Assigning Unskilled Workers on the Production Line According to the Fuzzy C-Means Clustering Method

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Abstract

Based on the recent trend toward higher consumer demand for customized products, the possibility of mass customization has become a topic of great importance for companies. In order to deal with seasonal fluctuations in demand, most companies require flexible scheduling of the manpower involved in product assembly; one means of achieving this flexibility is by hiring dispatch laborers. Ensuring the productivity of new employees and their departments under conditions of continuous employee turnover on the production line has become an essential element of the modern manufacturing business.

This research uses the fuzzy c-means clustering method to develop a new model for evaluating employees' ability to perform on the production line and identifying which operational capabilities are suitable for each employee. This study used a personal computer assembly process as an empirical analysis case. The results show that this evaluation model enables users to accurately determine what new employees are good at, which will inform them where each employee should be assigned so that the products can be assembled most efficiently. Our evaluation model can not only provide companies with a reference and judgment basis for more efficient staffing, but also help them reduce lead time when changing production lines or production line configurations and increase their production efficiency and profit.

Keywords: mass customization, fuzzy c-means, production efficiency

1. Introduction

The industrial production model has undergone continuous change according to market demand ever since the first industrial revolution, when machines replaced manpower and large-scale factory production replaced manual production in individual workshops.[1)]

The pace of this change has only increased since the second industrial revolution, brought about by the large-scale application of electricity. The resulting rapid development of industry and technology drove the expansion of the factory system into many more forms of production.[2)] The second industrial revolution also stimulated population growth and led many governments to introduce tariffs to protect their economies. These two large-scale industrial revolutions drew attention to the working class and consumer-based sales models.[3)]

The third industrial revolution is the digital revolution, which is still ongoing. Starting after World War II, people from all walks of life have acquired access to electronic inventions due to the spread of computers and electronic data application and to the ever increasing speed

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and convenience of information acquisition and transmission. As a result, not only has the factory production model shifted, the business operation model has also stretched to accommodate the category of electronic commerce.[4)]

Through these three industrial revolutions, people's lifestyles and shopping trends have also shifted such that brick-and-mortar stores have given way to online shopping, and the requirements for goods have gradually shifted to customization. The manufacturing strategy of the factory has gradually changed from its former focus on mass production to a new focus on customized production and even to the possibility of a mass customization production mode.

As e-commerce and online trading platform technologies become more mature, the business side of the global Internet of Things (IoT) is booming: companies are no longer facing competition for orders with other individual manufacturers, but must instead compete for market share with different supply chain systems. The changes in mass production strategy to date have allowed a shift from a seller-led market to a consumer-led market. Consumers are less willing to consume when they are offered only a few products provided by a few enterprises. Products that are mass-produced to a single specification, therefore, have lost their advantage in the market.

Consumers now have individual requirements for products that are different from the products purchased and owned by others. This trend is making product life cycles shorter and shorter. The popularity of this consumption model has driven a mass customization production strategy among industries, as Frank T. Piller and Paul Blazek (2008) have shown. The goal of this mass customization strategy is to efficiently provide customers with the products they want at an affordable price, while offering the two advantages of mass production and customized products.[5)] Therefore, production technologies in all industries will have to be capable of mass customization in the future to survive the complex demands of the global market.

In Taiwan, factory wages and retirement reserves have been increasing year by year under the influence of Taiwan's labor standards act and regulations, which have also increased corporate operating costs. In order to cope with the problem of direct cost increases, Taiwanese companies often hire dispatch labor to reduce their labor costs. Dispatch labor is already widely accepted as a convenient and cost-saving approach to corporate management. It has one major potential downside, however, in that it increases employee turnover; this presents a problem because the work level of new hires is uneven and difficult to manage, and it is impossible to know what kind of work a new hire will be best at before the new hire starts. Multiple job assignment issues can therefore be expected in the process of institutionalizing this corporate strategy. To help with this, we set out to create a convenient and simple evaluation model that would allow companies to evaluate new recruits and assign them to optimal tasks in accordance with their unique abilities.

The main purpose of this study is to use the fuzzy c-means clustering method to establish an evaluation model for evaluating new employees' work performance in diversified jobs as a solution to the high-turnover problem associated with dispatch labor. The results of this study will provide a reference for relevant companies to understand which jobs each new recruit does best. A good model for this data will facilitate more precise transfer of personnel and improve overall production efficiency.

1. Literature Survey

The problem of how to assign jobs to new recruits first arose in previous discussions of mass customization production models. Alvin Toffler predicted in his 1970 book Future Shock that future markets would become more short-term, novelty-driven and diverse.[6)] Later scholars have agreed that the seemingly oxymoronic production strategy of mass customization is technically feasible and predicted its widespread adoption in the future. According to these scholars, more and more companies will produce using mass customization production technologies in the future, such that the products they provide will no longer be standard products but rather products and services that appeal to a diverse population of unique customers and are produced through customer-led operations.

Stanley Davis proposed a more specific and complete description of the concept of mass customization in 1987, in which he defined mass customization as the ability to use customer information to produce personalized products at the low costs typically associated with mass production.[7)] In 1993, B.J. Pine emphasized that the purpose of mass customization is to meet the needs of individual customers, which is an important ability enabling companies to compete with others, without sacrificing production efficiency.[8)] Margaret A. Eastwood proposed in 1996 that, to make consumers completely satisfied, it is necessary to adopt "mass customization" and to give each customer a product tailored specifically to his or her needs.[9)]

Rebecca Duray (2000) identified mass customization as the concept that would allow manufacturers to limit manufacturing costs while generating unique products, and discussed the performance impact of mass customization in the actual configuration of the production system.[10)] In 2001, Y.H. Chen applied the concept of fuzzy theory to a large number of customized product design front-end operations, and specifically to the options that customers could choose as the back-end output data of production products.[11)] In the same year, Qiang Tu applied a time-based production method to mass customized production and discussed its value impact on customers; he pointed out that a factory with a high performance level according to a time-based production system could expect to have a similar performance level after the introduction of mass customized methods.[12)] In this way, he predicted, the value to customers would also increase as the degree of customization increased.

In 2008, Wei-wu Yu used a mathematical linear programming optimization model to calculate a company's short-term lowest labor cost and optimize its labor assignments to achieve the most efficient labor assignments and the shortest completion period.[13)] This was reported to make planning issues such as manpower and job assignments at small and medium-sized enterprises more efficient.

As the abundance of previous studies clearly shows, the topic of mass customization has been valued by industry professionals and academics in recent years. Yet most researchers have focused on large numbers of customized customer values, production methods, and product designs. Few of the existing studies have noted that the introduction of dispatch manpower as a business strategy has caused personnel problems related to high turnover rates. Therefore, companies will benefit from a model allowing them to evaluate the capabilities of new employees and assign personnel to appropriate tasks to reduce unnecessary manpower waste.

To address this need, the present study will develop a system of evaluating the operational capabilities of new recruits, which will not only serve as a reference for training and manpower deployment of small and medium-sized enterprises, but also provide large enterprises with criteria for reassessing their manpower deployment.

2. Fuzzy C-Means Application and Discussion

One problem that enterprises will face under mass customization production strategies is that assembly-line personnel will need to modify the operation process frequently, as each type of product will use different parts and processes. In general, production efficiency on the assembly line is improved when personnel are given more advance training. In traditional mass production assembly lines, personnel learn quickly to complete their assembly work efficiently, as their job is simply to place the same parts in the same position again and again. In mass customization production, in contrast, personnel must place different components in different positions in response to customer requirements, yet this has to be completed with the same efficiency achieved through mass production in the past.

Companies often respond to a sudden influx of orders and the resulting need for more assembly manpower in the production line by hiring dispatched manpower. While this solves the problem of an insufficient labor force, it creates a new problem related to manpower scheduling and ability classification. This study applies the Fuzzy C-Means algorithm as a solution to improve manpower scheduling and the evaluation and classification of employee abilities. This fuzzy C-Means algorithm is not a traditional dichotomy method but one based on fuzzy membership. This method enables us to simultaneously evaluate the performance of each operator in various group centers, which enables companies to improve their personnel scheduling operations and optimize production capacity.

Fuzzy Clustering is a clustering technique widely used in various fields. The Fuzzy C-Means algorithm (FCM) used in this research is a fuzzy clustering method proposed by J.C. Dunn in 1973[14)] and improved by James C. Bezdek in 1981.[15)]

FCM is an extension of the K-Means clustering method in which fuzzy logic is added to the K-Means algorithm to improve the rationality and correctness of the clustering effect. In the K-Means method, each data point can be classified into only one group according to its characteristics. FCM, in contrast, allows each piece of data to belong to various clusters at the same time: the difference is that each piece of data uses a number between 0 and 1 to indicate its membership in different clusters. In other words, the grouping is fuzzy, not dichotomous.

FCM is a mathematical method of grouping observation points according to certain preconditions when processing object data that falls into the fuzzy zone between two clusters to optimize the clustering result. An objective function is used and operates as an adjustment function during the calculation process. If the objective function can reach the minimum value, the best clustering effect can be obtained. Therefore, FCM can simplify the algorithm process while ensuring the most effective data clustering analysis.

The objective function of FCM is shown as follows:[15)]

$$J(X;U;V)=\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ik}^{m}\|x_k-v_i\|^2$$

$$U=[u_{ik}]$$

$$1\le i\le c$$

$$1\le k\le n$$

Where:

c : Number of clusters, $2\leqq c\leqq n$

n : Number of data points

X : Data set is a $n\times p$ matrix

x_k : Measurement data, k=1,2...,n, $x_k\in X$

U : Membership function is a $c\times n$ matrix

u_{ik} : Where each element u_{ik}=[0.1] tells the membership which measurement data x_k belongs to cluster G_i

V : Vector of cluster center

$V=[v_1,v_2,\ldots,v_c]$, $v_i\in R^p$, $1\le i\le c$

v_i : Center of cluster , G_i , i = 1,2...,c

m : m=[1,∞) Where m is the hyper-parameter that notes the degree of fuzziness of cluster G_i. The higher it is, the fuzzier the cluster will be in the end.

Steps of the Fuzzy C-Means algorithm:

Step 1 : Data set $X=\{x_1,x_2,\ldots,x_n\}$,$x_k=[x_{k1},xk_2,\ldots,x_{kp}]\in R^p$,$k$=1,2,...,$c$ Where C is the number of clusters and $2\leqq c\leqq n$, the degree of fuzziness m , m=[1,∞), initial setting $U^{(0)}$, u_{ik}, values are assigned randomly, number of loops I=1,2,..., assigned a loop stop condition value ε, the minimum change amount of cyclic calculation.

Step 2 : Calculate centroid of each cluster

$$v_i^{(I)}=\frac{\sum_{k=1}^{n}(u_{ik}^{(I)})^m X_k}{\sum_{k=1}^{n}(u_{ik}^{(I)})^m} \text{ , } 1\le i\le c$$

Step 3 : Calculate the fuzzy membership

$$u^{(I)}{}_{ik}=\frac{1}{\sum_{j=1}^{c}\left(\frac{\|x_k-v^{(I)}{}_i\|}{\|x_k-v^{(I)}{}_j\|}\right)^{2/(m-1)}} \text{ , } 1\le i\le c \text{ , } 1\le k\le n \text{ ,}$$

Step 4 : Calculate objective function $J(X;U,V)$, if $\|J^{(I)}-J^{(I-1)}\|\le\varepsilon$, then stop, else renew U matrix, set $I=I+1$, repeat step 2 and 3 if centroids do not change.

This study used a personal computer (PC) assembly process as a case study to simulate the ability of personnel to assemble various parts under a large number of customized production strategies. A total of 20 new employees were tested. The PC parts are divided into eight categories as shown in Table 1.

Table 1. PC parts

CD-ROM Drive	CPU	Motherboard	Fan
RAM	Hard Disk Drive	Power Supply (PSU)	Graphics Card (GPC)

Table 2 presents data on the new personnel who were assembling PC components for the first time without training in this case study. These 20 new personnel were assigned to assemble eight types of components. Each operation time was recorded with a digital stopwatch.

Table 2. Data on new employees' performance at assembling parts for the first time (sec)

parts / employee no	CD	CPU	MB	FAN	RAM	HDD	PSU	GPC
1	63.92	71.5	145.8	88.11	14.06	25.86	55.36	14.63
2	59.08	72.42	217.79	86.08	10.66	19.91	60.78	14.3
3	69.25	66.67	144.84	75.84	12.21	19.8	66.35	14.6
4	76.51	74.38	144.6	87.01	11.25	16.28	52.51	13.98
5	59.45	92.87	177.53	78.73	11.35	17.28	60.11	12.7
6	60.15	32.18	242.21	130.38	10.91	16.83	49.32	19.93
7	51.76	34	194.81	107.21	14.16	17.88	62.71	11.45
8	72.4	33.35	229.48	120.7	11.06	14.16	58.14	12.93
9	63.01	35.26	175.16	85	12.41	11.71	55.21	22.39
10	65.96	35.11	240.98	86.85	11.13	11.85	57.14	12.55
11	71.89	98.51	175.59	167.66	14.71	13.53	96.3	20.6
12	66.44	99.21	192.33	153.54	11.88	11.66	81.52	21.96
13	67.72	64.26	236.39	143.53	16.23	12.3	89.84	33.73
14	57.51	78.56	156.85	182.18	11.15	10.75	84.29	19.45
15	69.79	78.94	216.12	125.99	11.06	10.88	79.09	14.85
16	68.53	79.57	173.44	91.65	12.66	9.08	78.37	22.55
17	60.87	68.54	167.94	88.35	11.06	9.4	65.08	8.99
18	59.98	60.19	130.8	110.98	10.61	9.03	62.5	9.38
19	73.08	62.52	168.99	128.38	11.33	12.3	72.35	9.61
20	66.61	53.22	156.24	108.44	11.36	12.88	60.4	9.35

This study also analyzed data on the assembly process as performed by trained personnel. Twenty new employees were given five practice opportunities to assemble the eight parts in a training session. Table 3 presents the data on how these 20 personnel performed after training.

Table 3. Data on new employees' performance at assembling parts after training (sec)

parts / employee no	CD	CPU	MB	FAN	RAM	HDD	PSU	GPC
1	41.35	62.85	123.36	53.38	8.74	9.76	46.92	8.16
2	40.86	54.87	127.13	54.98	8.68	10.36	46.46	6.46
3	40.97	52.3	133.79	55.49	8.43	9.08	43.2	7.38
4	39.51	55.97	117.38	50.4	8.19	10.05	41.14	8.43
5	41.92	58.88	118.6	48.45	8.15	9.81	40.98	7.73
6	48.23	26.19	181.39	66.71	6.06	5.79	37.85	4.81
7	47.01	27.74	171.06	69.08	6.16	6.46	34.4	4.96
8	46.26	25.58	172.69	62.28	5.67	5.86	34.9	5.38

9	47.72	27.96	170.68	59.9	5.83	7.18	37.45	6.25
10	48.66	33.71	173.74	68.11	5.88	7.32	34.4	5.76
11	50.81	44.93	141.33	81.7	9.89	5	51.44	5.13
12	48.68	47.48	138.92	85.19	10.28	6.07	53.44	6.08
13	49.64	46.51	131.59	86.54	10.31	6.21	53.01	5.61
14	49.62	57.96	145.11	82.16	10.12	5.4	48.19	6.57
15	51.01	43.58	125.98	81.25	10.33	5.9	52.46	4.96
16	37.54	41.18	143.6	62.55	8.36	4.91	43.61	2.95
17	39.78	33.53	142.94	62.96	8.66	5.76	42.18	3.75
18	35.94	40.6	129.15	54.68	8.75	5.68	40.46	4.85
19	36.86	35.53	137.52	53.9	8.44	6.08	45.08	3.25
20	40.04	34.45	131.93	58.65	8.69	5.5	40.39	4.16

According to the FCM execution steps described above, each new employee's degree of membership, representing that individual's skill at assembling the eight kinds of parts, was assessed. The results of our analysis showed that the higher an employee's membership degree, the more suitable that employee is as a part assembler. First, the untrained data was processed through Matlab software. The central value of the assembly time of the seven components outside the motherboard and the membership of each data point to the central value were calculated. The central values of assembly time for the seven components outside the motherboard, corresponding to the motherboard assembly time, are shown in Table 4.

Table 4. Center values for assembly ability prior to training

	X-axis	Y-axis
CD	227.4512	65.3170
CPU	225.9072	50.1544
FAN	216.7881	128.6000
RAM	161.4101	12.0403
HDD	161.4714	13.9638
PSU	226.0982	65.8896
GPC	161.2621	14.8793

The membership degrees as calculated for each person who assembles various parts are shown in Table 5.

Table 5. Membership values for assembly ability prior to training

parts / employee no	CD	CPU	MB	FAN	RAM	HDD	PSU	GPC
1	63.92	71.5	145.8	88.11	14.06	25.86	55.36	14.63
2	59.08	72.42	217.79	86.08	10.66	19.91	60.78	14.3
3	69.25	66.67	144.84	75.84	12.21	19.8	66.35	14.6
4	76.51	74.38	144.6	87.01	11.25	16.28	52.51	13.98
5	59.45	92.87	177.53	78.73	11.35	17.28	60.11	12.7
6	60.15	32.18	242.21	130.38	10.91	16.83	49.32	19.93
7	51.76	34	194.81	107.21	14.16	17.88	62.71	11.45
8	72.4	33.35	229.48	120.7	11.06	14.16	58.14	12.93
9	63.01	35.26	175.16	85	12.41	11.71	55.21	22.39
10	65.96	35.11	240.98	86.85	11.13	11.85	57.14	12.55

11	71.89	98.51	175.59	167.66	14.71	13.53	96.3	20.6
12	66.44	99.21	192.33	153.54	11.88	11.66	81.52	21.96
13	67.72	64.26	236.39	143.53	16.23	12.3	89.84	33.73
14	57.51	78.56	156.85	182.18	11.15	10.75	84.29	19.45
15	69.79	78.94	216.12	125.99	11.06	10.88	79.09	14.85
16	68.53	79.57	173.44	91.65	12.66	9.08	78.37	22.55
17	60.87	68.54	167.94	88.35	11.06	9.4	65.08	8.99
18	59.98	60.19	130.8	110.98	10.61	9.03	62.5	9.38
19	73.08	62.52	168.99	128.38	11.33	12.3	72.35	9.61
20	66.61	53.22	156.24	108.44	11.36	12.88	60.4	9.35

According to the distribution of the degree of division, a scatter diagram of the relative central value of each assembler's installation time of each item can be obtained. The resulting scatter diagram shows which employees are more suitable as assemblers of these parts. Figure 1 shows a sample scatter diagram of the data on workers assembling a CD drive. As the figure shows, in most cases, employees are less suitable for the job of assembling optical disc drives when they lack training. Similar scatter diagrams for the remaining parts can be drawn according to the same rule.

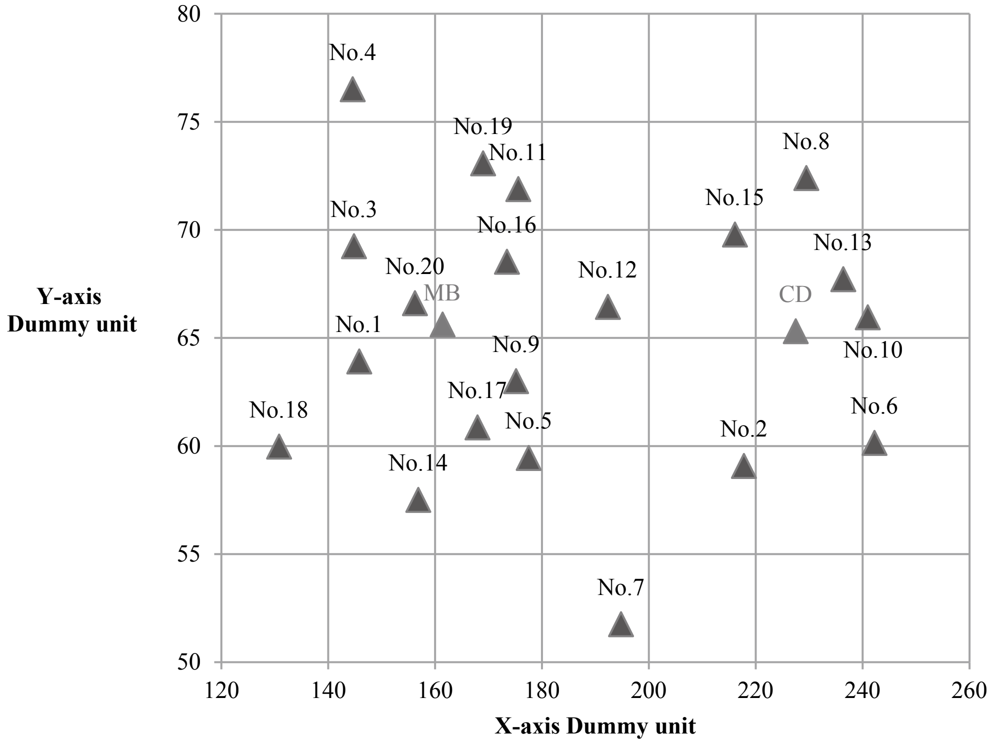

Fig. 1. Scatter diagram of ability to assemble MB and CD drive prior to training

By calculating the membership degree of each employee for assembling parts, we can judge whether the employee is competent at and therefore suitable for assembling certain parts, and use each employee's membership degree as the basis for ranking all employees. A higher membership degree represents greater efficiency and productivity at assembling the part, as Table 6 shows. Running these calculations reveals the membership degree and ranking of each new recruit's initial assembly skills prior to training, as shown in Table 6.

Table 6. Membership ranking of assembly ability prior to training

Ranking	employee no	CD	employee no	CPU	employee no	FAN	employee no	RAM
1	8	0.9885	8	0.9545	15	0.9982	14	0.9957
2	13	0.9850	13	0.9491	8	0.9596	20	0.9947
3	10	0.9719	10	0.9448	13	0.9288	17	0.9879
4	6	0.9641	6	0.9329	6	0.9229	19	0.9834
5	2	0.9606	2	0.8520	12	0.7768	1	0.9642
6	15	0.9531	15	0.7700	10	0.7370	3	0.9614
7	7	0.5117	7	0.6781	2	0.6499	4	0.9604
8	12	0.4369	9	0.3562	11	0.6210	16	0.9527
9	5	0.1057	12	0.3287	7	0.5749	9	0.9354
10	18	0.0936	11	0.1591	14	0.5323	11	0.9285
11	11	0.0810	5	0.1463	19	0.3216	18	0.9088
12	9	0.0669	18	0.1026	5	0.1290	5	0.9056
13	4	0.0542	20	0.0711	18	0.1258	12	0.5641
14	16	0.0498	16	0.0561	9	0.0853	7	0.4895
15	3	0.0403	19	0.0433	3	0.0789	15	0.0418
16	1	0.0356	3	0.0402	16	0.0536	6	0.0322
17	19	0.0315	4	0.0365	4	0.0483	2	0.0293
18	17	0.0181	1	0.0323	1	0.0423	10	0.0280
19	14	0.0169	17	0.0161	20	0.0385	13	0.0169
20	20	0.0054	14	0.0107	17	0.0285	8	0.0010

Table 6. Membership ranking of assembly ability prior to training (continued)

Ranking	employee no	HDD	employee no	PSU	employee no	GPC
1	20	0.9944	8	0.9853	14	0.9919
2	14	0.9937	2	0.9718	20	0.9892
3	19	0.9830	10	0.9562	17	0.9784
4	17	0.9828	6	0.9284	19	0.9753
5	4	0.9595	15	0.9211	1	0.9652
6	3	0.9567	13	0.9016	3	0.9618
7	16	0.9464	7	0.5418	4	0.9609
8	1	0.9462	12	0.4642	16	0.9337
9	9	0.9345	11	0.2362	11	0.9183
10	11	0.9311	5	0.1195	9	0.9163
11	18	0.9067	9	0.1124	18	0.9072
12	5	0.9031	18	0.0924	5	0.9026
13	12	0.5652	16	0.0892	12	0.5489
14	7	0.4897	4	0.0651	7	0.4895
15	15	0.0452	14	0.0578	13	0.0536
16	2	0.0375	1	0.0524	15	0.0420
17	6	0.0329	3	0.0376	6	0.0337
18	10	0.0288	19	0.0278	10	0.0329
19	13	0.0146	17	0.0156	2	0.0306
20	8	0.0009	20	0.0131	8	0.0060

As Table 6 shows, new employee No. 8 has the highest degree of membership as regards the assembly of the CD drive, CPU, and PSU. Therefore, the company now knows that, in their assignment of manpower along the production line, employee No. 8 should be assigned to assemble these three parts; this ability to make informed assignment decisions will enhance production efficiency.

Table 7 shows the central value calculated by the FCM for the assembly ability data of the 20 employees after training.

Table 7. Central values of assembly ability after training

	Y-axis	X-axis
CD	173.0709	47.5211
CPU	131.9461	47.8152
FAN	131.3129	61.8400
RAM	132.0787	9.0636
HDD	173.3083	6.5175
PSU	132.1125	45.9197
GPC	132.0603	5.7207

Table 8 shows the degree of membership with regard to assembly ability for each of these 20 employees after training.

Table 8. Membership values of assembly ability after training

parts employee no	CD	CPU	FAN	RAM	HDD	PSU	GPC
1	0.0289	0.9233	0.9466	0.9705	0.0320	0.9712	0.9684
2	0.0121	0.9743	0.9689	0.9886	0.0160	0.9889	0.9885
3	0.0043	0.9888	0.9693	0.9979	0.0044	0.9937	0.9963
4	0.0653	0.9319	0.9045	0.9353	0.0667	0.9293	0.9337
5	0.0558	0.9275	0.8985	0.9427	0.0591	0.9358	0.9418
6	0.9727	0.0270	0.0454	0.0258	0.9737	0.0269	0.0263
7	0.9972	0.0019	0.0039	0.0034	0.9967	0.0045	0.0035
8	0.9990	0.0043	0.0140	0.0003	0.9995	0.0008	0.0002
9	0.9962	0.0025	0.0285	0.0047	0.9951	0.0059	0.0051
10	0.9990	0.0135	0.0071	0.0001	0.9995	0.0014	0.0002
11	0.1311	0.9285	0.6844	0.9234	0.0809	0.9163	0.9222
12	0.0673	0.9685	0.6890	0.9614	0.0390	0.9354	0.9617
13	0.0266	0.9991	0.7573	0.9990	0.0006	0.9757	0.9999
14	0.2199	0.8546	0.5936	0.8265	0.1784	0.8445	0.8233
15	0.0440	0.9783	0.8438	0.9831	0.0169	0.9690	0.9835
16	0.1453	0.8485	0.8293	0.8698	0.1347	0.8727	0.8632
17	0.1193	0.7374	0.8493	0.8875	0.1151	0.8799	0.8833
18	0.0256	0.9715	0.9706	0.9956	0.0054	0.9808	0.9953
19	0.0462	0.8762	0.9246	0.9773	0.0235	0.9785	0.9728
20	0.0043	0.9049	0.9932	0.9999	0.0015	0.9826	0.9986

Figure 2 depicts the membership distribution diagram of the employees' ability to assemble the CD drive and the motherboard after training. This allows the company to analyze the degree of improvement achieved through training. By comparing Table 7 with Figure 2, we can see that the center point of the employees' ability to assemble the CD drive is (173.0709, 47.5211). After five training sessions, the employees' assembly ability is clustered a bit more densely than before, and is concentrated in an area near the affiliate center.

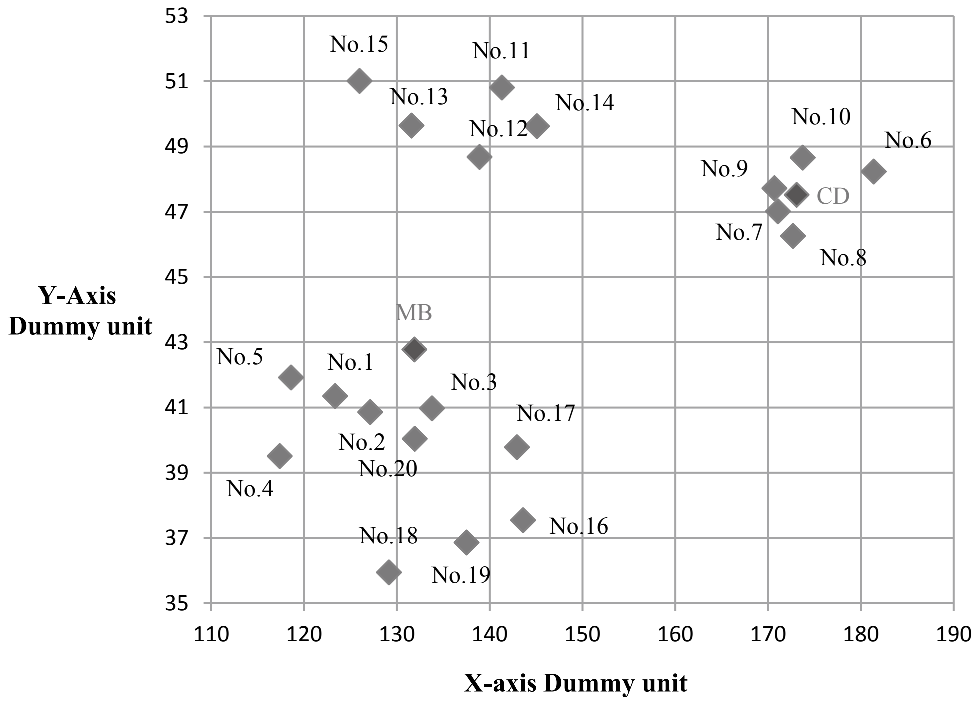

Fig. 2. Scatter diagram of MB and CD assembly ability after personnel training

As in the previous steps, the employees' degrees of membership with regard to the ability to assemble the parts are sorted in Table 9.

Table 9. Ranking of membership degree of assembly ability after training

Ranking	employee no	CD	employee no	CPU	employee no	FAN	employee no	RAM
1	10	0.9990	13	0.9991	20	0.9932	20	0.9999
2	8	0.9990	3	0.9888	18	0.9706	13	0.9990
3	7	0.9972	15	0.9783	3	0.9693	3	0.9979
4	9	0.9962	2	0.9743	2	0.9689	18	0.9956
5	6	0.9727	18	0.9715	1	0.9466	2	0.9886
6	14	0.2199	12	0.9685	19	0.9246	15	0.9831
7	16	0.1453	4	0.9319	4	0.9045	19	0.9773
8	11	0.1311	11	0.9285	5	0.8985	1	0.9705
9	17	0.1193	5	0.9275	17	0.8493	12	0.9614
10	12	0.0673	1	0.9233	15	0.8438	5	0.9427
11	4	0.0653	20	0.9049	16	0.8293	4	0.9353
12	5	0.0558	19	0.8762	13	0.7573	11	0.9234
13	19	0.0462	14	0.8546	12	0.6890	17	0.8875
14	15	0.0440	16	0.8485	11	0.6844	16	0.8698
15	1	0.0289	17	0.7374	14	0.5936	14	0.8265
16	13	0.0266	6	0.0270	6	0.0454	6	0.0258
17	18	0.0256	10	0.0135	9	0.0285	9	0.0047
18	2	0.0121	8	0.0043	8	0.0140	7	0.0034
19	3	0.0043	9	0.0025	10	0.0071	8	0.0003
20	20	0.0043	7	0.0019	7	0.0039	10	0.0001

Table 9. Ranking of membership degree of assembly ability after training (continued)

Ranking	employee no	HDD	employee no	PSU	employee no	GPC
1	10	0.9995	3	0.9937	13	0.9999
2	8	0.9995	2	0.9889	20	0.9986
3	7	0.9967	20	0.9826	3	0.9963
4	9	0.9951	18	0.9808	18	0.9953
5	6	0.9737	19	0.9785	2	0.9885
6	14	0.1784	13	0.9757	15	0.9835
7	16	0.1347	1	0.9712	19	0.9728
8	17	0.1151	15	0.9690	1	0.9684
9	11	0.0809	5	0.9358	12	0.9617
10	4	0.0667	12	0.9354	5	0.9418
11	5	0.0591	4	0.9293	4	0.9337
12	12	0.0390	11	0.9163	11	0.9222
13	1	0.0320	17	0.8799	17	0.8833
14	19	0.0235	16	0.8727	16	0.8632
15	15	0.0169	14	0.8445	14	0.8233
16	2	0.0160	6	0.0269	6	0.0263
17	18	0.0054	9	0.0059	9	0.0051
18	3	0.0044	7	0.0045	7	0.0035
19	20	0.0015	10	0.0014	8	0.0002
20	13	0.0006	8	0.0008	10	0.0002

3. Conclusion

In this paper, a PC assembly process is used as a case study to assess our model for evaluating new employees' skills and determining where they should be assigned on a production line. In the installation test, the motherboard is used as the basis for other parts such as the CD drive, CPU, fan and other parts; this method enables fuzzy grouping calculation. A total of 20 testers with no assembly experience were identified. Table 10 shows that, on the first attempt to assemble the parts after training, the number of employees with a membership degree greater than 0.9 for each part was relatively small, except for the relatively simple procedures for installing the HDD, RAM, and graphics card. These employees would ideally be assigned to a production line requiring flexible change due to frequent switching of the products.

After training, the new employees have increased their degree of membership with regard to installing various computer mainframe components, which also means that the manpower available for assembling each of these parts has increased, such that the company can be more flexible in planning the employees' assignments along the production line. This can help shorten production lead time. This article will focus on the top 25% of employees' assembly ability ranking for analysis.

Table 10. Data on the performance of the top 25% of employees prior to training

no	CD	no	CPU	no	FAN	no	RAM	no	HDD	no	PSU	no	GRA
8	0.988	8	0.954	15	0.998	14	0.995	20	0.994	8	0.985	14	0.9919
13	0.985	13	0.949	8	0.959	20	0.994	14	0.993	2	0.971	20	0.9892
10	0.971	10	0.944	13	0.928	17	0.987	19	0.983	10	0.956	17	0.978
6	0.964	6	0.932	6	0.922	19	0.983	17	0.982	6	0.928	19	0.975
2	0.960	2	0.852	12	0.776	1	0.964	4	0.959	15	0.921	1	0.965
15	0.953	15	0.770	10	0.737	3	0.961	3	0.956	13	0.901	3	0.961

With the knowledge revealed by this model, the company can assign each new recruit to an optimal position on the production line according to that employee's degree of membership as the basis for ranking. As Table 11 shows, the employees who are most highly skilled at installing the CD drive are No. 10, No. 8, No. 7, No. 9, and No. 6, while those who are better at installing the CPU are No. 13, No. 3, No. 15, No. 2, and No. 18. A special case is the HDD assembly membership degree: prior to training, the number of new employees with a high degree of membership for this component is large, but the scores are widely scattered. After training, as Table 4-2 shows, the number of people with high HDD membership has decreased, but the scores of the top 25% of employees are very concentrated. This phenomenon can also be observed in connection with other assembly tasks. Therefore, when assigning dispatch employees on the production line, the top 25% for each component should be regarded as highly specialized at operating and assembling that part.

Table 11. Data on the top 5 employees sorted by fuzzy membership function

ranking	no	CD	no	CPU	no	FAN	no	RAM	no	HDD	no	PSU	no	GRA
1	10	0.999	13	0.999	20	0.993	20	0.999	10	0.999	3	0.993	13	0.999
2	8	0.999	3	0.988	18	0.970	13	0.999	8	0.999	2	0.988	20	0.998
3	7	0.997	15	0.978	3	0.969	3	0.997	7	0.996	20	0.982	3	0.996
4	9	0.996	2	0.974	2	0.968	18	0.995	9	0.995	18	0.980	18	0.995
5	6	0.972	18	0.971	1	0.946	2	0.988	6	0.973	19	0.978	2	0.988

The aim of this study was to develop a new employee ability assessment model based on the FCM method. This method can easily be applied in industries that will require a mass customized production mode in the future. This work assignment mode saves a great deal of measurement and evaluation time and can be quickly deployed to reduce lead time when changing production lines.

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