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Supervised ANN-assisted modeling of seated body apparent mass under vertical whole body vibration

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Abstract

The modeling of human body response to whole body vibration has been a challenging task owing to the complex dependence on various factors related to anthropometry, and sitting and vibration conditions. This paper addresses the functionality of Artificial Neural Network (ANN) for prediction of seated body apparent mass under different levels of vibration excitations in the 0.5-20 Hz frequency range, while assuming two different sitting postures (with and without a back support). A multilayer feed-forward neural network with back propagation (BP) algorithm was developed with various structures to identify an optimal configuration. From preliminary simulations, a neural network structure with 20 neurons in the first and 20 neurons in the second hidden layers was selected, which resulted in least mean square error, MSE, and highest coefficient of determination R^2, when compared to those of the other model structures considered. Portions of the measured data acquired with 51 adult male and female subjects were used in the training and testing phases, which revealed MSE magnitudes of 4.83 and 5.97 kg^2, respectively, with R^2 values in excess of 0.96. Subsequently, the predicting ability of the model was assessed using the datasets for 14 unforeseen subjects. It was inferred that a well-trained ANN has the capacity to predict biodynamic responses of seated subjects as functions of the body mass, vibration magnitude and support condition. The model could predict the primary resonance frequency and the corresponding magnitude while the validity in predicting the responses were obtained at MSE of 2.13 and 1.83 kg and with R^2 values in excess of 0.98 for the male and female subjects, respectively.

Keywords: artificial intelligence; seated body biodynamic response; apparent mass; vibration biodynamics

1. Introduction

Occupational exposure to low frequency and high magnitude whole body vibration (WBV) of vehicles, especially off-road-vehicles, has been associated with discomfort, reduced performance rate and various spinal disorders among the exposed drivers [1]. The biodynamic response of the seated body exposed to WBV, widely expressed in terms of apparent mass (AM), has been considered to serve as an essential basis for an understanding of mechanical properties and thereby the vibration responses of the human body [2]. The AM is defined as the transfer function between the dynamic force developed at the body-seat interface and the acceleration beneath the ischial tuberosities in the frequency domain [3]. The AM of the seated body has been widely characterized experimentally, which invariably show highly complex dependency of the responses to many factors, especially the nature of vibration (magnitude and frequency). A deterministic characteristic, however, is that the apparent mass magnitude increases to a peak value at a frequency near the resonance frequency (≈5 Hz), while it decreases with further increase in the frequency [4-7]. The measured response data have been used to build biodynamic models for deriving vibration power absorption by the body [8], frequency-weightings for assessments of exposure risk, and for applications in seating [9-12] and vehicle suspension designs [13]. In order to distinguish the uncoupled biodynamic responses of the body at the seat-human interface, such analyses have been performed with individuals sitting on rigid seats.

Although considerable efforts have been made in deriving biodynamic models of the seated body, their applications have met only limited success thus far. This is due to highly nonlinear effects of a broad range of factors that can affect the human body response such as anthropometric factors, gender, vibration characteristics (magnitude and frequency) and sitting posture [2]. Moreover, the vast majority of response analyses have been limited only to vertical vibration, which is likely due to relative higher magnitudes of vertical vibration induced by either road or off-road surfaces than those in the other directions. The response analyses under vertical vibration are thus of greater concern for occupant health issues.

The biodynamic responses to vibration have been analyzed using different approaches such as experimental, and modeling and simulations using multi-body dynamic and finite element methods [3,14]. The models developed for characterizing apparent mass have also been used for predicting seat-to-head vibration transmissibility (STHT) [10,15]. The biodynamic models, however, are invariably identified from the measured data and the ranges of biodynamic responses that have been standardized (ISO-5982) [16]. An expedient FEM approach can not only be used to model the complex human body responses, but also the coupled body-seat responses and the local effects such as stress distribution and forces between spinal vertebrae foe understanding the injury mechanisms [14]. The ability to achieve body responses to multi-axis vibration is an added value of FEM models. Such models, however, impose complex challenges in characterization of soft tissues and their properties, apart from excessive computational demands to achieve a robust model.

The vast majority of the reported models have employed multi-body and lumped-parameters modeling approaches, wherein the biodynamic response such as AM and/or (STHT) responses are evaluated through attribution of mass-damping-stiffness parameters of the body segments [17]. Unlike the lumped-parameter models, the multi-body dynamics approach incorporates the body anatomy including the geometric and inertial properties of body segments and various joints by equivalent visco-elastic properties [18-19]. In both the approaches, the model parameters are obtained on the basis of mean measured data or the data for a specific individuals, and particular vibration magnitude and sitting condition. Such models are thus considered applicable in the vicinity of the conditions considered for parameter identification, namely, the body mass, gender, sitting posture and magnitude of vibration. The measured data, however, exhibit large inter-subject variabilities, which have been attributed differences in gender, anthropometric dimensions, and vibration and sitting conditions [6,12]. The reported models thus cannot be applied for the general population of drivers, and different vibration and sitting postures that are encountered during vehicle driving. Alternate modeling approaches that can incorporate nonlinear dependence of the biodynamics to various factors are thus desirable to enhance general applicability of the models for seating and suspensions designs, and more robust assessments of exposure risks.

Artificial intelligence has demonstrated its promising potentials for modeling of broad spectrum of phenomena in science and engineering. When compared to the analytical, phenomenological and statistical approaches, these methods can deal with problems that have a considerable degree of nonlinearity in the system or where a process is stochastic [20]. The artificial neural network (ANN) is an artificial intelligence (AI) technique, which has been widely used for output prediction, classifications, data fitting, and pattern recognitions of complex systems [21]. The core ideology is to construct optimal structures for analysis of the data. ANNs consist of numerous analyzing components, known as neurons, which are tightly interconnected or structured in multiple layers through appropriate weights in order to identify robust input-output patterns. ANN has the advantage of independence to damaged neurons and a segmentation of missing data, and can work even in the presence of some outliers through adoption of outlier detection and removal [21]. Moreover, in ANN, the neural representation established from the training phase can effectively predict outputs under a modified or new input values and re-establish the condition identified as a testing procedure.

The ANN approach is perhaps well-suited for predicting highly nonlinear vibration biodynamic responses of the seated human body. Only a few attempts, however, have been reported during the past few years on the applications of ANN for characterizing human body response to vibration [22-27]. Gohari et al. [23], proposed an ANN model for predicting the seat-to-spine acceleration transmissibility on the basis of data obtained with five adult male subjects seated in erect posture and exposed to harmonic vertical vibration at the pelvis. The study employed a feed-forward back propagation training algorithm using the input and response acceleration measured at the body surface near the spinous process of the L3 vertebra. The authors used the same approach to construct the ANN model using head acceleration data acquired in the same experiment together with different training algorithms and two different sizes of hidden layer [24]. This approach, however, can increase the computational complexity of the model considerably. The ANN has also been employed in a recent study [25] to facilitate seat-suspension for a class of off-road vehicles. The five different ANN models were formulated using the vibration attenuation properties of five different suspension seats subject to field-measured excitations due to different vehicles. Good performance of the resulting five different models for the five seats, obtained with total training data size of 170, was demonstrated. This approach may have some practical implications since a model is developed for each seat as opposed to a general model applicable to all seats.

It has been widely suggested that biodynamic models of the human body need to be developed for representative body mass, and postural and vibration conditions for effectively predicting the behaviour of the biological system and thus the potential injury mechanisms leading to a viable dose-response relationship [28-30]. Such models could further provide improved assessment methods and designs of effective interventions. As stated above, the ANN approach offers good potential for predicting highly nonlinear vibration biodynamic responses of the seated human body. The potential of this approach to deal with a holistic problem involving significant variabilities, however, needs to be assessed. To the best of authors' knowledge, the application of the ANN method for biodynamic modeling of the seated body under varying experimental condition has not yet been attempted. Owing to the limited applicability of the reported biodynamic models due to complex and nonlinear dependence of the vibration biodynamic responses on many factors, this study proposes the ANN modeling approach for predicting the AM responses over broader ranges of body mass, and vibration and posture-related factors. In Section 2, the AM response characteristics and the procedure to acquire measured data under different body mass, vibration excitation and sitting posture are described. In this regard, dividing the AM responses of 51 adult subjects into three sets for training, testing and validation after a preprocessing task for the removal of outliers are described in Section 3. Some portions of data should remain intact and unforeseen to the developed ANN model for the final verifications. Different training algorithms, transfer functions, and hidden layer configurations will be employed to identify the optimal representation. The outperforming model in terms of the least MSE and higher R^2 will be used for the prediction of AM responses, while the capacity of the developed model for tracking the inter-subject variability effect on AM responses will be of interest. Section 3 and Section 4 are dedicated to the results and discussions and concluding remarks, respectively.

2. Apparent Mass Response Characteristics

The biodynamic responses of the human body exposed to WBV have been widely characterized experimentally under broad ranges of vibration and postural conditions, which are expressed by the force-motion relation at the driving-point, namely, mechanical impedance or apparent mass, and by functions describing the flow of vibration through the body, such as seat-to-head and body segments vibration transmissibility. These have been mostly expressed in terms of AM due to relative ease of its measurement, which invariably show large inter-subject variability, and strong effects of body mass, vibration excitation and sitting posture [1]. For realizing a reliable model, it would be desirable to acquire measured data under different vibration and sitting conditions, apart from subjects of different body mass. In this study, the AM data acquired for 51 adult subjects, including 27 males and 24 females, acquired in an earlier study [7], are used. Briefly, selected subjects were free from musculoskeletal disorders such as back injuries and low back pain. The anthropometric characteristics of the subjects in terms of age, stature, body mass and body mass index (BMI) are summarized in Table 1 in terms of minimum, maximum, mean and standard deviation of the mean. Prior to the measurements, the experimental procedures and safety guidelines were described to each subject and each subject was asked for consent of the protocol that had been approved by the Human Research Ethics Committee of Concordia University.

In order to obtain the dynamic force data at the seat, a rigid seat with a 449×456 mm horizontal seat pan and a vertical backrest was installed on a whole body vertical vibration simulator (WBVVS) platform by means of a force plate. A uniaxial accelerometer (B&K 4370) was mounted on the force plate to measure the vertical acceleration of the platform. Additionally, a steering column with a steering wheel was provided as hands support for the subject. Each subject was asked to sit on the seat with and without the back support. The measurements of the driving-point force were performed under three different levels of white noise random vibration with flat acceleration PSD. The vibration excitation was synthesized using a vibration controller (VR 9500, Vibration Research Corp., Jenison, MI, USA) so as to attain overall rms accelerations of 0.25, 0.50 and 0.75 m/s^2. The force and acceleration signals were acquired in a multi-channel spectral analysis system (B&K PULSE 11.0, Atlanta, GA, USA) using a bandwidth of 50 Hz. The data during each measurement was acquired for 60s, and each measurement was repeated twice. The acquired data were analyzed with 75% data overlap and frequency resolution of 0.0625 Hz which resulted in 12 spectral averages [13]. The complex AM response was computed from:

$$M(j\omega) = \frac{S_{aF}(j\omega)}{S_a(j\omega)} \tag{1}$$

where $S_{aF}(j\omega)$ is cross-spectral density of the measured force and acceleration and $S_a(j\omega)$ is auto-spectral density of acceleration, and $M(j\omega)$ is the complex AM corresponding to excitation frequency ω. The computed AM was inertia corrected to account for contributions of the mass due to seat and the force plate, as reported in [12]. The resulting transfer function was subsequently expressed in terms of AM magnitude and phase responses of each individual. The means of two trials of each measurement were obtained to examine intra-subject variability. A trial was rejected when peak deviation in the frequency corresponding to the peak magnitude exceeded 10%.

3. Artificial Neural Network Modeling

The ANN architecture is formulated considering the data acquired for 51 adult subjects including 27 males and 24 females with different body masses, three levels of rms acceleration excitation, and two levels of sitting postures. Considering the mean measured magnitude corresponding to each subject, excitation and posture combination, a total of 306 datasets were available. Each dataset was acquired in the 0.5 to 20 Hz frequency range using a frequency resolution of 0.0625 Hz, which resulted in 313 data for each set. Some of these datasets revealed dominant frequencies either well below or above the expected fundamental resonance frequency in the 4 to 6 Hz range. A total of 34 datasets showing dominant frequency outside this range were thus not included. It is desirable to use relative greater number of datasets for training the ANN model, while fewer datasets may be retrained for the testing and validation phases. In this study, a total of 14 datasets were not included in the ANN modeling but retained for final testing of the model. The 14 datasets were selected from the different mass groups, genders excitation levels, and back support condition in order to reveal the effects of all inputs on the ANN predicted AM responses. The remaining 258 datasets were used for training (154), testing (52), and validation (52). These also provided a total of 80754 AM magnitude data points (258×313). The model input was constructed to incorporate the essential factors influencing the AM response, namely, frequency and magnitude of excitation, body mass, gender, and back support condition. Consequently, an input matrix of 80754×5 was generated to serve as the model input.

Multilayer perceptron (MLP) among the class of feed-forward networks has the capability of universal approximation of nonlinear phenomena and complex systems. Hence, a multilayer feed-forward neural network with back propagation (BP) algorithm was employed. The MLP neural network architecture consists of one input layer comprising 5 main factors (frequency of vibration, body mass, gender, back support condition, magnitude of vibration), one output layer, and two hidden layers, as shown in Fig. 1. Two hidden layers are chosen due to large size of the data and complex dependence of the response on selected factors (body mass, gender, and sitting and vibration conditions).

The challenging tasks for developing ANN models are to identify optimal number of neurons in each hidden layer, number of hidden layers, training algorithms, transfer functions, and tuning of learning rate and momentum. Determination of an optimal number of hidden layers generally involves difficult tradeoff between the prediction ability and computational demand of the model. The preliminary simulations performed with the ANN model with a single hidden layer revealed poor predictions of the AM over the entire range of body mass and excitation levels. The MLP neural network with two hidden layers with neurons ranging from 1 to 20 was subsequently employed, which showed improved convergence in terms of mean squared error (MSE). It is noteworthy that employing greater number of neurons in each hidden layer entails the over-fitting drawback, which reduces the forecasting ability of the model [21]. The neurons within the selected range did not exhibit over-fitting, ensured smooth learning of the ANN model and provided good correlations between the predicted and measured responses during the cross-validation phase.

The network selects the weights and biases in a random manner at the start of training phase, which not only entails greater computational demands but also may not yield satisfactory model performance. In order to overcome this drawback, each structure was trained three times so as to minimize the effect of random adoptions of weights and biases. Although increasing the number of repetitions may result in convergence toward zero MSE, it will impose excessive computational demands. The preliminary simulations revealed that the convergence towards minimal MSE could be realized within 700 iterations. Subsequently, the network structure with least MSE over 700 iterations was explored. To ensure that each input variable provides an equal contribution in the ANN simulation and to reduce the challenge of numerical instability in the process of adjusting the weights, the inputs to the model, excluding the gender and back support condition, were normalized and scaled into the numeric range [0, 1], such that:

$$X_n = \frac{X_r - X_{\min}}{X_{\max} - X_{\min}} \quad (2)$$

where X_n denotes normalized input variable, X_r is raw input variable, and X_{min} and X_{max} denote the minimum and maximum values of the raw input variables, respectively.

Although it is not common to include qualitative inputs in the ANN models, however, gender and sitting posture had to be introduced to the model. The gender was described as an input with the numeric value of 0 and 1 for the male and female subjects, respectively. Similarly, the sitting condition input was also described either 0 or 1 representing sitting without and with a back support, respectively. Both the gender and sitting posture inputs thus conformed to the normalized range of other inputs and were processed through the weights, biases and the transfer functions.

The *logsig* transfer function was selected that is compatible with the normalization range of input variables since it is known to show least sensitivity to the numerical method for computing the differentials. Moreover, the adaptive characteristic of *logsig* facilitates the operations over the entire range of inputs, which yields significantly higher slope of the transfer function curve under small input magnitudes and substantially lower slope under higher input magnitudes. This enhances the rate of the learning performance of the network.

Back propagation (BP) training algorithm employs the iterative-based gradient descent optimization technique to minimize the mean square error between the actual and predicted output. In this manner, the synaptic weights are updated in an iterative manner until the predefined goal of realizing either 0 or a minima of MSE within the preset 700 iterations is attained. Levenberg Marquardt training algorithm (*trainlm*) has been employed, which is known to yield rapid convergence during the training phase by updating the weights and biases according to the Levenberg Marquardt (LM) optimization approach [31]. The reliability of any neural representation is generally verified using different statistical indices for quantifying the closeness of the actual and predicted outputs [32]. In this study, the mean square error (MSE) between the predicted and actual AM magnitude and the coefficient of determination (R^2) are adopted to evaluate performance of the ANN.

4. Results and discussion

4.1. Neural Network performance

The gradual and continuous increment of neurons in the hidden layer is a crucial step in ANN model development to reach a comprehensive representation including the effect of number of neurons in the hidden layer(s), which may vary widely. Figure 2(a) illustrates the effects of number of neurons, ranging from 1 to 20, in the two hidden layers on the resulting MSE. The figure shows the mean error obtained for three repetitions of each configuration. Determination of optimal number of neurons leading to minimal MSE is generally the most challenging during the network training. Increasing the neurons in both layers gradually reduces the error, although in a non-smooth manner. The non-smooth trend in MSE suggests instability in the learning process, which is due to random selection of weights for the neurons corresponding to each updated configuration. The training with repetitions of each configuration helped realize relatively smaller variation in MSE with varying number of neurons. Higher neurons lead to higher synaptic weights, which are adjusted by the BP optimization algorithm during epochs, and thereby the minimal error. Increasing the number of neurons, however, may lead to saturation of weights and over-training. The results in Fig. 2(a) suggest a tendency towards saturation of MSE. The least MSE of 4.83 kg^2 is obtained in the search space at the topological configuration of 20 neurons in the first and 20 neurons in the second hidden layers, while the inter-layer variability effect on the training MSE is illustrated in Fig. 2(b). Figure 2(c) illustrates the error histogram, which signifies that the model training follows a nearly normal error distribution (shifted Gaussian function). The results also show that a total of 155 ANN models could yield MSE in the 6 to 6.5 kg^2 range, while only three structures provide lower MSE ranging from 4 to 4.5.

Figure 3(a) illustrates the effects of number of neurons in the hidden layers on the resulting MSE during the testing phase, while Fig. 3(b) shows the surface contour plot of inter-layer variability. The results show convergence towards relatively higher MSE compared to that observed in the training phase. Moreover, the variations in MSE are also higher. This is mostly attributed to the use of unforeseen data (52 datasets) in the testing phase. The histogram of the MSE, shown in Fig. 3(c), suggest highest density of models in the 7 to 8 range, while only three topologies yield lower MSE ranging from 5 to 6 kg^2. The histogram also appears to follow nearly Gaussian distribution, although slightly shifted as observed in the training phase.

Figures 4(a) to 4(c) illustrate scatter plots of AM magnitudes predicted from the optimal network configuration during the training, validation and testing phases, respectively, and the target AM data. These figures show coefficients of determination in excess of 0.96, suggesting very good correlations between the target and predicted AM magnitudes during all three phases. This is also evident from nearly unity slope and negligible intercept of the best fit lines in all three phases.

4.2. Apparent mass response predictions of the model

The effectiveness of the optimal network configuration is evaluated using the 14 datasets of subjects representing different body mass, excitation level, gender and back support condition. The datasets were obtained for 8 male and 6 female subjects with body mass ranging from 49.7 to 104 kg and subject to whole body vibration excitation ranging from 0.25 to 0.75 m/s^2 rms acceleration in the 0.5 to 20 Hz frequency range, while sitting with or without a back support. These datasets were not included in the training, testing and validation phases, and are used only to assess validity of the final model. These datasets were thus unforeseen for the network during all earlier trials. The inputs to the model included particular body mass, gender, excitation level and back support condition. The AM magnitude responses predicted for each subject and test conditions combination are compared in Figs 5 and 6 for the male and female subjects, respectively, to demonstrate validity of the model. The comparisons show that the ANN model can predict the AM response for the entire ranges of body mass, excitation level and back support condition considered in the 14 target datasets. The results show that the peak AM response of all the 14 subjects occurs in the 4.13 and 6.87 Hz frequency range, which is widely denoted as the fundamental resonance frequency. The ANN model predicted the primary resonance frequency and the corresponding magnitudes satisfactorily wherein the obtained results are suggestive of MSE of 2.13 and 1.83 kg and R^2 values in excess of 0.98 for the male and female subjects, respectively. This range corresponds well with the frequencies identified from the target datasets, and the ranges reported in the literature [6,7]. Moreover, the peak AM magnitudes predicted by the ANN model converged to those of the target datasets for all the subjects considered. The ANN model, however, only predicted the secondary peak in the 7.5 - 12.5 Hz range for 10 of the 14 subjects. This is likely due to relatively small magnitude secondary peak in the AM response, as seen in the figures. The model predicted the secondary resonance peak better for the female subjects (Fig. 6) than the male subjects. This is due to fact that the secondary peak is more pronounced in the female subjects' responses [33]. The ANN model architecture proposed in the study could effectively capture the secondary peak for the female subjects, since it was trained for two discreet inputs (0 and 1) representing the male and female subjects.

The predicted results, however, also show some deviations from the target values in both the resonance frequency and magnitudes. These differences may be considered within the intra-subject variability observed in the data acquired during repeated trials over most of the frequency range, which has been reported in a number of studies [34,35]. The results in Figs. 5 and 6 show the substantial effects of gender, body mass and excitation magnitude on the resulting AM magnitude. For instance, the fundamental mode resonance frequencies of female subjects are lower than those of the male subjects. Moreover, the peak magnitude is strongly influenced by the body mass and back support apart from the gender. The nonlinear effects of these factors on the AM responses have also been reported in [7,35].

Figures 7 and 8 illustrate the effects of body mass, excitation magnitude and back support condition on the predicted AM responses of the male and female subjects, respectively. Increasing the body mass from 60 to 100 kg of male subjects and from 50 to 70 kg for female subjects leads to decrease in the primary resonance frequency and notably higher peak response. The AM transfer function tends to shift upward with increasing body mass, as seen in Figs. 7(a) and 8(a). A number of reported studies have shown this tendency in the measured AM responses [6,7,12,36]. It is also explicit from the developed ANN models that the subject mass is the greatest contributor to apparent mass magnitude response near the primary resonance frequency.

Increasing the vibration magnitude yields only slight reduction in the primary resonance frequency and minimal increase in the peak magnitude, as seen in Figs. 7(b) and 8(b) for the male and female subjects, respectively. This tendency, referred to as body softening effect, has also been reported in other studies [12,34]. The primary resonance frequency and the corresponding AM magnitude varied in the order of 117.85±3.94 kg and 4.68±0.468 Hz, respectively, with the adoption of the back support for male subjects. With no back support, the primary resonance frequency and the corresponding AM magnitude were 4.72±0.07 Hz and 125.64±4.62 kg. These suggest only minimal variation (< 1%) in the primary resonance frequency due to the effect of back support condition (Figs. 7(b) and 7(c)). For female subjects, the primary resonance frequency and the corresponding AM magnitude varied in the order of 90.98±2.22 kg and 5.01±0.188 Hz, respectively, with a back support. The primary resonance frequency and the corresponding AM magnitude were obtained at 81.58±0.96 kg and 4.93±0.167 Hz with no back support (Figs. 7(b) and 7(c)). The conclusion that vertical back support slightly affects the primary resonance frequency and the corresponding AM magnitude for the rigid seat is confirmed by others [6,7,37]. Irrespective of back support effect, the softening trend of human body response is also simulated by the developed ANN model. Figure 7(d) and 8(d) invariably show the decrease of AM magnitude of male and female subjects due to the back support effect according to the results reported by Dewangane *et al.*, [7].

The lumped-parameters models are developed through mass-damping-stiffness parameters for each individual subject in order to analyze the AM responses. Unlike the lumped-parameters and multi-body models where the model validity is limited to a certain subject, the developed ANN model herein has the capacity of estimating AM responses free of damping-stiffness parameters irrespective of each subject visco-elastic properties. The ANN model revealed a satisfactory performance within the evaluated range of inputs while the extrapolations may result in undesirable prediction errors of AM responses due to the inherent limitation of the neural network models. The future studies can investigate the methods of minimizing the extrapolation errors via updated pattern recognition techniques of AI.

5. Conclusions

The predicting ability of artificial neural networks was investigated for modeling the seated body apparent mass under vertical whole body vibration. Different preprocessing and post-processing procedures such as outlier removal, normalization of inputs, and tuning of training parameters were carried out to achieve a model with minimum MSE for prediction of the seated body apparent mass under different levels of vibration excitations and frequency range. It was confirmed through the performance criteria that the outperforming architecture has the ability to predict the seated body response within the range of trained data, while an excessive extrapolation results in decreased prediction accuracy because the weight and bias are updated by BP training algorithm within the range of training dataset. ANN can be investigated as a promising tool to model biodynamic problems and can be employed to recognize the soft seat and human body interactions particularly if the model is trained well. It is recommended to hybridize meta-heuristic optimizations such as particle swarm optimization (PSO), ant-bee colony (ABC), and imperialist competitive algorithm (ICA) with ANN models to find the best weight matrix at a quick pace of convergence to the actual data. The upgraded ANN model by meta-heuristics can be then applied to the prediction of the human body response to vibration on the soft seats.

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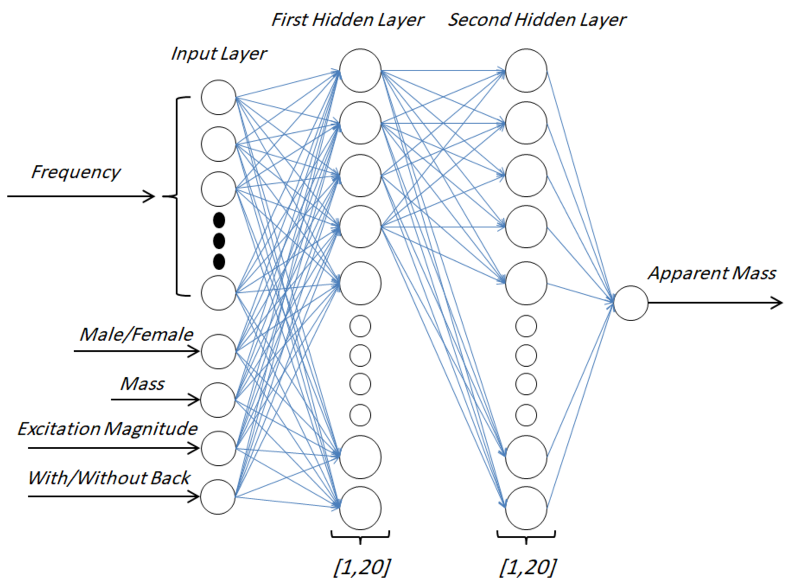

Fig. 1. The general multi-layered perceptron feed-forward ANN architecture with two hidden layers

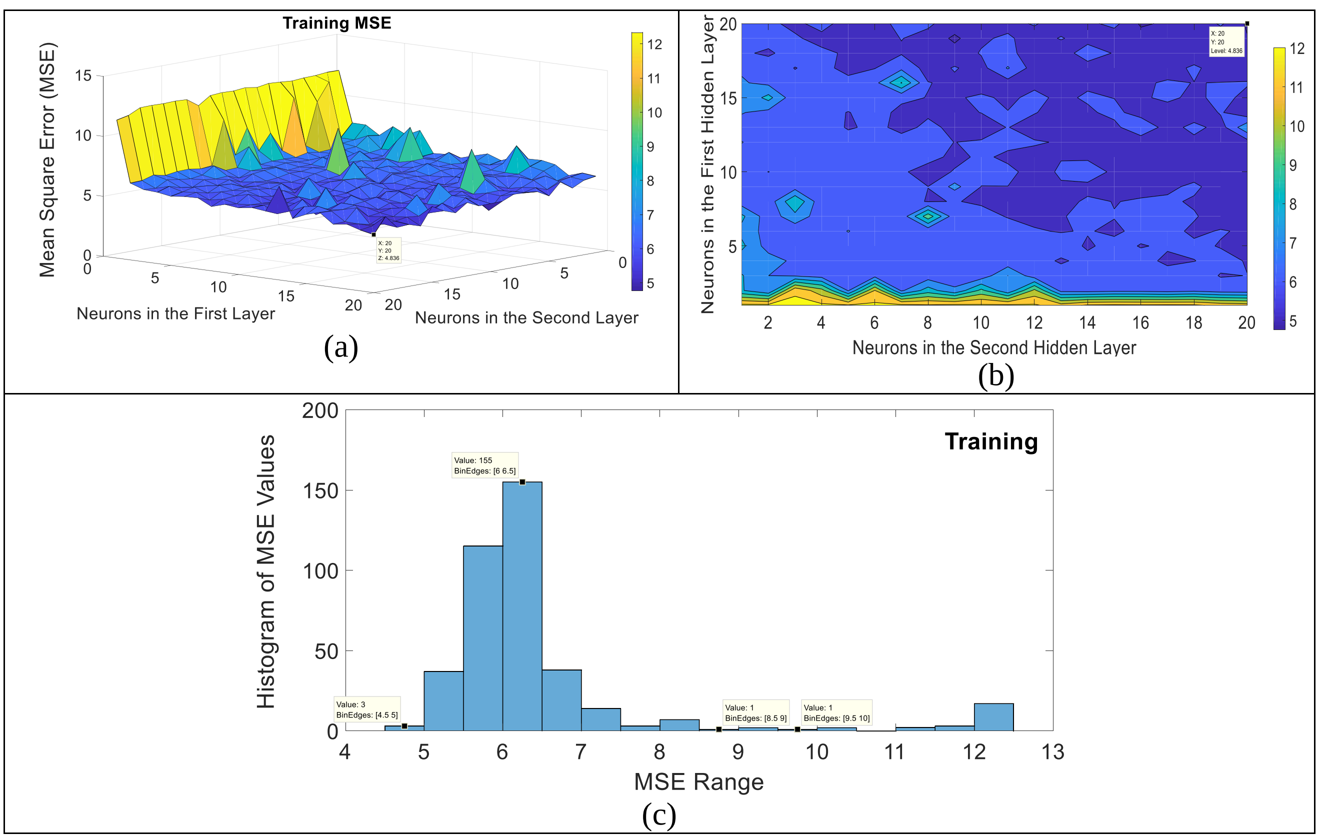

Fig. 2. a) Effect of number of neurons on the MSE during training phase, b) Contour plot of MSE as function of neurons in two layers, and c) Histogram of the MSE in the training phase

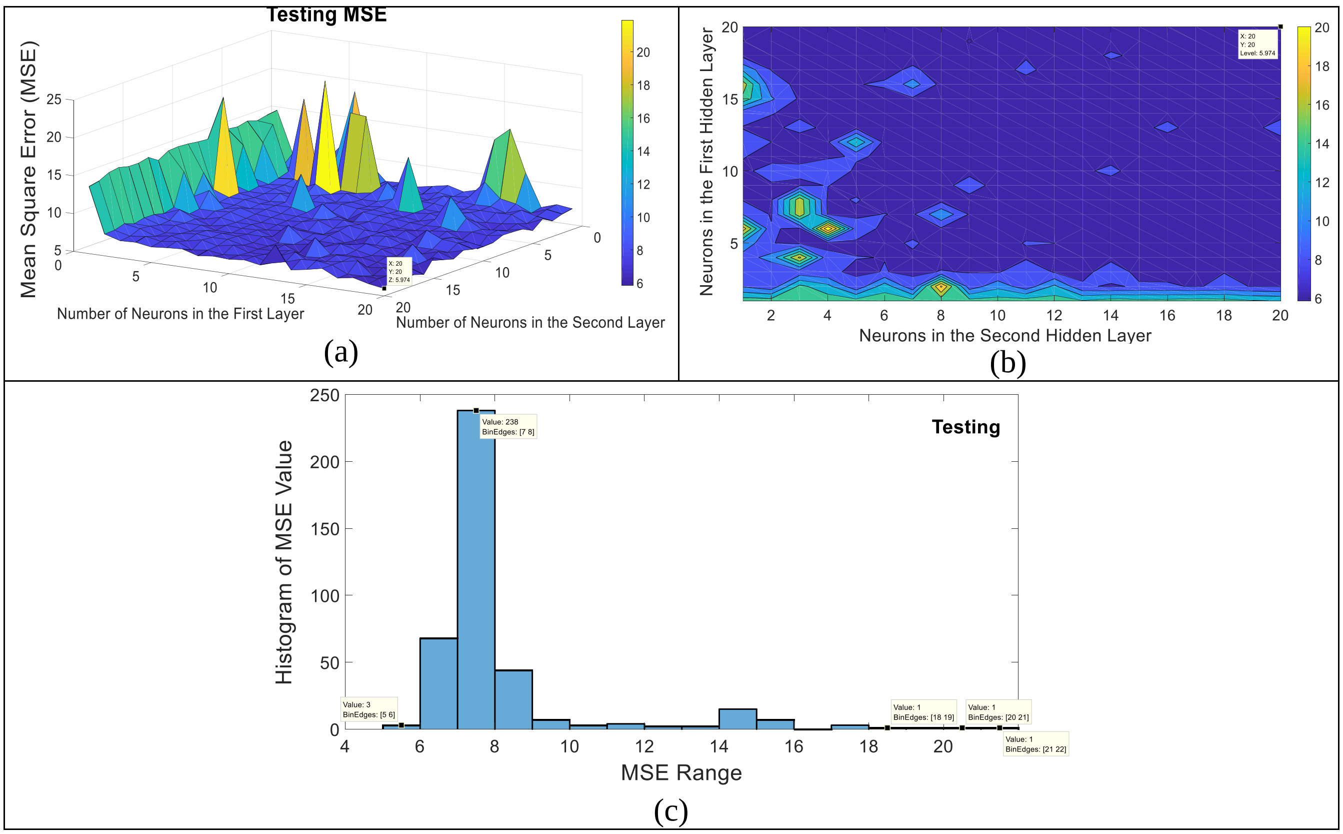

Fig. 3. a) Effect of number of neurons on the MSE during testing phase, b) Contour plot of MSE as function of neurons in two layers, and c) Histogram of the MSE in the testing phase

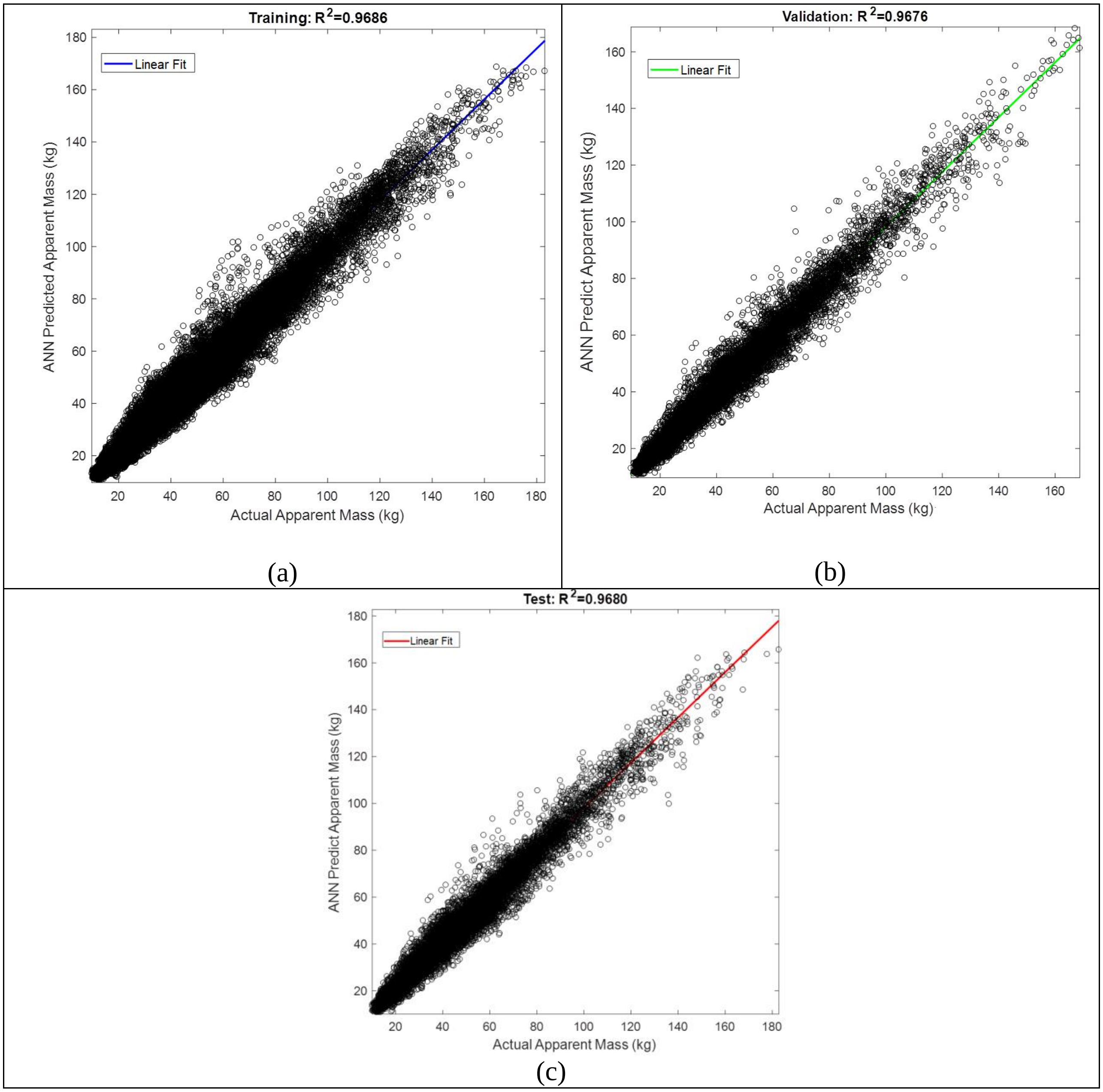

Fig. 4. Scatter plots of ANN model predicted and target AM response for (a) training, (b) validation and (c) testing phases

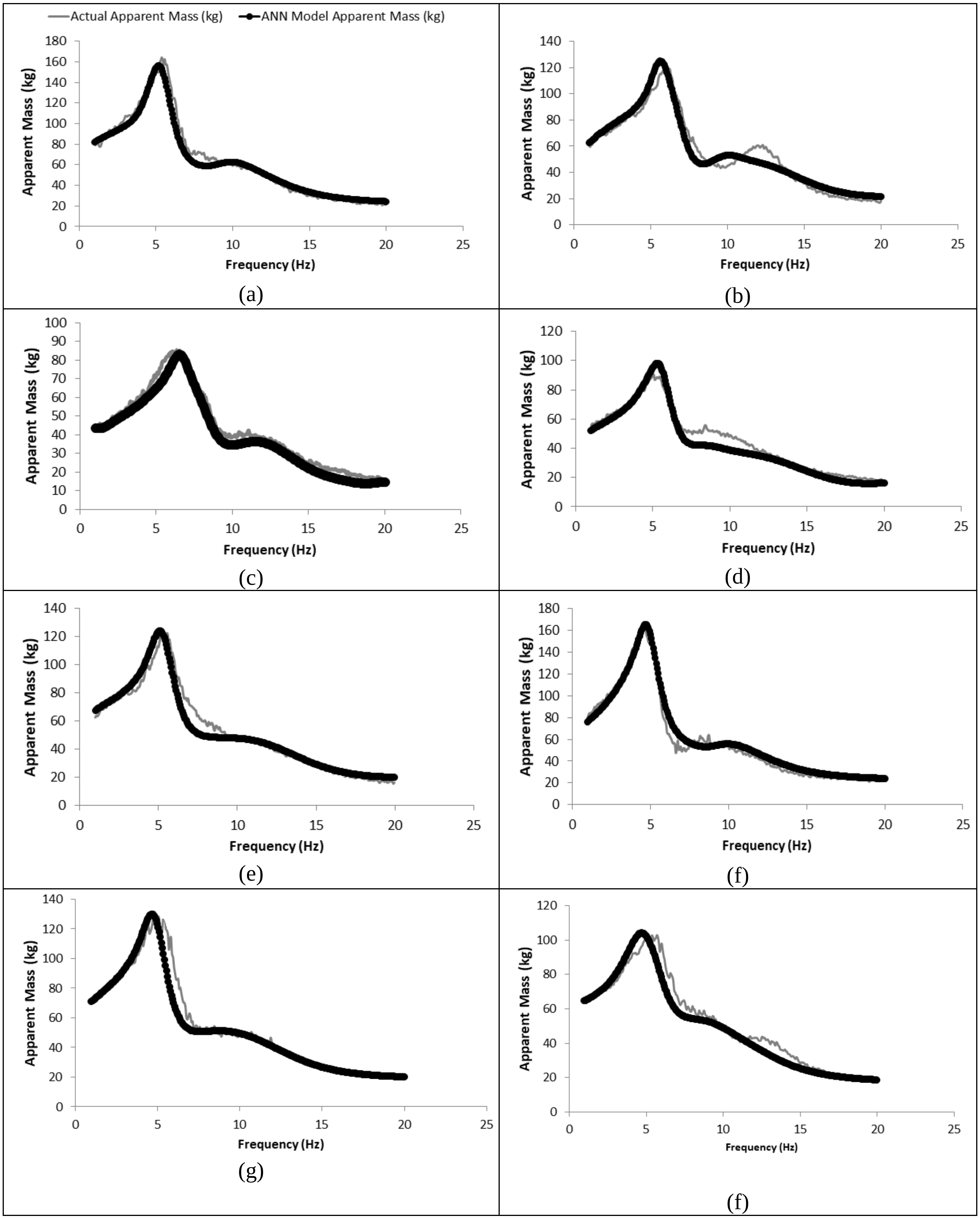

Fig. 5. Comparison of AM response predicted by the ANN model with the target values for male subjects: a) mass=103 kg, excitation magnitude= 0.25 m/s^2, NB, b) mass=81.9 kg, excitation magnitude= 0.25 m/s^2, NB, c) mass=57 kg, excitation magnitude= 0.25 m/s^2, NB, d) mass=72.5

kg, excitation magnitude= 0.5 m/s^2, NB, e) mass=85 kg, excitation magnitude= 0. 5 m/s^2, NB, f) mass=104 kg, excitation magnitude= 0. 5 m/s^2, NB, g) mass=91 kg, excitation magnitude= 0.75 m/s^2, B, h) mass=82.7 kg, excitation magnitude= 0.75 m/s^2, B

(NB-No back support; B-Back support)

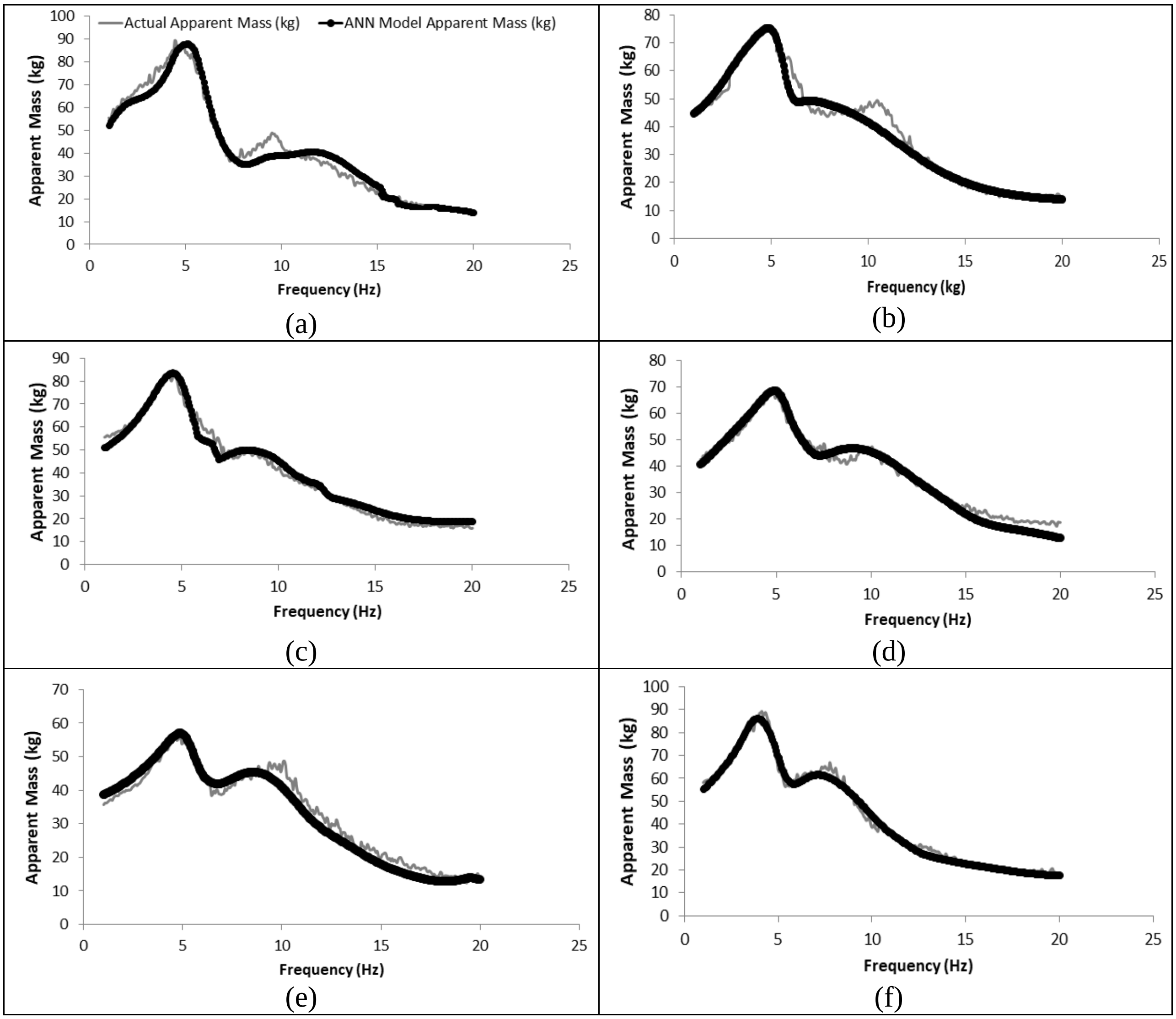

Fig.6. Comparison of AM response predicted by the ANN model with the target values for female subjects: a) mass=69 kg, excitation magnitude= 0.25 m/s^2, NB, b) mass=61 kg, excitation magnitude= 0. 5 m/s^2, NB, c) mass=69 kg, excitation magnitude= 0. 5 m/s^2, B, d) mass=56.4 kg, excitation magnitude= 0.25 m/s^2, B, e) mass=49.7 kg, excitation magnitude= 0. 75 m/s^2, B, f) mass=72.5 kg, excitation magnitude= 0. 75 m/s^2, B (NB-No back support; B-Back support)

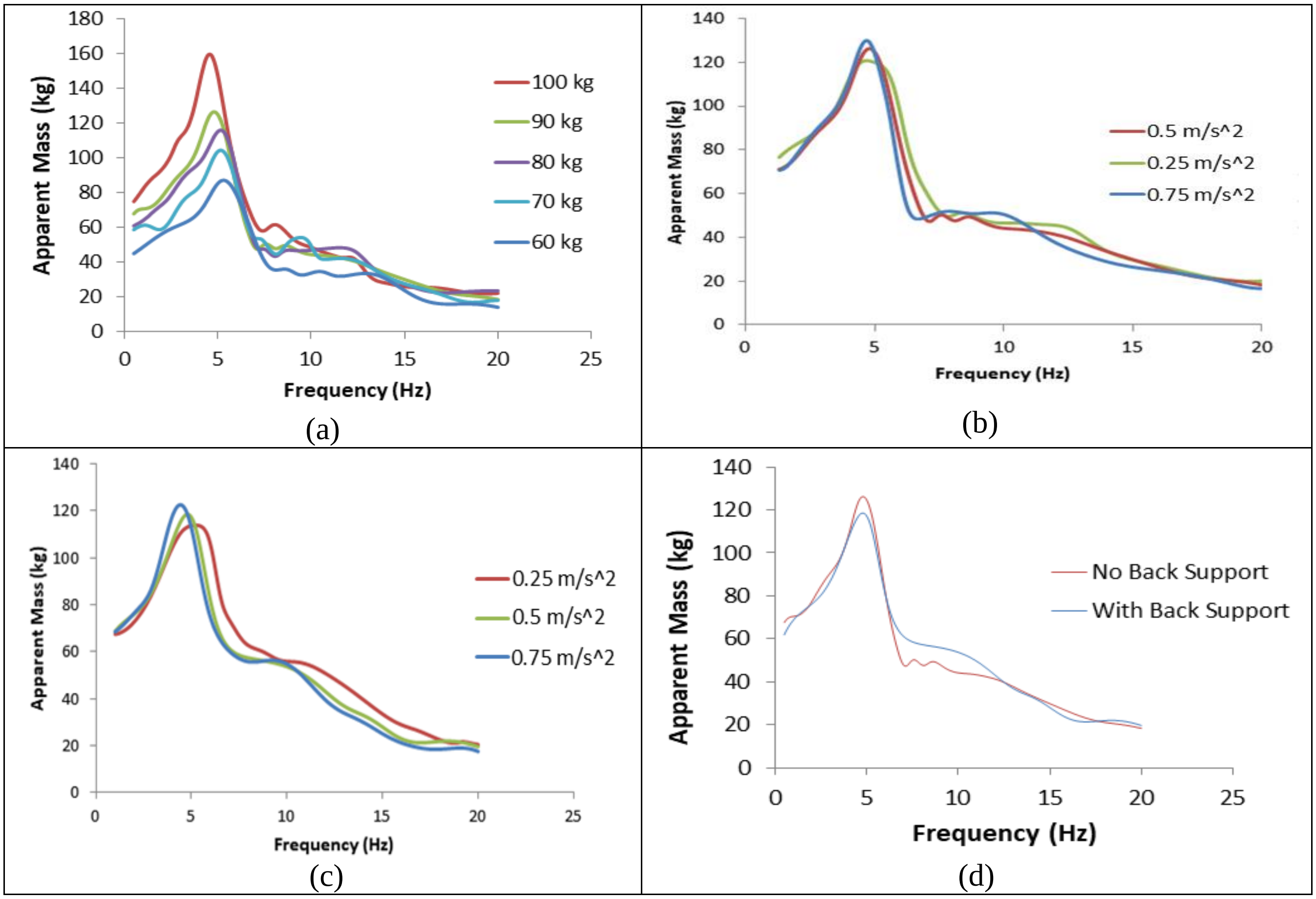

Fig. 7. The AM response of male subjects predicted by the ANN model with respect to the frequency under the effect of a) subject mass; excitation magnitude=0.5m/s^2 and NB, b) excitation magnitude; m=90kg and NB, c) excitation magnitude; m=90kg and B, and d) NB and B; m=90 kg and excitation magnitude=0.5m/s^2. (NB-No back support; B-Back support)

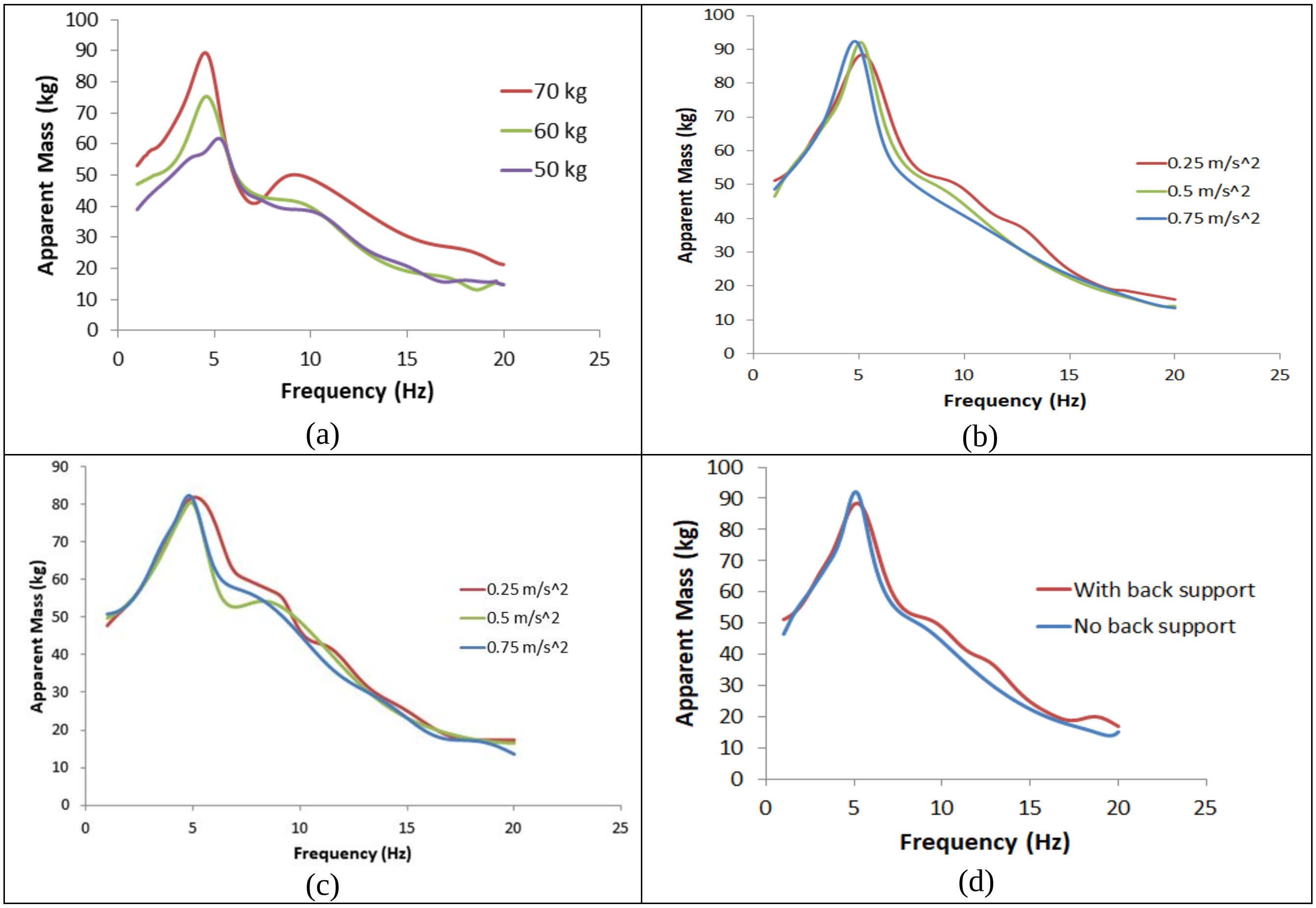

Fig. 8. The AM response of female subjects predicted by the ANN model with respect to the frequency under the effect of a) subject mass; excitation magnitude=0.5m/s^2 and NB, b) excitation magnitude; m=65 kg and NB, c) excitation magnitude; m=65 kg and B, and d) NB and B; m=60 kg and excitation magnitude=0.75m/s^2. (NB-No back support; B-Back support)

Table 1. The anthropometric parameters and their corresponding values for the test subjects

	Maximum, Minimum, **Mean**, Standard Deviation		
Parameter	Male (27)	Female (24)	All Subjects
Age (years)	58,23,**31.22**,7.22	49,19,**28.86**,7.20	58,19,**30.14**,7.23
Stature (m)	1.92,1.59,**1.75**,0.07	1.72,1.48,**1.62**,0.06	1.92,1.48,**1.69**,0.09
Mass (kg)	106,55,**80.55**,15.39	72.5, 45.5, **59.09**,8.01	106,45.5,**70.03**,16.29
BMI (kg/m^2)	34.98,19.95,**26.06**,4.29	26.3,15.8,**22.3**,2.71	35,15.8,**24.3**,4.02