International Journal of Industrial Ergonomics 44 (2014) 769–776

Contents lists available at ScienceDirect

International Journal of Industrial Ergonomics

journal homepage: www.elsevier.com/locate/ergon

Estimated anthropometry for male commercial pilots in Europe and an approach to its use in seat design

Emilie Poirson [a,*], Matthew Parkinson [b]

[a] LUNAM Université, Ecole Centrale de Nantes, IRCCyN, 1 rue de la Noë, 44300 Nantes, France
[b] Engineering Design, Industrial Engineering, and Mechanical Engineering, The Pennsylvania State University, 213 Hammond Building, University Park, PA 16802, USA

ARTICLE INFO

Article history:
Received 19 February 2013
Received in revised form
18 April 2014
Accepted 13 May 2014
Available online 26 September 2014

Keywords:
Human variability
Aircraft pilots seats
Genetic algorithm
Parallel graph
Multicriteria optimization

ABSTRACT

This research provides an estimate of the anthropometry of the male commercial pilot population in Europe and details a new method for applying these data in multivariate design problems: the cockpit seat. For the safety and vigilance, the pilot must fit the seat. Although the anthropometric variability of pilot can be readily quantified, the magnitude of variability and the associated physical requirements are large in this complex posture. The research presented here demonstrates an approach that allows the designer to explore combinations of advices for the seat adjustments that will fit a chosen population (for example 90% of all the pilots). The data were generated after the evaluation of relevant data synthesis methods. To explore the huge design space, genetic algorithm are used on a 4 variables application case and the results are presented through a parallel graph. The results of the study is a tool taking in input the target of population (ex 95%) giving in results family of combinations of percentage of population on each parameters to see who in the population database will fit the pilot seat.

Relevance to industry: The domain of transportation, in which pilots or driver can stay a long time sitting in their vehicle is very challenging in finding an adaptable seat for every driver to be adjust.

1. Introduction

In ergonomics, work station and particularly cockpit have a rich history. The work position on a seat is fundamental to avoid physical troubles and default of concentration. There are a number of factors in seat performance including safety, comfort, and the position of the user within the seat and seated environment. One factor that influences each of these is the body size and shape of the target user population. This study considers the spatial requirements of European pilots in the design of aircraft cockpit seats. Determining the spatial requirements of a particular population is usually confounded by the lack of appropriate data. While a number of detailed databases of body size and shape exist, they represent only a few, specific populations (e.g., the U.S. military, young Japanese civilians, etc.) and not the target user population of the artifact to be designed. Consequently, methods for estimating anthropometric variability within a specific population are very important. For this paper, summary statistics for male European commercial air pilots were provided by an airline. Data synthesis techniques were used to obtain an estimate of the detailed anthropometry in this population. Several methods were compared and the method mostly likely to provide accurate estimates was utilized.

A second difficulty in cockpit design is the multivariate nature of the problem. Univariate approaches to multivariate design problems (Mehta et al., 2008; HFES 300 Committee, 2004) are known to provide inaccurate estimates of accommodation (Moroney and Smith, 1972; Gannon and Moroney, 1998; Haslegrave, 1986). There are typically a number of relevant anthropometric measures (e.g., seated hip breadth, sitting height, lower leg length, upper leg length, arm lengths, etc.). Since the lengths and widths within individuals are not perfectly correlated, they must be considered simultaneously. Although the application of boundary manikins can simplify this aspect of the problem (Bittner, 2000), their use is fraught with other difficulties (Garneau and Parkinson, 2009, 2010).

The research presented here demonstrates an approach that allows the designer to explore combinations of measures that will achieve a fixed accommodation level (e.g., 90%). This is an opportunity to exploit the multivariate nature of the problem and improve accommodation where it is most efficient (e.g., in terms of

* Corresponding author.
E-mail addresses: emilie.poirson@irccyn.ec-nantes.fr, emilie.poirson@ec-nantes.fr (E. Poirson).

http://dx.doi.org/10.1016/j.ergon.2014.05.003
0169-8141/

cost or spatial requirements). For large multivariate problems, an exhaustive study of every possible combination of factors can be mathematically impossible. The problem can be significantly reduced, however, by immediately discarding designs that are obviously intractable. For example, there is no need to consider a design that excludes 30% of the population on a single measure when the target accommodation level is 90% across all of them. The designer can also be aided through the use of optimization strategies that systematically evaluate candidate designs and consider multiple design priorities. The result is a tool that allows designers to explore the relationships between measures, trading them off to identify the specific configuration that best meets their design requirements.

2. Relevance to industry

With the evolution of population explaining the higher heterogeneity of people, the industries must take into account the anthropometry. In the field of furniture, tools, clothes (…) everything is dependent on human measurements. The workstation is a subject studied in all businesses. Its lack of ergonomics and comfort is often the cause of physical problems for the user. The domain of transportation, in which pilots or driver can stay a long time sitting in their vehicle is very challenging in finding an adaptable seat for every driver to be adjust.

More importantly, the bad position can imply a loss of vigilance, completely unthinkable for example for an aircraft pilot where an error can be vital. For the manufacturer, optimizing seat adjustments means reducing unnecessary variation ranges and therefore reducing the weight of the plane, constant objective. New proposals in aeronautics include removing the sleeping area of a pilot. The seat becomes either a cockpit but also a place of rest/sleep. That explains the growing interest of companies to improve the quality and adaptability of their seats.

3. Synthesizing a population of anthropometric data for commercial airline pilots

Databases of detailed anthropometric data are necessary for conducting multivariate design. Unfortunately, while there are an infinite number of distinct target user populations, the data in the public domain represent only a few of them. These include US military personnel (Gordon et al., 1989), Japanese civilians (of Human Engineering for Quality Life, 1994), and Chinese civilians (SAIGLOBAL, 1988). Summary statistics such as the means, standard deviations, and selected percentile values for a number of measures are available for many other populations including agricultural workers in India (Dewangan et al., 2008) and civilians in England (Barkla, 1961). When the detailed databases are available, they can be used directly in multivariate design. When only the summary statistics are available, the data for the underlying distributions must first be estimated (Pheasant, 1982). That is the situation in the present work, where only summary statistics were made available.

3.1. Simulating virtual populations

Although specific measures such as those required for cockpit packaging (e.g., buttock-popliteal length, seated hip breadth) are critical to design decision-making, they are not commonly available for the population of interest. While invaluable to proper design, correctly measuring anthropometric data can be an expensive and time-consuming process. Consequently, the designer is often left with only gross body dimensions such as stature and mass for the user population. As a result, numerous anthropometry-simulation techniques that use these measures (and BMI) to estimate the specific measures of interest have been developed.

Proportionality constants (Drillis and Contini, 1966) are used as a basis for a number of them, including some software tools, textbooks, and templates. While inherently simple, these methods have been shown to be inaccurate, particularly in estimating values in the tails of distributions where most design decisions occur (Moroney and Smith, 1972; Roebuck, 1995; Fromuth and Parkinson, 2008).

Another approach is to formulate linear regression models relating the required anthropometry to easily-obtainable predictors such as stature, mass, and BMI (body mass index, a normalized ratio of weight to stature) as in Ryu et al. (2004).

These models can be based on information from comprehensive databases such as ANSUR (a database of US Military in the 1980s, Gordon et al. (1989)) or CAESAR (a convenience sample of North American and European civilians, Blackwell et al. (2008)). Relationships in these data are used estimate the measures in the relevant target user population (Nadadur and Parkinson, 2008). The main drawbacks of this technique are: (1) inaccurate estimations of anthropometry at the tails of the distribution and (2) the necessity of a detailed database from which to obtain the regression equations. The accuracy of the regression methodology, particularly in the tails of the distribution, is increased considerably with the inclusion of residual variance as a stochastic component in the model (Parkinson and Reed, 2006; Garneau and Parkinson, 2009).

When this approach is used, some resulting distributions in the virtual populations are statistically equivalent, in terms of means and variances, to the actual anthropometry (Nadadur and Parkinson, 2009). Approaches using Principal Components Analysis (PCA) have been shown to further improve accuracy (Parkinson and Reed, 2009).

3.2. Comparing the methods

The ANSUR database was selected as the baseline database for this work since, of the available detailed data, the military personnel of the ANSUR population were thought to be closest (e.g., in terms of fitness, body shape, etc.) to the members of the male European commercial pilot population. To identify which of the methods outlined above would be most appropriate, a series of 28 design scenarios were considered. Each of seven synthesis methods was used to estimate the entire distribution of four relevant body dimensions. The dimensions were selected as those particularly relevant to the problem at hand: cockpit design. Successful seating positions support a number of specific activities. For example, a pilot must align to small beads to ensure a good view of the environment. They must also have their feet on the ground and shoulder blades resting on the seat. The seat pan must be wide enough to provide adequate support and pressure relief for long durations. The selected variables (Fig. 1) are: popliteal height (l_p), buttock-popliteal length (l_b), seated acromial height (l_a), and seated hip breadth (l_h).

The stature, mass, and BMI for the 1774 members of the male ANSUR population ($\mathbf{r}$) were used to estimate the four measures selected for the pilot (l_p, l_b, l_a, and l_h) using the synthesis methods outlined above.

Method 1: proportionality constant. The principle is to identify the different measures of the body by applying the average ratio of that measure to stature for a population. For each measure of interest x, the proportionality constant c_x is then:

$$c_x = \left(\sum_{j=1}^{n} \frac{r_{x,j}}{r_{s,j}} \right) \Big/ n \quad (1)$$

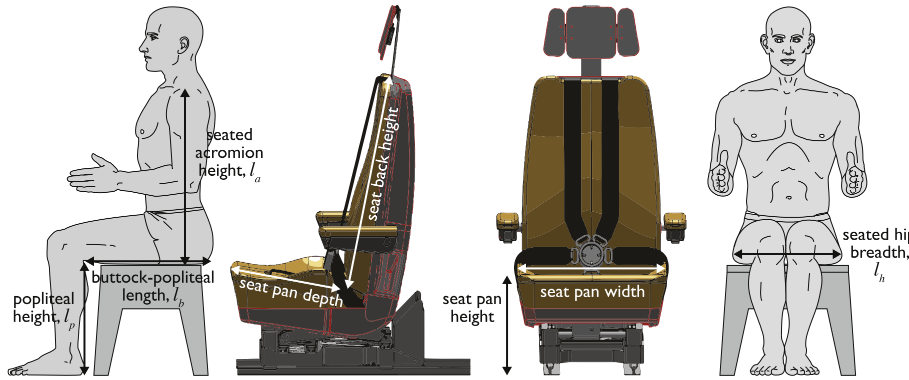

Fig. 1. The four body measures correspond to key seat design parameters. They are: popliteal height (l_p), buttock-popliteal length (l_b), seated acromial height (l_a), and seated hip breadth (l_h).

where n is the number of individuals in the reference population (1774) and s is the subscript denoting stature.

Method 2: boundary ratio. Boundary ratios were developed to improve the accuracy of proportionality constants in the tails of distributions (Fromuth and Parkinson, 2008). Instead of using the average value for all calculations, as proportionality constants do, different ratios were calculated for the 5th-, 50th-, and 95th-percentile values. For example, the 5th-percentile boundary ratio is:

$$c_{x,5} = \frac{r_{x,5}}{r_{s,5}} \tag{2}$$

where $r_{x,5}$ and $r_{s,5}$ are the 5th-percentile values for the measure of interest and stature, respectively, in the reference population. The user selects the ratio closest to the percentiles of interest. Table 1 presents the ratios utilized here, with percentiles 0–33, 34–67, and 68–100 using the 5th-, 50th-, and 95th-percentile boundary ratios, respectively.

Method 3: Simple linear regression (stature). Linear regression is performed on the ANSUR data ($\mathbf{r}$) to relate stature r_s to each of the measures of interest, l_p, l_b, l_a, and l_h. The stature from ANSUR is then used to estimate the measures for each individual, i, using the resulting model:

$$l_{x,i} = l_{s,i}\alpha_1 + \alpha_2 \tag{3}$$

where α are the regression coefficients and s is the square root of the residual variance.

Method 4: Multiple linear regression (stature and mass). Linear regression is conducted as in *Method 3*, but the relationship between the measure of interest and both stature (subscript s) and mass (subscript m) is modeled:

$$l_{x,i} = l_{s,i}\alpha_1 + l_{m,i}\alpha_2 + \alpha_3. \tag{4}$$

Method 5: Multiple linear regression (stature and BMI). Linear regression is conducted as in *Method 4*, but the analysis is conducted with both stature and BMI (subscript B):

$$l_{x,i} = l_{s,i}\alpha_1 + l_{B,i}\alpha_2 + \alpha_3. \tag{5}$$

Method 6: Simple linear regression (stature) + residual variance. Linear regression is performed on the ANSUR data ($\mathbf{r}$) to relate stature r_s to each measure of interest. The residual variance s^2 from the regression is the measure of the variation of the values around the regression line. That the non explained part of the variance, often called noise.

It is introduced into the prediction equation as a stochastic term:

$$l_{x,i} = l_{s,i}\alpha_1 + \alpha_2 + N(0, s) \tag{6}$$

where N(0, s) indicates a normal distribution with mean 0 and standard deviation s.

Method 7: Multiple linear regression (stature and mass) + residual variance. This is the same as *Method 6*, but both stature and mass are included in the model:

$$l_{x,i} = l_{s,i}\alpha_1 + l_{m,i}\alpha_2 + \alpha_3 + N(0, s). \tag{7}$$

Method 8: Multiple linear regression (stature and BMI) + residual variance. This is the same as *Method 7*, but both stature and BMI are included in the model:

$$l_{x,i} = l_{s,i}\alpha_1 + l_{B,i}\alpha_2 + \alpha_3 + N(0, s). \tag{8}$$

Methods 1–5 are deterministic: for a given set of data, the results of the calculations are the same every time they are run. Since Methods 6–8 include a stochastic term, each simulation produces slightly different results. Consequently, for assessing those methods the data were synthesized 1000 times and the results averaged. Performance was assessed by calculating the sum of the distances of the linear regression between the real values of the database ANSUR and simulated values:

$$\sigma_h = \sum_{i=1}^{n}\left(\left|\hat{l}_{h,i} - l_{h,i}\right|\right) = \sum_{i=1}^{n}\sigma_{h,i}. \tag{9}$$

where l_h stands for seated hip breadth and σ_h is the difference between the simulated l_h and the real value of l_h. This is depicted graphically in (Fig. 2).

Fig. 3 is a qq-plot showing the actual vs synthesized data for l_h, seated hip breadth. Ideally, in the case of a perfect model, the points would be aligned on the diagonal. Instead, the methods all work well in the middle of the figure near the 50$^{\text{th}}$percentile. Errors are more pronounced at the extreme values, in particular for Methods 1–3.

Table 1
The boundary ratios for each of the four anthropometric measures of interest.

Percentile	5	50	95
Popliteal height	0.240	0.247	0.255
Buttock-popliteal length	0.278	0.285	0.292
Acromion height, seated	0.333	0.341	0.346
Hip breadth, seated	0.191	0.191	0.191

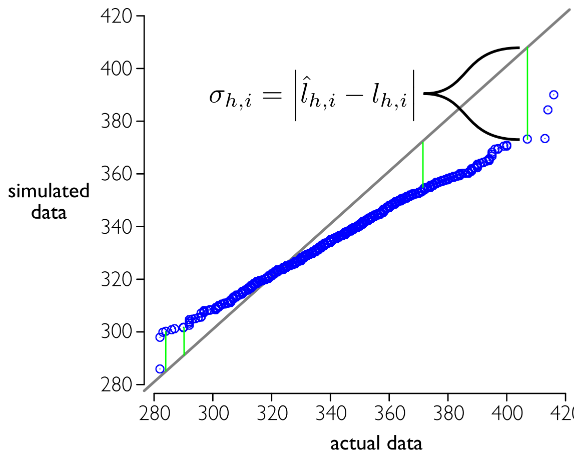

Fig. 2. Performance indicator for the data simulation methods.

It is now known that the length measurements are related to stature, much more than waistlines, hip or arm, mostly related to a combination of stature and weight. One may therefore ask whether it is appropriate to simulate the four parameters (including three length directly related to the stature and the latter more weight-related) with the same calculation methods. In our case, the target population is a physically driven population, approaching in the sense of military bases ANSUR data types. Hip breadth is connected to the stature without one can find themselves in extreme cases we could find among civilians (with big problems of overweight). Thus, the simulations show that these methods are valid for four selected parameters.

The results for all four measures are included numerically for all four measures in Table 2. Method 1, which uses proportionality constants, is the least accurate of all the methods. Method 2, which is tuned to both the middle and tails of the distribution shows significant improvement. Method 3 is also a poor predictor, in particular for hip breadth. This was anticipated since hip breadth and stature are not strongly correlated. Although Methods 4 and 5 include mass and BMI, respectively, as predictors, the improvement is limited to hip breadth—the remainder of the measures show large amounts of error. Methods 6–8, which include the residual variance in the model, are by far the best. Methods 7 and 8 are equivalent.

Table 2
Results of the methods tested, by distance to the target vector: sum of the absolute values of the difference between predicted and actual at each of the percentiles (Eq. (9)).

Method	l_p	l_b	l_a	l_h	Average
1	717	610	544	798	668
2	405	311	305	305	332
3	319	478	824	902	540
4	291	467	793	283	517
5	286	466	789	266	514
6	109	104	108	98.4	105
7	100	103	108	65.7	94.2
8	102	103	105	67.5	94.3

3.3. Estimating the anthropometry of commercial pilots

The objective is to obtain a virtual population of 1000 European pilots for each of whom the detailed measures of body size and shape are known. A French airline provided summary statistics for stature, mass, and BMI, collected from approximately 2500 male pilots (Table 3). The pilots are predominantly of European descent and the data have been rounded. Since the objective is to obtain detailed anthropometric data for this population, distributions of stature, mass, and BMI (and not just the summary statistics) are required. Stature is known to be approximately normally distributed and the mean is provided. For a virtual population of m individuals, the z-score (z) corresponding to $(m-1)/m$ is identified. The standard deviation s is then approximated using the equation:

$$s = \frac{\overline{x} - x_{\min}}{z} \tag{10}$$

where x corresponds to the measure of interest (i.e., stature). To obtain the m statures required for the virtual population, they are selected from a normal distribution with the calculated mean ($\overline{x}$) and standard deviation (s). The z-score was selected so that the tails of the distribution are near the reported limits. The minimum and maximum values are manually specified to be those observed in the actual population (Table 3). The ANSUR data, which are used to build the statistical models on which the detailed pilot data were based, are also included. They exhibit reasonable agreement with the pilot data for mass and BMI, while the stature data span those of the pilots, indicating that they may be appropriate for this situation.

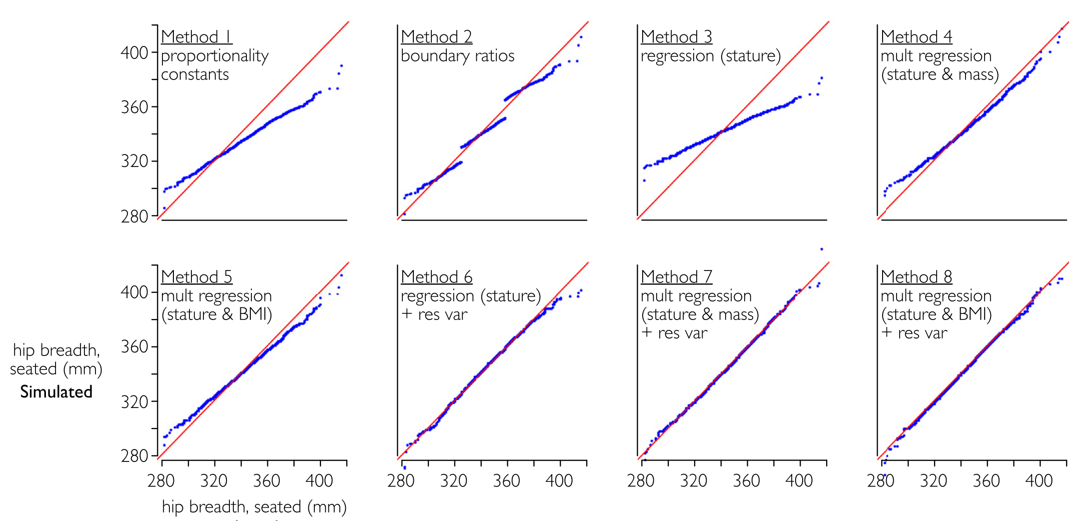

Fig. 3. qq-plot percentiles calculated on real vs. synthesized seated hip breadth for each of the synthesis methods.

Table 3
Summary statistics for ANSUR data (on which the relational models were built) and the real and synthesized European pilot data.

	ANSUR data			Actual data			Synthesized data			
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	sd
Stature (mm)	1497	1756	2042	1600	1800	2040	1600	1799	2040	65.8
Mass (kg)	48.5	80.0	130	51	82	127	51	81	127	12.7
BMI	18.1	25.9	39.5	16	25	42	16	25	42	0.138[a]

[a] This is the sd (log(BMI)).

BMI is not normally distributed, but the transformed data (by taking the logarithm of BMI) can be approximated as such (Brainard and Burmaster, 1992; Penman and Johnson, 2006; Veerman et al., 2007). The procedure outlined above was followed for log(BMI), then transformed back to obtain the m BMI values for the virtual population. Since stature and BMI are known to be uncorrelated, the two measures can be paired randomly. However, this must be done such that the summary statistics for mass (Table 3) are achieved. To do this, the error between the synthesized and actual mass summary statistics was calculated as the sum of the absolute value of the differences. The random pairing of stature and BMI was completed 1E6 times and the set with the smallest total error (0.91 kg) was selected.

The necessary predictors for the synthesized population (stature, mass, and BMI) are now available to use any of the methods outlined earlier for the synthesis of detailed anthropometry. Regression incorporating residual variance with either stature and mass (Method 7) or stature and BMI (Method 8) as predictors were shown to be the most accurate methods of estimating anthropometry for data closely approximated by ANSUR. Method 8 was utilized here. The measures of interested were selected to be representative of those typical for vehicle or cockpit packaging. When two measures were closely correlated (e.g., buttock-popliteal length and buttock-knee length; seated acromion height and seated eye height), only one of the measures was synthesized. When the inclusion of a second predictor (e.g., BMI as a predictor for popliteal height) did not improve the model, it was excluded from the analysis. Since the analysis incorporates a stochastic component, the population was synthesized 10,000 times and the summary statistics averaged and reported in Table 4. The multivariate nature of the problem precludes the use of univariate tables in design practice, requiring instead that databases of individual anthropometry be used. For those interested in creating a population database similar to the one presented here, the regression coefficients and the standard error of the regression (*SE*) for the prediction equation are included in the table. The summary statistics serve as targets when generating the final detailed population. The virtual population is synthesized many times (e.g., 10,000) and the population that produces summary statistics closest to the targets is the one that is used for subsequent multivariate design analysis (see Table 4).

4. Genetic algorithms in multivariate design problems

Seat design requires the simultaneous consideration of variability across several body dimensions within the target user population. As a multivariate design problem, achieving high levels of overall accommodation can be difficult since disaccommodation on a single measure excludes that user from the pool of those that fit successfully (Acar and Weekes, 2006; Flannagan et al., 1998; Roebuck, 1995). This section outlines an optimization-based method for considering the many solutions.

4.1. Background on genetic algorithms

Genetic algorithms Goldberg (1989) are evolutionary optimization methods developed originally by Holland (1992). Based on iterative generations of population of individuals, they converge step-by-step toward solutions. The term *individual* refers here to a specific set of values for the design variables. Genetic algorithms are often used in the literature to explore design space, encourage creativity Qian and Ben-Arieh (2009), or to help innovation Poirson et al. (2010a).

4.2. Set up of the genetic algorithms

The seat design problem for male European pilots can be formulated in 2 steps. First, the designer selects the overall accommodation target (e.g., 80% of the target user population). The second step is to identify the relevant measures and obtain (through measurement, a database, or synthesis) the measurements of the body size and shape.

Per Papalambros and Wilde (2000), the associated design problem can be posed as:

$$\begin{cases} \text{find the design variables } x^* = (x_1, x_2, \ldots, x_n) \in \Re^n \\ x^* = \text{argmin}(F(x,p)) = \text{argmin}(f_1(x,p), f_2(x,p), \ldots f_m(x,p)) \end{cases} \tag{11}$$

Where f is the fitness function described below; x_1, x_2 …,x_n take values between X and 100. This is a problem without constraints.

Table 4
Percentile values, regression coefficients, and standard error of the regression for the synthesized European commercial pilot data (averaging across 10,000 simulations).

	1st	5th	10th	25th	50th	75th	90th	95th	99th	α_1	α_2	α_c	s
Stature	1651	1694	1717	1756	1800	1844	1883	1906	1949	–	–	–	–
Mass	55.9	62.0	65.8	72.6	80.9	90.2	99.4	105	117	–	–	–	–
BMI	17.9	19.7	20.8	22.7	25.0	27.5	30.1	31.7	34.9	–	–	–	–
Popliteal height sitting	390	407	416	431	448	464	479	488	505	0.32	–	−124	13.0
Buttock popliteal length	452	470	480	496	514	532	547	557	575	0.31	–	−40.5	16.8
Acromion height sitting	542	562	573	591	611	630	648	658	678	0.29	–	86.5	22.3
seated hip breadth	308	324	334	349	367	386	404	415	435	0.16	6.3	−72.4	12.2
Bideltoid breadth	431	448	457	473	491	511	529	540	561	0.15	6.4	68.0	13.7
Acromion-radiale length	310	322	328	338	350	361	371	377	389	0.21	–	−20.3	10.3
Trochanterion height	844	877	895	924	956	987	1015	1032	1065	0.62	–	−156	24.0

Measure = α_1* stature + α_2* BMI + α_3 + $N(0,s)$.

Table 5
Example of coding of individual in genetic algorithm.

	Factor 1	Factor 2	Factor 3	Factor 4
Percentile of satisfied people	94	92,3	91,7	99,8
Level of factor	41	24	18	99
Coding in binary for GA	0101001	0011000	0010010	1100011

4.2.1. *Encoding of the design variables*

The combination of four selected factors must explain the percentage of the total population that is able to interact with the resultant design in the intended manner (i.e., they "fit"). A candidate design or individual is defined by the set of four parameters for the design variables (the accommodation targets for each of the measures). For example:

$$\text{Individual} = [94 \;\; 92.3 \;\; 91.7 \;\; 99.8]$$

A binary string represents a variable where the length of the string depends on the number of allowed levels for the variables. A example is given Table 5.

4.2.2. *The fitness function*

For each factor, the corresponding population (ex: 91% for the first factor) is determined and the union of these selected population is identified. The number of element of this final population allows us to calculate the overall accommodation level compared to the original population (Fig. 4).

To enhance the performance of the GA, the parameters must be finely tuned. The parameters are:

- Wheelrate Rw: weight given to the selected individual in the selection process,
- Crossrate ($0 \le Rc \le 1$)
- Mutrate ($0 \le Rm \le 1-Rc$)
- Selection rate Rs (Rs = 1−Rc−Rm)

The Wheelrate is the weight given to the best individuals in the selection of parents at the renewal of the population, fixed to 6 (Poirson et al., 2013). The first step is to estimate the number of generations needed to converge Poirson et al. (2010b). A simulation of 10,000 iterations allowed us to determine the convergence graphically (Fig. 5).

The graph represents the average and minimum distance of the percentile target. We can consider that keeping the limit of 100 generations is a good compromise between a useful result and a reasonable computing time.

As in the MOGA-II algorithm (Poles et al., 2004), each chromosome of the population is a parent of the following generation. That attribute gives robustness to the algorithm. Furthermore, the use of directional crossover helps to speed convergence. The second step is to tune the crossover rate and the mutation rate. We will check if the settings accelerate convergence. Mutrate varies from 0.1 (mutrate is decided not to be 0) to 0.9 (for Crossrate to exist) and

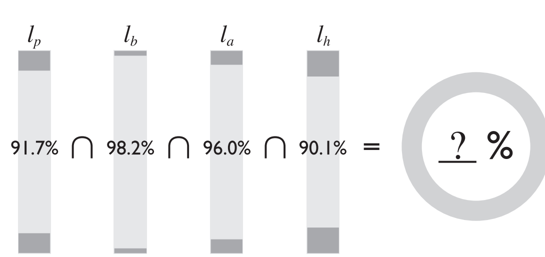

Fig. 4. Illustration of the fitness function of the GA.

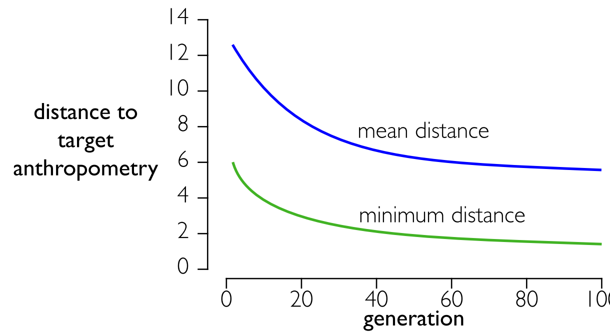

Fig. 5. The convergence of the genetic algorithm (measured as the mean and minimum fitness at each generation.

Crossrate varies from 0.1 to 1-mutrate (in 0.1). For each combination, 100 tests are performed and the mean minimum and the mean average distance of the last generation to the target (100th generation) is the indicator. The results are given Table 6.

From the results shown by Table 6, the rates of mutation and crossover are set at 0.1 and 0.7 respectively. The set-up of the genetic algorithm is summarize in Table 7).

4.3. *Genetic algorithm results*

Ideally, the seat must fit the most pilots. However, in this type of product where costs are extremely high, and where every gram and can save costs over the lifetime of the product, manufacturers require restrictions on the accommodation target. The genetic algorithm can help to identify the designs that product the best outcomes.

Starting from the design target and a table of anthropometric data, the GA give a list of combinations of percentages for each variable. These individuals are the product of the last generation of the GA. At each generation, a log of combinations that meet the target is also kept. This allows us to keep a variety of solutions that could have been eliminated. Indeed, in a generation, only two satisfactory solutions are selected to be favored by the wheelrate, although perhaps more were suitable for the user and are absent in the next generation. This "trace" will thus keep a significant diversity.

Table 6
The minimum and average distances of the last population to the target, depending on the mutation rate and crossrate.

Mutation rate	Crossover rate								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Minimum distances									
0.1	4.7	2.94	2.60	2.34	1.89	1.73	1.68	**1.59**	1.61
0.2	4.37	3.76	2.96	2.32	2.49	1.81	**1.59**	**1.59**	0
0.3	5.64	4.27	3.22	2.67	2.04	1.95	1.95	0	0
0.4	6.07	4.93	4.46	3.81	3.23	2.57	0	0	0
0.5	6.29	4.86	5.04	3.93	4.01	0	0	0	0
0.6	5.57	6.13	5.20	4.84	0	0	0	0	0
0.7	5.78	6.15	5.32	0	0	0	0	0	0
0.8	5.82	5.38	0	0	0	0	0	0	0
Average distances									
0.1	9.76	7.52	6.50	6.24	5.15	4.30	**3.85**	4.05	3.43
0.2	10.02	9.32	8.25	7.02	6.82	6.14	5.05	5.05	0
0.3	11.63	9.75	8.91	8.40	7.59	6.94	6.21	0	0
0.4	11.91	10.72	10.30	9.52	9.05	7.72	0	0	0
0.5	12.33	11.32	10.76	10.02	9.76	0	0	0	0
0.6	12.02	11.87	10.93	10.74	0	0	0	0	0
0.7	11.92	11.68	10.95	0	0	0	0	0	0
0.8	11.98	11.56	0	0	0	0	0	0	0

Table 7
Final settings for the genetic algorithm.

Variable	Target of the objective function	Population size	Nb max of generations	Wheelrate	Mutrate	Crossrate	Reproduction rate
$x = (x_1, x_2 \ldots, x_n)$ n = nb of factors	X, given by the designer	40	100	6	0.1	0.7	0.2

The number of elements in the list of combinations can be very important. The first step is to sort the list to remove duplicates and close combinations. For this, the notion of variant solution is defined. A solution will be different from another (and therefore regarded as an alternative) if one of its attributes varies by at least 0.5 and the sum of deviations greater than 1.5. This means a difference of about forty people in the present study. To define these variants, the final population was initially studied and the populations studied earlier are in descending order of generation. This will keep the convergence of the genetic algorithm and support elements of past generations.

In our case with four variables, the Table 8 presents the results. Gen.100 is for the last generation and AS for Acceptable Solution. Trace is the other collected AS of the GA, depending on the number of generation (Table 8).

The genetic algorithm produced a set of 49 candidate solutions. These need to be presented to the designer of seats. Parallel graphs are proposed as a tool for doing this. The designer can observe the evolution of solutions by manipulating the design parameters according to outside knowledge such as domain expertise and the relative costing of the design elements. For example, adjustability on one dimension might be a more economical alternative for achieving the target accommodation level than another.

The parallel graph (Fig. 6) is a tool for visualization and comparison of solutions. These can be examined in high-level dimensions (i.e., the number of design variables in a problem). The principle of the parallel graph is to represent each variable on a vertical axis. The lower and upper bounds of each vertical axis depend on the extrema in the relevant measures of body size and shape in the target user population. The data are normalized such that each vertical axis is spatially equivalent.

This parallel graph is also an interactive tool for the designer, who can visualize the distribution of the population and the fitness of the solution. The other particularity of this tool is that it can filter out solutions in real time. This perceptual exploration could help the designer to choose the best filtered solutions.

On the left of the graph (Fig. 6), the designer can select a variant or solution of the genetic algorithm and move the extrema of the variables around this solution to adapt it with his expertise. In this manner one can make a design decision on the product, depending on the mathematical optimization and the constraint of its precise domain.

The data for the seat scenario in which the target accommodation level is set to 90%. Two randomly selected results are given in Table 9, with the corresponding extrema for each scale.

5. Discussion

This study allows to identify which human measurements are critical for a given cockpit design. A good fitting of human body with the cockpit seat is essential and not only on the global stature.

Table 8
Solutions with or without "Trace" and variants of solutions of the GA.

# of AS in Gen100	# of variant in Gen100	# of AS in Trace	Total# of AS
16	2	3011	49

Every interaction parameter must be studied. The simplest way to consider X% of the population is to reduce the population at X% on each parameters (foot length, acromion height ...). This only works under the hypothesis that human is proportional: the taller have the longer arm, larger head size or larger feet. This assumption is too strong to be realistic.

The second strong point of the study is the number of parameters that could be taken into account. In Garneau (Garneau and Parkinson (2008)) a combination of two factors is studied. This methodology is not usable for more factors. When the number of human parameters to take into account increases (which is rapidly the case), the proposed method allows the designer to make universal design (or design for the greatest number).

Thirdly, the representation in broken lines allows the designer to see the evolution of the population in real time. One can imagine adding a price parameter settings for example, leaving the hand to the designer to make his choice. The next step is to link these results with measurements of the pilot seat and to deduce the necessary adjustments for the drivers considered.

Our method presents also some limits. Firstly, the use of a heuristic with the genetic algorithm prevents us to have every time the best solutions but give us family of good ones (the best seen by the algorithm). The comprehensive methods will give the best solutions but in a computation time too high, which does not allow interactivity with the designer, who often need some back and froths. Secundly, all the parameter are on the same line of priority in the multi-objective optimization tools. The opportunity to balance the result depending on the priority for the industrial (cost, weight ...) should be given to the user.

6. Conclusion and future work

The consideration of human factors in airline pilots is fundamental. Companies do not have the necessary data for the target

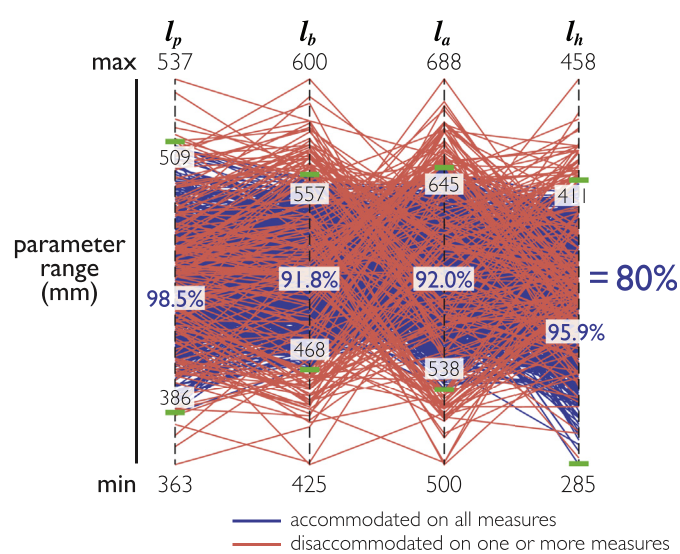

Fig. 6. The 800 accommodated and 200 disaccommodated individuals in a representative pilot population. Since measures are not perfectly correlated, high levels of accommodation on individual measures can result in overall accommodation that is much lower.

Table 9
Results of the GA: 2 examples of solutions for l_p, l_b, l_a and l_h

	Percentile				l_p		l_b		l_a		l_h	
	l_p	l_b	l_a	l_h	Min	Max	Min	Max	Min	Max	Min	Max
Solution 1	98.6	98.5	98.4	98.7	381	488	442	558	535	664	299	390
Solution 2	98.8	97.4	98.2	98.7	379	489	449	550	535	663	299	390

user population. This is the case for many other applications. Sometimes a few summary statistics are available, but they generally focus on gross body dimensions such as stature, mass, and BMI. For this reason, a comprehensive approach to synthesizing the necessary detailed anthropometry was presented. The second step was to generate the various measures of the pilots such that multivariate design could be conducted. Eight synthesis methods were compared: proportionality constants, boundary ratios, simple linear regression, multiple linear regression, simple linear regression with a stochastic term, and multiple linear regression with a stochastic term. The results show the performance of the method for adding an error (to complete).

In the second part, once the anthropometric data are available, genetic algorithms have been adapted to determine the optimal combinations of variables. Indeed, if the designer knows the target to be achieved (maximum percentile for example), it is difficult to associate directly the values of variables corresponding to them. Genetic algorithms provide families of solutions that meet the objectives of the designer. To allow the exploration of these solutions, the parallel graph is made available. It can explore the robustness of solutions and make sound business expertise. The next step will be to link the human data to the adjustment and interval of variation of these adjustments of the pilot seat.

Acknowledgments

This research was partially funded by the National Science Foundation under Award No. 0846373. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

Acar, B., Weekes, A., 2006. Measurements for pregnant drivers comfort and safety. Int. J. Vehicle Des. 42 (1–2), 101–118.
Barkla, D., 1961. The estimation of body measurements of British population in relation to seat design. Ergonomics 4 (2), 123–132.
Bittner, A.C., 2000. A-cadre: advanced family of manikins for workstation design. In: Proc. Human Factors and Ergonomics Society, pp. 774–777.
Blackwell, S., Brill, T., Boehmer, M., Fleming, S., Kelly, S., Hoeferlin, D., Robinette, K., 2008. Caesar Survey Measurement and Landmark Descriptions. Tech. rep.. Air Force Research Laboratory, Wright-Patterson AFB, OH.
Brainard, J., Burmaster, D.E., May 1992. Bivariate distributions for height and weight of men and women in the United States. Risk Anal. 12 (2), 267–275.
Dewangan, K.N., Owary, C., Datta, R.K., 2008. Anthropometric data of female farm workers from north eastern India and design of hand tools of the hilly region. Int. J. Ind. Ergon. 38 (1), 90–100.
Drillis, R., Contini, R., 1966. Body Segment Parameters. Office of Vocational Rehabilitation Engineering and Science, New York.
Flannagan, C., Manary, M., Schneider, L., Reed, M., 1998. Improved seating accommodation model with application to different user populations. In: Proceedings of the SAE International Congress and Exposition, vol. 1358. SAE, Warrendale, PA, USA, pp. 43–50.
Fromuth, R., Parkinson, M., 2008. Predicting 5th and 95th percentile anthropometric segment lengths from population stature. In: Proceedings of the ASME International Design Engineering Technical Conferences. No. 50091 in DETC2008.
Gannon, A.J., Moroney, W.F., 1998. The validity of anthropometric predictions derived from proportional multipliers of stature. In: Proceedings of the 42nd Meeting of HFES. Chicago, IL.
Garneau, C., Parkinson, M., 2008. Optimal product sizing through digital human models. In: SAE Digital Human Modeling Conferences. Pittsburgh, PA.
Garneau, C., Parkinson, M., 2009. Including preference in anthropometry-driven models for design. ASME J. Mech. Des. 130 (10), 6.
Garneau, C., Parkinson, M., 2010. A comparison of methodologies for designing for human variability. J. Eng. Design.
Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimisation and Machine Learning. Addison Wesley, Reading.
Gordon, C.C., Churchill, T., Clauser, C.E., Bradtmiller, B., McConville, J.T., Tebbetts, I., Walker, R.A., 1989. 1988 Anthropometric Survey of U.S. Army Personnel: Methods and Summary Statistics. final report. Tech. Rep. NATICK/TR-89/027. U.S. Army Natick Research, Development and Engineering Center, Natick, MA.
Haslegrave, C.M., 1986. Characterizing the anthropometric extremes of the population. Ergonomics 29 (2), 281–301. URL. http://www.informaworld.com/10.1080/00140138608968265.
HFES 300 Committee, 2004. Guidelines for Using Anthropometric Data in Product Design. Human Factors and Ergonomics Society, Santa Monica, CA.
Holland, J.H., 1992. Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control and Artificial Intelligence. MIT Press, Cambridge, MA, USA.
Mehta, C., Gite, L., Pharade, S., Majumder, J., Pandey, M., 2008. Review of anthropometric considerations for tractor seat design. Int. J. Ind. Ergon. 38 (5–6), 546–554.
Moroney, W., Smith, M., December 1972. Empirical Reduction in Potential User Population as the Result of Imposed Multivariate Anthropometric Limits. Tech. Rep. Tech. Rep. NAMRL-1164 (AD 752 032). Naval Aerospace Medical Research Laboratory, Pensacola, FL.
Nadadur, G., Parkinson, M., 2008. Extrapolation of anthropometric measures to new population. In: Proc.. of the SAE Digital Human Modeling Conferences. Pittsburgh, PA.
Nadadur, G., Parkinson, M., 2009. Consideration of demographics and variance in regression approaches to estimating body dimensions for spatial analysis of design. ASME J. Mech. Des. 132 (2).
Papalambros, P.Y., Wilde, D., 2000. Principles of Optimal Design: Modeling and Computation, second ed. Cambridge University Press, New York.
Parkinson, M., Reed, M., 2006. Optimizing Vehicle Occupant Packaging. SAE International 1 (2006-01-0961).
Parkinson, M., Reed, M., 2009. Creating virtual user populations by analysis of anthropometric data. Int. J. Ind. Ergon. 40, 106–111.
Penman, A.D., Johnson, W.D., July 2006. The changing shape of the body mass index distribution curve in the population: implications for public health policy to reduce the prevalence of adult obesity. Prev. Chronic Dis. 3 (3), 1–4.
Pheasant, S.T., 1982. A technique for estimating anthropometric data from the parameters of the distribution of stature. Ergonomics 25 (11), 981–992.
Poirson, E., Petiot, J.-F., Aliouat, E., Boivin, L., Blumenthal, D., March 2–4 2010a. Interactive user tests to enhance innovation ; application to car dashboard design. In: International Conference on Kansei Engineering and Emotion Research KEER2010, PARIS.
Poirson, E., Petiot, J.-F., Aliouat, E., Boivin, L., Blumenthal, D., 2010b. Study of the convergence of interactive genetic algorithm in iterative user's tests: application to car dashboard design. In: IDMME - Virtual Concept. Bordeaux, France.
Poirson, E., Petiot, J.-F., Boivin, L., Blumenthal, D., 2013-01. Eliciting user perceptions using assessment tests based on an interactive genetic algorithm. J. Mech. Design 135 (3). http://dx.doi.org/10.1115/1.4023282. Available in line.
Poles, S., Rigoni, E., Robic, T., 2004. Moga-II: performance on noisy optimization problems. In: Proceedings of the International Conference on Bioinspired Optimization Methods and Their Applications. Jozef Stefan Institute, Ljubljana, p. 51.
Qian, L., Ben-Arieh, D., 2009. Joint pricing and platform configuration in product family design with genetic algorithm. In: Proceedings of IDETC/CIE 2009, August 2009, San Diego, CA, USA.
Research Institute of Human Engineering for Quality Life, 1994. Japanese Body Size Data, Human Engineering for Quality Life.
Ryu, T., Jung, I.J., You, H., Kim, K.J., 2004. Development and Application of a Generation Method of Human Models for Ergonomic Product Design in Virtual Environment. Proceedings of the Human Factors and Ergonomics Society, 48th Annual Meeting.
Roebuck, J., 1995. Anthropometric Methods: Designing to Fit the Human Body. Human Factors and Ergonomics Society, Inc.
SAIGLOBAL, 1988. China Standards GB/T 10000–11988: Human Dimensions of Chinese Adults. Administration of Technology Supervision – People's Republic of China.
Veerman, J.L., Barendregt, J.J., van Beeck, E.F., Seidell, J.C., Mackenbach, J.P., 09 2007. Stemming the obesity epidemic: a tantalizing prospect. Obesity 15 (9), 2365–2370. URL. http://dx.doi.org/10.1038/oby.2007.280.