The following publication Ruixin, L., Yip, J., Yu, W., Chen, L. and Lau, N. (2020), "Computational modelling methods for sports bra–body interactions", International Journal of Clothing Science and Technology, Vol. 32 No. 6, pp. 921-934 is published by Emerald and is available at https://dx.doi.org/10.1108/IJCST-09-2019-0143

Computational modelling methods for sports bra–body interactions

Liang Ruixin, Joanne Yip and Winnie Yu

Institute of Textiles and Clothing, The Hong Kong Polytechnic University, Kowloon, Hong Kong

Lihua Chen

College of Mechanical Engineering, Beijing University of Technology, Beijing, China, and

Newman Lau

School of Design, The Hong Kong Polytechnic University, Kowloon, Hong Kong

Abstract

Purpose – The breasts are mainly fatty and connective tissues with no muscles that directly support them, so wearing sports bras is one of the most effective means of alleviating the discomfort of breast movement and potential injury during vigorous physical exercise. However, the design and development processes of traditional sports bras are time-consuming and costly. Hence, a novel method of simulating the static contact pressure between a sports bra and women's body based on the finite element (FE) and artificial neural network (ANN) models is developed in this study to contribute to the design considerations of sports bras.

Design/methodology/approach – Three-dimensional FE models of a female subject and sports bras with different fabric properties are developed to determine the amount of contact pressure exerted onto the body. The FE results are then verified by measuring the amount of pressure exerted by the sports bra on the skin with pressure sensors. The Taguchi technique is used to effectively reduce the number of trials from 625 to only 25 cases. These 25 results obtained through FE modelling are then used to provide the training set for the ANNs. Finally, a comparison between the FE and ANN results is carried out.

Findings – A novel model of the static contact pressure between a sports bra and human subject based on the FE and ANN methods is presented in this paper. The root mean square error values show that there is only a small difference between the FE and ANN results.

Originality/value – The ANN function established in this study can be used to predict the mechanical behaviours of breasts and has a fundamental impact on the computer-aided design of functional garments in general.

Keywords Artificial neural networks, Finite element analysis, Sports bra, Comfort, Breast

Paper type Research paper

1. Introduction

The breasts do not have muscles or bones which means that there is little anatomical support. Therefore, excessive movement during physical activities can cause embarrassment, discomfort, pain or even injury and sagging (Yu and Zhou, 2016). However, these can be remedied by wearing sports bras, which are designed to control excessive breast movement and reduce breast pain during vigorous activities. Sports bras have three major functions: controlling excessive breast movement, managing heat and moisture and providing support (Niemczyk *et al.*, 2017). Therefore, a well-designed sports bra should exert adequate contact pressure to limit the range of breast movement without causing discomfort to the wearer. Traditional sports bra designs, however, have been very complex and prone to human error. Hence, computational modelling is now on the verge of being more widely applied.

The work is supported by the RGC General Research Fund [PolyU 152510/16E] titled "Optimization of the Comfort of Compression Sports Bras" and a research studentship granted to Ms. Liang Ruixin (RH09) from The Hong Kong Polytechnic University.

The finite element (FE) method has been successfully and widely used to simulate many issues, including those related to engineering, or product optimizing and testing, as discussed in Sheng *et al.* (2018), who used the method to simulate and optimize the properties of a building material, Han *et al.* (2017) to optimize electric machines and Mueller *et al.* (2017) to examine dental implants. However, the FE method has been less frequently applied in research on intimate apparel or activewear. Recently, breakthroughs in the FE method have been made with its use to describe the biomechanical behaviours of breasts and bra–breast interactions with a high degree of accuracy (Chen *et al.*, 2013; Sun *et al.*, 2019a, b). However, FE modelling also has its issues because although the method provides detailed information and does not require the involvement of human subjects, it is still computationally expensive and time-consuming in most cases. Therefore, researchers have attempted to reduce the computational complexity of FE modelling by using different model reduction techniques, such as proper orthogonal (POD) or Karhunen–Loève decompositions (Niroomandi *et al.*, 2008). However, one of the emerging new methods is machine learning (ML), which has been used in a wide range of applications (Bottou *et al.*, 2018; Atta *et al.*, 2019; Huang *et al.*, 2019). ML algorithms can be used to build a mathematical function with given data to make predictions without background knowledge of the problem. The models trained by using ML algorithms based on sample data can predict the desired quantities in real time with reasonably little bias and variance. For instance, Martín-Guerrero *et al.* (2016) examined the biomechanical behaviours of the human liver and breast using tree-based ML methods and proved their sufficiency and accuracy. Martínez-Martínez *et al.* (2017) also used tree-based methods, which included decision tree, random forest and extremely randomized trees, to predict the displacements of the breast under compression. The mean error of the predicted displacements in the paper was under 2 mm, which is acceptable. Therefore, to further enhance efficiency in this study, an ML approach is used to investigate the contact pressure between the bra and breasts because FE modelling requires hours or even days to carry out the calculations.

This study uses artificial neural networks (ANNs), which are efficient ML algorithms, to predict the contact pressure between the body and sports bras with different fabric materials. The mechanical properties of the fabric used in the sports bras are highlighted because the optimization of comfort essentially involves the optimization of the fabric properties. In this respect, the most critical fabric property is the elastic modulus. Hence, the inputs of these ANNs are the different elastic moduli, and the output is the contact pressure at different locations. An ML model is built with accurate FE results (Martínez-Martínez *et al.*, 2017). To obtain accurate FE results, several experiments are first conducted. Then, an FE model is constructed and validated based on the experimental results. After an analysis of the FE results, they are used to train a prediction model which is subsequently established by using ANNs and require three sets of sample data: training, validation and testing sets. Finally, the results obtained from the FE and ANN models are compared. The ANN function established in this study can be used to predict the mechanical behaviours of the breasts and provide design considerations for sports bras.

2 Experimental work

Four different experiments are conducted in this study which involve 3D scanning, motion capturing, fabric tensile testing and pressure testing. A 50-year-old healthy female subject, with a bra cup size of 75D based on the metric sizing system, was recruited to voluntarily take part in the experiments.

The subject was scanned with a 3D laser body scanner (Vitus, Human Solutions, Germany) to construct geometric models of her body and breasts. The subject gave informed consent before taking part in the experiment, which was approved by the Human Subjects Ethics Sub-committee of The Hong Kong Polytechnic University (Approval No.: HSEARS20151207004).

As the accuracy of the material properties is crucial because they are the data inputted into the FE model, the material coefficients and damping ratio of the breasts were determined through a motion capture experiment which used 12 infrared cameras (Eagle Motion Analysis Corporation, USA). Spherical retro-reflective markers were placed on the skin of the subject to reflect the infrared rays for capturing displacement. The calibration of the cameras was the first step in this experiment (Park *et al.*, 2014). Then, the braless subject was asked to stand still and upright with her arms outstretched, which was the initial static condition for each cycle of movement. Third, the subject was asked to run on a treadmill until she reached a steady speed. Fourth, she was instructed to raise her breasts gently with her hands and hold them stationary after she stopped running. Then, she was to quickly remove her hands from her breasts and let them fall, which would allow them to freely vibrate due to gravity load and damping forces (Cai *et al.*, 2018). The time-dependent coordinates of the markers were recorded. The results were filtered, cleaned and smoothed by using EVaRT software (Motion Analysis Corporation, USA) to remove noise before analysis took place. The damping ratio was calculated by using a logarithmic decrement (δ) from the motion capture data, which is 0.273. The function is written as follows:

$$\delta = ln\left(\frac{y_n}{y_{n+1}}\right) \tag{1}$$

where y_n is the amplitude at the n_{th} peak of the damped waveform.

The damping ratio ζ is calculated as follows:

$$\zeta = \frac{\delta}{\sqrt{(2\pi)^2 + \delta^2}} \tag{2}$$

Five different sports bras with different impact ratings (high, moderate and low) are used in this study. The mechanical properties of the fabric of the sports bra were tested by using a constant-rate-of-extension tester, Instron 4411 (US). The sports bra was divided into four components, namely the shoulder straps, back panel, bra cup and elastic bra band (shown in Figure 1), and the parts were individually sewn into loop specimens. The specimens were then loaded at a specified rate to a pre-set loop tension and unloaded at a specified rate to zero loop tension. This cycle was repeated five times to find the mean value. The strain–stress behaviour of the fabric samples in the direction of the actual stretch mainly influences the amount of contact pressure. The direction of the stretch of the bra strap, bra cup and back panel is in the wale direction, while that of the elastic bra band is in the course direction. Hence, the FE model of sports bra fabric is assumed to be isotropic, and the Young's moduli from the experimental data are shown in Table 1 (Yu *et al.*, 2016).

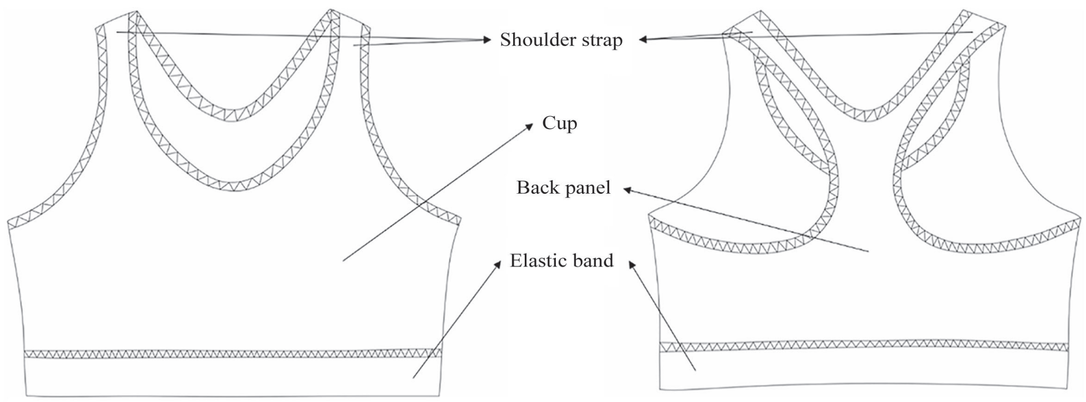

Figure 1.
Sports bra sketch

Fabric		Young's modulus/MPa
Bra 1	Strap	2.3159
	Cup fabric	0.3344
	Elastic band	1.5732
	Back panel	4.2027
Bra 2	Strap	1.8372
	Cup fabric	0.9626
	Elastic band	3.0017
	Back panel	0.5973
Bra 3	Strap	7.2167
	Cup fabric	0.3101
	Elastic band	2.5339
	Back panel	0.6363
Bra4	Strap	5.8943
	Cup fabric	0.3597
	Elastic band	1.7695
	Back panel	0.7771
Bra 5	Strap	1.3324
	Cup fabric	0.9474
	Elastic band	0.9127
	Back panel	0.5502

Table 1.
Material properties of the sports bra fabrics

Five pressure tests were conducted and their results were compared with the numerical results to validate the FE and ANN models. Female researchers ensured that the subject had donned the bra samples correctly. The pressure exerted onto the subject was then measured in triplicate with the Novel Pliance-X system, as shown in Figure 2. The contact pressure changes with each breath taken by the subject and with each small movement made. In this study, the tested pressure value is calculated by averaging the values during the stationary phase.

3. Finite element model and verification

A three-dimensional FE modelling approach was used to simulate the contact conditions between the sports bra and the body by using an FE software (MSC Marc 2014, US). Three-dimensional ten-node quadratic elements were used to model the breasts and body. The bra was meshed with quadrangular shell elements. Based on preliminary calculations with different element lengths, the geometric model of the body contained a total of 119,510 elements, in which the model of the breasts had 22,931 elements. The methods for building and validating the FE contact models for the interaction between the body and sports bra made reference to our previous study (Liang *et al.*, 2019), which provided the basis of this paper.

3.1 Determining material coefficients of breasts

Based on previous studies (Samani and Plewes, 2004; Sun *et al.*, 2019a, b), a Mooney–Rivlin material model was used to construct the model of the breasts by using Marc. The generalized Mooney–Rivlin polynomial function of strain energy, which is used in Marc, is written as:

$$W = \sum_{i,j=1}^{N} C_{ij}(I_1 - 3)^i (I_2 - 3)^j + \sum_{i-1}^{N} \frac{1}{D_i}(I_3 - 1)^2 i \tag{3}$$

where W is the strain energy potential; I_3 is the elastic volume ratio or third strain invariant;

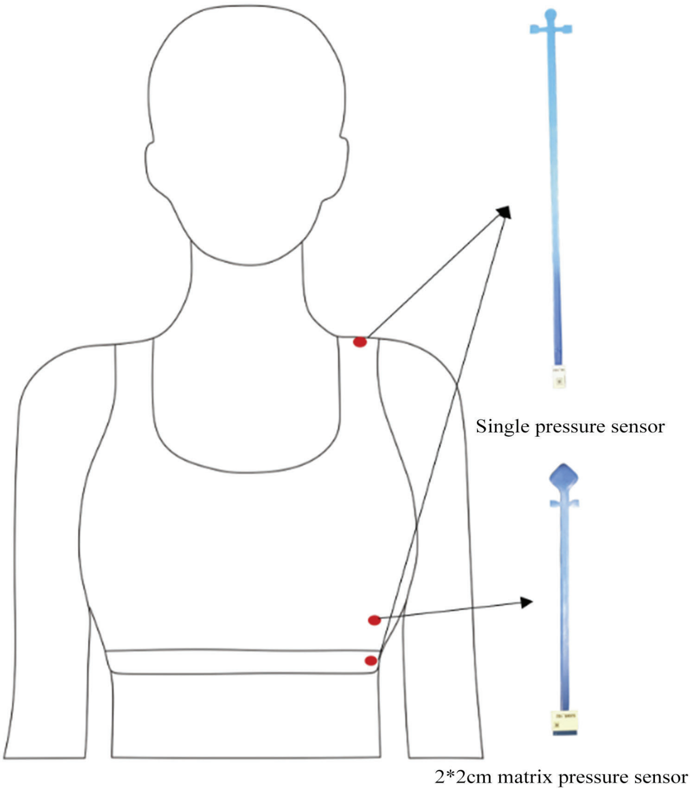

Figure 2.
Pressure tests

C_{ij} is a factor related to the shear behaviour of the material; D_i is the compressibility behaviour of the material; and N is order of the polynomial. I_1 and I_2 are the first and second strain invariants of the components of the left Cauchy–Green deformation tensor B, which is written as Equations 4 and 5.

$$\mathrm{I}_1 = tr(B) \tag{4}$$

$$\mathrm{I}_2 = \frac{1}{2}\left[(tr(B))^2 - tr\left(B^2\right)\right] \tag{5}$$

where $B = F.\,F^T$, and F is a deformation gradient.

In this study, five coefficients (C_{01}, C_{02}, C_{10}, C_{11} and C_{20}) are used to define the Mooney–Rivlin material model which accurately describe the biomechanical behaviour of the breasts.

A series of computing analyses were done to determine the appropriate coefficients of the breasts. The initial sets of the coefficients of the Mooney–Rivlin material model for the breasts and layer of subcutaneous tissues were based on the assumptions in Samani and Plewes (2004). To obtain the five actual coefficients for the subject in this study, iterative changes to the inputted coefficients were made to simulate breast displacement during running and compare the results with the experimental data. In this study, there are smaller displacements in the *x*- and *z*-directions versus the predominant displacement in the *y*-direction during treadmill running. Also, there are relatively more errors in the *x*- and *z*-directions due to shoulder rotation and body waggle. Thus, the displacements in the *x*- and *z*-directions were omitted. The criterion for the difference is the root mean square error (RMSE):

$$\mathrm{RMSE} = \frac{1}{n}\sqrt{\sum_{i=1}^{n}\left(\frac{nY_{exp,i} - nY_{FEM,i}}{nY_{exp,i}}\right)^2} \tag{6}$$

where nY_{exp} is the experimental rate of change in the y-direction of the nipple of the subject, nY_{FEM} is the rate of change in the y-direction of the nipple from the FE analysis results and n is the number of sample data points.

By minimizing the RMSE, the simulated results and the experimental data can reach an agreement, which corresponds to the optimum solution of the material coefficients [4]. Eight trial sets of the material coefficients of the breasts were run in Marc, and the corresponding relative RMSEs were calculated. The optimum material coefficients of the Mooney–Rivlin material for the model of the breasts are C01 = 0.108 kPa, C02 = 1.18 kPa, C10 = 0.094 kPa, C11 = 0.82 kPa and C20 = 0.84 kPa. This set of coefficients provides the lowest RMSE, which is 0.0405%. The entire process is schematically shown in Figure 3.

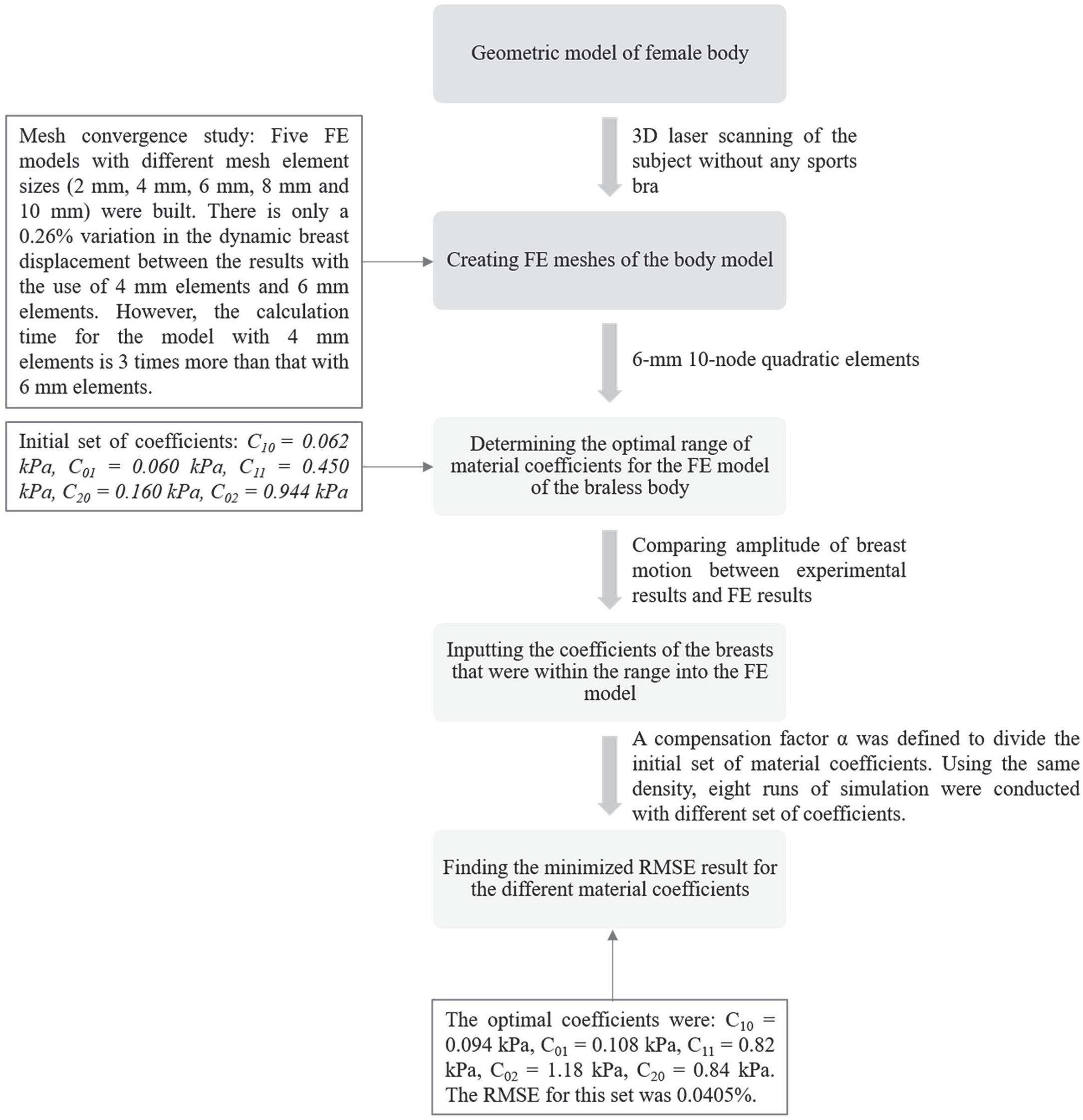

Figure 3.
Determination of material coefficients of the breasts

3.2 Contact surface and boundary conditions
The Marc software offers two types of contact – gluing and touching. In this study, the type of contact used is touching because there may be relative sliding at the contact interface between the sports bra and the body. To reduce the computational time, node-to-segment contact was used to construct the contact model due to its rapid convergence rate.

The initial equilibrium position of the model of the breast does not incorporate external forces. Hence, the first step was to apply an inverse gravity load to the model of the breast, which was based on the subject in a standing position. To simulate the contact pressure between the sports bra and body, the first problem that had to be solved is penetration. To do so, the model of the body was first geometrically reduced and then expanded, and the process is shown in Figure 4 (Liang *et al.*, 2019).

3.3 Model validation
The goal of this study is to predict the contact pressure between the wearer and sports bras with different material properties. Therefore, the static contact pressure simulated by using the corresponding FE models was compared with that from the experiments with the five sports bra samples to validate the accuracy of the FE model in this study, which is shown in Table 2. The correlation coefficient and RMSE between the values shown are 0.882 and 0.0329, respectively, which means that there is a good correlation between the experimental and predicted values (Figure 5).

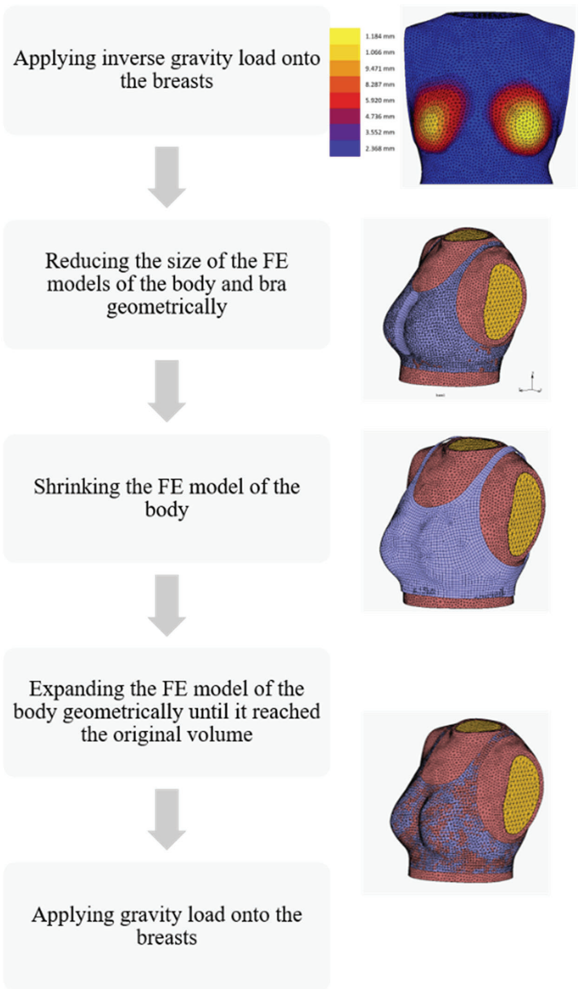

Figure 4.
Boundary conditions of the FE model

Sports bra	Position	Contact pressure from FEM/kPa	Contact pressure from experiments/ kPa
Bra 1	Shoulder	1.403	1.417
	Underarm	2.004	2.000
	Bottom of the cup	0.802	0.700
Bra 2	Shoulder	1.426	1.417
	Underarm	1.585	1.583
	Bottom of the cup	0.634	0.600
Bra 3	Shoulder	1.741	1.583
	Underarm	1.741	2.833
	Bottom of the cup	0.390	0.700
Bra 4	Shoulder	2.151	2.083
	Underarm	1.792	1.833
	Bottom of the cup	0.717	0.900
Bra 5	Shoulder	1.431	1.460
	Underarm	1.113	1.083
	Bottom of the cup	0.477	0.650

Table 2.
Comparison between the contact pressures from numerical and experimental work

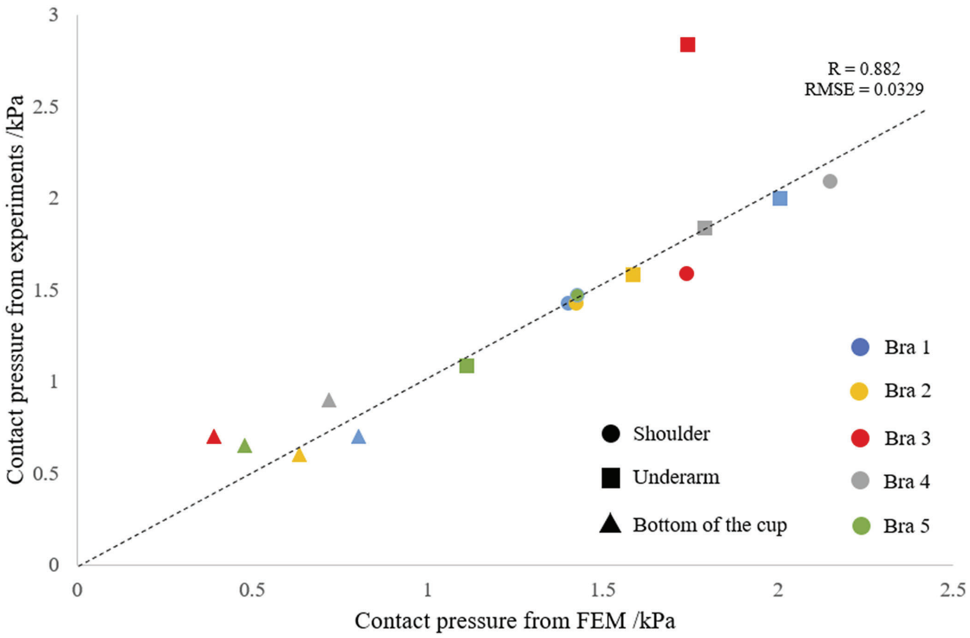

Figure 5.
Comparison between the contact pressures from numerical and experimental work

4. Artificial neural network building

The FE models provided good simulated results for the contact pressure between the sports bra and the body. The FE data were subsequently used to train the ANN model. The results were obtained under certain conditions as follows: (1) the FE model of the body is based on the same subject (a 50-year-old woman with a bra cup size of 75D), and (2) the FE models of the sports bra are based on the same design, which is a vest-style sports bra.

4.1 Data set generation

ANN modelling requires three sets of data – a training set, a validation set and a testing set, which were prepared with the FE models. The training set was used to fit every parameter of the ANN model. The validation set was used to evaluate the model which terminated when there are too many errors. The testing set was used to evaluate the final model. To generate the three sets of data, the sample data were split at a ratio of 70:15:15.

The sports bra has four components: the shoulder straps, back panel, bra cup and elastic bra band, which means that there are four parameters. When investigating the effect of the different fabrics, each parameter has five levels of the Young's modulus, thus resulting in $5^4 = 625$ full-factorial experimental runs. Therefore, the Taguchi method was used to reduce the number of experiments which is a powerful method to reduce the number of full-factorial runs. A standard orthogonal array (OA) of four parameters and five levels was selected, and 25 FE models were simulated to provide the training set for the ANN model. These runs were made with different sets of parameters and at different levels. As the training set consisted of 70% of the sample data, ten more sets of data were needed, and of these, five sets were calculated with the tested material properties of the five sports bra samples and the other five sets were calculated with random material properties. Table 3 shows the contact pressure at three different locations obtained from the 35 FE runs.

	FE parameters/MPa				FE results/KPa		
Exp. no.	Young's modulus of cup	Young's modulus of strap	Young's modulus of back panel	Young's modulus of band	Contact pressure on shoulder	Contact pressure at the bottom of cup	Contact pressure under arm
1	0.2	2	1	1	1.230	0.2459	0.8607
2	0.2	4	2	2	1.349	0.2362	1.349
3	0.2	6	3	3	1.401	0.2802	1.401
4	0.2	8	4	4	1.612	0.3281	1.881
5	0.2	10	5	5	2.261	0.4230	1.938
6	0.4	2	2	3	2.034	0.3515	1.743
7	0.4	4	3	4	2.342	0.5313	2.342
8	0.4	6	4	5	2.623	0.5747	2.248
9	0.4	8	5	1	2.383	0.5983	1.589
10	0.4	10	1	2	2.705	0.4057	1.803
11	0.5	2	3	5	1.757	0.4562	2.109
12	0.5	4	4	1	2.126	0.5252	1.701
13	0.5	6	5	2	2.479	0.5361	1.983
14	0.5	8	1	3	2.979	0.4964	1.986
15	0.5	10	2	4	3.120	0.6201	2.080
16	0.6	2	4	2	1.936	0.5227	1.936
17	0.6	4	5	3	2.743	0.6428	2.400
18	0.6	6	1	4	3.018	0.5311	2.156
19	0.6	8	2	5	3.286	0.8286	2.300
20	0.6	10	3	1	2.775	0.6775	1.665
21	0.8	2	5	4	2.687	0.5375	2.687
22	0.8	4	1	5	2.730	0.6768	2.184
23	0.8	6	2	1	3.024	1.008	1.344
24	0.8	8	3	2	3.626	1.209	2.015
25	0.8	10	4	3	4.164	1.249	2.915
26	0.3344	2.3159	4.2027	1.5732	1.403	0.802	2.004
27	0.9626	1.8372	0.5973	3.0017	1.426	0.634	1.585
28	0.3101	7.2167	0.6363	2.5339	1.741	0.390	1.741
29	0.3597	5.8943	0.7771	1.7695	2.151	0.717	1.792
30	0.9474	1.3324	0.5502	0.9127	1.431	0.477	1.113
31	0.3100	1.8270	3.5000	1.5700	1.944	0.5326	1.166
32	0.3100	1.8270	0.4400	2.7500	2.322	0.5220	1.935
33	0.4000	7.2000	4.2000	3.0000	2.900	0.6451	2.250
34	0.3100	6.5000	0.4370	1.5700	2.100	0.4791	2.000
35	0.3100	5.5000	0.4370	1.5700	2.024	0.6287	1.214

Table 3.
Finite element parameters and results

4.2 ANN structure

A multilayer neural network that uses a backpropagation algorithm was used. The Levenberg–Marquardt learning algorithm, which is one of the most rapid and often applied backpropagation algorithms, was used to establish a prediction model. The basic functions of this algorithm are shown as follows (Hagan and Menhaj, 1994):

$$H = J^T J \tag{7}$$

Then, the gradient can be calculated with:

$$g = J^T e \tag{8}$$

where H is a Hessian matrix; J is a Jacobian matrix that contains the first derivatives of the network errors with respect to the weights and biases; and e is a vector of the network errors.

Through this approximation, the Levenberg–Marquardt algorithm can be written as:

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \tag{9}$$

where μ is a scalar.

Furthermore, the multilayer structure included an input layer of four nodes (four inputs: Young's moduli of the four components of the sports bras), two hidden layers and an output layer of three nodes (the predicted contact pressure at three different locations), as shown in Figure 6.

5. Results and discussion

A comparison was made between the FE-simulated results and the ANN-predicted contact pressure of all the data sets. Table 4 shows the RMSEs of the FE versus the ANN results. The equation of the RMSE for this problem is shown in Equation (10). The RMSE values indicate that there is only a small difference between the FE and ANN results, especially for the contact pressure on the shoulder.

$$\mathrm{RMSE} = \frac{1}{n}\sqrt{\sum_{i=1}^{n}\left(\frac{P_{FEM,i} - P_{ANN,i}}{P_{FEM,i}}\right)^2} \tag{10}$$

where P_{FEM} is the contact pressure determined with the FE model, P_{ANN} is the contact pressure predicted by ANN and n is the number of sample data points.

Since the ANN function was already established, obtaining all 625 sets of data or any desired results was simple and fast. Some of the ANN results are used to investigate the relationship between the contact pressure and the elastic modulus of the sports bra, as shown in Figure 7, and the data easily show the effect of the elastic modulus of each component of the bra on the contact pressure. The Young's modulus of the other three components was selected at the same level (the highest or lowest level). The elasticities of the shoulder strap and bra cup fabric have the greatest effects on pressure. However, their effects are reduced as the elastic modulus of the other three bra components decreased. The back panel has basically no effect on the contact pressure. The elastic bra band effectively changes the contact pressure under the arm. However, it has much less influence on the contact pressure at the shoulder and bottom of the bra cup than the shoulder strap and cup fabric. Hence, it is more important to choose relatively rigid fabrics for the shoulder strap and bra cup when designing high-impact sports bras. When combined with research on the pressure comfort of bras, the results obtained herein can directly guide the selection of sports bra fabrics. The successful optimization of the algorithm not only will optimize the material modulus of sports bra fabrics

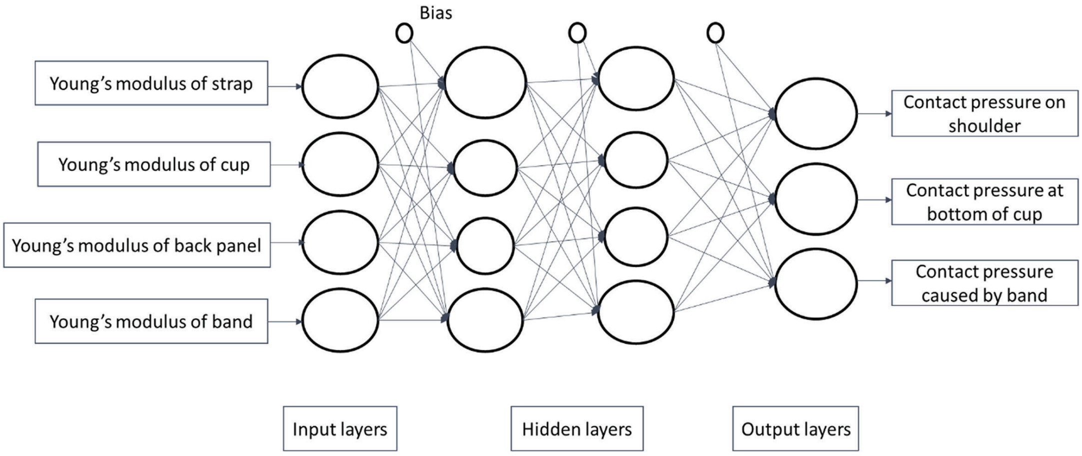

Figure 6.
The ANN structure

Predicted contact pressure	RMSE
Contact pressure on shoulder	0.0211
Contact pressure at the bottom of cup	0.0649
Contact pressure under arm	0.0404

Table 4.
RMSE between the FE results and ANN results

but also will provide the means for future research on pressure comfort, functional garments, wearable products and sports activities. Ultimately, this computer-aided method addresses a common need of the female population, so it has global relevance and applicability.

6. Conclusion

This paper presents a novel FE-method-based ML approach to predict the contact pressure between a sports bra and the wearer. With appropriate material coefficients and boundary conditions, the experimental results show that FE simulation can accurately calculate contact pressure between a sports bra and the body. Hence, the FE results can be used as input data to establish an ANN model. ANNs are an effective tool for making predictions. Specifically, the ANN results of the contact pressure, which uses a Levenberg–Marquardt learning algorithm, are in good agreement with the corresponding FE results based on the calculated RMSEs.

There are nevertheless limitations of this study. First is the lack of consideration of breast displacement during physical activities. A well-designed effective sports bra must limit the movement of the breasts relative to the body, which is the function of a sports bra. Future work on building an ML model should consider breast displacement as a criterion. Second is the limitation of sports bra style. Both the FE and ANN models are based on the same compression sports bra which is a vest-style garment. Encapsulation sports bras are also popular in the market and future works should also consider other styles of sports bras.

In general, the prediction system discussed in this paper can be used to calculate the contact pressure between a sports bra and body within a limit of allowable errors. This provides a more efficient, accurate and robust strategy for solving not only the complex problems of body–bra interactions but also other design applications where the materials properties are highly nonlinear and viscoelastic. The results can be directly used for the selection of sports bra materials, which can positively benefit a large percentage of the world's female population. The study of sports bras is also important for the well-being of women during physical activities, which are unique from that of men due to their different physiology.

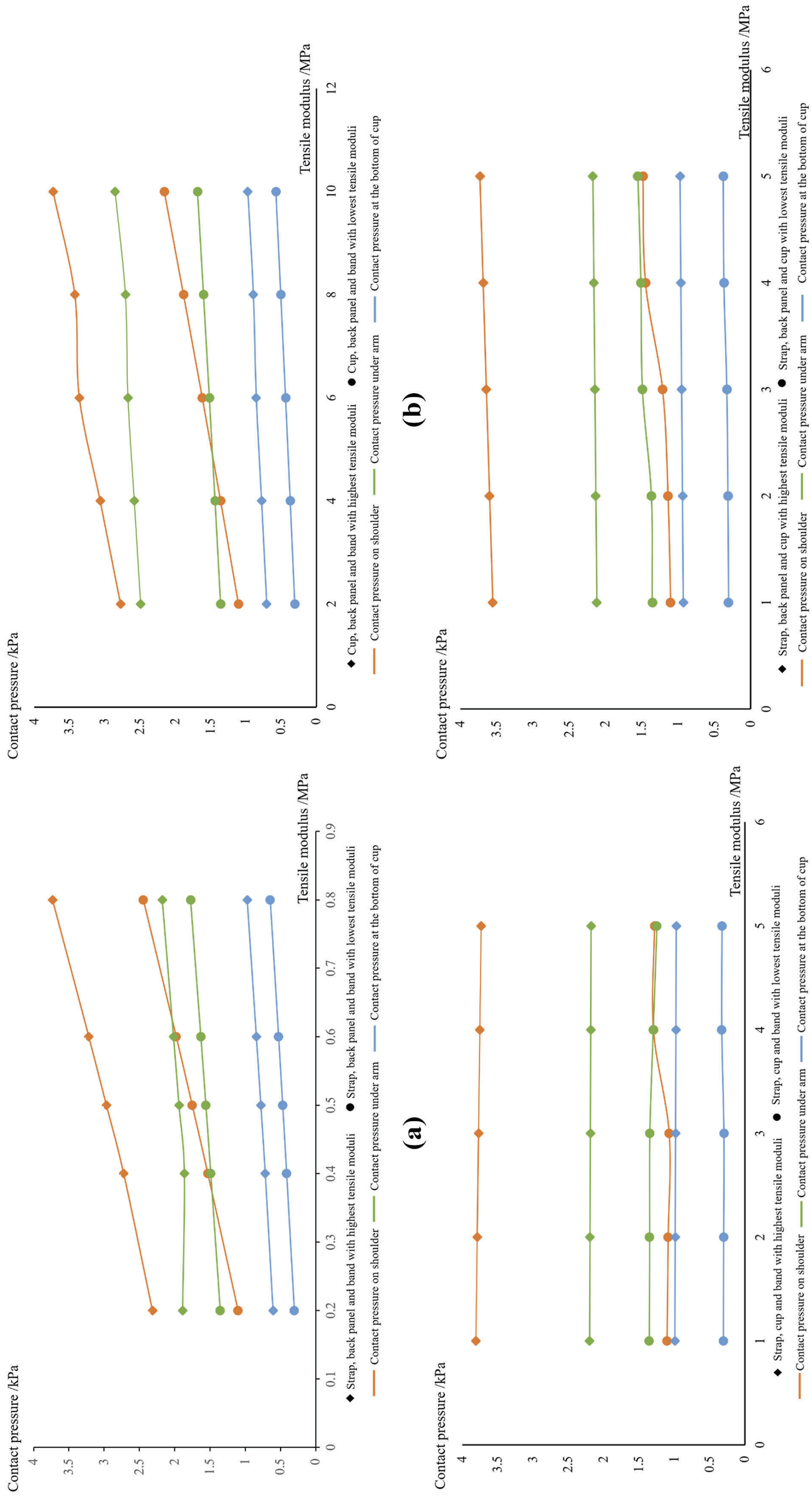

Figure 7.
Effects of sports bra fabrics with different elastic moduli. (a) Effect of elastic modulus of the cups on contact pressures at three points. (b) Effect of elastic modulus of straps on contact pressures at three points. (c) Effect of elastic modulus of back panels on contact pressures at three points. (d) Effect of elastic modulus of bands on contact pressures at three points

References

Atta, M., Abd-Elhady, A.A., Abu-Sinna, A. and Sallam, H.E.M. (2019), "Prediction of failure stages for double lap joints using finite element analysis and artificial neural networks", *Engineering Failure Analysis*, Vol. 97, pp. 242-257.

Bottou, L., Curtis, F.E. and Nocedal, J. (2018), "Optimization methods for large-scale machine learning", *SIAM Review*, Vol. 60 No. 2, pp. 223-311.

Cai, Y., Chen, L., Yu, W., Zhou, J., Wan, F., Suh, M. and Chow, D.H.K. (2018), "A piecewise mass-spring-damper model of the human breast", *Journal of Biomechanics*, Vol. 67, pp. 137-143.

Chen, L.H., Ng, S.P., Yu, W., Zhou, J. and Wan, K.F. (2013), "A study of breast motion using non-linear dynamic FE analysis", *Ergonomics*, Vol. 56 No. 5, pp. 868-878.

Hagan, M.T. and Menhaj, M.B. (1994), "Training feedforward networks with the Marquardt algorithm", *IEEE Transactions on Neural Networks*, Vol. 5 No. 6, pp. 989-993.

Han, W., Van Dang, C., Kim, J.W., Kim, Y.J. and Jung, S.Y. (2017), "Global-simplex optimization algorithm applied to fem-based optimal design of electric machine", *IEEE Transactions on Magnetics*, Vol. 53 No. 6, pp. 1-4.

Huang, J., Kwok, T.H. and Zhou, C. (2019), "Parametric design for human body modeling by wireframe-assisted deep learning", *Computer-Aided Design*, Vol. 108, pp. 19-29.

Liang, R., Yip, J., Yu, W., Chen, L. and Lau, N.M. (2019), "Numerical simulation of nonlinear material behaviour: application to sports bra design", *Materials and Design*, p. 108177.

Martínez-Martínez, F., Rupérez-Moreno, M.J., Martínez-Sober, M., Solves-Llorens, J.A., Lorente, D., Serrano-López, A.J. and Martín-Guerrero, J.D. (2017), "A finite element-based machine learning approach for modeling the mechanical behavior of the breast tissues under compression in real-time", *Computers in Biology and Medicine*, Vol. 90, pp. 116-124.

Martín-Guerrero, J.D., Rupérez-Moreno, M.J., Martinez-Martínez, F., Lorente-Garrido, D., Serrano-López, A.J., Monserrat, C.,. . . and Martínez-Sober, M. (2016), "Machine learning for modeling the biomechanical behavior of human soft tissue", *2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW)*, IEEE, pp. 247-253.

Mueller, A., Hinz, M. and Bracke, S. (2017), "Optimization of the dental implant testing based on FE method simulation of fatigue and accelerated life", *Risk, Reliability and Safety: Innovating Theory and Practice*, pp. 16-22.

Niemczyk, S.E., Arnold, L. and Wang, L. (2017), "Qualitative observations on the design of sports bras for wear under body armour", *KnE Engineering*, Vol. 2 No. 2, pp. 342-352.

Niroomandi, S., Alfaro, I., Cueto, E. and Chinesta, F. (2008), "Real-time deformable models of non-linear tissues by model reduction techniques", *Computer Methods and Programs in Biomedicine*, Vol. 91 No. 3, pp. 223-231.

Park, H.S., Park, K., Kim, Y. and Choi, S.W. (2014), "Deformation monitoring of a building structure using a motion capture system", *IEEE/ASME Transactions on Mechatronics*, Vol. 20 No. 5, pp. 2276-2284.

Samani, A. and Plewes, D. (2004), "A method to measure the hyperelastic parameters of ex vivo breast tissue samples", *Physics in Medicine and Biology*, Vol. 49 No. 18, p. 4395.

Sheng, P., Zhang, J., Ji, Z. and Wang, S. (2018), "FE method simulation and optimization on the elastic modulus and thermal expansion ratio of polymer-mineral composite", *Construction and Building Materials*, Vol. 167, pp. 524-535.

Sun, Y., Chen, L., Yick, K.L., Yu, W., Lau, N. and Jiao, W. (2019a), "Optimization method for the determination of Mooney-Rivlin material coefficients of the human breasts in-vivo using static and dynamic finite element models", *Journal of the mechanical behavior of biomedical materials*, Vol. 90, pp. 615-625.

Sun, Y., Yick, K.L., Yu, W., Chen, L., Lau, N., Jiao, W. and Zhang, S. (2019b), "3D bra and human interactive modeling using finite element method for bra design", *Computer-Aided Design*, Vol. 114, pp. 13-27.

Yu, W. and Zhou, J. (2016), “Sports bras and breast kinetics”, in Yu, W. (Ed.), *In Advances in Women’s Intimate Apparel Technology*, Woodhead Publishing, Duxford, pp. 135-146.

Yu, A., Yick, K.L., Ng, S.P., Yip, J. and Chan, Y.F. (2016), “Numerical simulation of pressure therapy glove by using finite element method”, *Burns*, Vol. 42 No. 1, pp. 141-151.

Further Reading

Samani, A., Bishop, J., Luginbuhl, C. and Plewes, D.B. (2003), “Measuring the elastic modulus of ex vivo small tissue samples, *Physics in Medicine and Biology*, Vol. 48 No. 14, p. 2183.

Corresponding author
Joanne Yip can be contacted at: tcjyip@polyu.edu.hk