Statistical Characteristics of Workers' Productivity and Their Clustering in Cell Production System

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Abstract: Major studies on cell production have put the emphasis on technical factors such as machine order / layout, family part grouping, workflow sequence, etc., it is still insufficient to investigate how human factors affect the productivity of production cells. Although many companies have introduced cell production systems and realized that productivity of cells varies greatly with workers, there are no reports published on the statistical characteristics and distribution of workers' productivity. In order to assess the impact of workers' aptitude on productivity, we have made a series of experimental studies and questionnaire analyses. In this paper, we summarize the results of our production experiments conducted for four years, show statistical characteristics of workers' productivity, and then conduct cluster analysis to provide some insights to the workers' aptitude toward to cell production. Through these examinations, it is clear that 18.6% of workers have higher aptitude than the majority (53.1%), and there are 22.1% of workers with lower aptitude to cell production. Meanwhile, It can be considered that 6.2% of workers are not suitable to assembly tasks in cell production.

Key Words: cell production, human factor, statistical analysis, workers' aptitude, clustering.

1. Introduction

Cellular manufacturing, often called cell production in Japan, arranges factory floor labor into semi-autonomous and multi-skilled teams, or work cells, where one or a few workers manufacture complete products or complex components. Properly trained and implemented cells are more flexible and responsive than the traditional mass-production line. Over the past 30 years, many manufacturing companies have improved their competitiveness through introducing cell production. These companies have obtained a lot of advantages in production management such as reduction in setup time, cycle time, tooling requirements and material handling. Cell production has enabled companies to achieve significant improvements in product quality, scheduling, space utilization, control of operations and employee morale [1],[2].

Meanwhile, a great number of researchers have also paid their attention to cell production system design problems, such as the best groupings for products, parts, or machine clusters. Some studies have also addressed problems of selecting tools, jigs, and fixtures, determining process flow, determining cell capacity and selection of equipment. However, as many researchers have reported, successful implementation of cell production is not just a technical issue (cell formation and design), it is also essential to focus on human issues including worker assignment strategies, skill identification, training (workforce multi-functionality), communication,

reward/compensation system, defining worker roles, teamwork, and conflict management [3]–[6].

Because human related issues are typically difficult to quantify, there is a singular absence of articles that deal with the human factors in cell production [4]. In order to evaluate impact of human factors, we have made a series of experimental studies [7]–[12]. In our previous studies [7], it has been clarified that both the experience (learning effect) and workers (individual difference) have significant impacts on productivity of production cells, the impact of the experience and workers on productivity are 19.63% and 67.01% respectively. As two-thirds of variance of the workers' productivity was decided by workers, the aptitude or individual difference of workers has a stronger impact than the experience on productivity of cell production.

In this paper, we summarize the results of our cell production experiments conducted in 2013-2016, show statistical characteristics of workers' productivity, and then conduct cluster analysis to provide some insights to the workers' aptitude toward to cell production. The aim is to make the following contributions:

- (1) Although many companies have introduced cell production systems and realized that productivity of cells varies greatly with workers, there are no reports published on the statistical characteristics and distribution of workers' productivity. This paper conducts statistical analysis of cell production experiment data and examines statistical characteristics and distribution of workers' productivity. Through this examination, it is able to provide some key points to fully understand workers' productivity in cell production.
- (2) We conduct a cluster analysis based on workers' productivity and examine the difference among these clusters.

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(Received May 21, 2020)
(Revised July 16, 2020)
(Accepted August 10, 2020)

From the workers clustering, we can provide an overall image to see how many workers have higher aptitude to cell production and how many have not.

The remainder of this paper is organized as follows. At first, we introduce briefly the cell production experiment conducted for four years. Then we give the basic statistics and distributions of the workers' productivity. Next, we conduct workers clustering and examine the difference among clusters. At last, we give some concluding remarks.

2. Cell Production Experiment

In order to investigate the workers' individual difference in production cells quantitatively, we have designed a laboratory experiment. This experiment uses a toy robot as the virtual product, which is built up of LEGO Mindstorms and consists of 106 parts. The assembly process is divided into 17 tasks and we use assembly time, operation time required to assemble one toy robot, to measure the workers' productivity. The details about this experiment were described in our previous study [7],[11].

The experiment has been conducted every year from 2006 to 2019. The workers participated in the experiment were students from Fukushima University. They are almost male, ages from 20 to 26. As minor adjustments on the instruction method and the experiment's content have been updated gradually, in this study, we chose the experiment results from 2013 to 2016 where the experiment was conducted under the same instructor and the same content. There were 59 workers in 2013, 65 in 2014, 69 in 2015 and 65 in 2016, 258 workers in total.

3. Basic Statistics of Workers' Productivity

3.1 Basic Statistics of Assembly Time

Table 1 shows the basic statistics of assembly times for 258 workers, where the workers were asked to repeat the assembly operation and time measurement five times, t_i ($i = 1, 2, \dots, 5$) represents the operation time at the i th assembly, and t_{avg} is the mean of every one worker's operation times for five assemblies.

Table 1 Basic Statistics of Assembly time (258 workers, min)

Statistics	Assembly time in five Experiences					Mean t_{avg}
	t_1	t_2	t_3	t_4	t_5	
Mean	10.88	8.98	7.94	7.31	6.81	8.38
Median	10.35	8.47	7.74	7.04	6.50	8.06
Std. deviation	3.45	2.50	2.08	1.84	1.71	2.12
Minimum	5.43	4.83	3.62	3.97	3.48	4.44
Maximum	27.23	20.25	15.08	15.90	17.00	17.88
Range	21.80	15.42	11.46	11.93	13.52	13.43
Outliers	3	2	0	5	4	1

From table 1, it is obvious that:

- (1) As the workers have no any experience of assembling the toy robot, they took longer time at the first assembly, and the average time required to assemble a toy robot got shorter from 10.88 minute at the first assembly to 6.81 minute at the fifth assembly. It is reasonable to consider that the decrease of operation times along with assembly experience comes from the learning effect.
- (2) The mean of assembly times is less than their median for each assembly, it suggests that the distribution of assembly

time is skewed to the right, that is, a few workers took very long time compared to the others.

- (3) The range of assembly times is from 11.46 minute to 21.80 minute and there is a difference more than three times between the slowest worker and the fastest one. Therefore workers' aptitude gives a strong impact to productivity of production cells.
- (4) The standard deviation of assembly times decreased from 3.45 minute at the first assembly to 1.71 minute at the fifth. However, the ratio of standard deviation to mean is almost unchanged from the third to the fifth assembly. This means that the mean assembly time decreased with the experience, but the relative difference in assembly time has not changed much.

Applying Grubbs test (double-sided with 95% confidence level) to the assembly times, we could detect three outliers in t_1 , two in t_2 , five in t_4 and four in t_5 . There was also one outlier in t_{avg} . These outliers were detected from the assembly times of just 11 workers. As these outliers occurred in the side of longer assembly time, the outliers imply the workers who have comparatively lower aptitudes to the assembly tasks.

3.2 Distributions of Assembly Time

Figure 1, figure 2 and figure 3 are histograms of assembly time t_1 , t_5 and mean time t_{avg} . We conducted Shapiro-Wilk test for normality to t_1 , t_5 and t_{avg} , all three tests have p values of 0 (null hypothesis: a variable is normally distributed).

Fig. 1 Distribution of t_1 : operation time at the first assembly

From figure 1 and the result of Shapiro-Wilk test, it is clear that the assembly time t_1 is not normally distributed. At the first assembly, more than half of the workers completed the assembly task in less than the mean time 10.88 minute. In contrast, 14 workers took more time than the mean plus 2 times the standard deviation.

At the fifth assembly, although the mean time decreased to 6.81 minute, the assembly time t_5 is not normally distributed either as shown in figure 2. Same as the first assembly, more than half of the workers completed the assembly task in less than the mean time 6.81 minute and meanwhile, 14 workers

Fig. 2 Distribution of t_5 : operation time at the fifth assembly Fig. 3 Distribution of t_{avg} : average operation time for five assemblies

took more time than the mean plus 2 times the standard deviation. However, because the standard deviation of t_5 is smaller than that of t_1 , the assembly time t_5 distributes in a narrower range close to its mean.

As the mean time for five assembly experiences, distribution of t_{avg} shown in figure 3 has the same characteristics as figure 1 and figure 2. Overall, the assembly time is not normally distributed. The distribution range of the assembly time below mean is narrow, while that of the assembly time above mean is wide.

4. Workers Clustering

4.1 Clusters and Aptitude

In order to understand workers' aptitude, we conducted workers clustering based on assembly time t_i ($i = 1, 2, \dots, 5$), where hierarchical cluster analysis algorithms in IBM SPSS 20 were applied. The dissimilarity measure is squared euclidean distance and the linkage criteria is the Ward's minimum variance method. As the cluster analysis is an unsupervised learning, we set the number of clusters to 3, 4 and 5 respectively, and determined the cluster for each worker. Taking the cluster as fac-

tors and assembly times as dependent variables, we conducted five analysis of variance (ANOVA) and multiple comparison to check if there is a significant difference in the means of assembly times among these clusters. Finally, we chosen the result with four clusters because all of means of assembly time t_i ($i = 1, 2, \dots, 5$) have significant differences with p -value of zero between each two clusters. The means and standard deviation of assembly times for each cluster are shown in table 2 and table 3 respectively.

Table 2 Means of assembly times for each cluster

Assembly time	Cluster			
	1	2	3	4
t_1	10.01	7.22	13.34	20.49
t_2	8.40	6.32	10.97	14.85
t_3	7.54	5.55	9.68	12.32
t_4	6.94	5.31	8.90	10.80
t_5	6.44	5.17	8.26	9.75
t_{avg}	7.87	5.91	10.23	13.64
Workers	137	48	57	16
	53.1%	18.6%	22.1%	6.2%

Table 3 Standard deviation of assembly times for each cluster

Assembly time	Cluster			
	1	2	3	4
t_1	1.30	0.67	1.50	2.83
t_2	1.12	0.65	1.55	2.72
t_3	1.06	0.61	1.43	1.76
t_4	0.84	0.55	1.61	2.10
t_5	0.82	0.69	1.46	2.72
t_{avg}	0.76	0.48	0.93	1.77

Fig. 4 Workers in each cluster by t_1 and t_5

Taking t_1 as the x -axis and t_5 as the y -axis, the scatter diagram

of workers in each cluster is shown in figure 4. From table 2, table 3 and figure 4, it is clear that:

- (1) The workers of cluster 2 have the shortest mean and the lowest of standard deviation of assembly times. This means that they could complete assembly tasks in the shortest time at all of five assemblies and therefore they are ones with the highest productivity. There are 48 workers in this cluster, accounting for 18.6% of the total workers. The workers in this cluster have the highest aptitude to cell production among the four clusters.
- (2) The second productive workers are ones in cluster 1. Averagely, they took about 25% longer time to complete the assembly tasks than the workers of cluster 2, and there were wider variation in their assembly times. There are 137 workers in this cluster and they are the majority (53.1%).
- (3) The workers of cluster 3 took third place in both the mean and standard deviation of assembly times. There are 57 workers in this cluster, accounting for 22.1% of total workers. Overall, this cluster is the workers with the low aptitude to cell production.
- (4) The workers of cluster 4 took the longest time at all of five assemblies and they are workers with the lowest productivity. They account for just 6.2% of total workers and all of outliers in assembly times occurred in this cluster. Therefore, this cluster is the workers with the lowest aptitude to cell production.

Furthermore, we take t_1 as the x -axis, t_2 , t_3 and t_4 as the y -axis respectively, the scatter diagram of workers in each cluster is shown in figure 5-7.

Fig. 5 Workers in each cluster by t_1 and t_2

From figure 4 to figure 7, we can observed that cluster 2 and cluster 4 separated clearly from the other clusters, but there is

Fig. 6 Workers in each cluster by t_1 and t_3

Fig. 7 Workers in each cluster by t_1 and t_4

some overlap between cluster 1 and cluster 3. The reason is that 89 (34.5%) in 258 workers could not shorten assembly time monotonously and the operation time they took at one or more assembly increased unexpectedly.

4.2 Clusters and Learning Effect

According to the learning curve theory, the time required to perform a task decreases as a worker gains experience. In order to measure the workers' learning effect, we calculated shortening rate $SR_{i(i-1)}$ of the i -th assembly time t_i relative to the previous $(i-1)$ th assembly time t_{i-1} ($i = 2, 3, 4, 5$) for each worker

according to the following equation:

$$SR_{i(i-1)} = \frac{t_{i-1} - t_i}{t_{i-1}}$$

Table 4 shows the means of shortening rate for the workers in each cluster, and figure 8 shows how the shortening rate change with the assembly experience.

Table 4 Means of shortening rate for each cluster

Shortening rate	Cluster			
	1	2	3	4
SR_{21}	15.5%	12.2%	16.8%	26.7%
SR_{32}	9.5%	11.7%	10.8%	15.6%
SR_{43}	7.3%	3.7%	7.4%	11.9%
SR_{54}	6.8%	2.6%	6.0%	9.0%
SR_{avg}	9.8%	7.5%	10.3%	15.8%

Fig. 8 Shortening rate with assembly experience

In order to clarify the difference in shortening rates among the workers of four clusters, we further conducted t-test for mean difference of shortening rates; table 5 shows the p -values of t-test between every two clusters.

From table 4, table 5 and figure 8, we can observed that:

- (1) Workers in all of four clusters have the highest shortening rate at the second assembly to the first, and their shortening rates decreased with assembly experience. This is consistent with the learning curve theory and our previous results [12]
- (2) Among four clusters, the workers of cluster 4 have the highest shortening rate at each assembly. This result comes from the fact that their assembly times are longer than other clusters and there were more room for them to shorten, not because they have high learning ability. From the same view point, the workers of cluster 2 took the shortest times to complete assembly tasks and it was not easy to shorten their assembly times further. Therefore, the workers of cluster 2 have comparatively low shortening rates.
- (3) According to the p -values below 5.0%, at the second assembly, the mean shortening rate of cluster 4 is significantly different from other three clusters, and cluster 2

and cluster 3 have also significant difference in their mean shortening rate. However, at the fifth assembly, only two clusters: cluster 1 and cluster 2 are significantly different in their mean shortening rate. In particular, the workers of cluster 4 have no longer significant difference in their mean shortening rate to other clusters at the fifth assembly. This suggests that not only are the workers of cluster 4 the least productive, they can't be expected to improve their productivity to catch up with the workers of other clusters.

Table 5 p -value of t-test for mean difference of shortening rates

Cluster		SR_{21}	SR_{32}	SR_{43}	SR_{54}
1	2	8.6%	28.7%	5.1%	3.0%
1	3	48.8%	51.3%	95.4%	67.9%
1	4	0.0%	6.1%	11.7%	46.5%
2	3	4.3%	69.9%	8.5%	12.7%
2	4	0.0%	27.0%	1.0%	5.4%
3	4	0.3%	16.4%	15.2%	36.1%

5. Conclusion

This paper intended to show the statistical characteristics of workers' productivity and conducted workers clustering in cell production system. The main results of this study can be summarized as the following:

- (1) More than half of the workers completed the assembly task in less than the mean time and meanwhile, a few workers took more time than the mean plus 2 times the standard deviation. As the result, assembly times are not normally distributed and the distribution curve skewed to the right.
- (2) Several outliers could detected in assembly times. As these outliers occurred in the side of longer assembly time, the outliers imply the workers who have comparatively lower aptitudes to the assembly tasks.
- (3) Based on assembly time, the workers could be divided in to four clusters where mean of assembly time for each cluster is significantly different from the others. The workers of cluster 2 have the highest aptitude to cell production and account for 18.6% of the total workers. The majority accounting for 53.1% of workers belong to cluster 1, they took about 25% longer time to complete the assembly tasks than the workers of cluster 2, but they were more productive than the others.
- (4) There are 22.1% of workers with lower aptitude to cell production. Meanwhile, 6.2% of workers took the longest time at all of five assemblies and they are workers with the lowest productivity. Totally, they are 28.3% of workers who have low aptitude to cell production.
- (5) Even considering the learning effect, the workers of cluster 4 are the least productive and they can't be expected to improve their productivity to catch up with the workers of other clusters. It can be considered that 6.2% of workers are not suitable to assembly tasks in cell production.

Acknowledgments

This work was supported by JSPS KAKENHI Grant Number JP20K01818.

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