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Apparel sizing: existing sizing systems and the development of new sizing systems

N. ZAKARIA, Universiti Teknologi Mara, Malaysia and
D. GUPTA, Indian Institute of Technology, Delhi, India

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Abstract: The chapter begins by discussing the importance of a sizing system for clothing and reviewing the existing sizing systems that have been developed from 1941 to 2012. A comprehensive compilation of sizing systems based on the techniques is discussed, each according to its strengths and weakness. Next, this chapter demonstrates the development of a sizing system combining statistical methods and data mining techniques, illustrated with a flowchart. The last two sections briefly discuss future trends in selecting key dimensions and list additional sources of information and advice.

Key words: anthropometric data, sizing systems, ready-to-wear clothing, clustering, data analysis, data mining.

1.1 Introduction

Clothing is a necessity in human life, and it is important to wear the right size clothes so that they are comfortable and fit the body well. During the early eighteenth century all clothing was custom-made, each garment hand-sewn for a particular individual. This custom-made clothing exactly fit the individual's body size and shape. Various sizing methods were employed by the dressmakers and craftsmen of the time, but problems in sizing did not really exist because each item was tailored according to an individual's needs.[1] However, starting from the middle of the 1700s, there rose a demand for clothing to be mass-produced.[1] The demand started with military uniforms, which needed to be available in bulk. Mass-produced clothes are based on pre-assigned sizes according to classified groups, and are known as ready-to-wear (RTW); this is the type of clothing which is sold at retail stores. Starting in the 1940s, RTW garments began to be popular in retail stores and increasingly demanded by customers.[1] This was a change in clothing buying trends, from getting a garment tailored to buying it off the rack. Because RTW clothing was based on average sizes, people with different body variations and ranges often had problems finding clothing to fit them. This was the origin of the need for a standard sizing system, since RTW resulted in many returns to stores and mail-order houses due to ill-fitting clothing.

1.2 Existing sizing systems: strengths and weaknesses

Table 1.1 summarizes a comprehensive collection of literature on all the sizing systems that have been developed by researchers all over the world from 1941 to 2012. This summary has been carefully researched and obtained from the journal literature and compiled in order to give a good background for those who want to develop additional sizing systems.

Sizing systems have been developed and improved throughout the years using more and more sophisticated methods: simple mathematical techniques such as bivariate classification; statistical techniques like correlation coefficients; multivariate techniques, namely principal component analysis (PCA) and factor analysis; programming techniques like linear programming (LP) and integer programming and non-linear optimization; data mining techniques such as cluster and decision tree analysis; and artificial intelligence techniques including genetic algorithms, neural networks, fuzzy logic and self-organization methods (SOM). All these techniques are briefly described in the following paragraphs to show the range of techniques available for sizing system development.

Referring to Table 1.1, the first recorded sizing analysis was performed in 1941 and it applied bivariate classification to cluster women according to bust and hip girth. Before this time, the classification of body types was based on height and weight.[2] Thirty years later, other researchers applied the same technique (bivariate classification) to develop sizing systems for different target populations.[3,4] In her studies, Otieno[4] identified areas of fit problems such as bust and waist girth and hip and leg length. After selecting the key dimensions, she classified children into sizes, first according to the primary key dimension of height and then according to the secondary dimensions of bust for upper body garments and height and hip for lower body garments.

In 1985, Salusso *et al.*[5] developed a sizing system known as PCSS (principal component sizing system) using the PCA technique. However, their application of PCA differed from that of O'Brien and Shelton.[1] In previous research, PCA was applied to reduce the data and then the components were analyzed for the selection of only one key dimension from each component. But in Salusso's[5] research, PCA was applied to the classification of the population. Here, the relationship of variables is looked upon in terms of the loading of factors of those variables on each component (correlation between a variable and a component). If the loading is high, it means that the variable is strongly associated with the component. This sizing analysis showed that two components were most important, namely PC1 as laterality, associated mainly with body girth, arcs and widths, and PC2 as linearity, associated with heights and lengths. PCCS is based on partitioning the PC1 and PC2 geometrically.[5] PC1 and PC2 behave like the control dimensions in conventional sizing system construction. The height and weight distribution are used to identify the PCCS sizes. It was concluded that PCSS represents a better

Table 1.1 Development of sizing system literature

Author	Title	Year	Samples	Method
O' Brien, R. and Shelton, W.	*Women's measurements for garment and pattern construction*. Washington, DC: US Dept of Agriculture	1941	10 041 adult females	PCA /bivariate classification of body types
Staples, M. and DeLury, D.	A system for the sizing of women's garments. *Textile Research Journal*, 19: 346–354	1949	10 000 adult females, 19 years and above	Correlation coefficient and bivariate classification
Kemsley, R.	*Women's Measurements and Size MSO*. W. F. F. Joint Clothing Council Limited	1957		
Rodwell, W.	*Toward Metric Sizing*. London: Clothing Institute	1968		
Croney, J.E.	An anthropometric study of young fashion students including a factor analysis of body measurements. *Man*, 12: 448–496	1977	317 young women, 13 body dimensions	Correlation coefficient
Green, M.E.	An application of US Army women's anthropometric data to the derivation of hypothetical sizing/tariffing systems. *Clothing Research Journal*, 9: 16–32	1981		Factor analysis
Salusso, C., De Long, M. and Krohn, K.	A multivariate method of classifying body form variation for sizing women's apparel. *Clothing and Textiles Research Journal*, 4(1): 38	1982	Adult females over 55 years old	PCA classification
DOB-Verband, *DOB-Grössentabellen*	*Women's Outer Garment Size system development*. Köln, Germany	1983		

(*Continued*)

Table 1.1 Continued

Author	Title	Year	Samples	Method
Tryfos, P.	An integer programming approach to the apparel sizing problem. *Journal of the Operational Research Society*, 37: 1001–1006	1986	10000 adult females	Integer programming to optimize number of sizes
Rosenblad, W.E.	An anthropometric study as the basis for sizing anatomically designed mittens. *Applied Ergonomics*, 18(4): 329–333	1987		
Workman, J.E.	Body measurement specifications for fit models as a factor in clothing size variation. *Clothing and Textiles Research Journal*, 18: 251–259	1991		
Chun-Yoon, J.	*Methodology for Devising an Anthropometric Size Description System for Women.* Vol.2, University of Wisconsin	1992		
Chun-Yoon, J. and Jasper, C.R.	Garment sizing systems: an international comparison. *International Journal of Clothing Science and Technology*, 5: 28–37	1993		
Yoon, J.C. and Radwin, R.G.	The accuracy of consumer-made body measurements for women's mail-order clothing. *Human Factors*, 36(3): 557–568	1994	103 females, 19–50 years old	
Chun-Yoon, J. and Jasper, C. R.	Key dimensions of women's ready to wear apparel: developing a consumer size labeling system. *Clothing and Textiles Research Journal*, 14 (1): 89–95	1996		

Paal, B.	Creating efficient apparel sizing systems: An optimization approach. Unpublished master's thesis	1997		
Beazley, A.	Size and fit: Procedures in undertaking a survey of body measurements. *Journal of Fashion Marketing and Management*, 2(1): 55–85	1997	100 females	Correlation coefficient and bivariate classification of body types
	Size and fit: formulation of body measurement tables and sizing systems – Part 2. *Journal of Fashion Marketing and Management*, 2(3): 18.	1998		
	Size and fit: the development of size charts for clothing – Part 3. *Journal of Fashion Marketing and Management*, 3(1): 66–84	1999		
McCulloch, C., Paal, B. and Ashdown, S.	An optimization approach to apparel sizing. *Journal of the Operational Research Society*, 49: 492–499	1998	2208 adult females	Optimization aggregate loss
Ashdown, S.	An investigation of the structure of sizing systems: A comparison of three multidimensional optimized sizing systems generated from anthropometric data with the ASTM standard D5585-94. *International Journal of Clothing Science and Technology*, 10(5): 324–341	1998	Adult female soldiers (US Army)	Nonlinear optimization method
Laing, R. and Holland, E.	Development of sizing system for protective clothing for adult males. *Ergonomics*, 42(10): 1249–1257	1999	691 adult males	Factor analysis and cluster analysis
Otieno, R.	Development of sizing system for female children in Kenya. *Journal of the Textile Institute*, 91(2): 143–152	2000	Female children 2–6 years old	Correlation coefficient and bivariate classification

(*Continued*)

Table 1.1 Continued

Author	Title	Year	Samples	Method
Meunier, P. and Yin, S.	Performance of a 2D image-based anthropometric measurement and clothing sizing system. *Applied Ergonomics*, 31(5): 445–554	2000		
Kang, Y. and Hee Do, H.	A study of sizing of children's wear. An analysis of the size increments utilized in children's wear based on anthropometric survey. *Journal of Korean Home Economics Association*, 2(1): 95–102	2001		
Szirovicza, L., Ujevic. D. and Drenovac, M.	The structure of body measurements for the determination of garment system for young Croatian men. *Collegium Antropologicum*, 26(1): 187–197	2002	4268 men, 18–22 years old	Discriminant analysis
Gupta, D. and Gangadhar, B.	A statistical model for developing body size charts for garments. *International Journal of Clothing Science and Technology*, 16(5): 458–469	2004	Indian adult females	Principal component analysis (PCA)
Yokota, M.	Head and facial anthropometry of mixed-race US Army male soldiers for military design and sizing: A pilot study. *Applied Ergonomics*, 36(3): 379–383	2005		
Hsu, C. and Wang, M.	Using decision tree based data mining to establish a sizing system for the manufacture of garments. *International Journal of Advanced Manufacturing Technology*, 26(5–6): 669–674	2005	Adult females	PCA and decision tree (classification and regression tree, CRT)

Huysteen, S.V.	Doctoral thesis: Development of standardised sizing systems for the South African children's wear market	2006	2600, 2–14 years old	Correlation coefficient and cluster analysis
Gupta, D., Garg, N., Arora, K. and Priyadarshini, N.	Developing body measurement charts for garment manufacturer based on a linear programming approach. *Journal of Textile and Apparel, Technology and Management*, 5(1): 1–13	2006	1900 Indian females	LP approach
Viktor, H., Paquet, E. and Guo, H.	Measuring to fit: virtual tailoring through cluster analysis and classification. Knowledge discovery in database: PKDD 2006. *Lecture Notes in Computer Science,* 4213:395–406	2006	670 females and males	Cluster analysis and multi-relational classification
Faust, M.	Doctoral thesis: The use of standard sizes in women's ready to wear and consumer fit	2006	6310 females	Clustering using PCA
Ujevic, D.	Anthropometric measurements and adaptation of garment size system. Project: 117-1171879-1887 Faculty of Textile Technology, Prilaz baruna Filipovića 30, HR-10000 Zagreb, Croatia	2007 2011		
Honey, F. and Olds, T.	The Standards Australia sizing system: quantifying the mismatch. In M. Marfell-Jones and T. Olds (Eds.), *Kinanthropometry X*. Routledge: London: 97–112.	2008	294 women, 18–30 years old	L statistic
Chung, M., Lin, H. and Wang, M.	The development of sizing systems for Taiwanese elementary- and high-school students. *International Journal of Industrial Ergonomics*, 37(8): 707–716	2007	7800 children, 6–18 years old	PCA and cluster analysis

(*Continued*)

Table 1.1 Continued

Author	Title	Year	Samples	Method
Lin, H., Hsu, C., Wang, M. and Lin, Y.	An application of data mining techniques in developing a sizing system for army soldiers in Taiwan. *WSEAS Transactions on Computers* 7(4): 245–252	2007	610 adult male army soldiers	PCA and decision tree CART (classification and regression tree)
Ng, R., Ashdown, S. and Chan, A.	Intelligent size table generation. Sen'i Comfort Model, Project No. S01-AE32, *National Gakkaishi*, 63(11): 384–387	2007	1000 adult females	Genetic algorithm (artificial intelligence)
Hsu, C.	Applying a bust-to-waist ratio approach to develop body measurement charts for improving female clothing manufacture. *Journal of the Chinese Institute of Industrial Engineers*, 25(3): 215–222	2008	542 females, 18–24 years old	PCA and bust-to-waist ratio classification
Gupta, D.	Anthropometric data analysis and garment sizing system for Indian population. Presented at 86th Textile Institute Conference, Hong Kong	2008	1500 adult females	PCA and cluster analysis
Hsu, C.H.	Data mining to improve industrial standards and enhance production and marketing: an empirical study in apparel industry. *Expert Systems with Applications*, 36: 4185–4191	2009	956 females	Factor analysis and two-stage cluster
Hsu, C. H., Lee, T. Y. and Kuo, H. M.	Mining the body features to develop sizing systems to improve business logistics and marketing using fuzzy clustering data mining. *WSEAS Transactions on Computers* 8(7): 1215–1224	2009		

Ariadurai, A., Nilusha, T. and Dissanayake, M.	An anthropometric study on Sri Lankan school children for developing clothing sizes. *Journal of Social Sciences*, 19(1): 51–56	2009	160 children, 5–12 years old	Bivariate classification using body types (height and girth)
Kwon, O. Jung, K., You, H. and Kim, H. E.	Determination of key dimensions for a glove sizing system by analyzing the relationships between hand dimensions *Applied Ergonomics*, 40(4): 762–766	2009		
Hsu, C. H.	Developing accurate industrial standards to facilitate production in apparel manufacturing based on anthropometric data. *Human Factors and Ergonomics in Manufacturing and Services Industries*, 19(3): 199–211	2009	755 females	Factor analysis, girth ratio, figure types classification
Doustaneh, A.H., Gorji, M. and Varsei, M.	Using self organization method (SOM) to establish a nonlinear sizing system. *World Applied Sciences Journal*, 9(12): 1359–1364	2010	670 Iranian men	Self-organization method (SOM)
Jung, K., Kwon, O., You, H.C.	Evaluation of the mutivariate accommodation performance of the grid method. *Applied Ergonomics*, 42(1): 156–161	2010	1774 men	Regression R^2 and multivariate accommodation performance (MAP)
Bagherzadeh, R., Latifi, M. and Faramarzi, A.	Employing a three-stage data mining procedure to develop a sizing system. *World Applied Sciences Journal*, 8(8): 923–929	2010	1050 males, 16–22 years old	PCA, cluster analysis and decision tree technique
Mpampa, M.L., Azariadis, P.N. and Sapidis, N.S.	A new methodology for the development of sizing systems for the mass customization of garments. *International Journal of Clothing Science and Technology*, 22(1): 49–68	2010	12 810 Greek men	Linear regression
Zakaria, N.	Doctoral thesis: The development of a children's sizing system using anthropometric data	2010	2035 children, 7–17 years old	PCA, cluster analysis and decision tree technique

(*Continued*)

Table 1.1 Continued

Author	Title	Year	Samples	Method
Ujevic, D., Zenjak, R.H., Dole, K., Mirko, Z. and Szirovicza, D.K.	Size designation system of clothes and footwear based on Croatian anthropometric system. *Journal of Fiber Bioengineering and Informatics*, 4(4): 311–319	2011		
Salehi, M., Esfandarani and Shahrabi, J.	Developing a new suit sizing system using data optimization techniques. *International Journal of Clothing Science and Technology*, 24(1): 27–35	2012		
Ujeviæ, D., Petrak, S., Hrastinski, M. and Mahniæ, M.	Development of the garment size system and computer-based body models. *Journal of Textiles and Engineering*, 19(85): 35–40	2012		
Jeyasingh, M.M. and Appavoo, K.	Mining the shirt sizes for Indian men by clustered classification. *International Journal of Information Technology and Computer Science*, 6: 12–17	2012		Clustering and classification

relationship for the sample studied, since it classified correctly 95% of subjects within less than 30 size categories.[5]

All the methods described above are based on a linear structure which has the advantages of easy grading and size labeling.[2] However, a new method of optimization was introduced by Tryfos[6] and McCulloch *et al.*[7] which they believed would yield a better sizing system. This method looked at aggregate loss efficiency, so that the sizes created would fit the wearer with minimum aggregate loss.

In Tryfos' study,[6] this distance is known as aggregate discomfort, and can help anticipate profit in clothing markets. He claimed that manufacturers are concerned with how many sizes should be created for clothing in order to maximize expected sales. He argued that consumers always resort to fit quality as an influence on their purchase decision, and that the concern of any sizing system is to ensure that the sizes created are as close as possible to the person's actual measurements for better fitting garments.

McCulloch *et al.*[7] made a breakthrough when they developed a method of calculating aggregate loss known as aggregate loss of fit, which means determining the fit of clothing by measuring the distance between actual sizes and assigned sizes (proposed sizes). Minimum aggregate loss means the distance between actual and assigned sizes is low and therefore the garment is expected to have a better fit.

Both studies used the same concept of optimization in a sizing system but Tryfos[6] is concerned with the viewpoint of customers and profitability whereas McCulloch[7] is concerned with the viewpoint of goodness of fit of the final product. Ashdown[8] also found the non-linear optimization technique to be the best for deriving an efficient sizing system from multidimensional anthropometric data. This method of calculating aggregate loss to validate the sizing system has been used extensively in apparel research.

Multivariate analysis – specifically the PCA technique – is still widely used by many researchers to detect the relationships between variables and in turn find key dimensions by which to classify a population.[1,2,5,9–11] Gupta and Gangadhar[11] used PCA to identify the key dimensions for their population. They classified each population according to these key dimensions using simple univariate analysis. The dimension of height resulted in three height ranges and bust girth gave six bust ranges. From that, 11 size charts were created for each size group for the target population. Finally, the size charts were validated using the aggregate loss method.

Later, a new method of clustering populations called linear programming (LP) was applied by Gupta *et al.*[12] to develop a sizing system. Using this technique, the key dimensions and the degree of fit desired for each target population can be easily changed. The strongest part of their research was that the system could give the exact number of people categorized under each size group, which allowed manufacturers to choose the best size for their target market and decide the quantity of each size to produce and keep in stock.

In recent years, apparel researchers have started to explore another method of classifying populations: data mining. This method is capable of analyzing huge amounts of data either by automatic or semi-automatic means. Data mining techniques include cluster analysis and decision trees. Cluster analysis is a data reduction technique used to solve classification problems. Chung and Wang[13] argued that little research has been done in the application of data mining techniques to the development of sizing systems.

The data mining technique known as clustering was utilized in 2007 to produce a good sizing system for school-age Taiwanese children.[14] This method proved to create a sizing system that has fewer sizes than the Korean sizing system, which was built from a similar appropriate own sizes. In another study by Viktor *et al.*,[15] clustering was used to classify body scan data resulting in five different sizes. The study showed that the interrelationships between different body measurements must be taken into account in order to create clothing sizes that will fit the body elegantly and hide obvious body flaws. To attain this goal, cluster analysis was used to characterize each size which yielded profiles of the population.

That same year, the decision tree technique was employed by Lin *et al.*[16] to classify a population for a sizing system for soldiers' uniforms. PCA was applied and important sizing variables were extracted. Next, the decision tree technique was applied to identify and classify significant patterns in the subjects' body shapes. The researchers showed that the decision tree technique was an advantageous choice because it results in a wider coverage of body shapes with a lesser number of sizes, gives sizing patterns and rules, and provides manufacturers with reference points by which to facilitate production.[16]

The difference between the cluster analysis technique and decision tree technique lies in the profile of the variables which are selected. The decision tree technique is able to predict the target and predictive variables, which means that the selection of the most important variables can be verified. Cluster analysis on the other hand uses centroid partitioning to divide the samples which only provides the range of the variables without the profiles. Nevertheless, both techniques have been shown by researchers to give good results in classifying a population for a sizing system.[13,14,17]

In 2010, both the cluster and decision tree techniques were employed to successfully develop sizing systems. According to Bagherzadeh *et al.*[18] a sizing system developed in this manner offered better accommodation. Futhermore, he stated that using the decision tree technique to profile the cluster groups seemed appropriate and effective in generating each size profile.

The most recent method applied to sizing system development is the artificial intelligence (AI) technique. So far, this technique has not been widely used for the development of sizing systems. However, Ng *et al.*[19] acknowledged the significance of this technique because its results offered more flexibility, a greater reduction in the number of sizes, and higher efficiencies compared to data mining. Artificial intelligence can greatly reduce the overall fit problems extant in sizing systems. Although intelligent sizing appears to be the best technique, it is still new and has not been widely applied; data mining techniques are more well-established among apparel experts.[10,13,14,20]

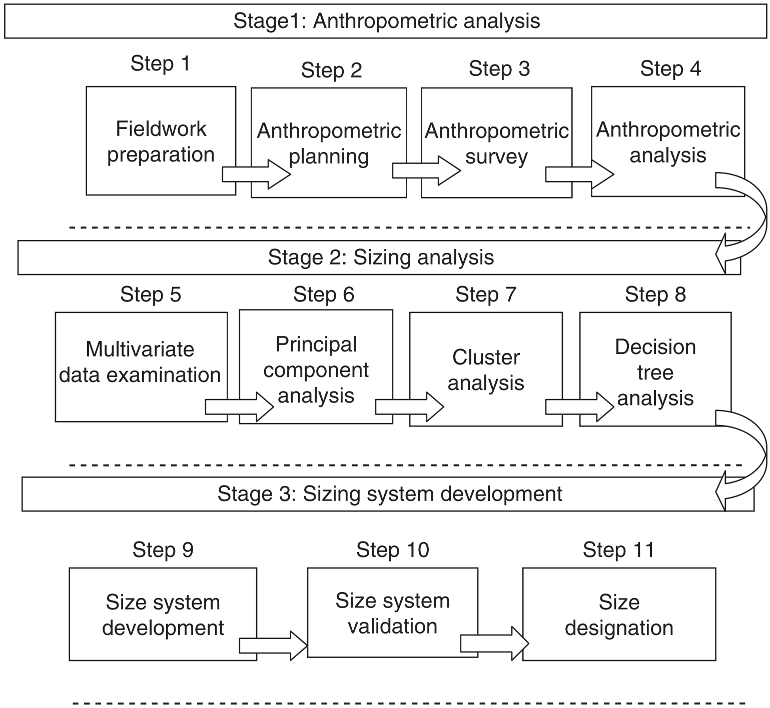
Since 2010, a few more techniques have been introduced and explored for the development of sizing systems. For instance, neural networks – a type of AI technique – has the capability to train itself on a sample population and then classify the population into their own groups. According to Chih *et al.* (2011), by applying a neural network-based data mining procedure, body types can be classified from an anthropometric database. The number of sizes produced for each size group can also be predicted correctly.[21]

This will enhance the accuracy of inventory control and production planning. Another promising method for predicting sizes for classified groups is the self-organizing method (SOM), which is a form of neural network. The SOM is highly efficient as it creates a nonlinear sizing system, results in a higher accommodation rate of population, and gives a smaller aggregate loss of fit compared to the statistical method.[22] Thus, by reducing the number of sizes, it yields manufacturing benefits since producing fewer sizes with a higher accommodation rate is the ideal goal.

The sizing studies that have been reviewed thus far demonstrate many different ways to develop a sizing system. Current sophisticated computer programs have proven to be more efficient when applied to the analysis and the classification of populations. Advanced AI techniques such as artificial neural networks (ANN) and genetic algorithms (GA) can accurately predict the sizes needed for a specific population and are less dependent on humans to make decisions about size classifications.[23] The AI process of designing the right sizes for different body types is more sophisticated and can be done more precisely and quickly. Sizing system development has been a continuous focus of garment research activities, and the necessary knowledge and techniques have been continuously developed and improved over time to ensure the satisfaction of clothing consumers and to produce a good fit for quality clothing. The concept of a garment sizing system has not only undergone many years of study in an attempt to improve the efficiencies of the system, but has been broken down into a comprehensive procedure made up of well-defined stages and steps. This procedure is discussed step by step in the following sections.

1.3 Sizing system development: Stage 1 – Anthropometric analysis

The detailed and comprehensive process of developing a sizing system is shown in Fig. 1.1. This diagram clearly shows how complex it is to develop a sizing system, encompassing three stages and eleven steps from beginning to end. Stage one is anthropometric analysis, stage two is sizing analysis and stage three is sizing system development. All 11 steps are explained in the following sections.



1.1 Methodology for sizing system development.

Stage 1 is anthropometric analysis. The goal of Stage 1 is to collect body measurements of the sample population and analyze those using simple statistical methods. The purpose of this analysis is to understand the body ranges and variations present in the sample population. This stage consists of four steps – fieldwork preparation, anthropometric planning, the anthropometric survey itself, and anthropometric analysis – each of which is described in the following sections.

1.3.1 Step 1: Fieldwork preparation

Paperwork

Fieldwork preparation refers to the preparation that must be done before conducting the anthropometric survey. Preparation activities could include getting permission from the authorities, developing the anthropometric protocol and training the measurers. When conducting an anthropometric survey, the process of preparing paperwork and getting the access from the authorities might involve asking formal permission from government bodies or agencies, various related ministries or even the Ministry of Education if one wants to deal with school-aged children. The paperwork granting permission to work with different target populations can be challenging which needs persistence and patience with the process of waiting for authorities to organize them. However, once the permission is granted it will be a really good experience to conduct the anthropometric survey meeting with many people of different walks of life.

Training the measurers

The next task is to prepare the measurers, if the anthropometry survey is conducted manually. If the survey is to be done using digital methods, such as a 3D body scanner, then training will be focused on using the sophisticated machine. The training for an anthropometric survey for clothing purposes is based on ISO 8559/1989, which defines the terms used for each different body dimension. Under this ISO standard, there are 49 body dimensions to be measured for a clothing system. These body dimensions are divided into three groups: vertical length, width and girth, as shown in Table 1.2. These dimensions are also divided

Table 1.2 List of body dimensions according to ISO 8559/1989

Length (vertical)	Width (vertical)	Girth (horizontal)
Height	1. *Shoulder length	*Weight*
1. *Under arm length	2. *Shoulder width	1. *Head girth
2. *Scye depth	3. *Back width	2. *Neck girth
3. *Neck shoulder point to breast point	4. *Upper arm length	3. *Neck base girth
4. *Cervical to breast point	5. *Arm length	4. *Chest girth
5. *Neck shoulder to waist	6. *7th cervical to wrist length	5. *Bust girth
6. *Cervical to waist (front)	7. *Hand length	6. *Upper arm girth
7. *Cervical to waist (back)	8. Foot length	7. *Armscye girth
8. *Cervical height (sitting)		8. *Elbow girth
9. *Trunk length		9. *Wrist girth
10. *Body rise		10. *Hand girth
11. *Cervical to knee hollow		11. Waist girth
12. *Cervical height		12. Hip girth
13. Waist height		13. Thigh girth
14. Outside leg length		14. Mid thigh girth
15. Waist to hips		15. Knee girth
16. Hip height		16. Lower knee girth
17. Crotch		17. Calf girth
18. Trunk circumference		18. Minimum leg girth
19. Thigh length		19. Ankle girth
20. Inside leg length/crotch		
21. Knee height		
22. Ankle height		

* Upper body dimensions. All others, lower body dimensions

into upper and lower body. The 29 dimensions suitable for upper body or whole body are marked with an asterisk (*), while the other 20 dimensions (not marked) are categorized as lower body dimensions.

First, the measurers have to be briefed about the objectives of the anthropometric survey. They can be introduced to the topic using a PowerPoint presentation and the objectives clearly explained laying emphasis on the consistency and precision of measurement process. Each of the trainees should be provided a copy of the anthropometric manual giving pictures of all the body dimensions. This is followed by a detailed explanation of each body dimension followed by a demonstration on a real body.

The measurers should ideally work in pairs and perform a hands-on practice on their partners for some days till they are comfortable and familiar with each body dimension. Each measurer uses a form, which lists all the body dimensions to record the measurements. The measurement practice should be continued until the measurers gain confidence and start getting consistent readings.

Anthropometric measurement protocols

Anthropometric protocols demonstrate how a manual anthropometric survey can be conducted. The measurement process starts with the subject changing into a tight-fitting garment for better and more accurate body measurements. In every anthropometric survey activity, a team of workers will attempt to finish the targeted number of measurements per day in order to achieve their daily goal. Manual measurement takes an average of 40 minutes per subject and the goal is to measure at least seven people daily. Using the 3D body scanner, it is much faster: the time from changing clothes to completion of measurement is about 5–10 minutes per person.

A consistent set of procedures should be employed for the manual measurement process, such as:

- Fill out demographic data (name, age, gender, ethnic group)
- Measure height
- Measure weight
- Measure upper body dimensions
- Measure lower body dimensions.

One member of the team can measure while the other records the measurements. All measurements should be taken from one side of the subject's body consistently. After completing the measurements of the day, the forms should be counted and the overall quality of anthropometric measurements checked. Forms with missing data are considered not valid and discarded. The number of subjects measured each day is recorded to ensure that the target number of samples has been achieved and that results are accurate.

1.3.2 Step 2: Anthropometric planning

Anthropometric planning comprises the preliminary study, sample size calculation and fieldwork coordination. The first purpose of the preliminary study is to test the whole process of measuring, to understand the nature of the survey and to solve any potential problems before undertaking the real anthropometric survey. The second purpose is to take the measurements needed to calculate the sample size for the anthropometric survey.

Preliminary survey

The preliminary survey can be conducted on a small scale and is usually called the pilot study. The sample size can range from 30 to 100 people. The main objective is to collect sufficient body measurements to calculate the sample size needed for the real anthropometric survey.

One common technique that can be used to calculate the sample size for a study is the proportionate stratified random sampling technique.[24,25] Proportionate stratified sampling refers to taking the same proportion (sample fraction) from each stratum.[26] For example, say there are three groups of students: Group A with 100 people, Group B with 50 people and Group C with 30 people. These groups are referred to as strata. The sample units are randomly selected from each stratum based on proportion. For example, a proportion of 10% from each group (strata) would mean that ten people were taken from Group A, five people from Group B and three people from Group C. The strata group for this study was based on two groups, age (7–17 years old) and gender (female and male).

A study can have for example, four demographic variables: age, gender, ethnic group and geographical area (rural and urban). If the study is focused on two factors such as age and gender, then the proportionate sample size will reflect the distribution of age and gender groups in the real population. The other two parameters, ethnic group and geographical area, can be selected according to simple random technique with the targeted number of subjects calculated from the proportionate sample size.

Data obtained from the preliminary study can be analyzed to calculate the total sample size using the stratified random sampling formula (Equation 1.1). Then, the number of subjects to be sampled from each gender and age group can be calculated using proportionate sampling based on the actual number of subjects present in the geographical area of interest. The steps are given in detail below.

Sample size determination

The sample size for a survey can be calculated using the stratified random sampling formula as shown in Equation 1.1[26]:

$$n = \frac{\Sigma_{i=1}^{l} N_i^2 \sigma_i^2 / \alpha_i}{N^2 D + \Sigma_{i=1}^{l} N_i^2 \sigma_i^2} \quad [1.1]$$

where

N_i^2 = sample size for stratum age group
σ_i^2 = standard deviation of variable
α_i = total population size in percentage
N^2 = total population size for stratum age
D = can be calculated using Equation 1.3 below

The body dimensions used to calculate the sample size are the common key dimensions for a sizing system: height, chest girth, bust girth, waist girth and hip girth. After figuring the total sample size, the sample size for each of the strata can be calculated using Equation 1.2 and then the total number of subjects for each age range and gender can be calculated based on the proportionate method formula (Equation 1.3).

First step:

$$\bar{y}_{st} = \frac{1}{N}[N_1\bar{y}_1 + N_2\bar{y}_2 + \ldots + N_l\bar{y}_l] \quad [1.2]$$

where

N = total population age 7–17
N_1 = total population age 7–12
N_2 = total population age 13–17
$\bar{y}$ = mean of variables for each age group

Second step:

$$D = \left(\frac{0.01 \times \bar{y}_{st}}{2.326}\right)^2 \quad [1.3]$$

Third step: Calculating the sample size using stratified random sampling
To calculate the sample size, the age range for the sample population is calculated and then the total population in the geographical area is calculated. For example: The total population in one state is 823 071 [*N*]. The number of subjects in each age group is then tabulated. Each age group forms a stratum and the sample for each stratum is calculated using the proportionate method according to the ratio of the real population. Each stratum age [*h*] is given by:

$$n_h = (N_h/N) * n \quad [1.4]$$

where n_h is the sample size for stratum, h, N_h is the population size for stratum h, N is total population size, and n is the sample size.

For example; the male-to-female ratio in the real population in one state is 51% male, 49% female. For each age range, the sample is divided into the corresponding ratio (n) of male and female.

$$n_m = N_h * n \quad [1.5]$$

$$n_f = N_h * n \quad [1.6]$$

Where n_m is the sample size for the male stratum and n_f is the sample size for the female stratum, N_h is the population size for stratum *h (age)*, and *n* is the total sample size.

1.3.3 Step 3: Anthropometric survey – manual method

A preliminary study is conducted before the main anthropometric survey in order to check the feasibility of the research approach and to improve the design of the research. ISO standard 8559:1989 (garment construction and anthropometric surveys – body dimension) can be used as a guideline for taking body measurements. In the traditional manual technique, measurement tools to be used include calibrated non-stretchable plastic measuring tapes, height scale with movable head piece, long ruler, elastic 5-meter tapes and digital weight scale. Since measuring a single subject can take from 20 to up to 40 minutes, provision for refreshments for measurers as well as the subjects should be made to incentivize them. The survey data collected in the form of categorical (demographic data) and continuous data were screened and stored in a standard format.

Data entry

All the collected data are keyed into software such as SPSS or MS Excel. The usual format is to key in the subject's name and data into a row, which is known as a case. The body variables are keyed into the columns. The demographic information (categorical data): gender, ethnic group, age and geographical area (urban or rural) comes first followed by columns containing numeric body measurements (continuous data).

Data screening

Data screening consists of examination for data entry errors, missing data or outliers. The entire data set is filtered to ensure that there are no errors or missing data. Errors can creep in due to mistakes in keying in the data; these can be rectified by cross-checking with the raw data.

The distribution of data can be tested using graphical as well as numerical methods. The graphical method makes use of histograms, while the numerical assessment is based on values of mean, median, skewness and kurtosis. Histograms provide a useful graphical representation of the data. Data are considered to be normally distributed if the histogram shows a Gaussian distribution. This involves evaluating the bell shape of the data distribution. When tabulating common key dimensions like height, chest girth, bust girth, waist girth and hip girth, the mean and median values should be the same while the skewness and kurtosis should show values of 0 and 3 respectively; this indicates that the data are normal.[26] Skewness refers to the asymmetry of the distribution. If the skew has a negative value, this means the data are skewed to the left; if positive; the skew is to the right. Kurtosis refers to the peakness or the flatness of the graph.

1.3.4 Step 4: Anthropometric analysis

The final step of Stage 1 is to analyze the data. The statistical method generally applied at this stage is the descriptive analysis also known as univariate analysis based on simple statistics. Categorical and continuous data can be analyzed as follows.

Categorical data

The categorical data are analyzed to understand the demographic profile of the sample population. The first classification to be made often is to divide the population into gender based subsets, namely male and female. Frequency distribution curves are plotted by quantity and percentage and results can be illustrated using tables and bar graphs.

Continuous data

Continuous data analysis based on descriptive statistics includes calculation of frequency distributions, range, mean, median, mode, standard deviation, coefficient of variation and Pearson correlation coefficients to determine the interrelationships between the various body dimensions.

The objective of anthropometric analysis is to profile the demographic data and the continuous data in such a way that the overall patterns of body dimensions are described and one can distinguish between genders and different age groups for selection of key dimensions.

The next section deals with Stage 2 – the sizing analysis.

1.4 Sizing system development: Stage 2 – Sizing analysis

In this stage, the objective is to divide the sample population into smaller groups composed of individuals who have similar key body dimensions. The center panel of Fig. 1.1 shows the phases of Stage 2, which consists of four steps (Steps 5 to 8). The analysis shown in Stage 2 is only one possible method of determining key dimensions and clustering the sample population. Besides the three methods shown here (PCA, cluster analysis and decision tree analysis), other methods like bivariate analysis, fuzzy logic, neural networks and artificial intelligence can also be used.

Step 5 is multivariate analysis, the purpose of which is to test the sampling adequacy of the collected data. In Step 6, PCA is employed to reduce all the variables into significant components. In Step 7, cluster analysis is used to segment the sample subjects into homogeneous groups with similar body shapes and sizes. In Step 8, the decision tree technique can be applied to classify sample subjects into groups based on profiles and to validate the cluster groups.

1.4.1 Step 5: Multivariate analysis

Prior to applying a PCA, a sampling adequacy test needs to be performed on the data to confirm the appropriateness of conducting PCA in order to ensure that the data can be factored well.[27,28] In addition, Bartlett's Test of Sphericity can also be used to add a significant value to support the factorability of the correlation matrix obtained from the items.[29]

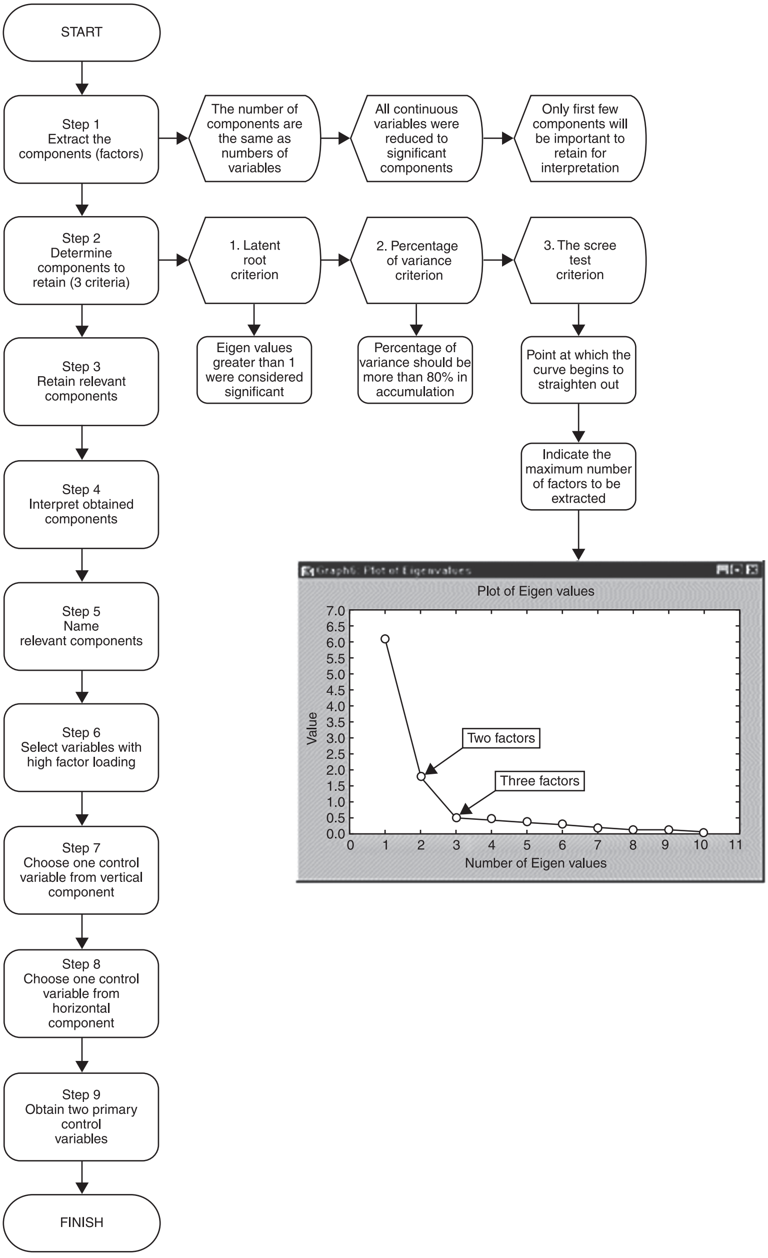
1.4.2 Step 6: Principal component analysis (PCA)

The objective of using PCA is to reduce the number of variables and to cluster these variables into a more parsimonious and manageable number of groups. Parsimonious means to summarize most of the original information (variance) in a minimum number of components for prediction purposes.[30] The process of PCA is shown in Fig. 1.2. The PCA technique is shown in nine steps whereby each step is explained in the diagram. In the first step, the variables are extracted using the orthogonal method called the Varimax technique. The Varimax technique is used as all factors are treated as independent and not correlated. In this step all variables are reduced into components.

Extract the variables

PCA uses an orthogonal method called the Varimax technique. This method is chosen as all the factors are to be treated as independent and are not correlated. In the first step, the variables are extracted and reduced. This is to transform all the data into components. The extracted numbers of components are usually the same number or about the same number with the variables that were chosen. Step 2 determined how many components were to be retained by using three criteria.

After extraction, the next step is to decide how many components need to be retained. In order to retain the most important components, three criteria are used:



1.2 PCA flow chart.

namely, the Kaiser criterion (also known as latent root criterion), the percentage of total variance and Scree plot evaluation.

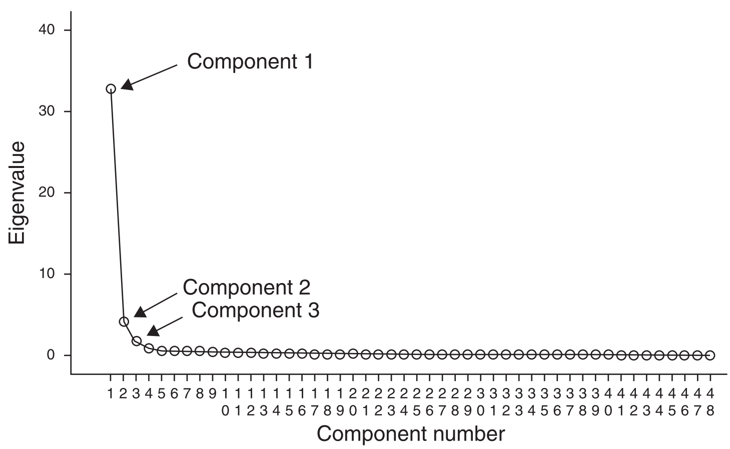
1. For the latent root criterion, the Kaiser rule ensures the Eigen value is greater than 1 which proves it is significant. Thus, all components more than 1 are extracted and retained.
2. Percentage of total variance
   All components should have a percentage of total variance of more than 80% for significant value as recommended.
3. Scree plot
   As shown in Fig. 1.3, for scree plot evaluation, the significant components are those curves that begin to straighten out. From Fig. 1.3, three points on the curve show three significant components. All the other steps from step 3 to step 9 are then illustrated as in Fig. 1.2.

1.4.3 Step 7: Cluster analysis

Cluster analysis is an exploratory data analysis tool used to segment a population into homogeneous subgroups. This means that each person in a group shares similar physical traits with others in the group and that people in one group differ from those in other groups.

1.4.4 Step 8: Classification analysis (decision tree)

Decision tree analysis is a data mining technique which is effective for classification.[17] The Classification and Regression Tree (CRT) technique can be



1.3 Scree plot.

used to verify and classify the sample population according to cluster groups; CRT is used where the data are continuous. The profile of the tree is useful when interpretation of the data set is required. By doing the classification analysis, important variables can be obtained and a simple profile can easily be extracted from the tree diagram.[31]

1.5 Sizing system development: Stage 3 – Developing and validating a sizing system

In this stage, the sizing system is developed based on the data analysis performed in the preceding steps. The process of sizing system development is shown in Fig. 1.4. This stage has three steps, namely: size system development, size system validation and size designation. Each step is described in detail in the following sections.

1.5.1 Step 9: Size system development

The purpose of developing the sizing system is to create sizes for each cluster group that are appropriate to the individual group's range. Two important decisions must be made. The first is to estimate the size roll which will accommodate most of the target population, and the second is to determine which samples go into the cluster groups obtained from the cluster analysis technique. The goal is to accommodate as many people from the target population as possible using one intersize interval.

For the development of the sizing system, the following elements have to be calculated: size range, size interval, size scale and size roll.

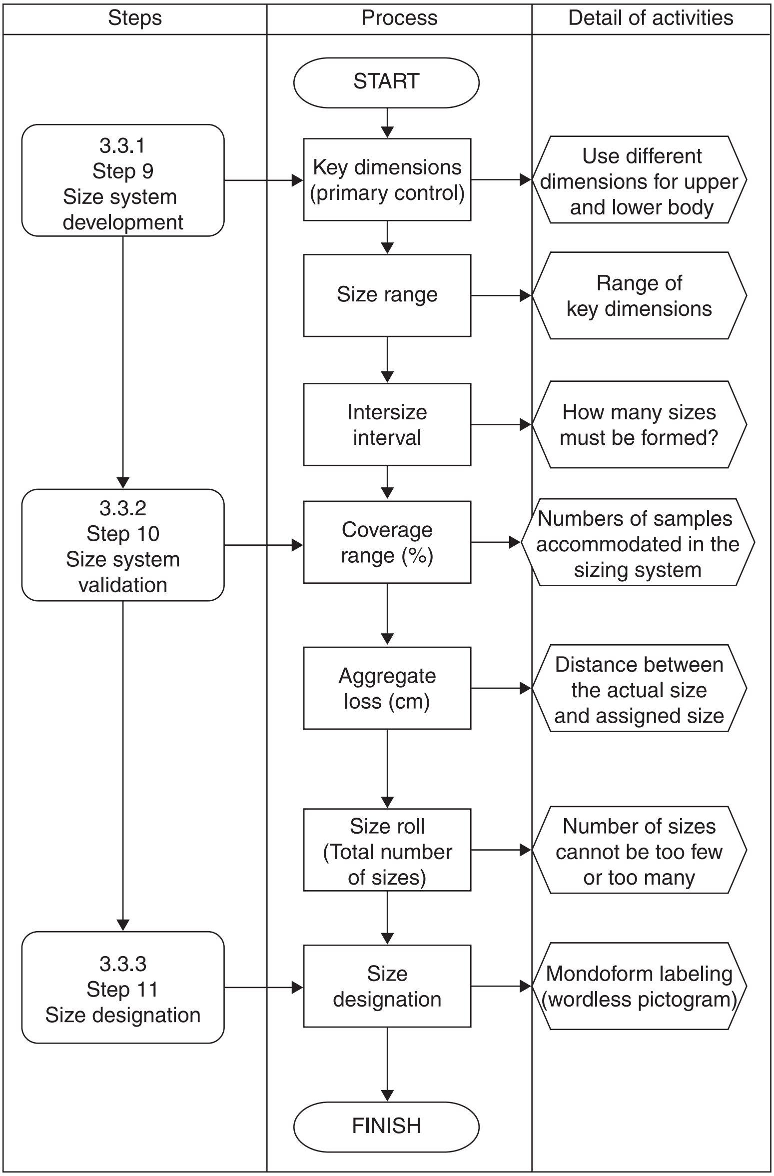
After the selection of the interval range, the classification profile obtained from the decision tree analysis is used as a guide to select samples matching the right body size and shapes. Using this profile, the samples are classified according to the body sizes and shapes. The last step is to validate the efficiency and accuracy of the sizing system thus developed.

1.5.2 Step 10: Size system validation

The aim of any sizing system is to enumerate a set of sizes that can accommodate most of the target population. Thus, the final step is to validate the sizing system based on cover factor (%), aggregate loss, and size roll.

Cover factor

For cover factor validation, the percentage of sample accommodated under each body type and each assigned size is calculated. Each assigned size is presented in the size table. The sizes that fall below 2% coverage are highlighted, as mentioned



1.4 Sizing development flow chart.

in previous studies.[32] Next, the percentages for each size are added together to give the total percentage covered by the system as a whole for each sample group. The cover factor should typically range from 65%–80%, meaning that the sizing system is able to accommodate 65%–80% of the population with the sizes proposed.[33]

Aggregate loss

The next item of validation for the sizing system is goodness of fit. For any sizing system, the sizes that are developed are based on measurements of the actual human body; therefore, the sizes developed must reflect the sizes of the measured bodies as closely as possible. In other words, the goal of any good sizing system is to produce sizes that are close to the wearer's actual body dimensions. This degree of closeness is referred to as goodness of fit. As much previous research has shown, aggregate loss is often employed as a measure of goodness of fit.[2,7,34,35] In aggregate loss, first the Euclidian distance (the distance between actual dimensions and assigned dimensions) is calculated. If the size fits the wearer well, then the distance from the assigned size to the actual size is said to be minimized. The average Euclidian distance is minimized when the aggregate loss value is low.

The formula for the distance between two points $X(X_{1,}\ X_{2}$, etc.) and $Y(Y_{1}, Y_{2}$, etc.) is calculated as follows: x_i and y_i are the coordinates of points where x is the actual size and y is the assigned size for the jth axis to represent the jth dimension. The distance is defined as:

$$d = \sqrt{\Sigma_{i=1}^{n}(x_i - y_i)^2} \qquad [1.7]$$

where:

x = assigned size
y = actual size

The ideal value of aggregate loss is calculated using the number of body dimensions used to segregate the population. Thus, the ideal value is calculated using Equation 1.8.

$$t = (n^{1/2}) \qquad [1.8]$$

where:

i = ideal aggregate loss
n = number of key dimensions used to divide the population into homogeneous groups.

If two control variables are used to cluster the population then the ideal aggregate loss is given as $2^{1/2} = 1.41$. This value is in inches. Since all measurements are taken in metric (cm), the aggregate loss is calculated as $1.41 * 2.54\,\text{cm} = 3.58\,\text{cm}$. This value is the ideal aggregate loss regarded as the benchmark for an accurate size. Using Equation 1.8, the aggregate loss can be calculated for each size developed in any sample population. The Euclidian distance is divided by the number of individuals in each size group. As a result, the distance between the two sizes can be calculated based on the ideal aggregate loss. If the actual aggregate loss is less than the ideal aggregate loss, then the fit is deemed to be good; if it is higher than the ideal aggregate loss, then the fit is deemed to be not so good.[7,11,36]

Size roll

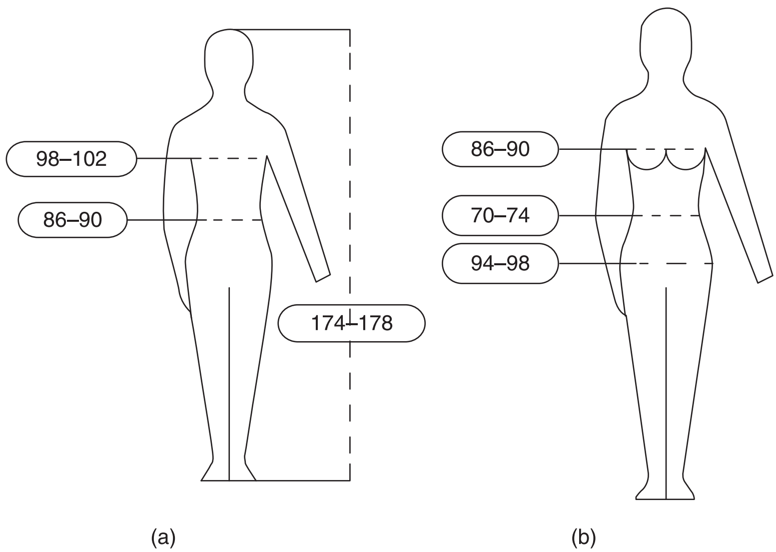
Size roll is simply the total number of sizes obtained for a sizing system, from the smallest to the largest, with fixed intervals between adjacent sizes. The size interval can be the same magnitude across all sizes or it can vary across the size range.[37] The more sizes, the better the fit, because the assigned sizes will be nearer to the actual sizes. Fewer sizes means the range of customers that fall into each size is wider and so some will be much farther than others from their actual size; fewer sizes therefore results in a less efficient sizing system. In terms of practicality and economics for the manufacturer, then, the optimum size roll should be neither too few nor too many.

1.5.3 Step 11: Size designation

Size designation refers to how each size is identified on the clothing or the tag. A size designation can be numeric, alphabetic or graphic. One such method is that of using the standard Mondoform labeling, which employs wordless picture of key dimensions, in conjunction with the numeric system used in the EN 13402-3 European standard for labeling clothing sizes.[38] The size labeling is based on key body dimensions used in segregating the population. The purpose of creating this type of sizing designation is to prevent confusion among consumers by clearly conveying the key measurements on a pictogram. Figure 1.5 illustrates one example of how a pictogram size designation might appear on male and female clothing.

1.6 Future trends

This chapter has successfully shown how important an accurate garment sizing system is to the RTW garment industry. The purpose of developing a sizing system is to produce garments in sizes that can accommodate a majority of customers within a set of fixed sizes. Without a sizing system that is able to generate an appropriate range of sizes for each size designation, producing good quality well-fitting garments is impossible and the overall objective of mass production cannot



1.5 Mondoform labeling of key dimensions for (a) male size labeling and (b) female size labeling. Units: cm.

be met. When a sizing system is introduced, researchers must relate it to the understanding of fit. An accurate sizing system must be built based on actual anthropometric data as the understanding of body sizes and shapes is the only way to cater to the needs of consumers. The method of producing a sizing system impacts the efficiency of that sizing system.

As can be seen from Table 1.1, the theory and practice of sizing system development has progressively evolved from 1940 to the present. This means that a sizing system needs a lot of improvement in order to be efficient. For mass production purposes, the sizing system must be flexible in nature; if there is a need to reduce the number of sizes to make mass production more efficient, the accommodation rate should not be negotiated. Every manufacturer understands that there is a need to accommodate a majority of their customers with a high-coverage sizing system.

Sizing system development began decades ago using only simple bivariate methods. As time went on, the sizing systems evolved to incorporate many highly intelligent methods such as data mining, neural networks and SOM. This was made possible by the experience of more than 70 years of exploring and understanding how to develop sizing systems that are efficient for manufacturers, customers and retailers. It is amazing that the study of sizing systems is still ongoing today – it seems that the study of anthropometric data, sizing systems and size designations never stops. Many discoveries have been made and the weaknesses of different sizing systems are being discussed in order to develop new methods as old methods become obsolete. Today, researchers are finding better ways of developing sizing systems by adopting different advanced machine learning methods like data mining and artificial intelligence methods. It is anticipated that newer sizing systems using newer advanced analysis techniques will produce better and better sizing systems resulting in a greater goodness of fit for clothing customers.

Today, researchers are still actively searching for ways in which to improve the efficiency of clothing sizing systems, many of which lie in the improvement of sizing validation. The key efficiencies lie between the accommodation rate and size roll. New advanced intelligent techniques are being applied to produce better sizing systems with higher accommodation rates and lower size rolls. New methodologies like artificial neural networks and genetic algorithms are some of the intelligent machine learning techniques that may prove useful in creating a predictive model for finding the right sizes for the right body shapes. This is very important to garment manufacturers, as a better model means that they can produce fewer sizes and still accommodate a majority of the population. This would yield tremendous benefits for both consumers and retailers, since such a model satisfies both parties.

1.7 Sources of further information and advice

Websites relating to sizing systems

TC 133 Sizing systems and designations for clothes

http://www.iso.org/iso/home/standards_development/list_of_iso_technical_committees/iso_technical_committee.htm?commid=52374

A Bibliography on Apparel Sizing and Related Issues

http://2011.fashion/networks.com/images/article_pdf/sizing%20for%20appareal%20(5).pdf

1.8 References

1. O'Brien, R. and Shelton, W. C. (1941), Body measurements of American boys and girls for garment and pattern construction, in *US Dept. of Agriculture Miscellaneous Publication 366*, M. P. 454, Ed.: Washington, DC: US Department of Agriculture, pp. 141.
2. Chung, M. J., Lin, H. F., Mao, J. J. and Wang, J. (2007), The development of sizing systems for Taiwanese elementary- and high-school students, *International Journal of Industrial Ergonomics* 37: 707–716.
3. Beazley, A. (1997), Size and fit. Procedures in undertaking a survey of body measurements, *Journal of Fashion Marketing and Management* 2: 55–85.
4. Otieno, R. and Fairhurst, C. (2000), The development of new clothing size charts for female Kenyan children. Part I: Using anthropometric data to create size charts, *Journal of the Textile Institute, 1754–2340* 91: 143–152.

5. Salusso-Deonier, C. J., DeLong, M. R., Martin, F. B. and Krohn, K. R. (1985), A multivariate method of classifying body form variation for sizing women's apparel, *Clothing and Textiles Research Journal* 4: 38–45.
6. Tryfos, P. (1986), An integer programming approach to the apparel sizing problem, *Journal of the Operational Research Society* 37: 1001–1006.
7. McCulloch, C. E., Paal, B. and Ashdown, S. P. (1998), An optimization approach to apparel sizing, *Journal of the Operational Research Society* 49: 492–499.
8. Amirul Ihsan, S. L. (2009), Beauty: One size doesn't fit all. *New Strait Times*, 27 April. Kuala Lumpur.
9. Pechoux, B. and Ghosh, T. K. (2002), Standard sizing system and fit testing applied to women's hosiery, *Textile Progress* 32: 11–33.
10. Hsu, H. C., Lin, H. F. and Wang, M. J. (2006), Development female size charts for facilitating garment production by using data mining, *Journal of the Chinese Institute of Industrial Engineers* 24: 245–251.
11. Gupta, D. and Gangadhar, B. (2004), A statistical model for developing body size charts for garments, *International Journal of Clothing Science and Technology*, 16: 458–469.
12. Gupta, D., Garg, N., Arora, K. and Priyadarshini, N. (2006), Developing body measurement charts for garment manufacture based on a linear programming approach, *Journal of Textile and Apparel Technology and Management* 5: 1–13.
13. Chung, M. J. and Wang, M. J. (2006), The development of sizing systems for school students, in *36th International Conference on Computers and Industrial Engineering*. Taipei, Taiwan.
14. Hsu, C. H., Lin, H. F. and Wang, M. J. (2007), Developing female size charts for facilitating garment production using data mining, *Journal of the Chinese Institute of Industrial Engineers* 24: 245–251.
15. Viktor, H. L., Paquet, E. and Guo, H. (2006), Measuring to fit: virtual tailoring through cluster analysis and classification, in *Knowledge Discovery in Databases: PKDD 2006*, vol. 4213/2006. Berlin/Heidelberg: Springer, pp. 395–406.
16. Lin, H. F., Hsu, C. H. and Wang, M. J. J. (2007), An application of data mining technique in engineering to facilitate production management of garments, presented at *Proceedings of the 11th WSEAS International Conference on COMPUTERS*, Greece.
17. Lin, H. F., Hsu, C. H., Wang, M. J. and Lin, Y. C. (2008), An application of data mining technique in developing sizing system for army soldiers in Taiwan, *World Scientific and Engineering Academy and Society (WSEAS) Transactions on Computers* 7: 245–252.
18. Bagherzadeh, R., Latifi, M. and Faramarzi, A. R. (2010), Employing a three-stage data mining procedure to develop sizing system. *World Applied Sciences Journal* 8(8): 923–929.
19. Ng, R., Ashdown, S. P. and Chan, A. (2007), Intelligent size table generation, *Proceedings of the Asian Textile Conference (ATC), 9th Asian Textile Conference, Taiwan*.
20. Abdali, O., Eric, P. and Marc, R. (2004), Exploring anthropometric data through cluster analysis, *International Journal of Consumer Studies* 32: 276–284.
21. Hsu, H. C., Lin, H. F. and Wang, M. J. (2007), Developing female size charts for facilitating garment production by using data mining. *Journal of the Chinese Institute of Industrial Engineers* 24: 245–251.
22. Doustaneh, A. H., Gorji, M. and Varsei, M. (2010), Using self organization method to establish nonlinear sizing system. *World Applied Sciences Journal* 9(12): 1359–1364.

23. Hsu, C. H., Tsai, C. Y. and Lee, T. Y. (2010), Neural network to develop sizing systems for production and logistics via technology innovation in Taiwan. *New Aspects of Applied Informatics, Biomedical Electronics & Informatics and Communications*. ISBN: 978-960-474-216-5, 421–424.
24. Bartlett, J. E., Kotrlik, J. W. and Higgins, C. (2001), Organizational research: determining appropriate sample size in survey research, *Information Technology, Learning and Performance Journal* 19: 43–50.
25. Scheaffer, R. L., Mendenhall, W. and Ott, L. R. (2005), *Elementary Survey Sampling*, Boston, MA: Brooks/Cole.
26. Hair, J. F., Anderson, R. E., Tatham, R. L. and Black, W. C. (1998), *Multivariate Data Analysis*, 4th edn, Upper Saddle River, NJ: Prentice Hall.
27. Tabachnick, B. G. and Fidell, L. S. (1996), *Using Multivariate Statistics*. Boston, MA: Allyn and Bacon.
28. Tabachnick, B. G. and Fidell, L. S. (2007), *Using Multivariate Statistics*, 5th edn, Boston, MA: Allyn and Bacon.
29. Hutcheson, G. D. and Sofroniou, N. (1999), *The Multivariate Social Scientist: Introductory Statistics Using Generalized Linear Models*. Thousand Oaks, CA: Sage.
30. Pallant, J. (2001), *SPSS Survival Manual*. Maidenhead: Open University.
31. Viktor, H. L., Paquet, E. and Guo, H. (2006), Measuring to fit: virtual tailoring through cluster analysis and classification, presented at 17th International European Conference on Machine Learning and the 10th European Conference on Principles and Practice of Knowledge Discovery in Database, 18–22 September, Berlin, Germany.
32. Kwona, O., Jungb, K., Youb, H. and Kimc, H. E. (2009), Determination of key dimensions for a glove sizing system by analyzing the relationships between hand dimensions, *Applied Ergonomics* 40: 762–766.
33. Petrova, A. (2007), *Creating Sizing Systems*. Cambridge: Woodhead Publishing Limited.
34. Hsu, C. H. (2008), Applying a bust-to-waist ratio approach to develop body measurement charts for improving female clothing manufacture, *Journal of the Chinese Institute of Industrial Engineers* 25: 215–222.
35. Gupta, D. (2004), A mathematical approach for developing a garment sizing system for Indian population, *International Conference on High Performance Textiles & Apparels (HPTEX 2004)*.
36. 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: 4185–4191.
37. Winks, J. M. (1997), *Clothing Sizes: International Standardization*. Manchester: The Textile Institute.
38. EN 1340-2 (1996), *Size Designation of Clothes*.