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INCLUDING PREFERENCE IN ANTHROPOMETRY-DRIVEN MODELS FOR DESIGN

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ABSTRACT

In the design of artifacts that interact with people, the spatial dimensions of the user population are often used to size and engineer the artifact. The variability in body dimensions (called “anthropometry”) is used to indicate how much adjustability or how many sizes are required to accommodate the intended user population. However, anthropometry is not the only predictor of these kinds of interactions. For example, two vehicle drivers with similar body dimensions might have very different preferred locations for the seat. The variability not predicted by body dimensions can be considered “preference”. Well-conceived models considering all sources of variability can facilitate the application of design automation tools such as optimization and robust design methodologies, resulting in products that are safer, cost effective, and more accessible to broader populations (including people with disabilities). In contrast, poor models and those that fail to include a preference component can produce misleading results that under- or over-approximate accommodation and prescribe inappropriate amounts of adjustability. This paper reviews common methods of designing for human variability, demonstrating the use and strengths and weaknesses of each. This is done in the context of a simple, univariate case study to determine the appropriate allocation of adjustability to achieve a desired accommodation level.

INTRODUCTION

An understanding of the body dimensions and capabilities of the population of potential users can assist engineers in creat-

ing artifacts that meet goals of fit, safety, and other performance metrics and systems-level design targets. Efforts since the 1950’s have produced tools that assist in basic assessments of *accommodation*, the degree to which a design meets the needs of the user population. This work has culminated in recommended tools and practices that are in common use today [1, 2, 3]. These indicate to the engineer how to design for the variability in body dimensions (or *anthropometry*), capability, and age, in the target user population. The application of design automation tools facilitates the simultaneous consideration of these and other aspects of designs [4, 5, 6, 7].

The goal of dimensionally optimizing a product with respect to its users is to accommodate a certain percentage of those users [3], often through adjustability, the creation of separate sizes, or both. There are two general approaches to achieving user accommodation: manikins and population models.

Manikin-based approach

“Manikins” are typically two- or three-dimensional representations of the human form with external contours intended to represent human body size and shape for design. They exist as 2D templates [8] and as 3D computerized manikins [9, 10]. A boundary manikin refers to a body geometry that lies at the limit of acceptability. Consider a design problem in which only one body dimension is relevant and both “small” and “large” people must be considered. In the typical boundary manikin approach, only two cases are necessary to describe the upper and lower limits of acceptability. For example, to accommodate 95% of the population, one might use the 2.5th-percentile and 97.5th-

percentile values of the measure of interest as boundary cases. In general, accommodation at the boundary is thought to ensure accommodation at interior points, as long as the adjustability of the product dimension is continuous [1]. Note that since the distribution of body sizes are continuous, the specific level of accommodation (95%) could be achieved by targeting any appropriate span (e.g., 0th to 95th-percentile; 2nd to 97th-percentile). Generally the range is selected to minimize the amount of adjustability or material (and therefore cost) required. For a single variable this is generally the lower (0th to 95th-percentile) or central (2.5th to 97.5th-percentile) portion of the distribution.

Since stature and weight data are most commonly available (e.g., NHANES [11]), distributions of those variables are often used to determine the sizes of the “small” and “large” virtual users. In the event that the true measure of interest is something besides stature, proportionality constants (Figure 1) are utilized [12]. These represent the average length of a particular body segment as a proportion of stature. This approach is problematic, however, since in a single individual the proportional lengths vary widely from the mean. Neither is there a “standard” person with all dimensions belonging to the same percentile [13]. For example, when a manikin representing the body as a kinematic linkage is scaled so that an overall dimension, such as stature, meets some target percentile, the body dimensions that make up the aggregate dimension do not themselves define useful design limits. That is, a person who is 5th-percentile by stature has other body dimensions that vary widely from the 5th-percentile for those measures.

Instead of proportionality constants, data from anthropometric surveys can be used. For example, the ANSUR database [14, 15] consists of 240 measurements taken from thousands of male and female US Army personnel in the late 1980’s. From these data, statistical measures such as the n^{th} -percentile value of some segment length can be calculated and used for design purposes. However, as with any anthropometric database, caution must be exercised when using a dataset from one population to represent a different population (i.e., the body dimensions of a military population can vary widely from those observed in a civilian one).

For multi-dimensional problems, a similar approach is sometimes used, in which small and large (by stature) manikins are created and adjusted to fit relevant product dimensions. For example, a designer seeking an overall accommodation of 95% in a vehicle interior might assume that if 95% of the population is accommodated on headroom, and 95% on legroom, and 95% on seat adjustability, that the overall goal has been achieved. However, considering each dimension separately and then combining the results will usually yield a significantly smaller than desired accommodation [16] since it is unlikely that the same 5% are disaccommodated on each measure. Consequently, methods incorporating principal components analysis have been developed to simultaneously consider the variability exhibited by a pop-

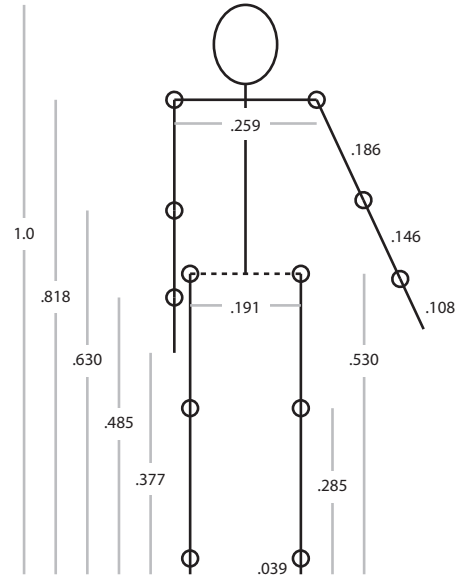


Figure 1. Body lengths expressed as a proportion of stature [12].

ulation across multiple anthropometric measures. These types of analysis yield many (e.g., 17 in [17]) “boundary” manikins which are used to evaluate the design, rather than just two or three. If all are accommodated, the engineer expects to achieve the level of accommodation equivalent to the amount of anthropometric variability encompassed by the selected manikins. Unfortunately, this approach only works in extremely constrained cases, can produce misleading results, and provides little information when the design is unable to accommodate one or more of the manikins [18].

Realistic posturing is required for any use of manikins in design [19, 4]. Sometimes, this posturing is performed manually by the designer, but to improve accuracy and repeatability it is increasingly done algorithmically. Data are gathered on a number of people performing similar tasks to the one in question (e.g., vehicle ingress/egress, sitting in a seat, interacting with an artifact, etc.). Statistical models of these data are then created to describe the mean anticipated behavior as a function of anthropometric and task conditions [20, 21]. When task-specific data are not available, optimization may be used to determine postures and interaction by minimizing objective functions such as torque at a joint and energy required [22]. However, this approach can produce inaccurate postures and lead to erroneous analyses. Both methods assume that user interactions can be predicted by the anthropometry and geometric constraints of the artifact, task, or environment.

Population model approach

An alternative to the boundary manikin approach is the task-oriented percentile model, described in [3]. These models are

created from experimental data taken from a sample population performing a task related to the dimension under consideration. Required adjustability is then defined by the selections or capabilities of the desired proportion of users. Both a sufficiently large representative sample population and a workable prototype are required. This approach forms the basis for the SAE International recommended practices [2], which are used for vehicle design.

These models are an improvement on manikin-based approaches in some ways, since they specifically model the outcome measure of interest, e.g., reach, eye location, driver-selected seat position, rather than trying to predict the population distributions of those outcomes from boundary cases defined by anthropometry. However, they (1) require extensive human-subject data from a similar task scenario, parameterized using the design variables of interest and representing a large amount of variability on the population descriptors, e.g., body dimensions, (2) have not historically been parameterized for population attributes, although recent models (new J941 and J4004) overcome these limitations, and (3) they are essentially univariate, dealing with only a single outcome measure (e.g., preferred seat height) at one time.

Hybrid approaches

In practice, some have sought to expand upon the manikin- and population-based approaches, by combining them into a hybrid method. Regressions of experimental data predict the outcome measure of interest as a function of related anthropometry (such as stature). This allows the population model to be extrapolated to populations different from the one from which the data were gathered. Unfortunately this procedure results in a practice where artifacts are designed to meet the mean behavior associated with a particular body size (i.e., two people with the same predictor value, such as stature, will have the same predicted performance). This ignores the residual variance in the experimental data—the preference component.

Recent research expands on this hybrid method by including preference in the outcome measure. Reed and Flannagan [23] investigated the effect of variability unrelated to body dimensions on driver seat position and eye location in an automobile. Parkinson, et. al., demonstrated a methodology for integrating design automation tools like optimization and robust design methodologies with models of anthropometric and behavioral variability that include preference [19, 18]. The present work expands on this research by generally considering how variability unrelated to body dimensions relates to traditional design approaches that consider only anthropometry. A case study is presented involving the adjustment of the seat height of a particular exercise cycle. This simple problem was selected because the preferred cycle seat height for an individual should be predicted very well by a single anthropometric measure such as stature or leg length.

METHODOLOGY

This paper considers several common ways in which manikins and population models are applied in product design. The product is an upright exercise cycle (PRO-FORM XP70). The metric of interest is the minimum seat height and its range of adjustability. *In each scenario, the engineer or designer applying it would expect 95% accommodation of the target user population.* The first two methods utilize traditional boundary manikin approaches considering only anthropometry to determine seat height. As discussed previously, one advantage to these methods is that they don't require any experimental data: either hip height or stature is used as the measure of interest. Following these, the use of a population model is illustrated. Then a hybrid manikin/population model in which the mean behavior for a given body size is predicted. Finally, these are all compared against the new methodology, in which the residual variance in the regression model is retained to account for user preference.

It is important to note that this case study is used only for the illustration of various methods of dimensionally optimizing a product. The actual results are highly dependent on the product and task to be performed, so general conclusions regarding exercise cycle seat height may not be drawn from this study. The target users are taken to be the male ANSUR population [14], selected because of the extensive anthropometric measures available for the sample.

Boundary manikins: proportionality constants and ANSUR

In the first two basic approaches toward determining range of seat adjustability, the way in which users will sit on the cycle, and therefore their desired seat height, is entirely unknown. It is proposed that they will sit such that their heel just touches the ground while seated (with legs unbent). This means that the seat height setting for each user will equal hip height. Boundary manikins with dimensions belonging to the 2.5th and 97.5th-percentile person are taken to represent 95% of the population.

Following common practice, the first approach uses two boundary manikins with hip height derived from the 2.5th and 97.5th-percentile stature (for males) using the proportionality constants in Figure 1. This approach is termed *Manikin-k* (boundary manikins-using proportionality constant k). The second approach uses two boundary manikins with hip height taken directly from the actual 2.5th and 97.5th-percentile hip height from ANSUR. This approach is termed *Manikin-ANSUR*.

Population model

Experimental data are required for the creation of the population model. The stature and preferred exercise bicycle seat height were measured for forty-two male engineering students in a study conducted at The Pennsylvania State University. The study received approval from an appropriately constituted inter-

nal review board. Since females are not adequately represented in the sample, the restriction that only adult males are to be accommodated is imposed. This leads to our choice of using only ANSUR males as a representative database but does not impact the validity of the results or the methodology.

Each participant was asked to get on the exercise cycle, pedal a few revolutions, and then adjust seat height setting. This process could be repeated as many times as necessary to achieve a desired position. After completing this task, the height of the seat top from the ground was recorded for each participant. A stature adjustment of 25 mm was included to account for the thickness of shoes (stature measures are generally taken without them). It should be noted that the seat post was unmodified, and the original pre-drilled stops were used that provided an adjustable range of 243 mm, in discrete increments of approximately 25 mm. Despite limits on the range of adjustability, the data are not thought to be censored since no member of the sample noted a preference for a higher or lower setting than those available.

To create the population model, statistical analysis is performed directly on the experimental data. The data were assumed to be normally distributed and the 2.5th and 97.5th-percentile values are determined using the mean and standard deviation. These results are termed *Population model*.

Hybrid: mean behavior

In a hybrid of the manikin and population model approaches, linear regression analysis is performed using the selected seat height and stature for the sample to create a *seat height preference model*. Stature is used as the predictor, instead of hip height, since stature data is widely available for a variety of populations. The resulting regression line is used to predict the selected seat height of two boundary manikins, characterized by 2.5th and 97.5th-percentile stature. This approach is termed *Hybrid-mean*.

Hybrid: with residual variance

Using a methodology described in [19] and [24], the fifth approach uses the regression parameters of the seat height preference model to generate a virtual population of 1000 users randomly sampled from the ANSUR database. The preferred seat height, including a component indicating how their preference deviates from the mean, is calculated for each virtual user. This is done by randomly sampling from a normal distribution about the mean seat height for that stature. This distribution is characterized by a mean equal to the seat height predicted by the regression equation and a standard deviation equal to the root-mean-square error of the regression (i.e. $\sigma = RMSE$) [25]. For this reason, this method will be termed *Hybrid-ResVar*.

RESULTS

The adjustment ranges calculated using each of the methods are reported in Table 1. The engineer anticipates achieving 95% accommodation with each of the methods, although they all produce different results. The results are all compared to the Hybrid-ResVar method, which has been shown in other studies to most accurately predict actual expected accommodation levels [23, 18].

Boundary manikins: proportionality constants and ANSUR

The 2.5th and 97.5th-percentile values of male stature from ANSUR are 1625 mm and 1887 mm, respectively. For the Manikin- k method, hip height is found as a proportion of stature ($H = 0.530S$), and so the lower and upper values are 861 mm and 1000 mm. Following the assumption that hip height equals selected seat height, and adding the 25 mm shoe thickness, the lower and upper limits of seat height adjustment become 886 mm and 1025 mm. For the Manikin-ANSUR method, hip height is found directly from ANSUR; the 2.5th and 97.5th-percentile hip height measures are 835 mm and 1022 mm. Therefore, the lower and upper limits of seat height adjustment are 860 mm and 1047 mm, with shoe thickness added.

Population model

The mean of the seat height selections of the sample population is 943.2 mm and the standard deviation is 46.3 mm. Using a k -value of 1.96, the lower limit for 95% accommodation is 852 mm and the upper limit is 1034 mm.

Hybrid: mean behavior

Figure 2 shows the plot of selected seat height versus stature (with shoes) for the sample population. The equation for the

Table 1. Summary of the results for all methods, showing required low and high seat settings, adjustable range, and % accommodated (compared with Hybrid-ResVar method). Dimensions in mm.

Method	Low	High	Range	% Accom.
Manikin- k	886	1025	139	82.5
Manikin-ANSUR	860	1047	187	93.2
Population	852	1034	181	93.6
Hybrid-mean	872	1007	135	82.5
Hybrid-ResVar	844	1036	192	95.0

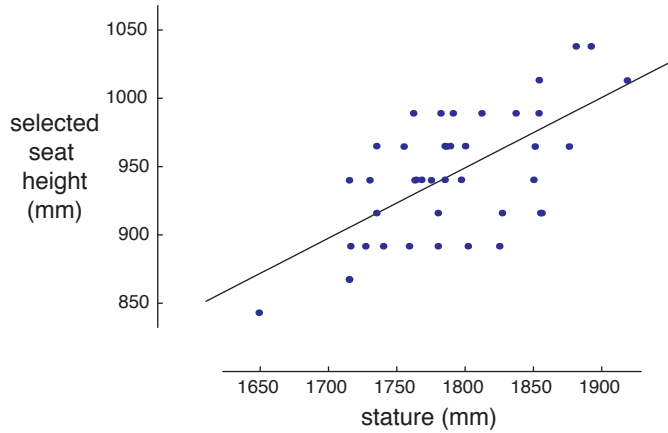


Figure 2. Selected seat height plotted against stature for the 42-member sample, with regression line.

resulting regression line is given by

$$P = 0.515S + 22.1 \quad (1)$$

where P is selected seat height position and S is stature. R^2 for the regression is 0.41 and the $RMSE$ is 35.2 mm. Table 1 denotes the results of entering the 2.5th and 97.5th-percentile statures (with shoe thickness added) into Equation 1, which subsequently defines the limits of required seat height adjustment for the Hybrid-mean method.

Hybrid: with residual variance

Figure 3 shows the distribution of the stature of the 1000 virtual users selected from the ANSUR database for use in the Hybrid-ResVar method. The mean of the distribution is 1756 mm, identical to the mean of all males in ANSUR. Figure 4 shows the result of plotting these statures using the regression line of Equation 1. Introducing a preference component by way of a term representing the residual variance to describe deviation from the mean gives

$$P = 0.515S + 22.1 + N(0, 35.2) \quad (2)$$

where N is a normal distribution with a mean of 0 and a standard deviation of 35.2 ($RMSE$ of the regression). Figure 5 shows the 1000 seat positions predicted for the 1000 statures using Equation 2. 95% accommodation is achieved by selecting the central 950 users with their seat height selections placed in order.

Figure 5 also compares the results of the Manikin- k , Manikin-ANSUR, Hybrid-mean, and Population model methods with the result of the Hybrid-ResVar method. The band of accommodated users given by the defined lower and upper limits

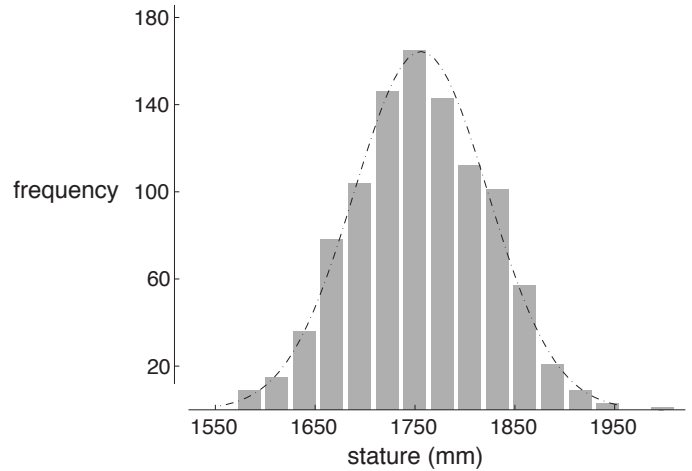


Figure 3. Distribution of 1000 random statures used in the Hybrid-ResVar method.

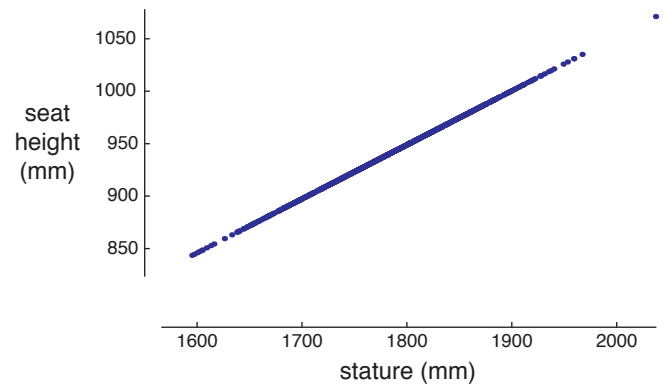


Figure 4. Seat height setting for 1000 random statures, located with regression equation with no preference component.

in Table 1 is shown for each method by the bars at left, and the results for the Hybrid-ResVar method are extended across the figure by the solid lines. Points above or below these limits represent disaccommodated users. Table 1 also denotes the number of accommodated users, expressed as a percentage.

DISCUSSION

The results show the wide range of recommended designs which these various methods—all of which are in common use—provide to this extremely simple univariate design problem. They also indicate the importance of including preference, the variability that is unrelated to body dimensions and artifact geometry. Ignoring this variability can result in designs with too much adjustability (thereby increasing cost unnecessarily) or, more com-

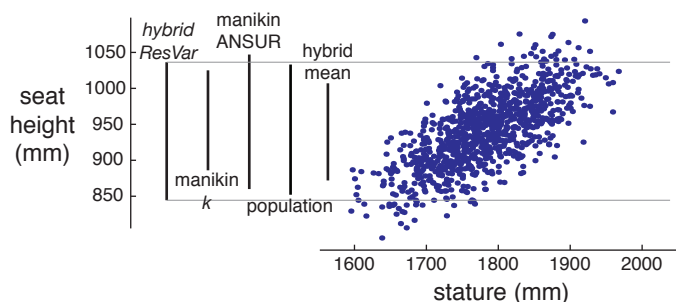


Figure 5. The stature and seat selections of the 1000 member sample are plotted with preference included. Adjustment limits defined by the Hybrid-ResVar method are denoted by the lines running the length of the plot, and adjustable range defined by the Manikin- k , Manikin-ANSUR, Hybrid-mean, and Population model methods are denoted by the bars at left.

only, too little adjustability (causing users to interact with the artifact, task, or environment in unexpected ways). Designers are often surprised when actual use indicates lower than expected accommodation and are unable to explain how this occurred. To prevent this under-approximation of accommodation, a designer may allocate an extremely large amount of adjustability to the problem, such that an accommodation level approaching 100% is expected. This would not constitute an optimal design, however, and in multivariate problems can be extremely impractical. Although the differences in results achieved using some of these methods (Table 1) may seem small or trivial for this application, many other applications that have limited physical space for adjustability or high costs for added adjustability benefit greatly from optimized solutions.

The discrepancy between the first two methods (Manikin- k and Manikin-ANSUR), which equate hip height with selected seat height, arises from the fact that there is not a perfect correlation between hip height and stature across the entire population. There is considerably more variability in hip height than indicated by using stature and proportionality constants. It is interesting to note that the Manikin-ANSUR method provided nearly 95% accommodation with little effort (i.e., no experiment needed to be run). However, this is a rare occurrence and attributable to the simple and univariate nature of this design problem. While the idea of modeling a large population with a very small set of manikins is an attractive one, the large amounts of variance that are not explained by body size or geometric constraints make it impractical. This finding is consistent with those in other studies involving more complex problems [23, 18].

Since the Population and Hybrid-mean methods are based upon functional models in which the preferred seat heights were measured, one might anticipate those values to better represent

the required adjustability. Additionally, since the behavior is measured directly, no assumptions (e.g., riders will select a seat height such that their heels can reach the floor) are required. Due to the simplicity of the problem and the relative similarities between the sample and target user (ANSUR) populations, the Population method predicted accommodation well. This is to be expected. Problems with population models arise in two situations: 1) when designers try to use a model gathered on one population to predict accommodation for another; and 2) when designers try to consider other factors simultaneously. For example, models predicting preferred handle bar location and preferred seat location might work well independently, but the results can not be combined to predict both [4].

The effect of including the residual variance is seen in the Hybrid-ResVar method. Since the regression model relating stature to seat height has an R^2 value of 0.41, 59% of the variance in seat height cannot be explained by stature. The effects of preference are clearly visible when comparing Figure 4, which includes no preference, with Figure 5, which does. It shows that when preference is included, for any particular stature, a variety of seat positions might be chosen about a mean value. The benefit of incorporating preference may be seen in the 12.5-percent increase in accommodation from the Hybrid-mean method to the Hybrid-ResVar method, corresponding to 125 additional people from the virtual 1000-member sample.

Another way to think of the Hybrid-ResVar method is the separation of user behavior into two quantifiable components: that defined by anthropometry (measured by the slope of the preference model regression) and that attributable to preference (measured by RMSE). The interrelation of anthropometry and preference may be easily examined by the shape and scatter of the preference model. Sometimes, anthropometry may be a driving consideration, and in such cases, the model may exhibit a steep slope with a high R^2 value. Other times, anthropometry may have little impact on the problem, and the driving consideration may instead be preference. In these cases, the model may exhibit a very shallow slope with a low R^2 and lots of scatter. For this example, the R^2 is 0.41, so anthropometry has a bearing on the problem but preference is nearly as important.

Although the Hybrid-ResVar method illustrated here still requires experimental tests, one advantage of the method is that data from a relatively small sample of users evaluating physical prototypes can be used to make models that can be used for quantitative analysis. In practice the sample population would deliberately contain a diverse group of people, with care taken to oversample the tails of the distributions of relevant parameters (e.g., lots of short and tall people in this example).

This study has limitations. A larger, more diverse sample would be required to validate the model across an entire population. Further study will seek to enlarge the sample size, particularly in the tails of the anthropometric distribution. To include females in the pool of prospective customers, data would need

to be collected from a large sample of female users as well. The inclusion of different types of bicycles would allow the model to be extrapolated more broadly. The mode of adjustability should also be improved, reconfiguring the cycle in such a way so as to have continuous, rather than discrete, adjustment. The preferred seat height was selected using a “quick sit” methodology. This might correlate well with acceptability in a store or for a short ride but is likely to differ from what might be selected for longer duration rides. Additionally, the expertise of the rider was not considered; it is likely that more experienced riders will select relatively higher seat heights.

One could imagine that a design with more than one adjustable dimension experiences a compounding of the unexplained variance seen in this problem. Therefore, it is even more important in such problems to include effects owing to preference. Future work will further examine the effects of preference on higher-dimensional problems. The notion of a “just noticeable difference”, that is the degree to which a user could be disaccommodated without experiencing negative effects, and its impact on preference and accommodation will also be investigated.

Recognizing that personal preference has a significant impact on population accommodation is important in the design of any device. This work shows that incorporating such variability into traditional statistical models improves accommodation and the confidence the engineer can have in their design.

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REFERENCES

- [1] HFES 300 Committee, 2004. *Guidelines for Using Anthropometric Data in Product Design*. Human Factors and Ergonomics Society, Santa Monica, CA.
- [2] SAE International, 2006. *Automotive Engineering Handbook*. SAE International, Warrendale, PA.
- [3] Roe, R., 1993. *Automotive Ergonomics*. Taylor & Francis, London, ch. Occupant Packaging, pp. 11–42.
- [4] Parkinson, M., Reed, M., Kokkolaras, M., and Papalambros, P., in press. “Optimizing truck cab layout for driver accommodation”. *ASME Journal of Mechanical Design*.
- [5] Michalek, J., Ceryan, O., Papalambros, P. Y., and Koren, Y., 2006. “Balancing marketing and manufacturing objectives in product line design”. *ASME Journal of Mechanical Design*, **128**(6), pp. 1196–1204.
- [6] Zou, T., and Mahadevan, S., 2006. “Versatile formulation for multiobjective reliability-based design optimization”. *ASME Journal of Mechanical Design*, **128**(6), pp. 1217–1226.
- [7] van der Vegte, W., and Horvath, I., 2006. “Including human behavior in product simulations for the investigation of use processes in conceptual design: A survey”. *Proceedings of the ASME International Design Engineering Technical Conferences*. Philadelphia, PA., ASME International.
- [8] Diffrient, N., Tilley, A., and Bardagjy, J., 1981. *Human-scale*. The MIT Press.
- [9] UGS, 2007. *Tecnomatix Jack*. UGS.
- [10] Human Solutions, 2007. *RAMSIS*. Human Solutions.
- [11] Centers for Disease Control and Prevention, 1994. *National Health and Nutrition Examination Survey III, 1988-1994*. National Center for Health Statistics, unpublished tables.
- [12] Drillis, R., and Conyini, R., 1966. *Body segment parameters*. Office of Vocational Rehabilitation Engineering & Science, New York, cited in [26].
- [13] Roebuck, J., 1995. *Anthropometric Methods*. Human Factors and Ergonomics Society, Inc., Santa Monica, CA, USA.
- [14] Gordon, C. C., Churchill, T., Clauser, C. E., Bradtmiller, B., McConville, J. T., Tebbetts, I., and Walker, R. A., 1989. “1988 anthropometric survey of U.S. Army personnel: Methods and summary statistics. final report”. (*NATICK/TR-89/027*).
- [15] Clauser, C., Bradtmiller, B., McConville, J., and Gordon, C., 1989. “Measurer’s handbook: US Army anthropometric survey 1987-1988”. *Technical Report NATICK/TR-88/043: United States Army NATICK Research, Development and Engineering Center*.
- [16] Moroney, W., and Smith, M., 1972. Empirical reduction in potential user population as the result of imposed multivariate anthropometric limits. Tech. Rep. NAMRL-1164 (AD 752 032), Naval Aerospace Medical Research Laboratory Report, Pensacola, FL.
- [17] Bittner, A. C., 2000. “A-CADRE: Advanced family of manikins for workstation design”. *Proc. Human Factors and Ergonomics Society*, pp. 774–777.
- [18] Parkinson, M., and Reed, M., 2006. “Optimizing vehicle occupant packaging”. *SAE Transactions: Journal of Passenger Cars—Mechanical Systems*, **115**.
- [19] Parkinson, M., Reed, M., Kokkolaras, M., and Papalambros, P., 2005. “Robust truck cabin layout optimization using advanced driver variance models”. *Proceedings of the ASME International Design Engineering Technical Conferences*. Long Beach, CA., ASME International.
- [20] Faraway, Julian, J., Zhang, X., and Chaffin, D., 1999. “Rectifying postures reconstructed from joint angles to meet constraints”. *Journal of Biomechanics*, **32**(7), pp. 733–736.
- [21] Chaffin, D., Faraway, J., Zhang, X., and Woolley, C., 2000. “Stature, age, and gender effects on reach motion postures.”. *Human Factors*, **42**(3), pp. 408–420.

- [22] Abdel-Malek, K., Yang, J., Brand, R., and Tanbour, E., 2004. "Towards understanding the workspace of human limbs". *Ergonomics*, **47**(1), pp. 1386–1405.
- [23] Reed, M., and Flannagan, C., 2000. "Anthropometric and postural variability: limitations of the boundary manikin approach". *Technical Paper 2000-01-2172. SAE Transactions: Journal of Passenger Cars—Mechanical Systems.*, **109**.
- [24] Parkinson, M. B., and Reed, M. P., 2006. "Improved head restraint design for safety and compliance". *Proceedings of the ASME International Design Engineering Technical Conferences. Philadelphia, PA.*, ASME International.
- [25] Flannagan, C., Manary, M., Schneider, L., and Reed, M., 1998. "Improved seating accommodation model with application to different user populations". *Proc. SAE International Congress & Exposition*, Vol. 1358, SAE, Warrendale, PA, USA, pp. 43–50.
- [26] Clauser, C., McConville, J., and Young, J., 1969. "Weight, volume and center of mass of segments of the human body". *AMRL-TR-69-70, Wright Patterson Air Force Base.*