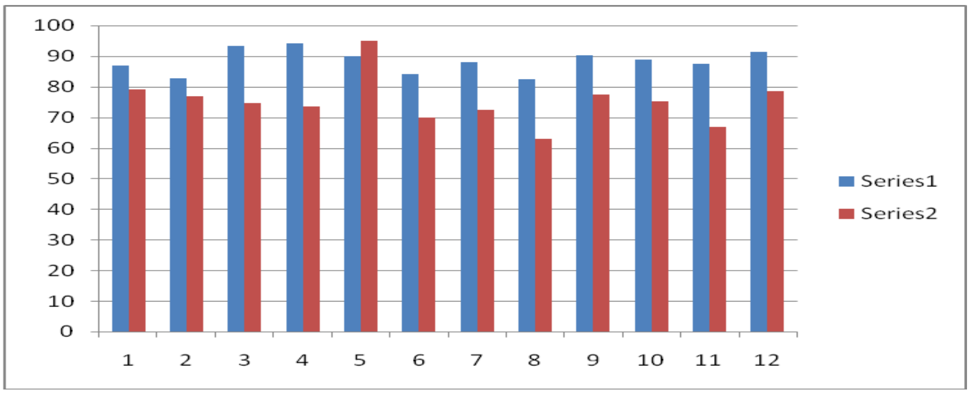
Based on these facts, it is found that for any problem, the average of the balancing efficiencies of the models 1 and 2 obtained using the single model approach will be greater that the average of the balancing efficiencies of the models 1 and 2 obtained using the mixed model approach. Now, the question is whether the difference between them is statistically significant. This can be answered using a carefully designed ANOVA experiment, which is already explained.

The results of ANOVA of the data shown in Table 5 are presented in Table 6. From this table, it is clear that the components of ANOVA, viz. Problem Size (A), ALB type (B), the interaction terms of AB and AC are significant and all other components are insignificant at a significance level of 0.05. Since, the number of levels of factor

B (ALB type) is only two, the best ALB type in terms of average balancing efficiency can be obtained by comparing their mean of the average balancing efficiencies. The mean of the average balancing efficiencies of the model 1 and the model 2 obtained using the single model approach is 89.77% and that obtained using mixed-model approach is 75.57%. From this comparison, it is evident that the best average balancing efficiency is obtained when the models 1 and 2 are solved by treating them as single model ALB problems.

Table 5 Results of Average Balancing Efficiencies of Model 1 and Model 2

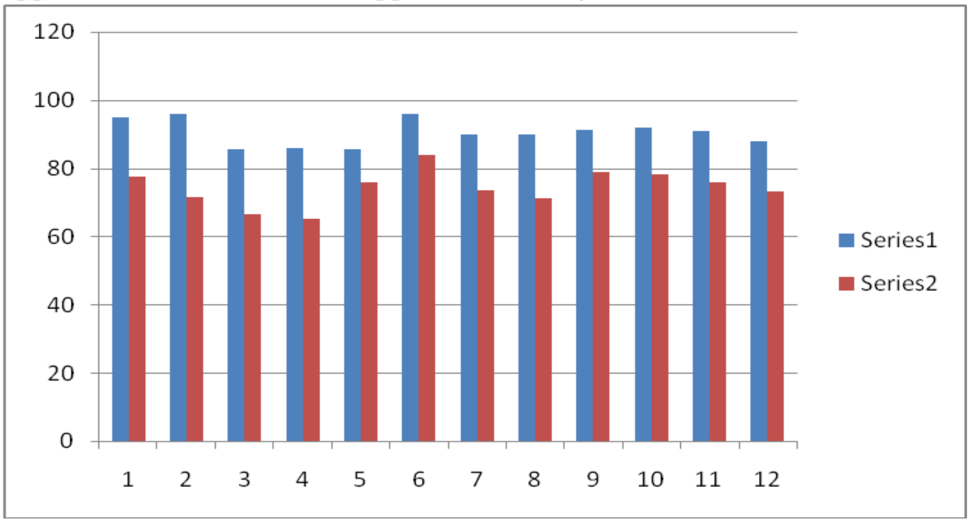
Problem size	Replication	ALB Type					
		Single Model			Mixed-model		
		Cycle Time			Cycle Time		
		20 min	25 min	30 min	20 min	25 min	30 min
15	1	86.92	95.00	79.17	79.17	77.50	79.17
	2	82.68	95.90	79.92	76.79	71.67	71.67
20	1	93.44	85.43	91.17	74.75	66.45	71.19
	2	94.07	86.00	91.84	73.5	65.34	69.96
25	1	90.11	85.50	95.00	95.00	76.00	81.43
	2	84.00	96.00	93.34	70.00	84.00	80.00
30	1	88.03	90.00	90.12	72.32	73.64	75.00
	2	82.36	90.02	95.09	62.94	71.33	79.26
35	1	90.37	91.11	90.21	77.32	78.73	80.19
	2	88.88	91.84	93.82	75.19	78.20	81.46
40	1	87.50	91.00	94.80	66.90	75.83	75.83
	2	91.35	87.82	91.76	78.42	73.17	81.29



Series 1Average balancing efficiencies of Model 1 and Model 2 using single model approach

Series 2: Average balancing efficiencies of Model 1 and Model 2 using mixed-model approach

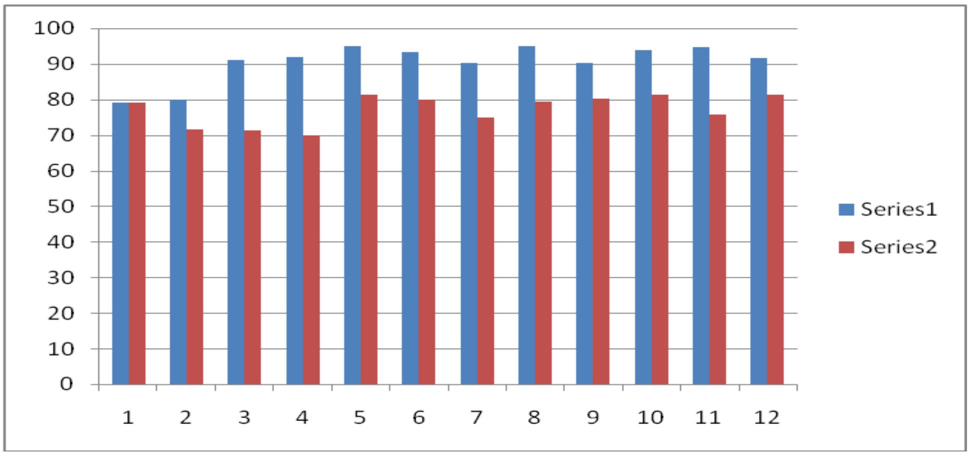
Fig.10 Average balancing efficiencies of Model 1 and Model 2 using single model approach and mixed-model approach when cycle time is 20 minutes



Series 1Average balancing efficiencies of Model 1 and Model 2 using single model approach

Series 2: Average balancing efficiencies of Model 1 and Model 2 using mixed-model approach

Fig.11 Average balancing efficiencies of Model 1 and Model 2 using single model approach and mixed-model approach when cycle time is 25 minutes



Series 1Average balancing efficiencies of Model 1 and Model 2 using single model approach

Series 2: Average balancing efficiencies of Model 1 and Model 2 using mixed-model approach

Fig.12 Average balancing efficiencies of Model 1 and Model 2 using single model approach and mixed-model approach when cycle time is 30 minutes

Table 6 ANOVA Results of Average Balancing Efficiency of Models

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Sum of Squares	F Ratio (calculated)	Table F value at α=0.05	Remark
Problem Size (A)	309.38	5	61.876	3.284	2.48	**Significant**
ALB Type (B)	3625.97	1	3625.97	192.461	4.12	**Significant**
AB	242.25	5	48.45	2.572	2.48	**Significant**
Cycle Time (C)	56.22	2	28.11	1.492	3.27	Insignificant
AC	431.41	10	43.141	2.290	2.11	**Significant**
BC	34.47	2	17.235	0.915	3.27	Insignificant
ABC	177.94	10	17.794	0.945	2.11	Insignificant
Error	678.25	36	18.84			
Total	5555.89	71				

The results of all the three subsections of this section indicate that it is better to solve each model by treating it as a single model to have the best solution in terms of balancing efficiency.

5. CONCLUSION

Assembly line balancing problem is an important issue in all mass production systems to improve their productivity as well as to meet customer demand. The mixed-model assembly line balancing problem gains importance because of the increased focus of batch manufacturing in mass production, which produces more than one product simultaneously in the same line.

If one examines the balancing efficiencies of the models that are assembled using the mixed-model approach with those of the models that are assembled using the single model approach, there will be differences.

In this paper, an attempt has been made to compare the balancing loss of the mixed-model assembly line balancing for a given set of models in comparison with that of the single model assembly line balancing. The analysis is done with respect to the balancing efficiency of each model and the average balancing efficiency of the models.

In each analysis, it is found that for most of the cases, the results using the single model approach are better than the corresponding results using the mixed model approach. But, to prove statistically, it is highly essential to conduct a design of experiment for this situation. So, a complete factorial experiment has been carried out in which three factors, viz. Problem Size (A), ALB Type (B) and Cycle Time (C) are considered, with two replications under each experimental combination. The number of models in the mixed-model is 2. In each of the three analyses, it is found that there is significant difference between the treatments of the factor “ALB type” (B). The mean balancing efficiency obtained using the single model approach is better than that obtained using the mixed-model approach.

Based on this analysis, practitioners are recommended to use the mixed-model assembly line balancing approach if there is a necessity to supply the models with small volume on daily basis. If the volume of each model is above medium level to justify a separate assembly line, then the company can setup a separate line for each model to take advantage of the best balancing efficiency.

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