

## A linear physical programming model for assembly line balancing problem

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### ABSTRACT

This paper deals with the mixed-model assembly line balancing problem. This type of line is applied to more than one similar model of a product in an intermixed order. Despite their widespread use, these lines have received little attention in the literature. Metaheuristics, heuristics and mathematical programming techniques are developed to solve these types of assembly line balancing problems. However, linear physical programming method has never used. In this paper, a linear physical programming model is proposed for balancing a mixed-model assembly line. The performance of the proposed model is applied to a numerical example to analyze the usage of the methodology. Five objectives are considered in the model and the outperformance of the methodology is demonstrated by comparing it to a different approach. According to the results, it has been seen that the proposed linear physical programming model is practical and useful approach for mixed-model assembly line balancing problems.

**Keywords:** Assembly; Assembly Line; Line Balancing; Linear Physical Programming; Mixed-Model Assembly.

### INTRODUCTION

The mechanical production methods that evolved as the development of machine tools and other production aspects form the basis of mass production with the vast development of industry in the 18th and 19th centuries. Simple one-piece products were manufactured in vast quantities at these centuries. Thus, the initial stage of the mass production process is started with the production of one-piece items. Complex units were beginning to be produced in the second stage of the mass production process. During this time, mass production was referred

to as flow production since the product was manufactured employing a flowing manufacturing method and assembly lines (Becker and Scholl, 2006).

Balancing an assembly line has crucial importance to provide effective assembly operations. A feasible balance can be accomplished for a line if the variation in idle times among all workstations as well as the needed number of workstations is minimized while satisfying all precedence relations (Razif et al., 2017).

Assembly lines can be grouped as multi-model, mixed and single assembly lines as well as the task times stochastic and deterministic (Kriengkorakot and Pianthong, 2007). The single-model assembly line is used only to assemble one model of a product. The mixed-model assembly line is applied to more than one similar model of a product in an intermixed order. The multi-model line is employed a greater variety of base products.

In a mixed-model assembly line different kinds of products are assembled. In other words, these are assembly lines in which more than one same product or distinctive models of a product are manufactured simultaneously or in a mixed manner. The models in the assembly line may be different from one another according to color or used tool because of their natural demands for different tasks, precedence relations, and assignment tasks. Minimization of the number of assembly workstations, minimization of cycle time, and line efficiency are different popular objectives used in Assembly Line Balancing Problem (ALBP) (Rashid et al., 2011).

With the development of the assembly line concept, the problem of assembly line balancing emerged and this issue has attracted and continues to be seen by many scientists. ALBP is a well-known assembly line design problem and it is about assigning tasks to stations to optimize a particular purpose. Because of optimizing critical purposes, ALBP also has a critical function particularly in the production lines (Caggiano et al., 2016).

The rest of the article is organized as follows. Firstly, literature review about ALBP is provided. Secondly, information about LPP is provided. Thirdly, the LPP formulation for ALBP is detailed. Later, detailed information and a numerical example of the proposed LPP-method are provided. Finally, a conclusions and future research directions are presented.

## **LITERATURE REVIEW**

The methodologies developed for the solution of ALBP can be grouped into three groups. The paper in the first group presents recent heuristic-based studies. Borba et al. (2018) developed an iterative beam search and branch-bound based hybrid heuristic approach. Aufy and Kassam (2020) proposed a consecutive heuristic algorithm. The second group includes studies

using metaheuristic approaches. Genetic algorithm (Gurevsky et al., 2012; Alavidooost et al., 2015; Mura and Dini, 2016; Jusop and Rashid, 2016; Zhang et al., 2020), artificial bee colony algorithm (Tang et al., 2016; Zhao et al., 2016; Zhang et al., 2018), ant colony optimization (Zheng et al., 2012; Samouei and Dezfoulian, 2017; Huo et al., 2018; Huang et al., 2020), discrete cuckoo search (Li et al., 2018), hybrid genetic algorithm (Lin et al., 2009), simulated annealing (Dong et al., 2018; Li et al., 2018), memetic algorithm (Pereira et al., 2018), fish school search algorithm (De Albuquerque et al., 2016); migrating birds optimization metaheuristic (Janardhanan et al. 2019), multi-objective evolution strategies (Yoosefelahi et al., 2012; Zacharia & Nearchou, 2016).

The studies in the final group use mathematical programming techniques. GAMS-CPLEX algorithm (Esmailbeigi et al., 2015), excel (Wei and Chao, 2011). Two recent studies by Make et al. (2017) and Eghtesadifard (2020) ensured a comprehensive review of the assembly line balancing literature with their solutions. The reader may also refer to Sivasankaran and Shahabudeen (2014) for more studies. Although many objectives are taken into account in the methods based on the ALBPs model in the literature, the most important disadvantage of these methods is that the decision-maker cannot make his/her options in a physically expressive way while considering each objective. In other words, since the decisions made by the decision-maker do not have any tangible meaning, the consistency of the criteria weights obtained as a result of the comparisons is very low.

In this study, the Linear Physical Programming (LPP) method is used which enables the decision-maker to define his/her options in a physically expressive way for each of the objectives. Thanks to this proposed method, the process of determining exact weights, which causes consistency problems in previously proposed methods and forces decision-makers to make subjective decisions and intangible comparisons, has been eliminated. The importance of this study is primarily to fill the gap caused by the fact that the LPP method has not been used in ALBP before in the literature. Another aim is to analyze whether this method provides an advantage over the previous methods used in the literature.

### **LINEAR PHYSICAL PROGRAMMING METHOD**

In multiple criteria decision-making methodologies such as analytical network process and goal programming, the main difficulty for decision-makers is to determine the weights within the benefits function. The LPP overcomes this challenge by allowing decision-makers by expressing their preferences for each criterion using 4 class functions. Criterion weights are determined by an algorithm specific to LPP according to the preference values for each

criterion decided by the decision-maker. Thus, the decision-maker is not directly involved in the weight determination process (Messac et al., 1996). In LPP, the decision-maker can use one of the 4 class functions presented in Figure 1. This figure contains the values ( $t_p$ ) for the criteria evaluated on the horizontal axis. As for the vertical axis, it contains the class function ( $z_p$ ) which is desired to be minimized for each of the criteria. The class function is asked to take small values and its ideal value is zero. Preference intervals on the horizontal axis while evaluating any alternative  $p$ . It is used to categorize the values related to the criteria. These intervals can be expressed as follows for the 1S class:

- $g_p \geq t_{p5}^+$  (Unacceptable interval)
- $t_{p4}^+ \leq g_p \leq t_{p5}^+$  (Highly undesirable interval)
- $t_{p3}^+ \leq g_p \leq t_{p4}^+$  (Undesirable interval)
- $t_{p2}^+ \leq g_p \leq t_{p3}^+$  (Tolerable interval)
- $t_{p1}^+ \leq g_p \leq t_{p2}^+$  (Desirable interval)
- $g_p \leq t_{p1}^+$  (Ideal interval)

The preferences for the  $p$ th criterion are expressed by specifying the physical values of the quantities  $t_{p1}^+$  through  $t_{p5}^+$ . Assume that a decision-maker collects the following values in order to determine the cost parameter from  $t_{p1}^+$  to  $t_{p5}^+$  in pounds: (7000, 5000, 3500, 2500, 1500). With these values, the cost of the £1000 alternative will be included in the ideal interval, while the cost of the £4000 alternative will be included in the undesirable interval, and so on until the determination of interval procedure is completed. The LPP steps are as below:

1. For each criterion used in evaluating alternatives, the decision-maker selects one of the class functions provided in Figure 1.
2. For each criterion, the decision-maker establishes distinct intervals (target values) of attraction degrees. As seen in the horizontal axes of the functions given in Figure 1, there are five intervals in class 1S, five intervals in class 2S, nine intervals in class 3S, and ten intervals in class 4S.
3. The LPP weight algorithm is used to calculate the weights as given below:
  - a. begin:  $\alpha = 2.2$ ;  $r_{p1}^+ = 0$ ,  $r_{p1}^- = 0$ ,  $\tilde{s}^2 =$  small affirmative value (say, 0.02)  
 $p = 0$ ;  $m = 1$ ,  $m_c =$  is criteria number
  - b. set  $p = p + 1$ ,
  - c. set  $m = m + 1$  evaluate the sequence:

$\tilde{s}^m, \tilde{t}_{pm}^+, \tilde{t}_{pm}^-, \tilde{r}_{pm}^+, \tilde{r}_{pm}^-, r_{pm}^+, r_{pm}^-, \tilde{r}_{min}$  if the pre-determined small positive number (say, 0.002)

is greater than  $\tilde{r}_{min}$ , increase  $\alpha$  then go to ii.

d. if  $m \neq 5$ , go to step c.

e. if  $p \neq m_c$ , go to step b.

where  $m$  is the interval factor,  $m_c$  is the numbers of criteria,  $p$  is the criteria factor,  $r_{pm}^-$  and  $r_{pm}^+$  are negative and positive weights for the  $p$  criteria in interval  $m$ ,  $\tilde{r}_{min}$  is the minimal value of  $\tilde{r}_{pm}^+$  and  $\tilde{r}_{pm}^-$ ,  $sp$  is the function included in the interval for  $p$  criteria;  $\tilde{s}^m$  is the changes in  $sp$  value against interval  $m$  value,  $\tilde{t}_{pm}^-$  and  $\tilde{t}_{pm}^+$  are the negative and positive sides of the  $p$ th criterion in the size of  $s$ th intervals,  $\tilde{r}_{pm}^-$  and  $\tilde{r}_{pm}^+$  are negative and positive normalized weights for the  $p$ th criterion in interval and convexity factor represented with  $\alpha$  (Messac et al., 1996).

4. Calculate the total score for each alternative.

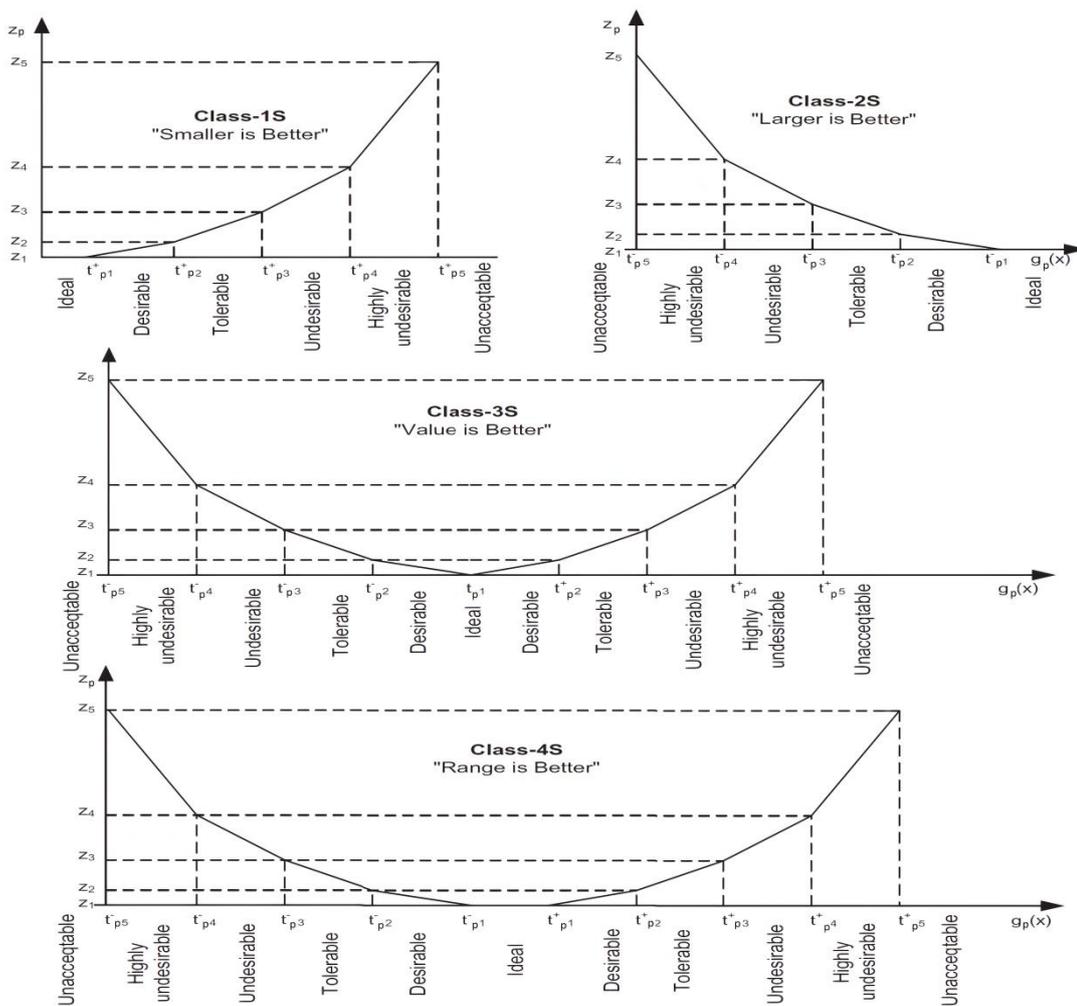


Figure 1. Class functions in LPP.

## PROBLEM DESCRIPTION AND FORMULATION

In this section, the applicability of the proposed LPP-based method in a home appliances industry is discussed. One of the most difficult stages in a decision-making process for the decision-maker is defining a weight process. This process is not an effective way to gather the exact preferences because of subjectivity. In LPP, assignment of exact physically meaningless weights to goals does not require. Instead of this, LPP permit to decision-maker defining their choices by considering physically expressive preference intervals for each objective. Thus, the data collection process is being much more facilitated. Furthermore, the uncertainty of each objective is intentionally regarded by allowing the decision-maker to define her/his options as intervals in place of exact scores.

A LPP methodology for mixed-model assembly line balancing problem is improved in this study by considering Samouei and Ashayeri (2019), Choi (2009), Fathi et al. (2018), Gokcen and Erel (1997) mathematical models. The decision variables are as follows:

- $D$         the total number of tasks
- $S$         the total number of workstations
- $P$         the total number of product kinds
- $t_{in}$      Process time for  $i$ th task of  $n$ th model  $i = 1, \dots, D; n = 1, \dots, P$
- $C_n$       $n$ th model cycle time,  $n = 1, \dots, P$
- $A_{is}$      1 if  $i$ th task is assigned to  $s$ th workstation, 0 otherwise,  $s = 1, \dots, S; i = 1, \dots, D$
- $Y_{sn}$      1 if  $n$ th model is assigned to  $s$ th workstation, 0 otherwise,  $n = 1, \dots, P; s = 1, \dots, S$
- $X_s$      1 if  $s$ th workstation is used for all models, 0 otherwise,  $s = 1, \dots, S$
- $U_{in}$      1 if  $i$ th task is needed for  $n$ th model, 0 otherwise,  $n = 1, \dots, P; i = 1, \dots, D$

The LPP-based methodology assumptions are as follows:

On a one-sided straight assembly line, different models of the same basic product with identical production features are built. The assembly line is a fast-moving line that produces a mixed-model product. Priority restrictions link the assembly tasks together. A task that requires assembly cannot be distributed among numerous workstations. At any given time, only one task can be completed at a workstation. The amount of time it takes to complete a task is independent of the workstation to which it is assigned. Work-in process, set-up times, and parallel workstations are negligible. Any workstation can be used to complete a task. Each assembly task's processing time is known and deterministic.

### MATHEMATICAL MODEL

The mathematical formulations of the proposed ALBP model are improved by considering five objectives. Objective first (equation-1) is to minimize cycle time for all models. The second objective (2) minimizes the number of used workstations. The third objective (3) minimizes the different models' slack time differences while the fourth objective (4) minimizes the total idle time. The final objective (5) aim is to maximize the line efficiency of the line.

$$O_1 = \min \sum_{n=1}^P C_n \quad (1)$$

$$O_2 = \min \sum_{s=1}^S A_{is} = 1 \quad \forall i = 1, 2, \dots, D \quad (2)$$

$$O_3 = \min \sum_{n=1}^P \alpha \quad (3)$$

$$O_4 = \min \sum_{s=1}^S \sum_{n=1}^P h_{sn}^- \quad (4)$$

$$O_5 = \max \sum_{s=1}^S \sum_{i=1}^D t_{in} \cdot A_{is} / (C_n \cdot S) \quad n = 1, \dots, P \quad (5)$$

$$\sum_{i=1}^D U_{in} \cdot A_{is} - U_{in} \cdot Y_{sm} \leq 0, \quad s = 1, \dots, S, \quad n = 1, \dots, P \quad (6)$$

$$\sum_{n=1}^P Y_{sn} - P \cdot X_s = 0 \quad s = 1, \dots, S \quad (7)$$

$$Y_{sm} - \sum_{i=1}^D U_{in} \cdot A_{is} \leq 0, \quad s = 1, \dots, S, \quad n = 1, \dots, P \quad (8)$$

$$\sum_{s=1}^S X_s \leq WS, \quad s = 1, \dots, S \quad (9)$$

$$\sum_{s=1}^S X_s + d^{ws-} - d^{ws+} = WS, \quad s = 1, \dots, S \quad (10)$$

$$\sum_{i=1}^D t_{in} \cdot A_{is} \leq C_n, \quad s = 1, \dots, S, \quad n = 1, \dots, P \quad (11)$$

$$\sum_{i=1}^D t_{in} \cdot A_{is} + h_{sn}^- + P_{sn} = C_n, \quad s = 1, \dots, S, \quad n = 1, \dots, P \quad (12)$$

$$P_{sn} \leq (1 - Y_{sn}) * N, \quad s = 1, \dots, S, \quad n = 1, \dots, P \quad (13)$$

$$|h_{sn}^- - h_{s(n+1)}^- - (1 - Y_{sn}) * C_n| \leq \alpha, \quad s = 1, \dots, S, \quad n = 1, \dots, P - 1 \quad (14)$$

$$\sum_{s=1}^S s \cdot A_{is} - \sum_{s=1}^S s \cdot A_{js} \leq 0, \quad \forall i \leq j, i = 1, \dots, D \quad j = 1, \dots, D \quad (15)$$

$$\sum_{s=1}^S A_{is} = 1, \quad \forall i = 1, \dots, D \quad (16)$$

$X_s, A_{is}, Y_{sn}, U_{in} : 0 - 1$  integer value

Constraints (6) – (8) guarantees that if an unassigned task is assigned to a new workstation, a new workstation must be allocated. A new workstation will be allocated for whole assembly line models only when the workstation is allocated just for at least one assembly line model. Allocated workstations for each assembly line model will be included a task from different assembly line models. Constraint (9) handles to restrict the opened number of workstations. Constraint (10) ensures the necessary deviation factors. Constraint (11) is for the calculation of cycle time and with the task, assignment operations are ended for all assembly models the total time of tasks assigned to a workstation must less or equal to cycle time. Constraints (12) and (13) guarantees that  $h_{sn}^-$  will not take a value and  $P_{sn}$  factor takes value only when the workstation  $s$  is not used for model  $n$ . Constraint (14) evaluates that a pre-defined  $\alpha$  value can be limit the difference of  $h_{sn}^-$  deviation factors. By using this limitation idle time differences among the workstations will not be greater than  $\alpha$ . Constraint (15) preserving the precedence relations during the assignment of tasks to the workstations. Constraint (16) ensures that each assembly model's task assignment is limited to one workstation.

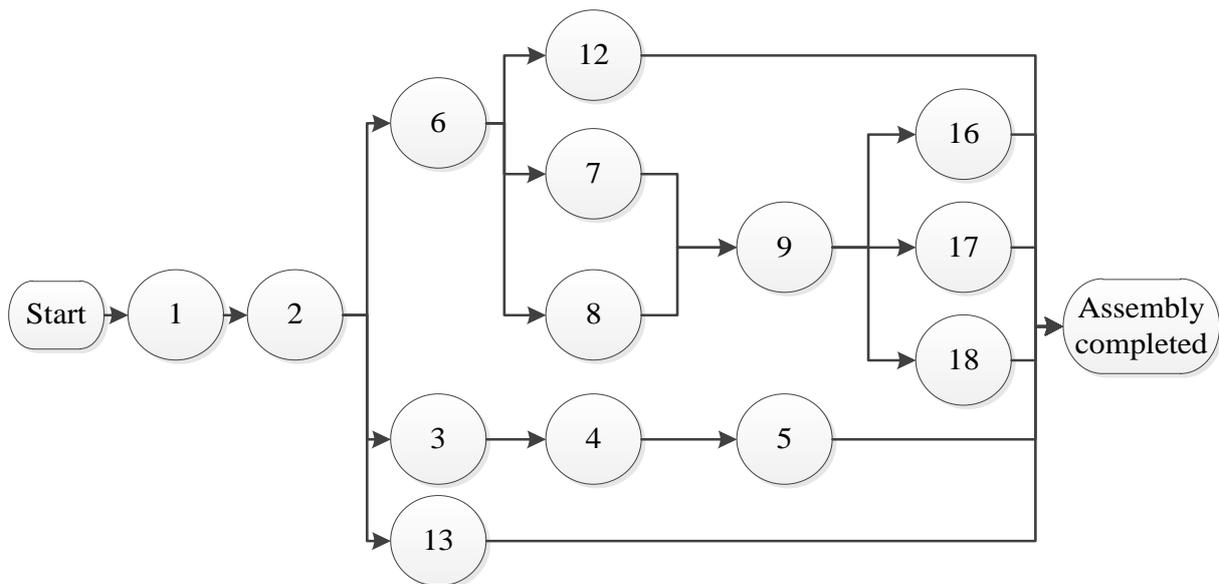
### APPLICATION OF THE LPP METHOD

This study considers the design of an assembly line for the assembly of machines. Two different product types are considered: washing machine and tumble dryer (dryer machine). Precedence relations and processing times of products are illustrated in Table 1. Precedence relations graph for washing machine and tumble dryer are presented in Figures 2 and 3 respectively. Figure 4 represents an integrated precedence graph.

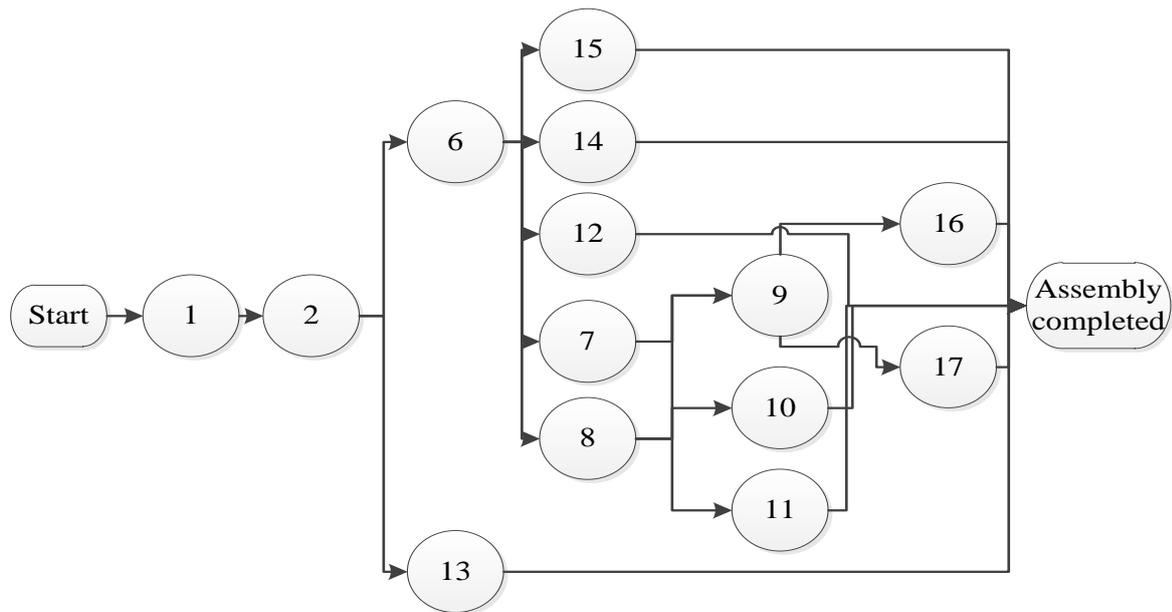
All five goals described in the LPP formulation section were modeled by considering Class 2S LPP functions. Table 2 presents the payoff table for upper and lower values of one objective and the limitation of Class 2 LPP functions were decided by regarding these values.

LPP limitation values are given in Table 3. LPP weight algorithm is used to decide LPP weights. Proposed LPP based assembly line balancing methodology weights are provided in Table 4.

Abd El-Wahed and Lee (2006) comparison procedure is used to compare the performance of the proposed LPP to Fuzzy Goal Programming (FGP) performance. The numerical example model was solved by using Lingo 12.0. Table 5 presents the workstations times and task assignments of each model. Table 6 presents the outcomes of LPP and concerning results; the first objective ( $O_1$ ) function values are 35s and 45s for model 1 and model 2 respectively. The difference is 10s and this value is considered for comparison. The second objective ( $O_2$ ) function minimizes the summation of workstations and the deviation from the predetermined workstation number (4) is 1 workstation since the summation of workstations to be allocated was stated as 5. The third objective ( $O_3$ ) function value is 7s and this objective minimizes the slack time differences between assembly models in a workstation. To minimize the solution of the fourth objective ( $O_4$ ) function there is a 29s total idle time. The fifth and the final objective ( $O_5$ ) function take the value of 0.923 as maximized line efficiency value.



**Figure 2.** Precedence relation graph for washing machine



**Figure 3.** Precedence relation graph for tumble dryer

**Table 1.** Precedences and processing times for washing machine and tumble dryer

Task Number	Part Name	Process time (WM) (s)	Process time (TD) (s)	Precedence relationships
1	Drum support rollers	8	12	-
2	Drum	20	30	1
3	Drain pump	15	-	2
4	Filter	10	-	3
5	Drain hose	5	-	4
6	Motor	35	30	2
7	Drive Belt	20	25	6
8	Heater	15	15	6
9	Outer cover	45	40	7,8
10	Thermostats	-	10	8
11	Vent	-	15	8
12	Power supply	3	3	6
13	Water supply hoses	6	-	2
14	Blower	-	20	6
15	Exhaust duct	-	10	6
16	Door	15	20	9
17	Control panel	10	15	9
18	Detergent drawer	10	-	9

**Table 2.** Payoff values

	$Z_1$	$Z_2$	$Z_3$	$Z_4$	$Z_5$
$O_1$	0	5	18	113	0.908
$O_2$	46	0	7	49	0.863
$O_3$	66	2	1	186	0.856
$O_4$	18	3	5	33	0.924
$O_5$	0.923	0.838	0.889	0.917	0.819

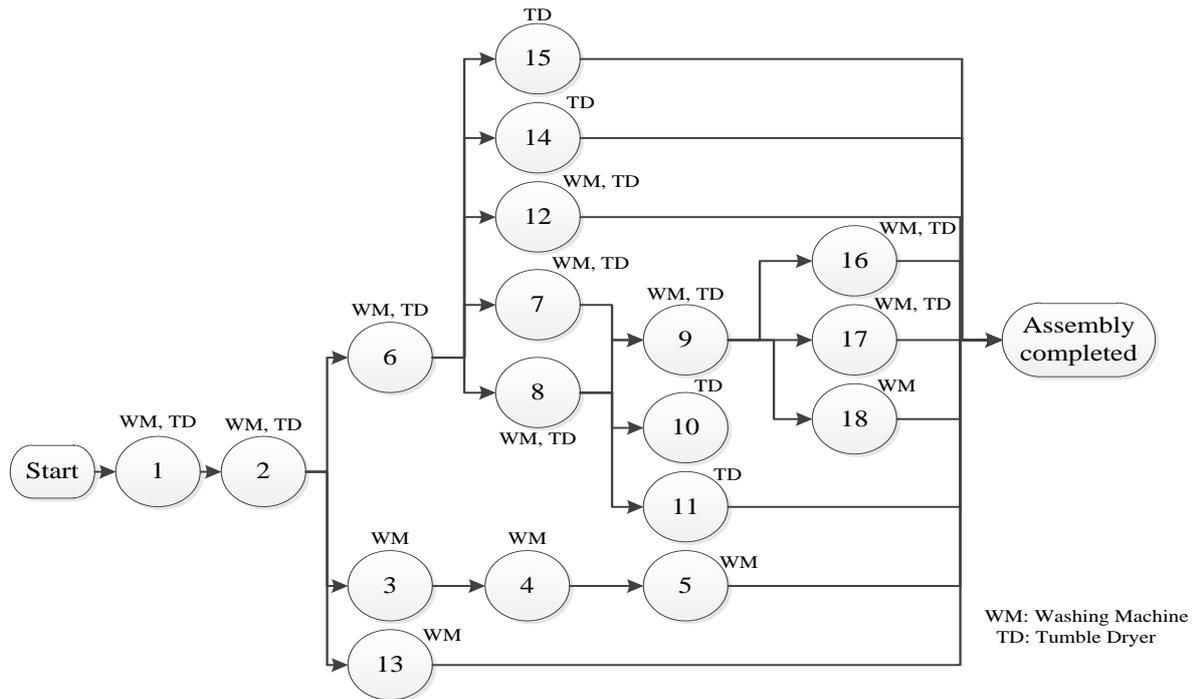
**Table 3.** LPP limit values

	$t_{p5}^-$	$t_{p4}^-$	$t_{p3}^-$	$t_{p2}^-$	$t_{p1}^-$
$O_1$	56.5	45	20	15	0
$O_2$	8	6	3	2	0
$O_3$	20	15	5	3	0
$O_4$	186	65	42	34	25
$O_5$	0.969	0.919	0.881	0.851	0.818

**Table 4.** LPP weights

	$r_{p5}^-$	$r_{p4}^-$	$r_{p3}^-$	$r_{p2}^-$
$O_1$	33.561	0.823	0.352	0.052
$O_2$	138.600	11.300	1.100	0.102
$O_3$	6.866	3.560	0.250	0.051
$O_4$	9.356	0.510	0.110	0.014
$O_5$	60.450	9.690	0.420	0.112

Table 6 represents the best value of ideal solution for a definite objective function considering Table 2 payoff values. As shown in Table 6, for A values, the LPP method put forwards quite promising performance compared to FGP (Abd El-Wahed and Lee, 2006). All these outcomes represent that to solve ALBP, the LPP method is an encouraging solution approach.



**Figure 4.** Integrated precedence relation graph

**Table 5.** Assigned tasks to allocated workstations

Stations	Tasks	Model 1 (Washing Machine)		Model 2 (Tumble Dryer)	
		Tasks	Station Time	Tasks	Station Time
1	1,2,3,4,7	1,2,3	43	1,2	42
2	5,6,8,10	4,5,6	50	6,7	55
3	9,12,14	7,8	35	8,9	55
4	11,13,16	9,12	48	10,11,12,14	48
5	15,17,18	13,16,17,18	41	15,16,17	45

**Table 6.** LPP-based methodology and FGP results comparison

	Linear Physical Programming	Fuzzy Goal Programming
O <sub>1</sub>	10	15.568
O <sub>2</sub>	1	3
O <sub>3</sub>	7	5.458
O <sub>4</sub>	29	32.454
O <sub>5</sub>	0.923	0.912
A <sub>1</sub>	0.915613547	0.915658650
A <sub>2</sub>	0.536914523	0.556845390
A <sub>3</sub>	0.514858586	0.524958400
A <sub>4</sub>	0.335894752	0.345589420
A <sub>∞</sub>	0.241070500	0.246080600

## CONCLUSIONS

Mixed-model assembly line balancing research is crucial to consider for adaptability and productivity because it has a direct impact on the production system's efficiency. Mixed-model assembly lines are preferred over single-model assembly lines in the current market, which is characterized by a growing pattern for a bigger product or item variation. To meet open market demand, more and more businesses, such as the home appliances industry, are transitioning from traditional and manual methods to semi- and fully-automated systems. In this study, an assembly line balancing approach based on LPP was developed for white good products. The LPP-based method was implemented to balance a machine assembly line including mixed-model assembly lines. Five different objective functions are considered and the values are for ( $O_1$ ) is 10, ( $O_2$ ) is 1, ( $O_3$ ) is 7s, ( $O_4$ ) is 0.29s and ( $O_5$ ) is 0.923. These results show that the LPP-based assembly line balancing approach provides quite promising result.

The proposed approach can provide the following managerial insights:

- Deterministic or stochastic process times could be seen in the assembly operations. While balancing mixed-model assembly lines, the proposed approach allows decision makers to consider deterministic issues.
- The LPP technique gives decision-makers the option of employing interval ranges.

The limitations of the study are as follows:

- In real-life problems, processing times can be stochastic. However, stochastic processing times were not taken into account in this study.
- The number of components considered in the proposed method is reasonable. More complex models or components can take a long time to solve.

The proposed LPP-based method should be enhanced by considering stochastic process times by using simulation optimization methodology. Although the proposed approach is applied to mixed-model ALBP, it could also be tested by applying to different ALBPs for further research.

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