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Abstract: The relationship between garment design parameters, wearer morphology, posture, fabric properties and ease allowance values is very complex and uncertain due to the presence existence of various human factors related to designer and consumer perception. The aim of this work is to set up a series of mathematical models to characterize and determine the relationship between these parameters. For this purpose, fuzzy modelling techniques were proposed to extract IF-THEN rules by learning from the experimental data. First, the general modelling principle and related concepts were outlined. The different samples collected to obtain the learning data were described in detail. The samples were then characterized by instrumental measurements and sensory evaluations to form the input and output data for modelling. Based on the obtained input and output learning data, it became possible to determine the modelling procedure to extract relevant fuzzy rules. The computation then helps in determining the 3D ease allowance values from the desired human perception on fit, comfort and other design parameters. For a new sample and consumer morphology, the relevant degree of input datawith respect to all the fuzzy rules was also calculated to find the most appropriate ease allowance value. The developed mathematical model followed by experiments also provides advantages in controlling and adjusting patterns according to perceptions of the designer and consumer. The concept of determining 3D ease allowance could be further integrated into the 3D clothing CAD approach to obtain a suitable garment surface on specific virtual human model environments to customize any garments in the fashion industry.

Keywords: computer-aided design; virtual garment; three-dimensional (3D) ease allowance; mathematical modelling; fuzzy techniques; garment Industry.

1. Introduction

3D human body generation and its human-centred design is a growing research topic in various applications areas and has received much in the product design process [1][2]. To this end, many efforts have been made to generate an accurate and reliable digital human model to analyse the effects between the human user, materials, and final products [3][4]. In the garment design process, not only the modelling of human body shape is very important for realizing the proper garment design, but also the integration of various parameters. For example, fabric materials are stretchable but cannot be deformed well during the garment design process. Therefore, an additional measurement and ease allowance calculated from body sizes could be added to obtain a space gap and allow movement between garment and body surface[5–7]. The presence of such a space gap during the garment design process determines both the functionality and comfort, fit, design and style of the final garment [8, 9]. It is also an essential design element in both two- and three- dimensional pattern development process. Moreover, ease allowance along with the fabric physical properties, features, proportions/correlations between the body and the garment play a major role in the comfort and fit of the garment fitting [10]. Different researchers have developed different approaches to quantify and determine ease allowances for garments. For example, the ease allowance could be determined as a linear distance at a different location and added to the flat pattern during the traditional 2D pattern making process [11–13]. Such a basic method helps to quantify the ease allowance by measuring the circumference difference between the garment and the human body [14–17]. In another study, different levels of ease were also determined based on widely used pattern construction methods and compared with the original body measurements. The result showed that the assessed ease could be used more for selected block patterns and direct design methods [18]. Similarly, another study investigated the relationship between the ease allowance and the pressure of clothing acting on different parts of the body (breast/chest, back and waist) [19]. A theoretical model was also developed to numerically account for the comfort allowance in the clothing pattern [20]. Such a developed model suggests the need to quantify the partially coincident variables of ease, which will allow greater control over garment fit and function, using traditional or CAD/CAM methods. Recent research has also proposed a method for defining 2D ease allowance based on fuzzy logic techniques, sensory evaluation and data aggregation [21]. Such methods provide an opportunity to develop a new automatic pattern generation system to improve the wearer's fit perception and then validate it with experimental methods using already defined ease allowance values. Another research work also developed and analyzed the distribution of ease allowance in a jacket as a function of size and material used [22]. However, this research work could be criticized because it was created using the notion of morphotypes only for large sizes. The 2D ease allowance has also been determined using different methods, including measuring the change in body surface length [23, 24]. Three-dimensional motion capture (3DMCS) was also used to investigate the distributions of 2D ease at different garment positions using [25]. However, the determination of 2D ease allowance in garment design based on body lengths and circumferences could not provide complete information about the three-dimensional body shape. Therefore, quantifying and determining the ease allowance in the 3D environments is very important and advantageous over 2D ease allowance to properly consider the 3D shape of the wearer. Various researches and developments of 3D CAD (Computer-Aided Design) for virtual garment simulation to interact with various design applications help to avoid the inherent problems of the 2D CAD paradigm [26–37]. The technology significantly reduces the developments of real prototypes, but also introduces difficulties for the wearer to sense whether a garment is correctly fitted to the real try-on morphology or not [38]. To solve such problems, several solutions have been proposed to evaluate the fit of garment during virtual try-on. For example, the first approach uses the empirical knowledge of evaluators with different measured indicators, the 3D ease allowance or the air layer thickness between the garment and the human body [39]. Another proposed approach was the visual rating system based on fashion designers/experts on a 3D garment [40, 41]. Such a method uses pressure, stress and fit maps to evaluate the fit of garment generated by virtual try-on software. However, the quality of the evaluation has been criticized as it strongly relies on mathematical models [42]. Another researcher has also proposed a Naive Bayes-based model to evaluate garment fit [43]. The use of pressure was found to be much better than 2D ease allowance for evaluating garment fit. Various virtual prototyping technologies have also been developed to innovate the apparel industry by using specialized tools for body capture, modelling and simulation of garments. For example, in one study, great attention was paid to the design of made-to-measure garment, i.e. capturing the customer's measurements [44] and Tailor Tracking, to obtain the measurements by interacting with the customer's avatar with their hands as in the traditional way. On the contrary, a study developed a collaborative garment design method using the 3D-to-2D virtual draping, which is realized through the interaction between designers, pattern makers, and customers [45]. The work used a knowledge base for fashion design and knowledge base for 2D pattern design to enable the automation of collaborative design for disabled people with scoliosis. Moreover, the existing methods for automatic pattern generation using CAD systems mostly consider standard ease allowance and are not able to calculate the corresponding values of ease allowance to describe the wearer's shapes and movements. Therefore, several research works have proposed a 3D ease allowance model that is directly created in the 3D space of the virtual environment to correctly shape the surface of all zones with strong contact [46]. For example, the distribution of the 3D ease allowance of the garment was modelled by analyzing the difference between the shapes of the cross-sections of the garment and the human body at different vertical positions. The prediction model allows it possible to improve the shape of these cross sections by integrating the width of the horizontal section, the number of wrinkles, the amplitude of these wrinkles and the bending stiffness of the fabric. However, the proposed model could not yet be directly applied to garments as they are not conceivable. Another study also developed a method to analyze the 3D ease allowance by defining the different levels and capturing the gap between the garment and the body [41]. Later, the total 3D ease allowance was determined and evaluated by an image processing method on ellipses and a reverse methodology. Similar work has been done by another research group to calculate the pattern change of women's suits based on 3D ease distribution [47]. Based on our discussion above, the calculation and determination of 3D ease allowance has better advantages than 2D ease allowance for garment specifically designed in 3D space. However, the relationship between ease allowance and garment design, styles, wearer morphology, postures, fabric properties, fit etc. is still very complex and can only understood by analytical methods. In our previous work [48][21], a fuzzy logic-based method was used to generate ease allowance values only on important body parts considering standard ease and dynamic ease. However, it calculates the general 2D ease allowance with the fuzzy model corresponding to a certain key body part and movement of the wearer. However, to the author's knowledge, there is no research study on the determining of the various mentioned parameters with the easy allowance during the garment design in the 3D environment for better fit and comfort of the garment. To achieve this, we used the fuzzy models to characterize and determine the relationship between ease allowance and these elements for the following reasons:

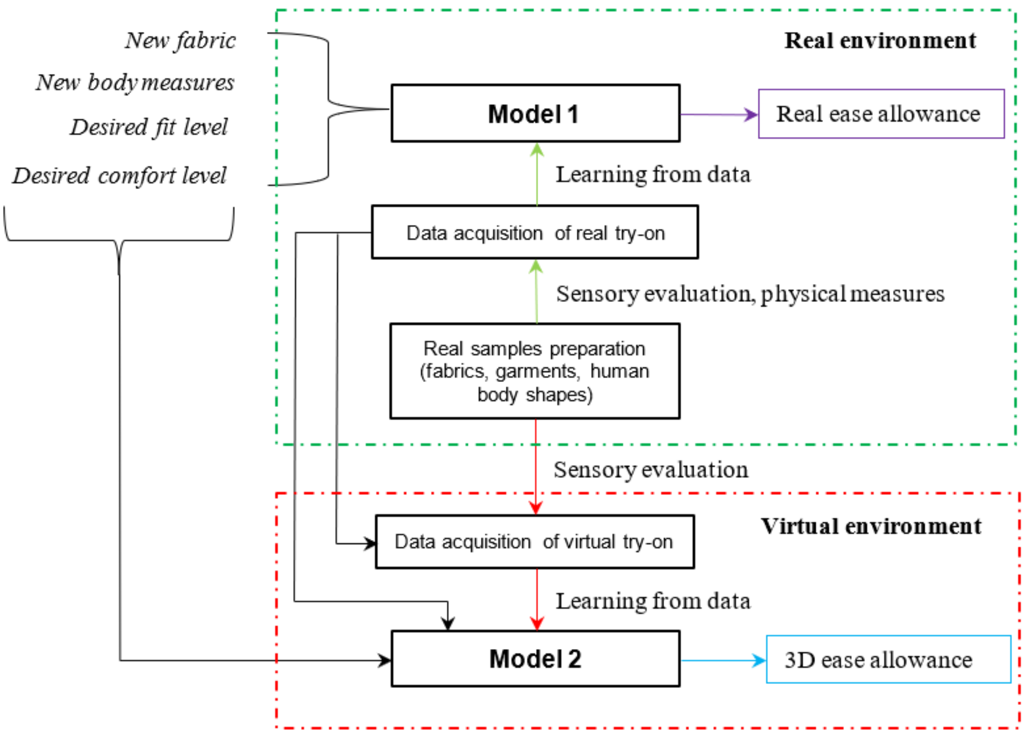
i) The relationship between the different sample parameters (garment style, design, posture, fabric properties) and the ease allowance is very complex and cannot be modelled using only analytical equations. Therefore, the application of a fuzzy model facilitates the characterization of these complex relationships by using both numerical data and human knowledge.
ii) Moreover, the computed model integrates the wearer's perception of comfort (subjective evaluation criterion) with a set of linguistic expressions, since it can handle both linguistic and numerical variables simultaneously.

iii) Fuzzy rules are easy to interpret models; therefore, fashion designers could easily understand the structure and parameters of the model to compare with their professional knowledge and experience.

Therefore, our current work established a series of fuzzy modelling techniques to determine the relationship between ease allowance and other important design parameters. First, the general modelling principle and various samples to obtain the learning data were well described. The samples were then characterized by both instrumental measurements and sensory evaluations to obtain input and output learning data for modelling. Then, the modelling procedure was designed to extract relevant fuzzy rules to predict the 3D ease allowance values from the desired human perception to fit, comfort, and other design parameters. Further calculations were presented to determine the most appropriate ease allowance value for different sample parameters and consumer morphologies with suitable input data. The developed mathematical model helps in controlling pattern generation according to designer and consumer perceptions. It can also be integrated with the 3D ease allowance with the 3D CAD garment approach to obtain a suitable garment surface on a specific human model to efficiently fit the garments in virtual environments.

2. General principles for determining the 3D ease allowance

In this study, we considered the best strategy of a remote custom apparel design system using virtual reality tools to optimally manage and control the interactions between real and virtual design environments. For example, in the real design environment (*Model 1*), various real fabric types, garment patterns and wearers' body shapes are used to determine the relationship between ease allowance and various factors (real garment fit and comfort, human



morphologies, and material properties). With this model and another associated learning database (obtained from the real samples), a real fitting garment is used to validate all proposed design solutions in terms of comfort and fit. On the contrast, in remote garment design, there are neither real fabrics/samples nor physical contact between consumer/designer. Therefore, the 3D CAD tools were used in a virtual environment to create virtual 3D garments.

Figure 1. The general principle for predicting 3D ease allowance by using a data-based modelling approach

A virtual garment try-on was also developed to validate all the proposed design solutions in relation to a given body shape in terms of virtual clothing comfort and fit. In this way, the relationship between 3D ease allowance, virtual garment fit, and other concerned elements should be quantitatively quantified. However, in the virtual environment, neither the garment comfort nor the garment fit can be visualized or necessarily adjusted compared to the real environment. In this case, it is very important to quantitatively determine the relationship between the real fit and comfort of the garment with virtual garment fit and other influencing factors (*Model 2*).

The two design models then help us to control the interactions of garment design elements in both real and virtual environments. Therefore, based on these two models, it is possible to effectively predict and determine the 3D ease allowance values for a particular wearer, fabric material and other design parameters. It is also very important to determine the 3D ease allowance values to obtain a perfectly fitting garment for the wearer's morphology at different postures. The general principle of this modeling procedure is shown in Figure 1**.** The modelling procedure is mainly based on the data collected from a number of real samples such as selected wearers/subjects, fabric types, and samples/garments. Thus, data acquisition was implemented using physical measurements and sensory evaluations system for fabrics and garment fit and comfort, respectively. *Model 1* helps to characterize the relationship between real ease allowance and perceived real garment fit and comfort, fabric properties and human body measurements (i.e., Real ease allowance = Model 1 (garment fit perception, comfort perception, body measurements, fabric properties). In addition, *Model 1* was also responsible for defining the most relevant ease allowance value that corresponds to comfort and fit desired by consumers and designers for each specific body shape, fabric selected, and clothing style. Meanwhile, *Model 2* supports the characterization of the relation of the 3D ease allowance and the garment real fit and comfort, the garment's perceived virtual fit, fabric properties, and body measurements (i.e.,3D ease allowance = *Model 2* (real garment fit, comfort, virtual garment fit, ease allowance, body measurements, fabric properties). In *Model 2,* virtual garment fit was introduced as a new input variable to control the interaction between the real and virtual environments and predict the 3D ease allowance from both real learning data and the desired fit and comforts of desired real garments compared to *Model 1*.

3. Different data acquisition

3.1 Formalization and preparation of samples

3.1.1 Formalization of fuzzy model

The fuzzy model, which is considered a universal approximator, has been used to characterize complex relationships in uncertain environments (linguistic variables, imprecise human knowledge and judgments, etc.) [49–53]. This kind of model can be developed using numerical data, human knowledge, and linguistic variables, and integrates the wearer's perception of comfort, which is a subjective evaluation criterion corresponding to a set of linguistic expressions (very comfortable, comfortable, uncomfortable). Fuzzy logic models have also been used to quantify the different levels of garment ease allowance (standard ease, movement ease, and fabric ease). In our current research work, the commonly used MATLAB software package fuzzy control with inference mechanisms called Mamdani [50] was used. This is not only because the rule bases are more intuitive and easier to understand for the expert system, but also because our rules only deal with the relations between linguistic values from the experience of human operation, where the output of each rule is a fuzzy set. Such a fuzzy rule involves includes linguistic values (from linguistic inputs to linguistic outputs) using membership functions to describe the concepts. The full Mamdani inference process (including fuzzification and defuzzification) consists of three basic steps: Fuzzification, implication process, defuzzification [54] as shown in Figure 2**.**

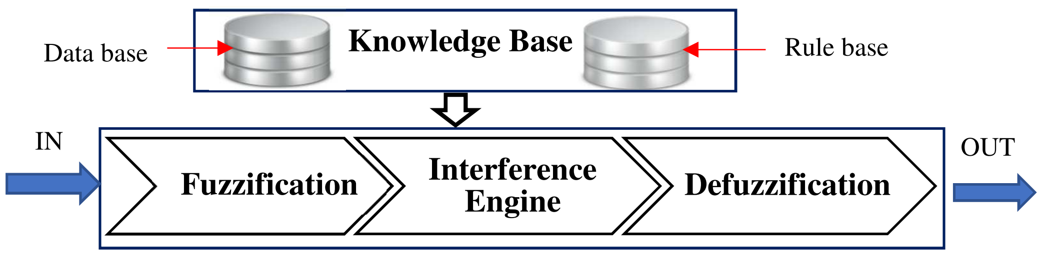
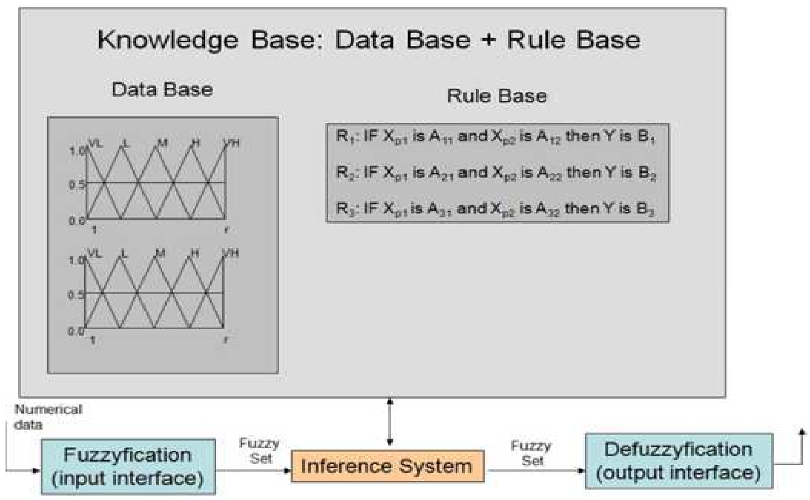


Figure 2. Schema of the fuzzy system

Fuzzification converted a numerical value into a vector associated with several linguistic



variables using assumed membership functions and their parameters. Meanwhile, we defined a set of IF/THEN fuzzy rules by learning from human knowledge/measured data as shown in Figure 3. In the learning phase, the input and output data are converted into linguistic values using the associated degree of membership and the IF/ THEN rules have been created. In Fuzzy Inference System, on the other hand, all new input data are transformed into a fuzzy value (fuzzy set) at the fuzzification stage. The fuzzy value is then formed by aggregating all rules.

Figure 3. Structure of Fuzzy Rule System.

In this study, the learning dataset constitutes the foundation to set up the proposed model. Therefore, it is composed of the following learning database issues.

- {W1, …, Wn}: the set of n selected wearers with different morphologies covering the whole target population.
- {F1, …, Fm}: the set of m selected representative fabric materials for the garment to be designed.
- {EA1, …, EAp}: the set of p ease allowance values selected for different sizes of the garment.
- {P1, …, Pq}: the set of q postures in which the designed garment is evaluated.

Based on this, there are s fuzzy rules in the knowledge base under the form:

$IF\ \ x\ is\ A_i\ \ THEN\ \ y\ is\ B_i\ i = 1, \ldots\ldots, s$

Where $\mathrm{x} = (x_1, x_2, \ldots, x_m)$ and y are the inputs and outputs, respectively.
$A_i = (A_{i1}, A_{i1}, \ldots, A_{im})$, and B_i are the linguistic values corresponding to x and y respectively.

For each new input (crisp value), $\mathrm{x_p} = \left(x_{p1,} x_{p2,} \ldots, x_{pm}\right)$, different operations were performed. First, the computation of Matching Degree is realized by fuzzification. The degree of membership of the inputs to each input fuzzy set is determined. In order to calculate the matching degree of the input fuzzy set previously determined to satisfy with the requirements of each rule, a conjunction operator *C* is applied. The minimum t-norm is advised by the Mamdani method.

$$\mu_{A_j}(x_p) = C\left(\mu_{A_{j1}}(x_{p1}), \mu_{A_{j2}}(x_{p2}), \ldots, \mu_{A_{jm}}(x_{pm})\right) \tag{1}$$

This operation allows the evaluation of the membership functions used in the predicates of the rules. Later, the Indication Operator is applied using the implication method. The input fuzzy set $\mathrm{x_p}$ and the output fuzzy set y are combined using an intersection operation. The implication operator *I* can be a t-norm operation (we take the minimum in most cases).

$$\mu_{B'_j}(y) = I\left(\mu_{A_j}(x_p), \mu_{B_j}(y)\right) \tag{2}$$

Finally, the resulting output fuzzy set $\mu_{B'_j}(y)$ is converted transformed into a crisp value y_0 using the defuzzification process. To obtain the output value, two approaches can be applied, "first aggregation, then defuzzification" or "defuzzification first, aggregation after". Figure 4 shows the different methods of defuzzification. The Mamdani method proposes to apply the first approach by calculating the centroid of the fuzzy set $\mu_{B'_j}(y)$.

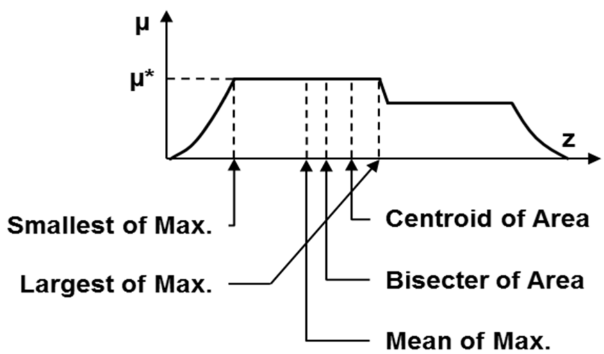
$$\mu_B(y) = Y_j \mu_{B'_j}(y) \tag{3}$$

$$y_0 = \frac{\int_y y.\mu_B(y)dy}{\int_y \mu_B(y)} \tag{4}$$

Figure 4. A different method of defuzzification.

However, the fuzzy rules extracted from the data become less efficient and difficult to interpret when the number of input variables increases. Therefore, the Principal Component Analysis (PCA) [55] with XLSTAT complete and flexible feature was used to reduce the number of input variables before extracting the fuzzy rules. By using this technique, a lower-dimensional input space is obtained from the projection of the original high dimensional space.

3.1.2 Subjects/Wearers body shapes

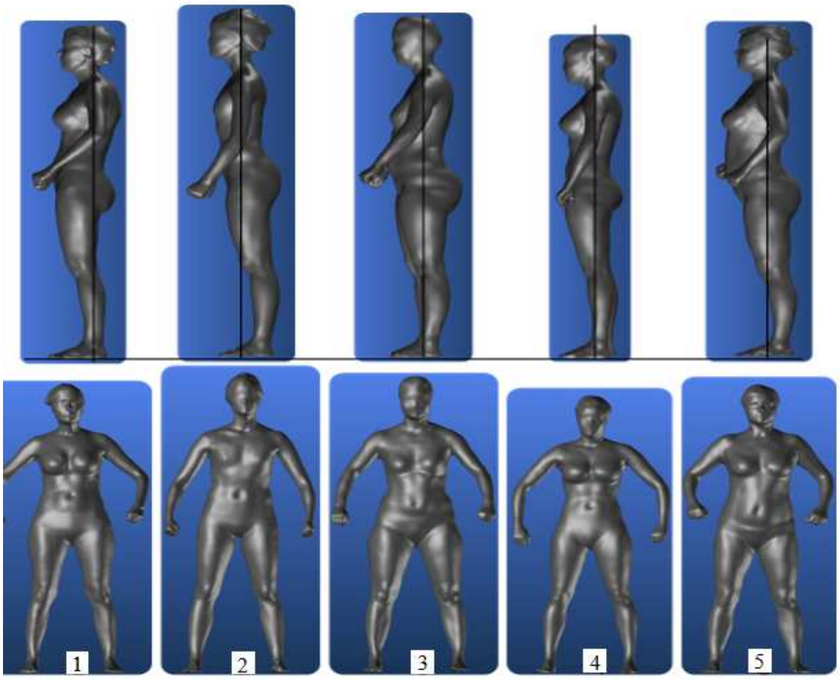


Although the outline of the general formalization process was used for all garment design and categories, the current study focused on customized design of sleeveless tops for five types of female body shapes (n=5). Subjects were drawn from a white female population from France and aged groups between 35 and 42 years. The wearers/subjects were selected based on their individual characteristics, such as bent forward (subject 1), small breasts (subject 2), prominent hips (subject 3), prominent breasts (subject 4) and slightly abdomen forward (subject 5) as shown in Figure 5. In addition, the selected subjects were not diagnosed with severe spinal problems, but they have different postures and body sizes.

Figure 5. Lateral and Posterior view of the virtual models.

3.1.3 Anthropometric equipment

Subjects are scanned with a Tecmath 3D body scanner from Human Solution to capture body measurements for virtual fitting. The subjects are dressed in underwear and stand in a predefined position set within the reach of the laser. The scanner was able to capture the body measurements with an accuracy of ± 1 mm, following the international standard DIN EN ISO 20,685.



3.1.4 Software

The acquired raw data from the body scanner is then corrected using Rapidform software [39] to convert the point cloud into a surface. The corrected surface can then be directly used by the 3D CAD tools for the modelling process. The virtual garments and virtual fitting effects were developed using Modaris 3D software [56] commercialized by the French Lectra Company. The side and rear views of the virtual models were used to analyze the posture of each subject (Figure 5). The figure analysis was calculated using the DesignConcept software tools [57] and all adjustments were made directly on the virtual body models. The different body dimensions for the selected wearers are shown in Table 1.

Table 1.Body measurements of the five selected wearers/subjects.

Body measurements (cm)	Height	Chest girth	Waist girth	Hip girth	Chest width	Under-bust circumference	Shoulder width (left)	Shoulder width (right)
W1	162.0	92.0	70.1	101.0	38.1	73.7	13.8	13.8
W2	165.5	83.2	67.5	95.8	36.9	75.2	12.4	12.6
W3	162.9	87.5	73.3	109.2	35.5	77.0	12.4	12.0
W4	156.5	88.3	63.3	96.0	37.9	70.8	14.9	14.7
W5	161.0	95.8	77.5	101.0	44.9	80.0	13.1	13.4

As it is observed from Table 1, the body measurements data among the subjects are different and somehow not proportional. This indicated that the subject data could represent the various body shapes of the target population.

3.1.5 Fabric materials

The different fabric properties also affect the comfort and fitness of the final garment. Four fabric materials with different fibre compositions were selected for the study. The selected fabric materials are 100% cotton (F1), 100% PES (F2), 100% linen (F3) and 65% PES and 35% cotton (F4). The different fabric materials with specific fibre composition were selected because they are not only commonly used for designing block patterns but also have quite different physical properties.

3.1.6 Ease allowance

The ease allowance may vary for the same type and style of garment depending on the purpose of wearing. For the current study, three values of ease allowance {EA1, EA2, EA} were suggested for each selected wearer based on the designer's experience to develop three different styles of garment {loose, normal, tight}. It is also considered that for each ease allowance (EA), the values of ease are different for certain body positions. Table 2 shows the values of the 3D ease allowance (EA) for the specific body positions.

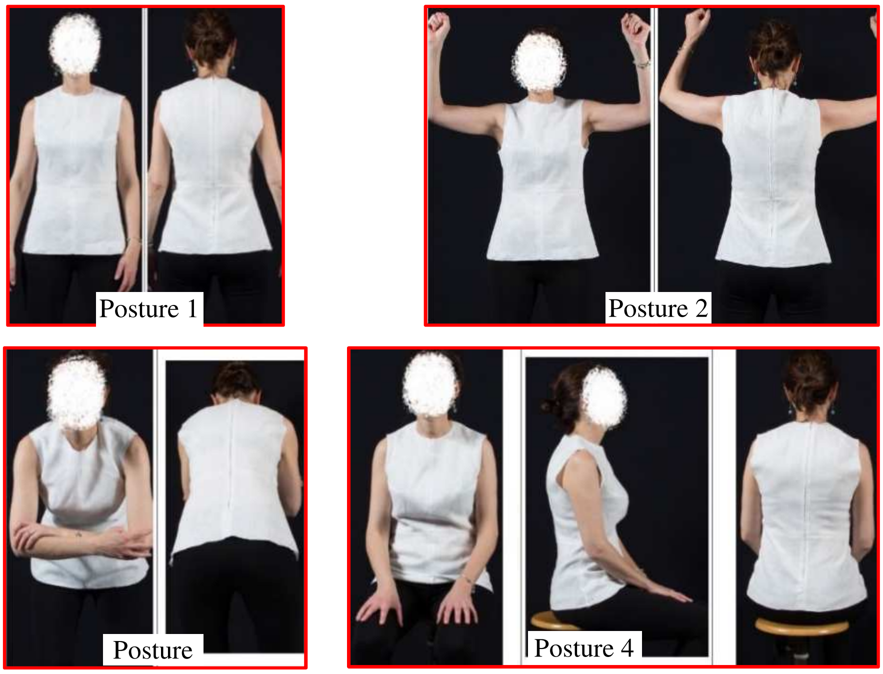
Table 2. 3D ease allowance values for different body positions.

3D EA (mm)	Chest	Waist	Hip	Collar
EA1	6.4	8	8	4
EA2	11	12.7	9.5	4.8
EA3	16	17.5	11	5.6

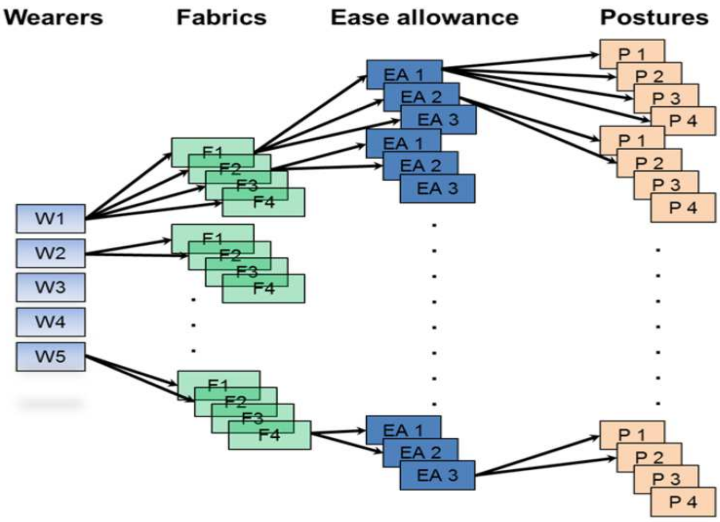
3.1.7 Body posture/position

Four different body postures {standing straight, standing with two arms raised, leaning forward and sitting} were used for the study. All garments are visualized and analyzed during the evaluation by the wearer and some selected design experts based on the four body postures. For example, Figure 6 shows the physical fit effects of the garment design (upper blouse) made for body shape (W1) with the fabric material F3 (100% linen fabric) and ease allowance EA1. However, sixty (5×4×3) different possible garments were produced considering the combinations of five wearers/subjects {W1, W2, W3, W4, W5}, four fabric materials {F1, F2, F3, F4} and three values of ease allowance {EA1, EA2, EA3} for further learning data generation (Figure *7*). During the evaluation process, each wearer/subject was rated based on one a fitting with the twelve concerning garments (combinations of four fabric materials and three styles) by the wearer herself and some design experts for all four postures. Therefore, the rating for each expert and evaluations for each subject/wearer becomes two hundred and forty (12×5×4=240) and forty-eight, respectively.

Figure 6. Fitting effects of a linen upper blouse on a wearer W1 with a fixed ease allowance EA1



Moreover, based on the previous real garment design parameters (measured physical fabric parameters and allowance values), and the morphology of the selected subjects, sixty virtual



garments with the corresponding virtual fitting effects were generated using the four body postures. For such a process, the Modaris 3D software, a commercial software of French Lectra Company, was employed.

Figure 7.Total possible combinations of subjects, garments, and postures.

The software includes a special tool to model different types of fabric to mimic and see the physical properties (tensile, flexural, shear, etc.) of a fabric. This greatly helps in observing the effects on the virtual garment in terms of style and fit while trying it on. Moreover, the model also helps to control the stretch rate of each fabric during virtual try-on fitting process for specific values to maintain the original dimensions after digital draping.

Figure 8 (a) shows a generated example of virtual garments and their fit effects from the front, side and back views on wearer W1 made with the same fabric material, F1 (100% cotton) and different ease allowance values {EA1, EA2 and EA3}. From the visual observation, we can easily see the effects of different ease allowance on the fitness effects of the virtual wearer regardless of the wearer and fabric properties.

For comparison purposes, we also plotted the front view of the generated virtual garment with strain distribution in the virtual garment considering the same wearer model, W1, and with the same ease allowance value but using different fabric types (100% cotton (F1), 100% PES (F2), 100% linen (F3) and 65% PES and 35% cotton (F4), as shown in Figure 8 (b). The result shows that the fabric properties also have an impact on the fitness of the virtual garment on the virtual wearer. The various data collected from all these samples including the real and virtual garments, fabric parameters and human perception of the fit and comfort of the garments are presented in the next sections and used to build the mathematical model using fuzzy techniques.

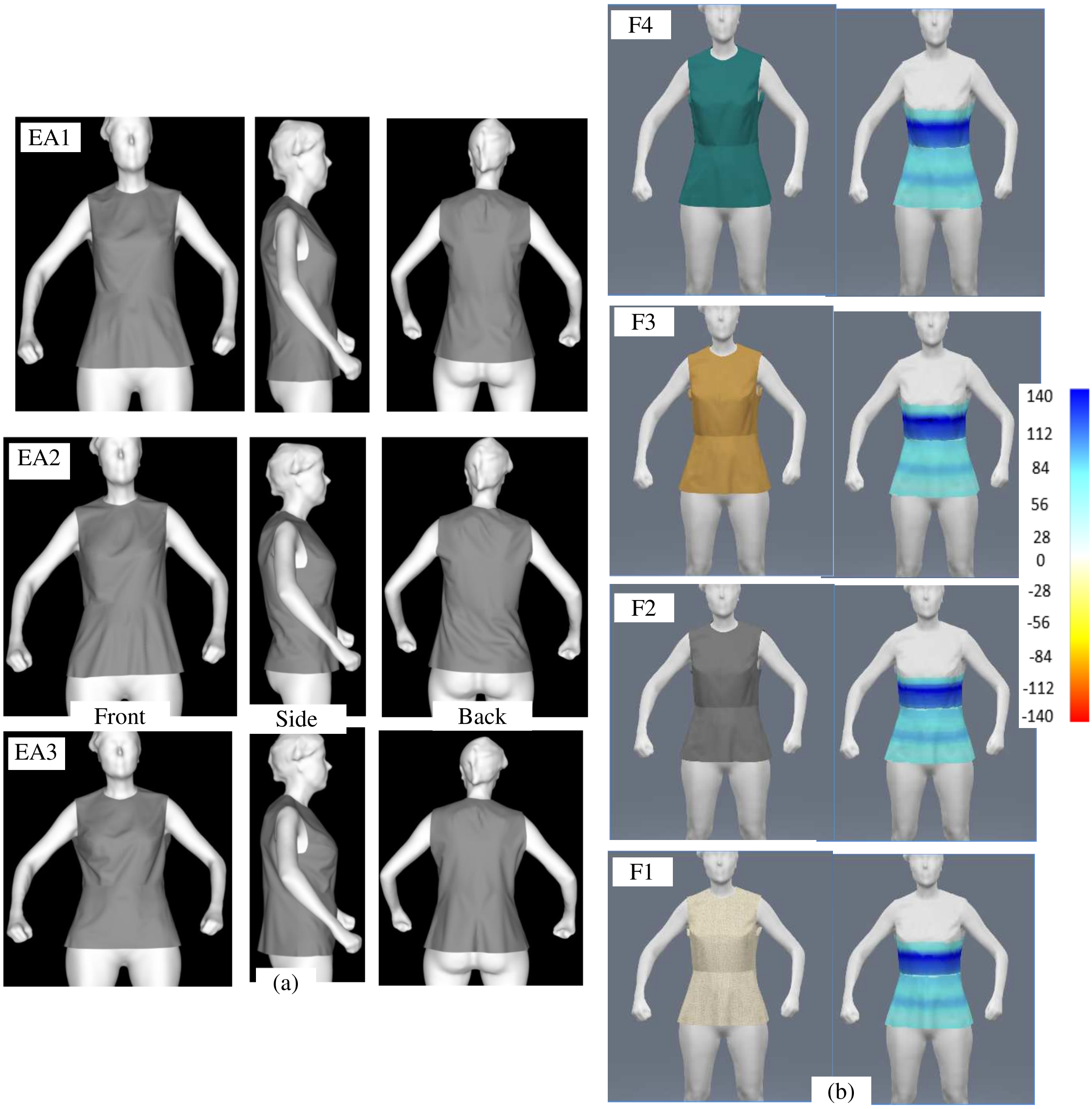


Figure 8 Virtual garments and their fitting effects (a) from the front, side, and back views on the wearer W1 made with fabric material, F1 (100% cotton) and different ease allowance values {EA1, EA2 and EA3}, and (b) of the four fabrics on the same wearer model W1 and same ease allowance value {EA2.

3.2 Technical fabrics parameters acquisition system

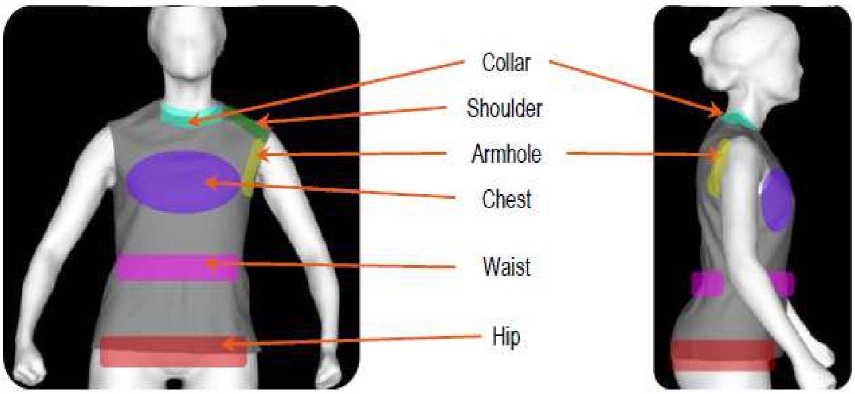
In the garment development, fabric hand feel, and visual appearance are two important selection parameters that contribute to the fabric quality of the final product. For example, the fit and comfort of the garment may change as the fabric properties change. The hand feel parameters of the fabric can be evaluated using human sensory evaluation technology and instrumental measurements. However, for a particular industrial application, the choice of evaluation method depends on the real-life conditions of the company. For example, sensory evaluation session becomes important when expert specialized in fabric quality are available with lower cost and human interpretation. In contrast, a set of instrumental tests could be used when either no expert is available, or the company wants more normalized results to characterize the fabric quality. For our study, the Kawabata Evaluation System (KES) was used to measure the various fabric properties including friction, bending, tensile and shear strength. In addition, standard test methods were also used to measure the material thickness and density. Later, the measured KES fabric properties were inputted Modaris 3D software to generate 3D virtual garment prototypes. These 3D prototypes are linked to the Modaris 2D pattern design environment. Thus, the compilation of these tools result in a realistic simulation of a garment with specific fabric properties on a 3D mannequin. Table 3 shows the different fabric properties {F1, F2, F3, F4} used for the garment simulation in the Modaris software. All the fabric properties were then stored in the Modaris 3D software to create the different 3D clothing simulation based on their unique parameters.

Table 3. Mechanical properties of different fabrics materials for generating 3D garment prototypes

Mechanical Fabric Properties	**F3 100% Linen)**		**F1 (100% Cotton)**		**F4 (35% PES / 65% Cotton)**		**F2 (100% PES)**	
	Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft
Density								
(g/m²)	234		125		210		280	
Material Thickness								
(cm)	0,09		0,06		0,07		0,08	
Bending resistance								
B(1e-6N.m)	13,02	6,43	3,44	1,43	7,43	5,23	5,26	1,47
Tensile resistance								
EMT (%)	3,980	11,790	2,830	8,000	4,980	4,680	17,930	22,470
LT	0,543	0,616	0,629	0,668	0,558	0,632	0,580	0,525
WT (N/m)	5,296	17,799	4,364	13,092	6,816	7,257	25,497	28,930
Shearing resistance								
G(N.m-1/°)	1,010	1,442	1,471	1,599	2,952	3,579	0,922	1,147
T(N.m-1)	30,246		68,972		131,786		19,628	
Friction								
MIU	0,1627	0,1563	0,1467	0,1517	0,1670	0,1623	0,2633	0,2178

3.3 The human data acquisition system

The human perceptions of the fit and comfort of the garments, which are the quality characteristics of the product, are strongly related to the ease allowance at different body positions, the fabric material, and the morphology of the wearer. So, the main objective is to control the relationship between the above factors and determine the choice of design parameters according to the desired fit and comfort of the garment for a particular consumer. Meanwhile, for each wearer, the real comfort perception on the corresponding twelve garments was directly evaluated by the wearer. The sensory process in evaluating the fit and comfort evaluation of garment differs from the quantitative, descriptive methods of analysis often used. The evaluation dimension is unique and there is no need to generate normalized sensory descriptors. The normalized rating values are used are employed to describe both fit level (design experts) and comfort level (consumers) at various key body locations using a five-point linguistic scale, such as loose, a little loose, adequate, a little tight and tight. In general, fit and comfort assessment involves complex interactions between the garment and the human body that cannot be directly measured by instrumental methods. In this situation, more relevant quantitative results with numerical values could be obtained through a sensory evaluation system by combining both design experts and concerned consumer perceptions. This helps a lot in controlling the various design parameters. In this study, a sensory evaluation system is used to characterize the human perception of garment fit given by a group of five design experts in real and virtual try-on environments on the produced sixty garments (combinations of five body shapes, four fabric types and three styles controlled by ease allowance values) on the five wearers/subjects. This involved five design experts as a sensory panel consisting of five female design experts, aged 34 and 58. They all have good experience in garment design and pattern construction. Before the evaluation session, they were informed about the general principle and basic methodology of sensory evaluation, but they did not receive strict training on it. An assessment with fewer constraints can effectively



cover all aspects of garment fit as perceived by different design experts. Six key positions on the human body are considered when evaluating the real/virtual fit of garment by the design experts and the comfort of wear by the wearer, as shown in Figure *9*.

Figure 9. Key positions on the human body to be considered during the evaluation

Each evaluator received the images of each wearer/subject which include different poses, fabric materials, and ease allowance values. Then, they can select the rating for all key positions on the body from the five-level linguistic scale according to their perception of the impact of the garments on the wearers/subjects. The designated five linguistic values are Loose, A little Loose, Appropriate, Somewhat Tight and Tight. These five linguistic values were then labeled with the corresponding numerical values of 2, 1, 0, -1, and -2. The relevant bibliography does not specify the optimal number of panelists and depends on the domain, financial resources, and research. Table 4 shows one of the examples of garment fit score set by a design expert for a particular real/virtual garment on a body shape for posture one (standing up) with the five key positions.

Table 4. One example of a virtual garment fit evaluation given by a design expert

		Evaluation scores				
	Positions	Loose	A little loose	Adequate	A little tight	Tight
Posture one (straight standing)	Shoulder			x		
	Collar			x		
	Armhole		x			
	Chest			x		
	Waist		x			
	Hip		x			

Based on the rating of this design expert, the numerical evaluation values of posture at various position are 1 (somewhat loose) and 0 (adequate/appropriate). In this example, the design expert considers the positions at the shoulder, collar, and chest to be "adequate" and those at the armhole, waist, and hip to be "somewhat loose".

4. Modelling procedure

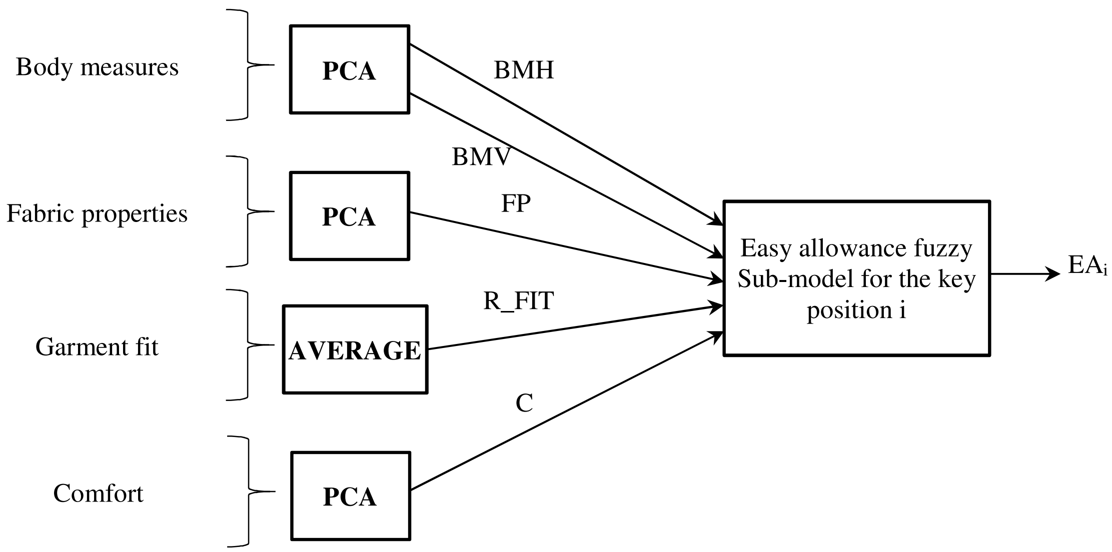
4.1 Modelling procedure for Model one

As discussed in the general principle of predicting 3D ease allowance section, Model one can be considered as a function of the model with real garment fit, comfort, body measures, fabric properties and ease allowance.

<Real ease allowance> = Model one (real garment fit, comfort, body measures, and fabric properties).

Based on this principle, the input and output variables of this model could be defined as follows. According to our previous analysis, eight (8) body measurements, nine (9) fabric properties, and one hundred and twenty (5×4×6=120) garment fit perception variables were considered. In addition, the corresponding results of five (5) design experts for all four (4) body postures and six (6) main key body positions and six (6) comfort perception variables given to the concerned wearer were considered. The number of output variables is four (4) corresponding to the four (4) main key body positions of the garment (chest, waist, hip, and collar) as shown in Table 2. In addition, sixty (60) learning data were obtained, each value corresponding to one produced customized garment. The inclusion of this very large number of input variables could complicate not only the extraction of fuzzy rules but also the final data interpretation. Therefore, a Principal Component Analysis (PCA) was proposed to extract two variables {BM1, BM2: the first two principal components} from all body measurements based on a previous study [151]. In practice, all body measures are considered to be highly correlated. Based on the computations with the learning data of the body measures, BM1= (-0.04 -0.66 0.31 -1.11 1.50) and BM2= (-0.13 0.83 1.19 -1.15 -0.74) were obtained for all wearers/subjects (WP1, …, WP5). The explanation rate of these two principal components is 83%, indicating that the accuracy is high enough for further treatment. With the same idea, PCA was also applied to extract a variable {FP: the 1st principal component} from all nine (9) fabric properties. For example, calculating the learning data of fabric properties, FP= (-0.19 -

0.68 -0.60 1.46) was obtained for the four (4) fabric types such as F1 (Linen 100%), F2 (Cotton 100%), F3 (PES 35%, cotton 65%), F4 (PES 100%). In this case, the corresponding explanation rate was 78%, which means that the accuracy can be accepted (the total explanation rate of the first two principal components is 95%). In addition, for the clothing fit perception levels (reported by the five (5) design experts) and the four (4) postures in the main body position with the specific ease allowance EAi, all variables were aggregated by calculating their mean values to form an input variable {R_FIT}. Similar data aggregation procedures for the comfort perception by the concerned wearer of the six (6) main body positions were applied to form an input variable {C}. Although the data {R_FIT} and {C} are theoretically distributed in the range of [-2, 2], the practical evaluation of the fit or comfort of the garment near "very tight" (-2) and "very loose" (2) rarely occurs for all key positions and postures. Therefore, the minimum and maximum values of the sixty (60) learning data were considered to form the ranges of these two variables. The corresponding range results for {R_FIT} and {C} are [-1.2, 1.3] and [-0.9, 1.5], respectively. Moreover, it is very important to emphasize that both values ({R_FIT} and {C}) are not only correlated with each other, but also quite different in some scenarios. For example, for F3 (100% linen), EA1 and W3, the averaged garment fit for {R_FIT} and {C} are 0.63 and -0.13, respectively. Figure *10* shows the general structure of model 1. It is composed of four (4) sub-models each corresponding to the ease allowance at a key garment position. For each of the five (5) input variables, some fuzzy values (from 4 to 5) are formed with triangular membership functions according to the distribution of the sixty (60) learning data (60 garments produced). For both BM1 and BM2, five (5) triangular fuzzy values corresponding to the body shapes of five (5) wearers were



defined (output of the concerned PCA). The values are then labeled as {very small, small, medium, large, very large}. Figure 11 shows the membership functions of BM1 and BM2.

Figure 10. Structure of the fuzzy model for predicting the real ease allowance at the key position i.

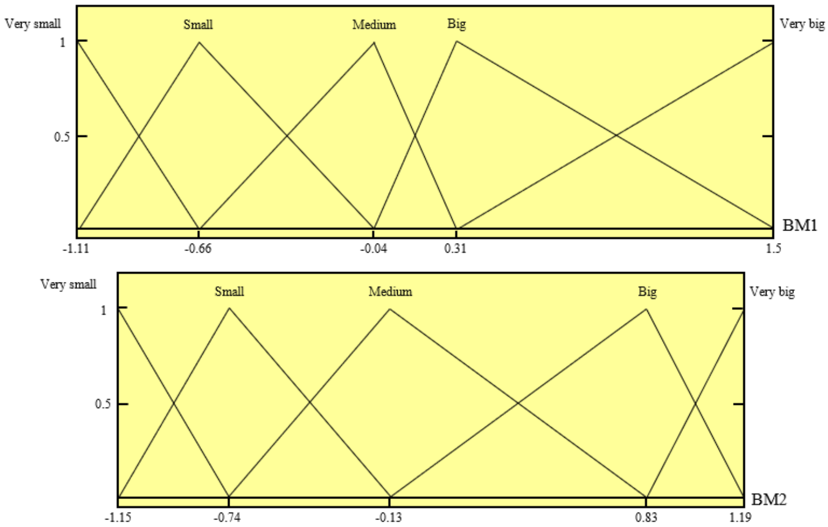
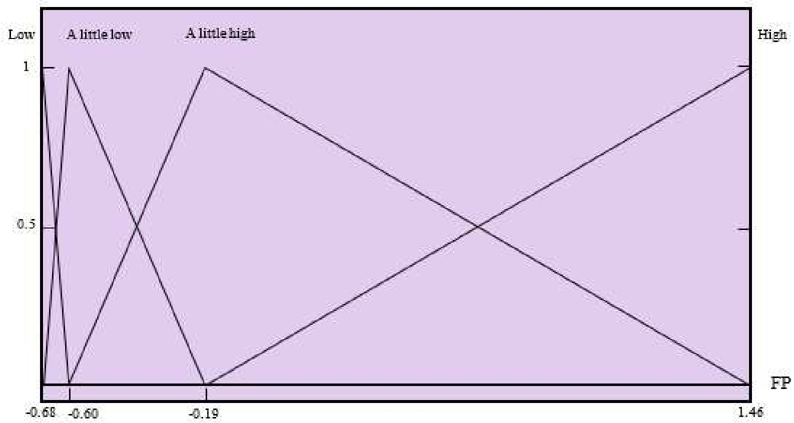


Figure 11. Membership functions of BM1 and BM2



For the fabric properties (FP), four (4) triangular fuzzy values corresponding to the four (4) selected fabrics were also formed (output of the concerned PCA). The values are denoted as {low, a little low, a little high, high} as shown in Figure 12.

Figure 12. Membership function of FP.

Similarly, five (5) triangular fuzzy values were defined for {R_FIT} and {C}, which are uniformly distributed on their real ranges of [-1.2, 1.3] and [-0.9, 1.5], as described previously. Their values are denoted as {tight, a little tight, adequate, a little loose, and loose}. The membership functions of {R_FIT} and {C} are illustrated in Figure 13.

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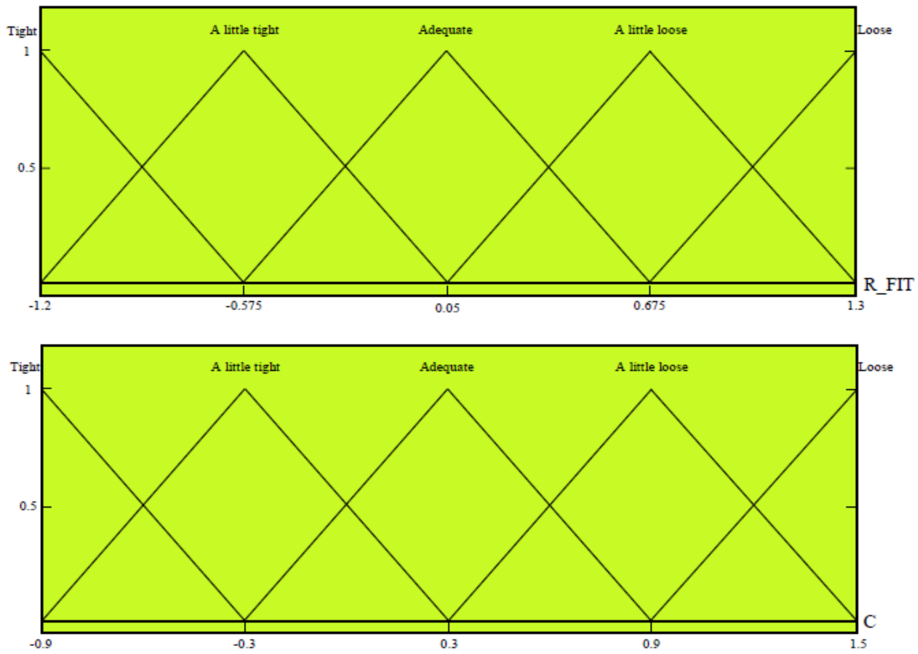
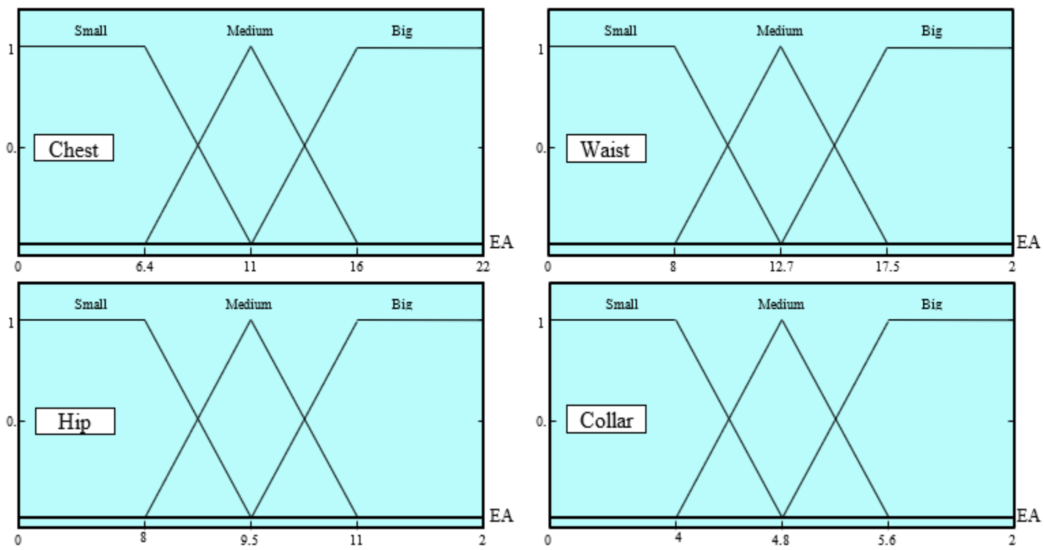


Figure 13. Membership functions of R_FIT and C.

For each sub model, model one is predicts the actual real ease allowance at key position i, where its output EAi (i∈{1 (chest), 2 (waist), 3 (hip), 4 (collar)}) is also a linguistic variable that takes triangular fuzzy values {small, medium, large}. These fuzzy values are respectively centred on the ease allowance values EA1, EA2 and EA3 of the produced garments (Table 2)



as shown in Figure 14. Then, it is possible to obtain sixty (60) fuzzy rules; each corresponding to a garment prototype, by exploiting the relationship between the combinations of the fuzzy values of the five (5) input variables and the ease allowance at each key position (EAi) in the learning database measured from sixty (60) produced garment prototypes.

Figure 14. Membership functions of EA for the chest, waist, hip, and collar

Based on this principle, several fuzzy rules can be generated, some examples which are given below. Example one: given a prototype with the parameters of wearer/subject one (W1), fabric property F1 (100% linen), EA1 (tight fitting style for chest), the corresponding averaged comfort perception and averaged fit of the garment is found to be -0.375 and 0.25 respectively.

Therefore, by converting these data into fuzzy values, the following rule can be developed:

Rule 1: *IF BM1=medium, BM2=medium, FP=a little high (somewhat high), R_FIT=adequate(sufficient) and C=a little tight (somewhat tight), THEN EA1=small (chest).*

Second example: the prototype with the parameters such as the wearer/subject one (W1), fabric F1 (100% linen), EA2 (normal style for chest), the corresponding averaged comfort perception and the averaged fit of the garment are -0.13 and 0.7, respectively. Then, using the same procedure and principle, the following rule is established:

*Rule 2***:** *IF BM1=medium, BM2=medium, FP=a little high, R_FIT=loose and C=a little tight, THEN EA1=medium (chest)*

The comparison between rule 1 and rule 2 shows that with the same wearer/subject (W1) and fabric property F1 (100% linen), the style was changed from tight style (EA1) to normal style (EA2) and loose garment perception.

Third example: The wearer's parameter is now changed to the wearer (W5) with the same fabric property, F1 (100% linen) and EA1 (tight style), the corresponding averaged comfort perception and averaged garment fit are 1.5 and 0.55. Then the following rule is obtained:

Rule 3: IF BM1=very large, BM2=small, FP=a little high, R_FIT=loose and C=very loose, THEN EA1=small (chest)

This rule is significantly different from rule 1 and rule 2 due to the different morphology of W5. For example, wearer W5 has similar height but larger chest circumference compared to wearer W1. Therefore, in all sixty (60) fuzzy rules, the combinations of different fabric properties, body shapes, garments fit, and comfort perceptions were considered. However, theoretically, all these sixty (60) fuzzy rules cannot cover the entire input space, where some combinations of input values cannot be controlled by any fuzzy rule. The total number of combinations of fuzzy values for all five (5) input variables is 2500 (5×5×4×5×5), which is much higher than 60. This is due to the fact that some regions are not physically significant due to the limitations of the corresponding combinations of fuzzy values, especially at extreme values. In general, the integration of more fabric properties and human samples can effectively increase the accuracy of the rules and the corresponding models.

For each new wearer/subject and new fabric, given a desired garment fit and comfort level, the Mamdani method can be applied to aggregate the relevance degrees of all fuzzy rules and obtain the result. For example, let us define a new wearer/subject W6 with a body shape between W1 and W5, with body measurements of 161cm of height, 93.5 cm of chest circumference, 73 cm of waist circumference, 103 cm of the hip, 41 cm of chest width, 76 cm of underbust circumference, 13.5 cm of shoulder width (left) and 13.8 cm of shoulder width (right). Similar fabric properties (F1), desired fit of the garment (adequate) and comfort perception (R_FIT=0 and C=0) are considered. Based on the given data, the corresponding ease allowance values could be calculated as follows. First, BM1 and BM2 were calculated by the linear combination already obtained from the PCA approach with five (5) learning data (5 wearers/subjects). Here, the values of BM1and BM2 are 0.39 and 0.53, respectively. The

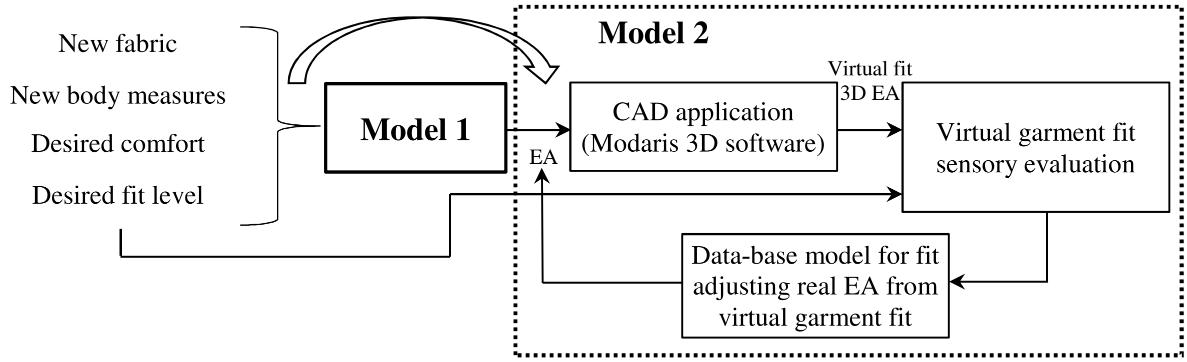
fuzzy value of BM1 is characterized as large and very large for 0.92 and 0.08 values, respectively. While the fuzzy values of BM2 are presented as medium and large for 0.21 and 0.79 values, respectively.
Fabric F1 still has values of (FP=-0.19), which corresponds to a small high value. Moreover, the fuzzy values of R_FIT and C are {M} and {a little tight: 0.5, medium: 0.5} respectively. Therefore, considering all sixty (60) fuzzy rules on the data of W6, it was possible to obtain their relevance degrees (most of them are 0) and then aggregate the corresponding results using Mamdani method. Finally, the result for ease allowance was obtained as 9.5, 9.2, 10.7 and 4.9 for chest, waist, hip, and collar, respectively.

4.2 Modelling procedure for Model 2

Usually, *model 1* aims to predict the real 2D ease allowance from the real design parameters, the wearer's body measurements, and the desired fit and comfort level of the garment. It can be validated against the real try-on of garments made from the predicted ease allowance values. However, in a remote design that refers to a virtual environment, the real try-on of the designed garments is not available. Therefore, any design solution must be validated with virtual try-on of garments, and then adjusted by checking and determining the 3D ease allowance in the virtual environment. As described in the introduction, the 3D ease allowance refers to the distances in 3D space between the human body model and the designed virtual garment. Based on the general principle of ease allowance, *Model 2* was created to allow the model to predict and validate the 3D ease allowance. It is then considered as a function of the model with the real garment fit, comfort, virtual garment fit, body measurements, fabric properties and ease allowance as follows:
< 3D ease allowance > = model two (real garment fit, comfort, virtual garment fit, ease allowance, body measurements, fabric properties).

The general principle of *model 2* is given as follows.

During the modelling process, it is assumed that the 3D ease allowance can be developed through performing a series of interactions between the design in the real environment and the evaluation of the virtual fit of the garment. The design in the real environment allows the control of the real values for the ease allowance based on the design parameters. Here, for simplicity, the process was considered as a function of the real ease allowance (EA) and the virtual fir evaluation a 3D ease allowance (3D EA). The relationships are shown as follows.
<3D ease allowance > = model 2(ease allowance, virtual fit of garment)
Moreover, model two is a repeated procedure as described in Figure 15. For any new data, such as fabric properties or wearer, model 1 is first used to calculate the ease allowance for various key positions of the garment. With the predicted values of ease allowance and other predefined design parameters, the corresponding 3D virtual garment can be generated using the application of CAD (Modaris 3D software). Later, the virtual prototype is evaluated in terms of fit at the four key positions as presented earlier. According to the differences between the desired fit and the virtual fit evaluation, model 2 is used to adjust values for the real ease allowance to generate the new fit of the virtual garment. This process is repeated until the fit of the virtual garment is satisfactory with respect to the desired level. The values



of the 3D ease allowance are obtained from the fitting effects of the final virtual prototype on the human model of the wearer.

Figure 15. The general principle for generating 3D ease allowance in terms of virtual garment fit and real ease allowance

5. Discussion

In the introduction, it was discussed that the 2D ease allowance between a garment and the human body cannot be a good indicator of the reflective fit of the garment. This is due to the complex and uncertain relationship between a garment's design parameters, the wearer morphology, posture, and fabric properties as well as the existence of various human factors, including designer and consumer perception. The proposed models then allow us to characterize and determine the relationship between the ease allowance and these parameters during a real fitting through a series of fuzzy modelling techniques for extract IF-THEN rules by learning from the experimental data. The developed models were used to predict the 3D ease allowance values from the desired human perception of fit, comfort and other design aspects considering the given specific parameters. With the help of such models, for a new sample and consumer morphology, it is possible to measure the relevant degree of input data with respect to all fuzzy rules and determine the most appropriate ease allowance value. The developed mathematical model followed by experiments is also important for controlling and adjusting the ease allowance and other parameters including the different mechanical properties of the fabric. Moreover, the determination of the 3D ease allowance enables the determination of the appropriate garment surface on a virtual human model and the fitting of any garment by integrating it with the 3D garment CAD approach.

Specifically, the fit evaluation of virtual garment is performed by design experts at the same key positions as the fit evaluation of real garments by using the five-point scale {-2 (tight), -1(a little (somewhat) tight), 0 (adequate), 1(a little (somewhat) loose) and 2(loose)}. The real ease allowance (EA) at one of the four key positions (chest, waist, hip, collar) is adjusted according to the difference in the virtual fit of the garment with respect to the desired fit at the same key position using the following three rules:

1) *IF (V_FIT-R_FIT) at position i is between -0.5 and 0.5, EAi is not changed.*

2) *IF (V_FIT-R_FIT) at position i is less than -0.5, THEN EAi: =EAi+*δ*;*

3) *IF (V_FIT-R_FIT) at position i is greater than 0.5, THEN EAi: =EAi-*δ*.*

δ is a small positive value representing the step length of each loop in the procedure of model 2. In each loop, the change if EA is bounded, then 3D ease allowance and virtual fit changes become progressive and easily controllable. For an example of setting the ease allowance, see Table 5. In this example, the desired fit of garment, the selected body shape and the selected fabric properties are considered to be 0 (adequate), W3 and 100% linen, respectively. The initial ease allowance values for these key positions were calculated using model 1. The value of δ is set to 0.3. Later, the results of the virtual fit evaluation and the adjustments of the ease allowance for these key positions were determined using the previous rules of model 2.

Table 5. One example of ease allowance adjustment by virtual garment fit evaluation.

	Ease allowance and virtual garment fit scores					
	Initial values		**After the 1st loop**		**After the 2nd loop**	
Positions	EA	Virtual fit	EA	Virtual fit	EA	Virtual fit
Collar	6.4	-0.3				
Chest	3.7	-0.3				
Waist	7.8	-1	8.1	-0.7	8.4	0.4
Hip	7.8	-0.6	8.1	-0.2		

In this example, the virtual fit scores for the initial ease allowance values at the collar and bust positions were close to 0. Therefore, it was not necessary to adjust the corresponding EA values. However, for the waist and hip positions, the virtual fit rating were less than -0.5, so we adjusted the corresponding ease allowance values from 7.8 to 8.1. After the initial adjustment of EA, the virtual fit rating become -0.7 and -0.2 for waist and hip, respectively. Thus, 8.1 is the final rating value of the ease allowance for the hip. By continuing another adjustment for the waist, the virtual fit rating for the waist after the second adjustment was 0.4 (<0.5). Therefore, 8.4 can be considered as the final value for the ease allowance for the waist. However, fit and comfort are never precise. Mostly, only 2D ease related to a fixed garment pattern can be precise. Due to the involvments of various paraameters including fabric property, real garment fit, comfort, virtual garment fit, ease allowance and body measures, fabric properties, their overall combinations are complex, uncertain and strongly related. Therefore, the current model might not be very precise but acceptable to estimate the 3D ease values.

6. Conclusion

In this paper, a series of models based on fuzzy modelling techniques were proposed to control and predict the 3D ease allowance values of the garment at different key positions in the remote design environment. The experiment was conducted with several real wearers/subjects and their virtual counterparts to check the credibility of 3D garment modelling in different style scenarios (loose, tight, appropraite). Furthermore, the real ease allowance was calculated considering standard, dynamic and fabric aspects and implemented directly on the garments in contrast to the 2D garment modelling. The mathematical models presented in this work allowed us to characterize the relationship between the ease allowance, the garment design parameters, the wearers' morphology and posture, and the individual comfort and fit requirements of the garment. An customized garment could be designed by adapting the real ease allowance values. The hypothesis is that the fit of a garment in a remote design enviroment can be fully personalised after adjusting the 3D ease allowance, as the 3D design strategy acts directly on the wearer's virtual counterpart. Compared to traditional methods that design garments based on a standard morphotype without considering the effects of different fabric types on the garment patterns, the newly proposed methods could help adjust the 3D ease allowance values based on individual body measurements and fabric properties. Moreover, the method also controls the interactions of garment design elements in the real and virtual environments, which could effectively predict the 3D ease allowance for each specific wearer, fabric material and other design parameters. However, the efficiency of the developed model strongly depends on the variety of experiments conducted on different human body types as well as the choice of input variables including the different mechanical properties of the fabric. Moreover, the proposed method could not only provide the pattern maker with information before cutting the material to reduce the number of resources but also produce a more accurate pattern and a well-fitting garment. Besides, further study by involving higher amount of data date could be done to precisely predict and validate the current approach.

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