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RESEARCH ARTICLE

A CUSTOMER PAIR-WISE MATRIX-BASED ALGORITHM FOR GARMENT SIZING PROBLEM

*Adepeju A. Opaleye (Ph.D) and Dr. Kolawole, A.

Department of Industrial and Production Engineering, Faculty of Technology, University of Ibadan, Ibadan Nigeria

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ABSTRACT

One of the most complex and diverse products in the buyers' market is the garment item. This is due to the multifaceted problems with fitting leading to poor sales performance in retail and increased garment return rate. This study proposes an algorithm based on customer pair wise matrix for improving the fit of the garment size system. The proposed algorithm is applied successfully to an anthropometric dataset consisting of 286 female Corp members. Its performance was compared with the existing KMedoid algorithms using the aggregate loss of the fit function and a novel percentage degree of fit function. Analysis of the observed result using t test statistics suggests a statistically significant difference at ($t(18)=5.728$, $p=2.46E-05$) and ($t(18)=5.188$, $p= 7.4E-05$) exist between the percentage degree for the proposed algorithm and the K-Medoid algorithm by Spath and Kaufman and Rousseeuw respectively. A similar result was obtained for the aggregate loss of fit. The algorithm enables a balance between percentage degree of fit and number of size groups for a target population

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INTRODUCTION

One of the most complex and diverse products in the buyers' market is the garment item. This is due to the multifaceted characteristics of garment quality in relation to consumers' functional, expressive and aesthetic needs. *Functional needs* relate to garment *fit*, mobility, comfort, and protection. Expressive requirement of a consumer provides an opportunity for the wearer to communicate his or her self-image while the aesthetic needs are related to appeal of a clothing product in terms of style, colour, appearance, fashionability or attractiveness (Kasambala, *et al*., 2016; Wheat and Dickson 1999). However, from various designer-mediated perspectives, garment fit seems to be the most important quality characteristic as it has a direct consequence on the rational buyers' willingness to pay for certain garment item (Shin and Damhorst, 2018). Currently, the two modes of acquiring garment items include: custom made and ready-to-wear. The custom-made approach either offer standard sizes with different designs which is a combination of style details, fabrics and special monograms or standard garment designs modified to suit customer's anthropometric measurements.

Corresponding author: **Adepeju A. Opaleye (Ph.D),**
Department of Industrial and Production Engineering, University of Ibadan, Nigeria.

On the other hand, ready-to-wear garment production system does not depend on the use of personal measurement of individuals but depends on the use of sizing systems to produce same garment design for a target group or populace. While the custom made approach produces garments with good fit and maximum differentiation, it has been found to fail the key test of global quality elements such as delivery speed, and availability. It also diminishes relative advantages of the RTW system, primarily, the economies of scale inherent in the mass production system. An emerging concept in the garment industry is the mass customisation system. It is devised to serve the individualized needs of consumers and increase their satisfaction percentage (Anderson *et al*., 1999) through production of customized garments at affordable cost (Mpampa, *et al*., 2010). However, a successful garment mass customization system is consequent on the development and maintenance of a sizing system which satisfy majority of a target population and at the same time results in a cost-effective and affordable production process (Mpampa, *et al*., 2010). Ashdown (2007) defined a size chart as a table of numbers which present the values of each of the body dimensions used to classify the shapes encountered in a target population (Ashdown, 2007). It is the most effective means of communication between the designers and the wearers. The development of a size chart involves collection of anthropometric body measurements of the target population and its division into homogeneous groups for the purpose of garment manufacture (Pretrova and Ashdown, 2012; Oluah, 2014). The lesser the discrepancies between the wearers' anthropometric measurements and the specified garment size along certain critical dimensions, the better the fit and the more effective a sizing system. According to Mcculloch *et al*., (1998), a sizing system is both effective and economical only if it provides the fewest sizes group possible for the best fit possible for a large percentage of a target population (Mcculloch and Paal, 1996). In spite of various models and techniques that have been developed for improving sizing systems, complaints relating to misfit and return of garment items persist (Kim and Damhorst, 2013). Recently, data-mining techniques, most especially clustering analysis, have been considered by a number of researchers (Hsu, *et al*., 2009; Opaleye, *et al*., 2019; Simbolon, *et al*., 2014) for sizing problems. Other commonly used techniques employed for sizing problems include statistical and multivariate techniques (Gupta and Gangadhar 2004; Gupta 2015; Chun-yoon and Jasper, C. R. 1996; O'Brien, Rand Shelton 1941) and optimisation modelling techniques (Gupta,*et al*., 2006; Tryfos 1986; Mcculloch and Paal 1996; McCulloch, *et al*., 1998). For example, Gupta and Gangadhar (2004) observed that statistical strategies extending from basic percentiles to complex combinations of multivariate and regression analyses have been utilized for distribution of target population into size groups. Salusso (1982) classified the adult body form variation in USA using the principal component analysis.

The researcher stated that the success of body shape classification relies on special selection of the key body dimensions. The residual variance analysis and factor analysis are also considered for the selection of these key dimensions (Chun-yoon and Jasper, 1996). Beshah *et al*., (2014) proposed the percentile analysis. These statistical techniques assume linear relations between dimensions and the techniques enhance easy classification of dataset into size groups. On the other hand, Tryfos (1986), McCulloch *et al*., (1998) ,Ashdown (1998) and Gupta *et al*., (2006) considered more rigorous mathematical optimisation techniques. They noted that the common practise of using one or two key body dimensions does not provide a good fit for populations with large variations in body proportions. However, increase in the number of constraints compromise the performance of these sizing systems.

The rapid increase in the capability for automatic data acquisition and storage necessitates the use of data mining techniques – specifically the clustering technique in garment sizing problem. Clustering is referred to as the process of organizing data set into clusters (high intra-cluster likeness and low inter-cluster likeness) or natural groupings, which indicates the internal structure of the data set. According to (Zdenek Sulc, 2014) the similarities present in a known data set as a result of the distance measure aids the data points to be divided into homogenous numbers of groups ensuring that the membership of a cluster differs from the others. They are also regarded as unsupervised techniques that do not depend on presumptions common to customary statistical strategies, such as the primary statistical dispersion of data. Thus, they are valuable in circumstances where little earlier knowledge exists. It has been found useful as a tool in various fields such as pattern recognition, image processing, bioinformatics etc.

Despite, the vast number of flexible models and algorithms for clustering problem, K mean remains the preferred technique in many real life applications. K-mean minimises the squared Euclidean distance between a data point and its cluster center. Hsu (2009) developed a sizing systems for adult Taiwanese females using a database of their anthropometric data and a combination of Ward's minimum variance method with the K-means algorithm. Others also found the clustering technique appropriate for the same problem (Hsu, *et al*., 2009b; Simbolon, *et al*., 2014; Opaleye, *et al*., 2019). Perhaps, the main reason for wide acceptability of K mean is attributed to its conceptual simplicity and computational scalability. Nonetheless, it is known that the restrictive underlying assumptions of the K mean come with a high cost when violated, often leading to severe inaccuracy (Raykov, *et al*., 2016).

An alternative to the K-mean techniques is the KMedoid algorithm. It is considered more robust to outliers as it minimises the sum of pairwise dissimilarities instead of the Euclidean distance. There exist two algorithms of the K-Medoid; Spath (1985) and Kaufman and Rousseeuw (1990) algorithms. The formers use random starting cluster configurations while the latter makes special use of silhouette statistics to help determine the appropriate number of clusters. It uses the most centrally located point in each cluster at each iteration step. The caveat, however is the large computation time of the customer pairwise matrix at each iterative step. This study is based on the customer pairwise matrix (CPM) model proposed by Kolawole and Charles-Owaba (2018) for improving the fit of the garment size system. The algorithm which is not based on a random selection of the initial cluster center calculates the customer pair wise matrix once and uses it for finding a new cluster center at each iterative step. The proposed algorithm also harnesses the advantage of customer's tolerance for garment sizing problems.

Proposed Methodology

Garment fit for a group of customer: The customer pairwise matrix (CPM) based technique defines garment fit quantitatively and relates fit to other garment sizing parameters such as garment design dimensions, tolerance, and the number of customers in the target population. It is assumed that a garment size whose dimension perfectly fits a customer i is known. Suppose 'k' is the customer whose fit is to be compared with customer i, a binary state of fit between ideal customer 'i' and 'k' on dimensions 'j' may be expressed as ω_{ikj} where

$$\omega_{ikj} = \begin{cases} 1, if \ |x_{ij} - x_{kj}| \leq t_j \\ 0, \quad Otherwise \end{cases} \tag{1}$$

$$B_{ik} = \begin{bmatrix} \omega_{ik1} \\ \omega_{ik2} \\ \omega_{ik3} \\ \vdots \\ \vdots \\ \omega_{ikm} \end{bmatrix} \tag{2}$$

where x_{ij} and x_{kj} are measurements of customers i and k for dimension j and t_j is the tolerance on dimension j.

The scalar expression of fit between any pair of customers *'i'* and *'k'* may be defined as

$$r_{ik} = \left[\frac{(B_{ik}{}^{T})B_{ik}}{(B_{ii}{}^{T})B_{ii}}\right] \quad (3)$$

$B_{ik}{}^{T}$: is the transpose of and is theoretically the identity of a customer compared to himself. Notice that the influence of customer's dimension relative to all other customers in the target group may be defined as its degree of centrality in the group as described in social network theory. The eigenvector centrality in social network analysis measures both the number of related links and quality of those links. This means that a node having connections with high prestige nodes in a network contributes to the centrality value of the node in question (Arif, 2015). The eigenvector centrality of a customer can be defined using Equation (4), where is a constant.

$$R_i = \frac{1}{\gamma}\sum_{k=1}^{N} r_{ik} \qquad for\ i \neq k \quad (4)$$

Therefore, measurement of customers i with high R_i values will most likely suit other customers k in the group. However, the level of satisfaction of members in the group, the percentage degree of fit, h_α *is* described as a measure of the similarity in the anthropometric measurements of the set of customers in a size group α (Kolawole A. and O.E. Charles-Owaba, 2018). For a given group of customers, it is estimated as

$$h_\alpha = \frac{\sum_{i=1}^{g\alpha}\sum_{k=1}^{g\alpha-1} 100 r_{ik}}{n_\alpha(n_\alpha - 1)}; \quad (5)$$
$$i, k \in g_\alpha; i \neq k$$

where n_α is the number of customers assigned to group α.

A sizing system may be evaluated as follows (2018);

$h_\alpha = 100$ *, perfect fit (all members in this group can wear the same size)*
$h_\alpha =< 100$, *only some of the members in the group may wear same size*
$h_\alpha = 0$, *none of the memebers wear the same size*

The higher the h_α , the better the sizing system. However, for a given population of customers, the different number of sizes which accommodates its customers has a degree of fit $h_1, h_2 \ldots\ldots h_q \ldots\ldots\ldots h_C$ expresses as

$$H_\alpha = f(n_\alpha, C;\ t, m, N) = \sum_{\alpha=1}^{C}\frac{h_\alpha}{C} \quad (6)$$

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$$H_\alpha = f(n_\alpha, C;\ t, m, N) = \sum_{\alpha=1}^{C}\frac{h_\alpha}{C} \quad (6)$$

This represents the overall degree of fit for the garment sizing system. For completeness, we provide a detailed description of the algorithm used in this study.

Customer Pair-Wise Matrix-Based Algorithm: This procedure iterates on a set of customers denoted as set S. S is initially set as a sorted list of customers in descending order of R_i. In the process of iteration, a customer is considered ideal if it has the maximum R_i in set S and it is not in any of the existing cluster α $(\alpha = 1,2 \ldots C)$.

Step 1: Initiation:

(i) Set α $(\alpha = 1,2 \ldots C)$
(ii) Set S

Step 2: Assignment:

(i) Find customer i with maximum relation index R_i and form a subset (I) of all candidate ideal customers. *I is a subset of all possible ideal customers at this stage*)et i $(i \in I)$ as ideal customer for cluster .
(ii) For $i \neq k$, find maximum value of r_{ik} $(say\, r_{ik} = 1)$, assign all customer k with $max\,(r_{ik})$ into cluster α
(iii) Compute percentage degree of fit for cluster α: $h_\alpha = \frac{\sum_{k=1}^{n_\alpha} 100 r_{ik}}{n_\alpha}$
(iv) For $i > 1$, repeat (ii) – (iv) and select i as ideal customer for cluster α, if $h_\alpha^i = \max(h_\alpha^1, h_\alpha^2 \ldots\ldots h_\alpha^I)$. Else, go to step 3

Step 3: Updating

(i) Eliminate i and k assigned to cluster α from set S.
(ii) Update $\alpha = \alpha + 1$
(iii) Update set S

Step 4: Stopping:

If $\alpha < C - 1$, go to step (1). Else, group all unassigned customers to cluster C and go to step (5).

Step 5: Output

(i) Compute percentage degree of fit for each cluster $\alpha = 1,2 \ldots .C$ $h_\alpha = \frac{\sum_{k=1}^{n_\alpha} 100 r_{ik}}{n_\alpha}$
(ii) Compute percentage degree of fit for the system: $H_\alpha = \sum_{\alpha=1}^{C}\frac{h_\alpha}{C}$

Performance Evaluation: The proposed algorithm is illustrated by applying it to the development of a sizing system for a target population known as "Corp members". Corp members (also known as Corpers) are young Nigerian graduates from universities and polytechnics call to serve the nation. This is a National Youth Service Corps (NYSC) program of the federal government of Nigeria. The program aims to involve the youth in nation-building and increase mutual understanding among the different ethnic groups in the country. Every year, NYSC mobilizes hundreds of thousands of both locally and foreign-trained graduates for the year-long compulsory national service at places other than their place of residence. The Corper's uniform which is a pair of green khaki trousers and shirt is like the military uniforms. It serves as a crucial symbol to servicemen during the one-year service period. For the performance evaluation process, first, primary data was simplified and fourteen anthropometric parameters (Waist, thigh, hip, back width, chest, bust, neck size, wrist, ankle, nape to waist, skirt length, sleeve length, top arm and height) relevant to the development of the corper's uniform were collected analyzed by factor analysis. This is to assess their interrelations and determine representative variables.

Second, the key variables and their tolerance values serve as input to the proposed CPM algorithm and two existing K-Medoid techniques used in the sizing problem. The first (K-Med1) by Spath (1985) and the second (K-Med2) by Kaufman and Rousseeuw (1990). This K-Medoid clustering was performed on NCSS 10 Statistical Software package. Finally, the performance of these algorithms in solving the sizing problem was evaluated using two different measures; the aggregate loss of the fitness method (Gupta and Gangadhar 2004; McCulloch, *et al.*, C.E.,1998) and the percentage degree of fit (Kolawole and Chales-Owaba, 2018). The aggregate loss of fit index measures the absolute value of fit. According to Gupta and Zakaria(2014), the benchmark for an accurate sizing system is an ideal value of aggregate loss calculated as $2.54\square^{1/2}$, (metric in centimetres) where 'n' is the number of key anthropometric dimensions used to segregate the target group. If the actual aggregate loss is less than the ideal, the system is considered good for the target population. On the other hand, the proposed percentage degree of fit measures the degree (or percentage) to which a certain sizing system "satisfies" the target population. The percentage degree of fit for a sizing system may be evaluated as follows (2018);

$$h_{\square} = 100\ ,perfect\ fit\ (all\ members\ in\ this\ group\ can\ wear\ the\ same\ size)$$

$$h_{\alpha} =< 100,\ \ only\ some\ of\ the\ members\ in\ the\ group\ may\ wear\ same\ size$$

$$h_{\alpha} = 0,\quad none\ of\ the\ memebers\ wear\ the\ same\ size$$

RESULTS AND DISCUSSION

A total of 286 sets of female anthropometric data relevant to the development of the corper's uniform was collected and simplified. The descriptive analysis of the data: means, median, range, standard deviation and coefficient of variation were also obtained. As shown in Table 1.0, the mean waist is 80.77cm while the mean thigh, hip, back width and bust are 70.44cm, 96.96cm, 40.20cm and 109.97cm, respectively for 286 corper's anthropometric data. The waist girth varied more (coefficient of variation = 15.94 %) while the skirt length (coefficient of variation = 4.44%) varied the least for the set. As expected, data for all dimensions show a near normal distribution.

Factor Analysis: In structuring the size system of uniforms, not all anthropometric parameters need to be considered because these variables are very highly correlated. The Eigen values from the factor analysis (Table 2.0) shows that 100% of variation observed in data can be explained by the first five factors. Therefore, only five factors will be considered as representative variables in the problem. To identify these key factors, the factor loading of the factor analysis technique was used. Table 3.0 shows that the nape to waist (-0.941), skirt length(-0.982) and height(-0.607) are most related to factor 1. These are representatives of linear dimensions. The key anthropometric variable here is the skirt length with a load of -0.982. The wrist (0.986) and ankle (0.982) measurement are related to factor 2 with the key variable being the wrist measurement. Factor 3 relating to the waist, thigh, hip and bust girth measurement has its main variable as the hip measurement with a factor loading of -0.961. Meanwhile, factor 4 and 5 relates to the neck size and sleeve length. The selected key variables (hip girth, neck girth, wrist girth, skirt length and the sleeve length) in each case are those with the highest factor loading

Comparison with K-Medoid: The K-Medoid algorithms and the CPM algorithm were used to classify corpers uniform sizes. The sizing systems considered group ranging between 3-20 using the five identified anthropometric data and associated tolerance values. The tolerance values determined based on practitioner's evidence are given as follows; the hip girth(5cm), neck girth(1cm), wrist girth(1cm), skirt length(4cm) and the sleeve length(2cm). The K-Medoid functions were implemented on NCSS 10 Statistical Software package while python 3.0 was used as the programming language for coding. The first step in this algorithm is to initialise the data by importing data in excel spreadsheet into python environment. Then, the function for fit in python takes in the data, the tolerance values and required number of size groups for assignment into groups and updating thereafter. Table 4.0 shows sample of the CPM results obtained.

From Table 4.0, with three size groups, the first, second and third group accommodates 10, 8 and 268 Corpers at 83.11%, 78.11% and 36.06% degree of fit respectively and the sizing system has an overall degree of fit of 65.9%. The overall performance for the size systems considered can be seen on Table 5.0. Aside, systems with 3 and 4 size groups, CPM algorithm promotes integral fitness between 0.34% - 9.97% among wearers of same garment size more than the K-Medoids; and a decrease of in aggregate loss between 55.13%-83.92%. The graphical representation of these performances is presented on Figure 1.0 and 2.0. The percentage degree of fit for the CPM algorithm range between 65.91% - 79.89% while the percentage degree of fit for the K-Medeoid using Spath and Kaufman-Rousseeuw algorithm is between 71.32%-73.77% and 71.24%-74.94%. Similarly, the aggregate loss of the proposed algorithm is between 4.26-7.17 while that of the two K-Medoid techniques is between 12.96-46.07 and 12.19-35.48, respectively. On Table 6.0, it is observed that the mean (standard deviation) of the percentage degree of fit of the proposed size system was 76.67 (3.63), whereas that of the K-Mediod clustering techniques are 72.01(0.77) and 72.89(1.00) respectively. Relative to the mean, the coefficient of variation shows that the results of CPM algorithm varies more at 4.73%.This implies that as the number of cluster is increased, the percentage degree of fit using CPM algorithm becomes more variable compared to the two other K-Medoid algorithms. On the other hand, mean (standard deviation) of the aggregate loss of fit 5.673(0.592) for the CPM is least variable as shown on Table 6.0. According to Gupta and Zakaria (2014), the ideal value in this case is 5.68, none of the sizing system proffered by the K-Medoids is deemed good for this target group.

Table 1.0: Descriptive Statistics

Variable	Mean	Median	Range	Standard Deviation	Coefficient of Variation
Waist	80.77	78.74	33.02	6.305	0.078
Thigh	70.43	71.12	20.32	3.217	0.146
Hip(cm)	96.96	106.52	40.64	5.759	0.159
BackWidth	40.2	40	16	3.396	0.08
Chest	38.69	35	81	13.203	0.34
Bust	109.97	109.06	66.72	8.156	0.074
Neck Size	38.72	38	20	3.006	0.077
Wrist	26.1	26	20	5.933	0.127
Ankle	32.08	32	24	6.113	0.191
Nape toWaist	77.51	77.3961	17.687	3.795	0.049
Skirt Length	104.98	104.14	22.86	4.661	0.044
Sleeve Length	68.46	66	29	7.918	0.116
Top Arm	29.38	31.5	84	11.391	0.388
Height	173.46	172.72	46.472	9.802	0.056

Table 2.0: Eigenvalues after Varimax Rotation

Number	Eigenvalue	Individual Percent	Cumulative Percent
1	2.376318	30.65	30.65
2	1.964835	25.34	55.99
3	2.302734	29.7	85.69
4	0.75491	9.74	95.43
5	0.361488	4.66	100.09
6	0.095402	1.23	101.32
7	0.040662	0.52	101.85
8	0.015711	0.2	102.05
9	-0.00014	0	102.05
10	-0.00409	-0.05	101.99
11	-0.01388	-0.18	101.81
12	-0.02822	-0.36	101.45
13	-0.05237	-0.68	100.78
14	-0.0601	-0.78	100

Table 3.0 Factor Loadings after Varimax Rotation

	Variables	Factor1	Factor2	Factor3	Factor4	Factor5
1	Waist	-0.01383	0.035928	-0.518	0.137552	0.013171
2	Thigh	-0.3291	-0.11972	-0.47053	-0.0602	0.003984
3	Hip(cm)	-0.14092	-0.05755	-0.9606	-0.01261	0.134074
4	BackWidth	-0.05776	-0.01051	-0.08872	0.104311	0.153873
5	Chest	-0.03034	-0.01608	-0.07351	0.302782	0.06434
6	Bust	-0.1381	-0.00879	-0.91015	0.00139	0.065971
7	Neck Size	0.07581	0.048617	0.018535	0.554211	-0.05775
8	Wrist	-0.01168	0.986687	0.028825	0.048968	-0.03865
9	Ankle	-0.0091	0.982365	0.042548	0.035073	-0.04351
10	Nape toWaist	-0.94106	0.004358	-0.13037	-0.01021	0.123995
11	Skirt Length	-0.98156	0.013099	-0.10995	0.01144	0.085189
12	Sleeve Length	0.005825	-0.02896	-0.00883	-0.16189	0.459144
13	Top Arm	-0.01387	0.055722	0.034576	0.540708	-0.25952
15	Height	-0.60777	0.019064	-0.12361	0.007746	-0.06029

Table 4.0: CPM Garment Sizing Output

Number of size groups	Size(α)	Number of customers to wear the same size	Fit of size hα	Fit of sizing system
3	1	10	83.11	65.913
	2	8	78.57	
	3	268	36.06	
5	1	10	83.11	76.922
	2	8	78.57	
	3	7	87.62	
	4	2	100	
	5	259	35.31	
8	1	10	83.11	79.1425
	2	8	78.57	
	3	7	87.62	
	4	2	100	
	5	28	56.88	
	6	3	100	
	7	3	93.33	
	8	225	33.63	

A paired t-test was conducted to determine the level of significance in the difference observed. The computed value of the t test statistics suggests a statistically significant difference ($t(18)=5.728$, $p=2.46E-05$) between the percentage degree of fit using the proposed CPM algorithm and the K-Medoid algorithm by Spath (1985); and a statistically significant difference ($t(18)=5.188$, $p= 7.4E-05$) for Kaufman and Rousseeuw ((1990) algorithm.

Table 5.0: Performance Measures

No of Clusters considered	CPMA		K-Med1		K-Med2	
	PF	AgLoss	PF	AgLoss	PF	AgLoss
3	65.91	7.17	71.48	47.07	71.56	35.48
4	71.20	6.55	71.32	39.56	71.64	29.91
5	76.92	5.80	71.45	39.43	71.24	26.37
6	73.37	6.25	71.52	29.90	71.37	26.34
7	77.14	5.40	71.69	27.95	71.70	27.70
8	79.14	5.46	71.38	27.35	73.57	27.72
9	73.08	4.26	71.44	26.52	72.83	24.51
10	79.06	5.49	71.49	29.76	73.01	27.22
11	79.43	5.50	71.51	20.07	73.29	25.11
12	77.51	5.80	72.06	26.34	73.10	29.24
13	76.03	5.95	73.44	23.45	73.41	31.37
14	77.73	5.70	71.87	22.24	73.16	29.65
15	79.21	5.45	71.57	14.79	73.04	13.24
16	78.11	5.65	71.92	14.29	73.89	12.82
17	79.40	5.31	72.33	13.08	74.94	12.31
18	78.05	5.56	72.66	12.96	73.61	12.93
19	78.85	5.35	73.77	13.21	73.22	12.88
20	79.89	5.47	73.22	13.72	73.54	12.19

K-Med1: Spath (1985); K-Med2: Kaufman and Rousseeuw (1990)
PF: Percentage degree of fit AgLoss: Aggregate Loss

Table 5.0: The t-test results for the proposed algorithm and K-Medoid techniques

Measure	Sizing Algorithm	Mean	Standard Dev.	Coef.Variation(%)	t statistics	p-value
Percentage degree of fit	CPM	76.67	3.63	4.735		
	K-Mediod 1	72.01	0.77	1.069	5.728	2.46E-05
	K-Medoid 2	72.89	1	1.372	5.188	7.4E-05
Aggregate loss	Proposed Algorithm	5.673	0.592	10.433		
	K-Mediod 1	24.537	10.219	41.645	-8.101	3.07E-07
	K-Medoid 2	23.166	7.977	34.432	-9.618	2.73E-08

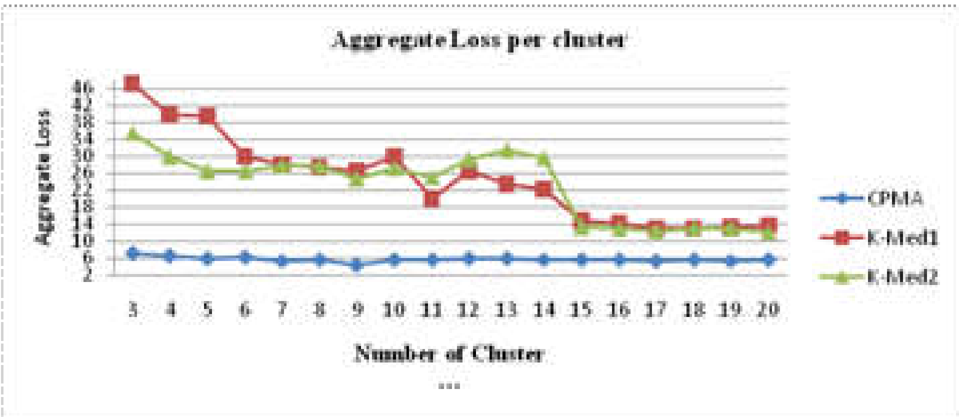

Figure 1.0: Aggregate Loss of fit

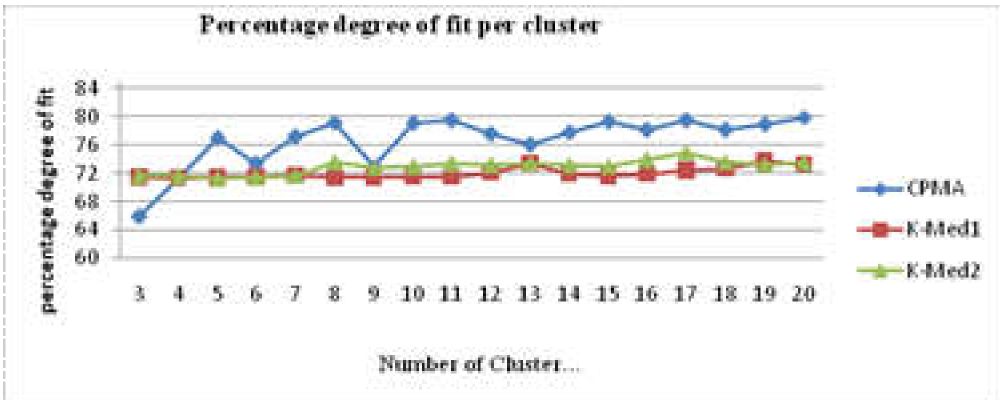

Figure 2.0: Percentage degree of fit

Similarly, the mean (standard deviation) for the aggregate loss (standard deviation) of the proposed size system is 5.673 (0.592), whereas that of the K-Mediod clustering techniques are 24.537(10.219) and 23.166 (7.977) respectively. The statistically significant difference (t = -8.101, p = 3.07E-07) and (-9.618, p=2.73E-08) with the K-Medoid algorithm by Spath (1985) and Kaufman and Rousseeuw ((1990) suggests that the proposed CPM algorithm results in a lower aggregate loss of fit than the K-Medoid techniques for sizing problems. The results of the paired *t*-test results show that the CPM does not only perform better in terms of the percentage degree of fit, but also with respect to the aggregate loss of fit. It can improve the number of corpers satisfied with their uniform and integral fitness considerably. It also shows that at a desired level of satisfaction, the proposed CPM algorithm can provide a better fit with fewer numbers of clusters compared with the two K-Medoid algorithms.

Conclusion

Anthropometric data required in making female NYSC uniforms in Nigeria were collected and clustered using customer pair wise matrix based algorithm. The proposed customer pair wise based algorithm implemented on python environment is designed to improve fit of garment sizing system. The CPM algorithm does not require random initialisation of cluster and repetitive computation of pair wise matrix. The result from various analysis using anthropometric data of female corp members shows that the proposed method has better performance than K-Medoids and that it requires few size groups than K-Medoids for higher customer satisfaction. However, proper implementation of garment mass customisation model will require determination of tolerance or ease from customer's perceptive (Ashdown and Delong 1995; Kolawole 2016; Lin, *et al*., 2018). Garment tolerance may be determined as a function of customer's willingness to pay for certain garment item with measurements slightly different from their anthropometric measurement of a particular design.

REFERENCES

Arif, T. 2015. 'The Mathematics of Social Network Analysis: Metrics for Academic Social Networks', *International Journal of Computer Applications Technology and Research*, 412, pp. 889–893.

Ashdown, S. P. 1998 '"An investigation of the structure of sizing systems', *International Journal of Clothing Science and Technology*, 105, pp. 324–341.

Ashdown, S. P. and Delong, M. 1995. 'Perception testing of apparel ease variation', 261, pp. 47–54.

Beshah, Birhanu, Berhane, Belay, Shimelis Tilahun, Betsha Tizazu, A. M. 2014. 'Anthropometric data of Bahirdar city's adult men for clothing design', *International Journal of Vocation and Technical Education*, 65, pp. 51–57.

Chun-yoon, J. and Jasper, C. R. 1996. 'Key Dimensions of Women ' s Ready-to-Wear Apparel: Developing a Consumer Size-Labeling System', *Clothing and Textiles Research Journal*, 141, pp. 89–95.

Gupta, D., Zakaria, N. 2014. *Anthropometry, apparel sizing and design*. Edited by N. Gupta, D., Zakaria. United Kingdom: Woodhead Publishing.

Gupta, D. and Gangadhar, P. 2004. 'A statistical model for developing body size charts for garments', *International Journal of Clothing Science and Technology,* 16, pp. 458–469.

Gupta, Deepti, Garg, Naveen, Arora Komal, P. N. 2006. 'Developing body measurement charts for Garment Manufacture Based on a Linear Programming Approach', *Journal of Textile and Apparel, Technology and Management*, 51, pp. 1–13.

Gupta, D. 2015. 'COMMUNICATIONS A statistical model for developing body size charts for garments', October 2004. doi: 10.1108/09556220410555641.

Hsu, C. 2009. 'Data mining to improve industrial standards and enhance production and marketing: An empirical study in apparel industry', *Expert Systems with Applications*, 36, pp. 4185–4187. doi: 10.1016/j.eswa.2008.04.009.

Hsu, C., Lee, T. and Kuo, H. 2009. 'Mining the Body Features to Develop Sizing Systems to Improve Business Logistics and Marketing Using Fuzzy Clustering Data Mining', in *WSEAS TRANSACTIONS on COMPUTERS*, pp. 1215–1224.

Kaufman,L., Rousseeuw, P. J. 1990. *Finding Groups in Data: an Introduction to Cluster Analysis.* john Wiley & Sons.

Kolawole, A. 2016 *Investigation of The Relationship between Fit and Garment Sizing Parameters*. University of Ibadan, Nigeria.

Kolawole A. and O.E. Charles-Owaba 2018. 'Customers Pairwise Fit Matrix Approach to Garment Sizing', in *Proceedings of the International Conference on Industrial Engineering and Operations Managment*. Pretoria/Johannesburg, South Africa, pp. 1409–1420.

Lin, E.M.H., Tseng, M. 2018. 'Tolerances of Customers' Requirements: A Review of Current Researches', in *51st CIRP Conference on Manufacturing Systems*. Procedia CIRP 72, pp. 1208–1213.

McCulloch, C.E., Paal, B. and Ashdown, S. P. 1998 'An optimization approach to apparel sizing', *Journal of the Operational Research Society*, 495, pp. 492–9.

Mcculloch, C. E. and Paal, B. 1996 'An Optimization Approach to Apparel Sizing by'.

O'Brien, Rand Shelton, W. C. 1941 *Women's Measurements for Garment and Pattern Construction, Miscellaneous Publication*.

Opaleye, A. A., Kolawole, A. and Charles-owaba, O. E. 2019 'Application of Fuzzy Clustering Methodology for Garment Sizing', 41, pp. 24–31. doi: 10.11648/j.ajdmkd.20190401.15.

Raykov, Y.P., Boukouvalas, A., Baig, F., Little, M.A. 2016 'What to do when K-Means clustering fails: A simple yet principled alternative algorithm .', *PLoS ONE*, 111–28.

Salusso 1982 *A method for classifying adult female body form variation in relation to the US Standard for apparel sizing.* Doctoral Dissertation, University of Minnesota.

Shin E Damhorst M 2018 'How young consumers think about clothing fit?', *International Journal of Fashion Design, Technology and Education*, 113, pp. 352–361.

Simbolon, A., Kuo, R.-J., Wijaya, A. 2014 'Developing a novel apparel standard sizing system using fuzzy clustering technique.'

Spath, H. 1985 *Cluster Dissection and Analysis: Theory, FORTRAN programs, Examples.* Ellis Horwood Ltd.

Tryfos, P. 1986 'An integer programming approach to the apparel sizing problem', *Journal of the Operational Research Society*, 3710, pp. 1001–6.

Zdenek Sulc, H. R. 2014 'Evaluation Of Recent Similarity Measures For Categorical Data', *Application of Mathematics and Statistics in Economics*, pp. 249–258. doi: DOI: 10.15611/amse.2014.17.27.

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