

---

This is an electronic reprint of the original article.  
This reprint may differ from the original in pagination and typographic detail.

Peltokorpi, Jaakko; Tokola, Henri; Niemi, Esko  
**Comparison of Balancing Policies in Multi-Item Assembly**

*Published in:*  
FAIM 2012 22nd International Conference on Flexible Automation and Intelligent Manufacturing, Helsinki, Finland, June 10th-13th, 2012

Published: 01/01/2012

*Document Version*  
Peer reviewed version

*Please cite the original version:*  
Peltokorpi, J., Tokola, H., & Niemi, E. (2012). Comparison of Balancing Policies in Multi-Item Assembly. In *FAIM 2012 22nd International Conference on Flexible Automation and Intelligent Manufacturing, Helsinki, Finland, June 10th-13th, 2012* (pp. Paper ID 1115). Tampere University of Technology.

---

This material is protected by copyright and other intellectual property rights, and duplication or sale of all or part of any of the repository collections is not permitted, except that material may be duplicated by you for your research use or educational purposes in electronic or print form. You must obtain permission for any other use. Electronic or print copies may not be offered, whether for sale or otherwise to anyone who is not an authorised user.

# Comparison of Balancing Policies in Multi-Item Assembly

Jaakko Peltokorpi\*, Henri Tokola

Department of Engineering Design and Production  
Aalto University School of Engineering  
Espoo, 02150, Finland

## ABSTRACT

*A flexible workforce and the efficiency of manual assembly are important competitive factors in make-to-order production. Worker specialisation in single products or tasks is one way to make production efficient. However, specialisation with a varying workload makes production inefficient if balancing or flexibility between assembly stations is not considered. In addition, balancing is often not easy to achieve because of the different learning levels of the workers. Moreover, learning becomes more important as a result of a high turnover of workers. This paper combines all of the above and studies how learning and turnover affect workload balancing. This is done by comparing different balancing practices between parallel work stations. These practices consist of very simple and more complex ones. Different cases are explored using numerical experiments. The results show the effect of learning, balancing policies, and worker turnover on the assembly performance and also on the training costs.*

*Keywords: make-to-order, parallel assembly, learning curve, balancing policy, worker turnover, simulation*

## 1. INTRODUCTION

Demand for an agile response to changing market situations has led companies to use flexible workforce and intensify manual assembly in make-to-order production. Traditionally, worker specialisation in single products or tasks is one way to make production efficient. However, with a varying workload lead times and manufacturing costs increase if balancing or flexibility between assembly stations is not considered. Balancing by worker allocation is challenging because of the different learning levels of the workers. The system complexity increases again when high worker turnover affects learning. This paper combines all of the above and studies how learning and turnover affect workload balancing, and also how the use of those methods affects training costs.

Assembly system balancing with variation in workload and labour is a very widespread research problem in the academic world. As a representative example, in a paper by Vidic [1], worker learning in order to solve the assignment problem on a serial assembly line was examined. The study compares the performances of dynamic work sharing and static assignment policies without and with learning and forgetting conditions. The results were reported as optimum throughput levels and worker assignments. The most significant conclusions were that with dynamic work sharing, worker training for different tasks on a line is easier because there are dedicated line segments where they are to work. With a static assignment policy, workers can be allocated to any station and thus they must be trained to perform all tasks. The dynamic assignment policy seemed to work better in short production periods, whereas the use of a static assignment policy produced good results in long production periods in relation to maximum throughput. The warming-up of the system was taken into account by means of initial WIP with a static assignment policy.

The impact of worker turnover and learning on average item flow time with different numbers of parallel assembly lines was studied in [2]. The study pointed out that the flow time will grow disproportionately when the number of parallel lines increases. When existing and new systems were compared, the latter seemed to require more effort for balancing because of the significant learning (rates of 55% and 70%) involved. That is why turnover (rates of 8% and 3% monthly) was also a significant factor with new systems.

---

\* Corresponding author: Tel.: +3589-470-23523; E-mail: jaakko.peltokorpi@aalto.fi

The literature review showed that there are many studies on balancing serial lines with system variables of worker skills and turnover. However, balancing parallel single stations in circumstances with learning effect and varying workforce turnover seems to have received little attention. Thus there is room for comparing different practical balancing methods in order to find out how they affect system performance.

The object of this paper is to study different balancing policies by means of simulation experiments. A simulation study is justified because empirical research on a system where learning, worker turnover, and balancing policies affect performance would be very laborious.

The rest of the paper is organised as follows. Chapter 2 presents more previous results on learning, worker turnover, and different balancing policies to motivate the dynamics of the system being modelled. The simulation model and results of the experiments are presented in Chapter 3, followed by discussion in Chapter 4. Finally, the conclusions in Chapter 5 will act as a summary of the paper.

## 2. LITERATURE REVIEW

This chapter presents some previous results on the essential factors that affect the assembly performance. The first two sections, 2.1, Learning, and 2.2, Worker turnover, deal with the basic factors affecting performance in repetitive work, and thus have been extensively studied in the literature. Section 2.3, Balancing policies, discusses balancing policies generally used in previous literature.

### 2.1. LEARNING

Individual learning strongly affects the productivity of a worker. In repetitive work, the learning level rises as a result of completed tasks while worker specialises. The learning rate,  $\phi$ , depends on task type, which comprises task character and overall task complexity. Yelle [3] reviewed studies from the manufacturing industry (Hirschman, 1964, and Jordan, 1958) and noted an estimation of 80% learning rate for a system in which 25% of labour was machine-paced. For more manual tasks, the progress ratio  $1 - \phi$  increases and learning is faster.

Since work is mainly performed manually, one of the best-known formulae for learning was developed by Wright (1936) [3]. This learning curve is widely used for industry tasks. The formula is

$$Y = KX^n \quad (1)$$

where  $Y$  = the number of direct labour hours required to produce the  $X$ :th unit,  $K$  = the number of direct labour hours required to produce the first unit, and  $X$  = the cumulative unit number. The learning index is

$$n = \frac{\log \phi}{\log 2} \quad (2)$$

where  $\phi$  = the learning rate.

### 2.2. WORKER TURNOVER

Learning is a process which takes a certain amount of time to take place. In some cases this process ends as a result of worker job dissatisfaction or for other reasons. Loss of motivation can lead to the worker resigning from the job.

The characteristics of assembly job and task content in repetitive work are the main factors affecting worker turnover rate. An experimental study of the consumer electronics industry [4] showed that the monthly turnover rate was 21.9% on a repetitive line and 12% in repetitive batch production. A more recent study of traditional Chinese assembly plants [5] indicated an overall monthly turnover rate in factories from 2.9% to 7.5%.

In real working life, the worker turnover rate is not evenly distributed during their tenure. Hutchinson et al. [6] cited this finding according to Stoddard (1987), who studied the maquila industry in Mexico. The Weibull probability distribution was used to characterise the probability of leaving as a function of tenure days. Stoddard drew a conclusion

that turnover is most likely to occur during the first 60 to 90 days of employment. Hutchinson studied serial assembly lines and got a result of a 12.6% annual drop in throughput with a 6% monthly turnover rate during an average year, while mean tenure was 507 days. With a 12% turnover, annual throughput dropped by 16.3%. The study examined work content allocation for workers with different levels of experience in order to maximise throughput, but replacement policies had a minor impact on performance in relation to turnover rate.

The dependence of turnover rate on cycle time was modelled by Globerson and Crossman [7], who cited Livingstone's (1972) studies from the Swedish car industry. Livingstone noticed that by increasing the cycle time from 2 minutes to an average of 20 minutes, the annual turnover rate can be reduced from about 100% to 50%.

### 2.3. BALANCING POLICIES

This section presents some general workload and worker balancing policies which have been used in the manufacturing industry. The applications of these policies can be used in different cases, as this paper shows. Some well-known balancing policies – *complete chaining*, *floater*, and balancing *in pairs* – are presented here with their reported applications. Some other policies, tested in the present paper, are presented in the next chapter.

#### *Complete chaining*

Jordan et al. [8] introduced the *complete chaining* policy in the context of maintenance in the manufacturing industry. According to this policy, the workers act as servers on parallel lines for repairing errors of different types. In this model one worker from each work pool was cross-trained for one task in addition to their primary work task. The skill level of the cross-trained worker for the secondary task was assumed to be the same as the primary worker's. In the study, the *complete chaining* policy was compared with no cross-training, total cross-training, and specific configurations and randomly generated policies. The performances, measured by mean time to repair, of the best configurations were only slightly better than with *complete chaining*. The numbers of cross-training links were equal in the best policies and *complete chaining*.

#### *Floater*

Floaters are workers with multiple skills and flexibility qualities [9]. These moving workers are used on assembly lines to reduce buffers and prevent starvation of fixed workers. Usually floaters do not have a home station and thus they are used to replace absent workers and workers who are taking a break in order to keep the line running. Senott et al. [9] examined a one floater balancing policy on short assembly lines and noted that optimising the combination of a floater and fixed workers is challenging because of unevenly distributed flexibility and obligations. Long assembly lines with only one fully trained worker were seen to be impractical because of the long walking distances.

#### *In pairs*

Assembly balancing *in pairs* can be thought of as complete chaining with a specific configuration of pairs. An advantage of this method could be the dynamic duo aspect, in which two workers get used to working together, knowing each other's ways of working. In the context of assembly workload balancing, working *in pairs* is often included in methods of paralleling. In paralleling, an assembly task can be performed, for example, at two stations, as Pinto et al. [10] determined in their study of assembly lines. Another method for assembly workload balancing is two-sided assembly, which can also be performed *in pairs*, according to Bartholdi [11].

### 3. EXPERIMENTS

In this chapter, the experimental model of this study is described. First, Section 3.1 describes the system that is the basis for testing the dynamic behaviour in focus. In Section 3.2, simulation experiments are described, followed by results in Section 3.3.

#### 3.1. SYSTEM DESCRIPTION

In the experiments we study a system with a certain number of parallel work stations, each producing a different product. Each station has one designated worker. At the beginning of each week, the stations get the number of orders they must produce in the given week. Workers get faster when they repeat their job and learn according to a basic log-linear learning curve (Equation 1). At the beginning of each simulation run, all workers are inexperienced. The system studied here assumes only product-specific learning, which means that only the experience of each individual product-specific station determines the learning level and thus the pace of work there. The rate of learning is assumed to be 85%, since assembly work is repetitive and clearly manual.

After producing the given number of products at a single station, the workers can go to help other stations, according to the balancing policy being used. Training for a new task is assumed to take place by doing it without any contribution of a co-worker. Additionally, no efficiency loss as a result of congestion etc. is taken into account because of both workers having their own product. All of the products allocated to a period of one week have to be finished, no matter how long it takes. At the end of the week the worker may resign from the workplace, in which case he is replaced by a new worker without previous experience of any of the products. In this paper, the worker turnover rate, reviewed in the literature, is also used over a large range in order to find out its effect.

The simulated system uses one of eight balancing policies at a time in order to see how they affect performance. In addition to the three well-known policies introduced in Section 2.3, we study some practical balancing policies which are suitable for the system that is described. Those balancing policies, like all the policies used in this context, can be called helping methods since balancing is used to help with the weekly workloads at each station. A common feature of the whole system is that workers have a home station where they are specialised and the tasks of which they have to complete before moving to help others. In addition, the maximum number of workers at one station is two. The new balancing policies are presented in the sections below.

##### *Next free*

This method allows a little more freedom to move in comparison to *complete chaining* in Section 2.3. In it, after completing work at his home station, the worker will move forward to help the next station that has work left, but is not yet being helped. The number of different stations helped during a week is not limited to one. Finally, this method needs no control because of the simple helping rule.

##### *Most experience*

As explained above, workers gain product-specific experience at each station. This helping rule allocates a released worker to the station of which he has the most experience, which is cost-efficient. Additionally, the *most experience* rule is reasonable from workers' point of view and thus receives their approval.

##### *Helping the less experienced*

In some cases, especially with a large amount of workload, a new worker will need help to complete tasks. *Helping the less experienced* is a priority which takes this aspect into account. Although the workload for each station is randomly generated, the working pace of the newest worker varies most, and thus his performance cannot be predicted exactly, and helping takes place. This method allows a released worker to help only a newer worker than himself. The first worker to be helped is the newest one.

##### *Only one (floater) helps*

This method is a simple modification of the previously discussed *floater* policy: only the most experienced worker helps, if he is released from his home station. When released, the worker moves according to the *next free* policy. This role will not change during the simulation period, except in the situation of worker turnover. The advantage of the

method is low training costs, because there is only one multi-skilled worker. However, helping in the whole system is strongly limited.

### *Most work left*

Since the weekly workload for each station is known in advance, the differences in weekly task completion times between stations can be estimated. Moreover, workers with a little weekly workload can anticipate moving to help those with most work left.

All eight selected balancing policies, applied from the literature review and the authors' experience, are listed in Table 1 below:

Table 1: Principles of selected balancing policies

Balancing policy	The station to move to
Complete chaining	Only the next
Pairs	Neighbouring station with which the helper forms a pair
Next free	Next with work remaining
Most experience	In which the helper has most experience
Helping less experienced	In which the worker of the home station is least experienced
Only one (floater) helps	Next with work remaining
Most work left	Most work content remaining
No helping	-

### 3.2. EXPERIMENTS

The simulated assembly systems have the following parameters:

- $n$ : number of parallel stations (1-8)
- $d$ : weekly demand for single station
- $p$ : default duration of the task
- $w$ : run period in weeks
- $q$ : base turnover rate
- $\phi$ : learning rate
- balancing policy

Weekly demand,  $d$ , is evenly distributed between 0 and 200 units for all stations. In the model, the task duration,  $p$ , is set to 1 per one item. The run period,  $w$ , for the system is 52 weeks, and the number of runs is 100 for all the cases. The same random demand values are used in each experiment.

The base turnover rate,  $q$ , defines the turnover percentage for each week and each worker during the first 15 weeks according to Stoddard's findings [6]. After 15 weeks of work tenure, the turnover is set to one tenth of the base turnover rate in order to simulate the Weibull probability distribution of leaving. The default weekly turnover rate is 3%.

The learning rate,  $\phi$ , defines how easy it is to learn the tasks. It is 85% for all stations.

The balancing method defines which balancing policy the system uses. The methods were introduced in the previous section.

The average task content,  $t$ , according to the weekly demand,  $d$ , and task duration,  $p$ , is 24 minutes if tasks are completed in one shift of 40 hours per week ( $h_w$ ). Thus, the equation from which the task content is obtained is

$$t = \frac{h_w}{d \cdot x \cdot p} \times 60 \text{min} \quad (3)$$

That is in line with a tolerable cycle time in repetitive work, discussed in Section 2.2

The simulator used was written in Microsoft Visual Basic for Applications (Excel). Time was handled in discrete 0.005-unit steps. The following results were got from the simulations:

- Average time: average time in minutes to finish one task in a run period
- Amount of training: total number of times a worker has to be trained for a new job. This may be due to new worker recruitment or the balancing method. Training for new (first) workers at the beginning of the run period is counted.

### 3.3 RESULTS

Figure 1 presents how the number of machines and different balancing policies affect the average task time. In this experiment, the learning rate was set to 85% and weekly turnover was set to 3%.

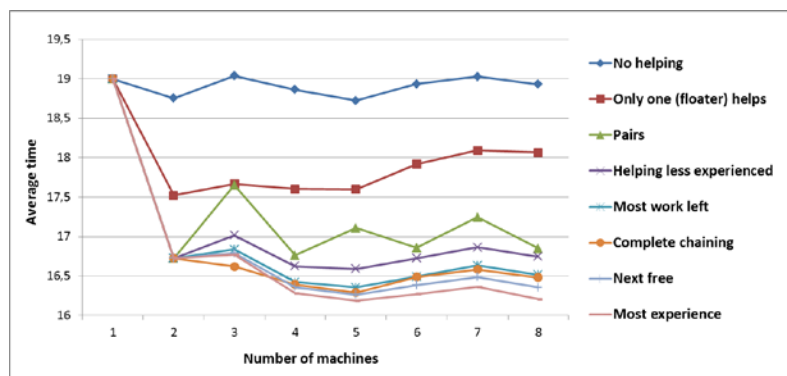


Figure 1: Average task time in relation to number of machines

Figure 2 presents the average task time as a function of turnover rate with different balancing policies. The base weekly turnover rate varies from 0 to 5% in steps of 1% of a unit. In this experiment, the learning rate was set to 85% and the number of machines was set to 4.

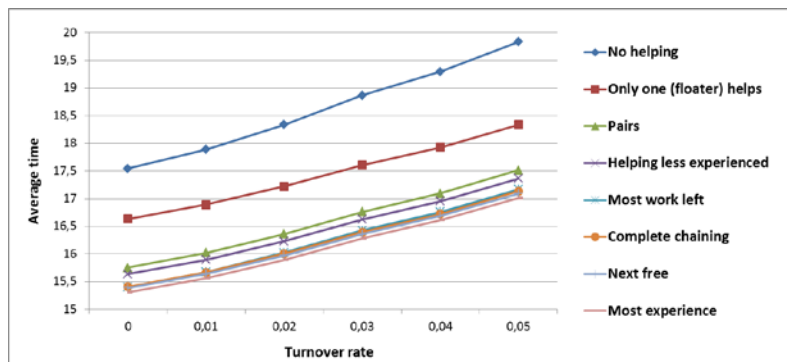


Figure 2: Average task time in relation to turnover rate

Figure 3 presents how many tasks an average worker in a 4-station system with different balancing policies is trained for. In these experiments the learning rate was set to 85% and weekly worker turnover was set to 3%. For example, in policy 6 (one floater), three workers are trained for only one task (home station), and one worker (floater) is trained for all four tasks.

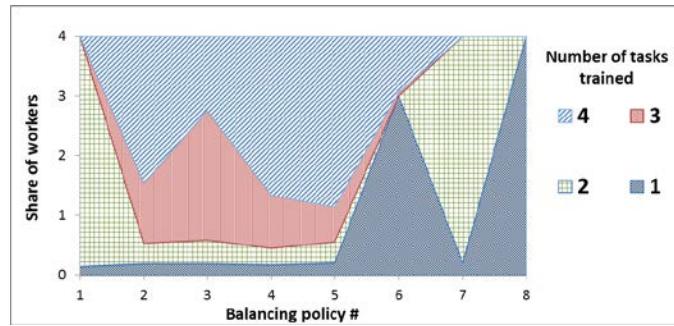


Figure 3 : Average worker skill levels in 4-station system with different balancing policies (1 = Complete chaining, 2 = Next free, 3 = Most experience, 4 = Helping less experienced, 5 = Most work left, 6 = Only one (floater) helps, 7 = Pairs, 8 = No helping).

Figure 4 presents the total amount of annual training and the average task time for each balancing policy. The negative impact of both factors on costs is lower when the marker is closer to the bottom left-hand corner. In these experiments, the learning rate was set to 85% and turnover was set to 3%. The number of stations was set to 8.

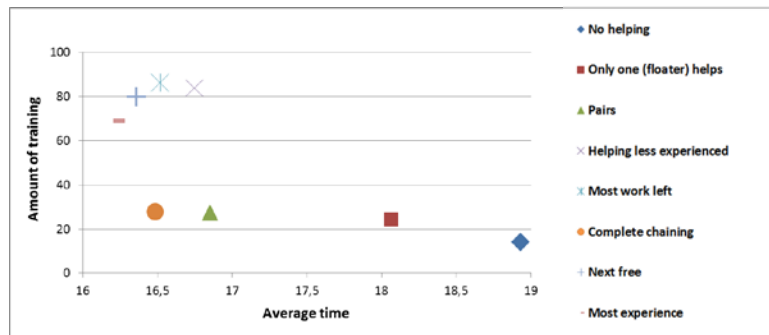


Figure 4: Amount of training for each balancing policy in relation to average time

#### 4. DISCUSSION

As Figure 1 shows, increasing the number of parallel stations affects the task time, depending on the balancing policy used. In general, helping strategies seem to be useful as task times drop by 8 to 12% as soon as the number of stations is doubled to two. Again, if the number of stations is increased to eight, the average task time of the six best policies decreases by 12 to 15% from the initial level. The *floater* policy loses its efficiency, because there is only one multi-skilled worker helping. The *helping in pairs* and *helping the less experienced* policies produce very similar results with each other except for the impact of an odd number of stations on pairwise policy, causing time peaks there. The *most experience* policy stands out from four stations forward, producing the best results in terms of task time. The three next best policies have only minor differences in performance.

Figure 2 presents the impact of turnover on average task time. Perhaps unexpectedly, different turnover rates do not affect the differences between balancing policies. However, the increase in task time is about 12% when the weekly turnover increases from 0 to 5%.

The worker skill distribution in a 4-station system is shown in Figure 3. As Figure 3 shows, *most work left*, *helping the less experienced*, *next free* and the *most experience* policies lead to the most even distribution of skills between workers. With these balancing policies the number of moves to new stations is not limited, and the number of skills learned is thus greater. This kind of job enlargement may affect job satisfaction. The similarity of multi-skills between these above-mentioned policies can also be found in Figure 4. In the figure the annual amount of training and average task time of different policies are presented in order to indicate their cost effects. The figure also shows that the one movement balancing policies, *complete chaining* and balancing *in pairs*, produce very good overall results, being closest to the lower left-hand corner.

As expected, allowing worker movement strongly affects system performance and costs. There are two main aspects to moving: the *where to move* aspect contains *station sequence* and *task experience*-based moving with possible



limitations, as well as *work load*-based moving. The *times to move* aspect indicates the number of possible stations to move to in a week. No one balancing policy can be seen to be clearly the best one when the overall effects of the policies are judged. In addition to this chapter, the characteristics of these policies were discussed in Section 3.1, System description.

## 5. CONCLUSIONS

In the paper, a simulation model of 1 to 8 parallel assembly stations was modelled. The workload of each week in the run period of 52 weeks was distributed similarly for all stations. The model combined individual learning curve, worker turnover, and different balancing policies in order to see how they affect assembly performance and the amount of training, as well as workforce skill distribution.

The results show that, in general, assembly performance is improved by using balancing policies, as expected. The shortest average task times were got with the policy in which a released worker helps the station where he has *most experience*. The three next best policies have only a minor difference in performance in comparison to the best one. Generally, the best results were achieved with policies which allowed unlimited numbers of moves.

The question of the most reasonable balancing policy is not easy to answer. On the one hand, the best results are achieved with experience-based moving, e.g. the *most experience* policy, but these policies demand good co-ordination and self-balancing skills between workers. On the other hand, balancing can be organised with easily controlled one movement policies, e. g. balancing *in pairs* or *complete chaining*, but these policies resulted in worse task times in this study. As a conclusion, the ideal configuration would be a combination of experience-based moving and an easily coordinated balancing policy with unlimited numbers of moves.

Although the turnover rate did not affect the differences between balancing policies in this study, it was found to affect the overall task times significantly. For this reason too, the model of the learning process must be carefully examined to ensure it is correct for the system being studied.

For further research, identifying realistic parameter values of assembly processes needs more empirical study. The system simulated in this paper should also be empirically tested as a whole in a laboratory environment to confirm the results obtained and gain new insights.

## REFERENCES

- [1] N. Vidic, "Developing methods to solve the workforce assignment problem considering worker heterogeneity and learning and forgetting", Dissertation submitted to Swanson School of Engineering at the University of Pittsburgh, 2008.
- [2] A. K. Chakravarty and A. Shtub, "Modelling the effects of learning and job enlargement on assembly systems with parallel lines", *International Journal of Production Research*, vol. 26, no. 2, pp. 267-281, 1988.
- [3] L. E. Yelle, "The Learning Curve: Historical Review and Comprehensive Survey", *A Journal of the Decision Science Institute*, vol. 10, no. 2, pp. 302-328, 1979.
- [4] M. D. Kilbridge, "Turnover, Absence and Transfer Rates as Indicators of Employee Dissatisfaction with Repetitive Work", *Industrial and Labor Relations Review*, vol. 15, no. 1, pp. 21-32, 1961.
- [5] G. Brown, "Genuine Worker Participation - An Indispensable Key to Effective Global OHS", *New Solutions*, vol. 19, no. 3, pp. 315-333, 2009.
- [6] S. T. Hutchinson, J. R. Villalobos, and M. G. Beruvides, "Effects of high labour turnover in a serial assembly environment", *International Journal of Production Research*, vol. 37, no. 11, pp. 3201-3223, 1997.
- [7] S. Globerson and E. Crossman, "Minimization of worker induction and training cost through job enrichment", *International Journal of Production Research*, vol. 14, no. 3, pp. 345-355, 1976.
- [8] W. Jordan, R. Inman, and D. Blumenfel, "Chained cross-training of workers for robust performance", *IIE Transactions*, vol. 36, no. 10, pp. 953-967, 2004.
- [9] L. Sennott, M. Van Oyen, and S. Iravani, "Optimal dynamic assignment of a flexible worker on an open production line with specialists", *International Journal of Production Research*, vol. 170, no. 2, pp. 541-566, 2006.
- [10] P. Pinto, D. Dannenbring, and B. M. Khumawala, "A branch and bound algorithm for assembly line balancing with paralleling", *International Journal of Production Research*, vol. 13, no. 2, pp. 183-197, 1975.
- [11] J. J. Bartholdi, "Balancing two-sided assembly lines: A case study", *International Journal of Production Research*, vol. 31, no. 10, pp. 2447-2461, 1993.