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Original scientific paper

Artificial Neural Network for Prediction of Seat-to-Head Frequency Response Function During Whole Body Vibrations in the Fore-and-Aft Direction

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Abstract: Vibrations while driving, regardless of their intensity and shape, have the most obvious effect of reducing driving comfort. Seat-to-head frequency response function (STHT) is a complex relationship resulting from the movement of the head due to the action of excitation on the seat in the form of vibrations in the seat/head interface. In this research, an artificial neural network model was developed, which aims to simulate the STHT function through the body of the subjects based on the data obtained experimentally. The experiments were conducted with twenty healthy male volunteers, who were exposed to single-axis fore-and-aft random broadband vibration. All the results of the experiment were recorded on the basis of which the artificial neural network (ANN) was trained. The developed ANN model has the ability to predict STHT values in the range of trained values both when changing the anthropometric measures of the subjects and changes in the input characteristics of vibrations. The mathematical models based on recurrent neural networks (RNN) used in this paper show with high accuracy STHT values in case there exists prior information about the anthropometric measures of the subjects and the input characteristics of vibrations. The results show that the expensive real-time simulations could be avoided by using reliable neural network models.

Keywords: ANN model; human body response; STHT function; whole body vibration

1 INTRODUCTION

The behaviour of the human body due to the action of vibrations has been studied for many years. Numerous factors such as body posture, muscle condition, amplitude and vibration strength affect the sensitivity of this complex biomechanical system [1]. Vibrations are considered not only an engineering problem, but also a health problem, since they affect human body [2, 3]. Passenger vehicles users in real operating conditions are exposed to random broadband vibrations. The greatest impact on the driver is exerted by vertical vibrations and fore-and-aft vibrations, defined by ISO 2631-1: 1997/Amd 1:2010 [4], so this standard is the basis for dynamic tests.

Early studies primarily addressed the effects of vibration frequency variation. Subsequent research has studied more complex conditions, including multifrequency vibrations, multiaxial vibrations, and shocks. The human body exposed to vibrations is widely evaluated in terms of the function of the biodynamic response. In the 1980s, there was talk of finding a way to identify the extent of the human body's biodynamic response to vibration. The ISO standards [5, 6] suggested that the STHT magnitude, driving-point mechanical impedance, apparent mass and phase characteristic be used for this purpose [7-9].

Several factors affect the value of the STHT function such as body weight, seat back angle, gender of the subject, then type, magnitude and frequency of vibration [10, 11].

The influence of the seat back on the reactions of the body in the sitting position, which was exposed to vertical and fore-and-aft vibrations, showed a strong influence. Coermann [12] concluded that the state of relaxed muscles, when the subjects occupy a sitting position, leads to an increase in STHT magnitude and a decrease in the frequency of primary resonance, in contrast to the upright position of the body. The authors [13] concluded that upright body posture causes higher mean STHT values at frequencies above 6 Hz but lower below 6 Hz compared to relaxed sitting. The responses of STHT function with relaxed posture were comparable to the normal position, at frequencies above 10 Hz. The upright posture resulted in a significantly higher magnitude of the seat-head transmission function at frequencies above 5 Hz, especially at peak magnitudes in the frequency range of 10 Hz - 15 Hz. Similarly, Cho and Yoon [14] found a significant difference between seat-to-head frequency response functions on a seat with and without a seat back. The main resonant frequency for a seat without a backrest is 3.4 Hz, which is significantly lower than that of a seat with a backrest of 4.2 Hz. The authors hypothesized that displaced resonant peaks may be caused by differences in posture, muscle tension, or direct transmission of acceleration from the backrest.

Many researchers have been researching for many years the influence of the magnitude of vibrations transmitted through the body in order to determine whether the body behaves linearly or nonlinearly. They also studied whether the vibration magnitude had an effect on STHT function. Griffin [15] conducted experimental research to prove the existence of nonlinear behaviour in the human response to vibration. During the experiment, vertical head movements were monitored for twelve men sitting in a seat during vertical vibrations. The author found that the vibration strength had a significant effect on the vertical STHT function, with a greater effect at lower frequencies. Research in [16, 17] showed that increasing the vibration magnitude leads to a decrease in both primary and secondary resonant frequencies. The responses of STHT function show changes in resonance on the next way increasing vertical vibrations lead to shift values to lower frequencies.

In the last ten years, researchers have begun to use the possibilities brought by the development of new technologies artificial neural networks (ANN). By learning based on input and output signals, ANN can model complex nonlinear systems, so they have a wide application [18, 19]. Artificial neurons of ANN are connected to other neurons in layers, and because of that, ANN-based systems have the advantage over systems with standard algorithmic methods. An ANN can learn from examples and adaptability is one of the main properties [20].

Although a large number of papers have been published on the study of the effects of vibration on the human body, much more attention has been paid to vertical vibrations. Knowledge of the values of STHT functions during the action of fore-and-aft vibrations on the human body is still incomplete. Vibration in the fore-and-aft direction can produce large movements of the head. In that sense, it is very important to know the factors that affect such movements in order to make unwanted contact of the head with the environment. Based on previous studies, this research is an extension of the study of the influence of fore-and-aft vibrations on the human body due to different sitting conditions and different values of stimuli using a new concept - ANN.

The main contribution of this paper was the development of an ANN model based on the results of frequency response functions obtained by experimental measurements. The developed model is able to predict the STHT functions in different seating conditions under different excitation and different anthropometric characteristics of the subjects. The application of ANN for the development of the driver model made it possible to predict the vibrational loads of the driver's body exposed to random broadband fore-and-aft vibrations. The developed model takes into account: nonlinearity of the human body, intersubjective and intrasubjective variability, anthropometric parameters and sitting position. The models that have been developed so far have not had these capabilities, so there is no such model in the available literature.

2 MATERIALS AND METHODS

2.1 Laboratory Research

In this paper the electro-hydraulic pulsator HP-2007 was used. It contains the car seat on which the respondents seat during the experiment. Its role was to provoke excitations of different amplitudes and frequencies. With this pulsator it is possible to generate independent vibrations in multiple directions. During the experiments, the subjects wore a plastic helmet on head. Over this helmet, a system of a three-axis accelerometer AC102-1A, with frequency range 0.5 Hz -15 kHz and 90 grams, was mounted. The MetravibNetdB PRO-132 system was used for data acquisition (Fig. 1). During the experiments, the sampling rate was 51.2 kHz, the block duration 80ms, and the number of samples was 4096. In addition to these data, data on the number of averaging of 2 and the sampling step of Δt = 0.0195 ms were also known. The frequency step was Δf = 0.3906 Hz and the bandwidth was up to 39 Hz, while the signal overlap was 75%.

Twenty healthy male subjects aged 30.7 ± 6.15 years, height 183.25 ± 4.43 cm, weight 89.4 ± 11.72 kg, BMI (BMI Body Mass Index) 26.57 ± 2.96, seating height 88.35 ± 4.79 cm were used in the experiment. They were exposed to random uniaxial vibrations in fore-and-aft direction.

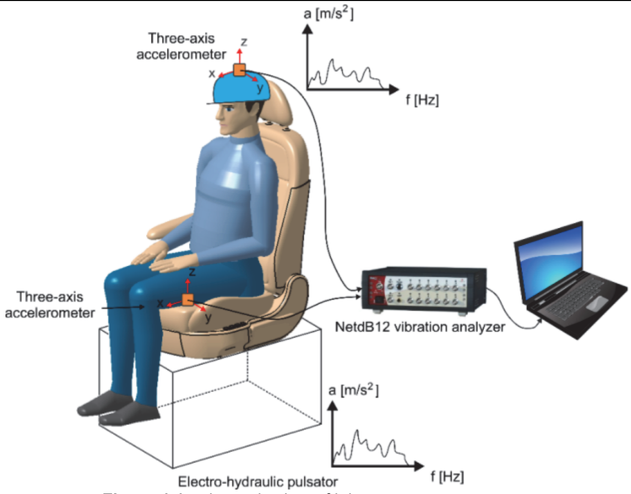

Figure 1 A schematic view of laboratory measurements

2.2 Test Procedure

Human response to whole-body vibration is a very complicated process. For example, if one person under a certain condition test for several times, then his/her response will not be the same at each time. There are many reasons behind this behaviour, because human response to vibration can be affected by muscle activation, mass, stature, gender, posture, vibration magnitude, vibration frequency, and interaction with the surrounding equipment. Therefore, researchers usually do many experiments and then take the mean or the median of these tests. A similar process will be done when a group of people exist, and while there are differences, we always use the mean or the median of these tests, and the more people involved, the better the mean or median becomes. By doing this, people working in this area were able to define ISO standards [4-6].

In this research, subjects were informed before performing the test about the manner and role in the experiment. Their task was to sit in the seat, as they normally do in their vehicle, and to put their hands on their thighs, because there are studies that show that the position of the hands does not have a significant effect on the transmission of vibrations [10, 11]. In order to avoid unintentional head movements, the respondents were instructed to direct their eyes to the cross-shaped symbol (+) that stood on the wall. The distance of the wall was about 2 meters. The subjects were exposed to uniaxial vibrations in the fore-and-aft direction for three different excitations of 0.45 m/s^2r.m.s., 0.8 m/s^2r.m.s., and 1.1 m/s^2r.m.s. The frequency range that is important for the oscillatory comfort of the vehicle was used in range from 0.5 Hz to 20Hz. Measurements were made for three different seating angles of 90°, 100° and 110° degrees with respect to the *Z* axis. The test for each excitation lasted 1 minute. A total of 2 tests were performed for each vibration amplitude/sitting angle and mean values were adopted. Daily, the measurement lasted about 1 hour with breaks between sessions of 5 minutes.

2.3 Seat-to-Head Transmissibility

There are many types of frequency response functions that can be used in the analyses of biodynamic response of the human body. The frequency response function in a complex form is defined as the ratio:

$$H\left(j\omega\right)=\frac{G_{io}\left(j\omega\right)}{G_{ii}\left(j\omega\right)} \tag{1}$$

where $G_{io}(j\omega)$ is cross-spectrum between seat and head acceleration, $G_{ii}(j\omega)$ input autospectrum. In this experiment, two frequency response functions are defined as fore-and-aft head motion= X_h/X_s and vertical head motion Z_h/Z_s, where X_h and Z_h are the acceleration magnitude of head motion in fore-and-aft and vertical direction respectively, while X_s and Z_s are the acceleration magnitude of seat motion in fore-and-aft and vertical direction, respectively, Fig. 1.

The STHT values represent a sequence of data points that occur in successive order over some period of time, which gives us the ability to apply algorithms for time-series forecasting. Time series forecasting is the process of analysing time series data using statistics and modelling to make predictions and inform strategic decision-making. Recently, the frequent use of the recurrent neural networks (RNN) has been noticeable, because they have shown high performance in solving this task. Taking into consideration that the best results in STHT values forecasting were achieved by using recurrent neural networks, only a brief description of this method is given.

2.4 Recurrent Neural Networks

The recurrent neural networks are ANNs in which the outputs of the neural elements of the next layers have synaptic connections with the neurons of the previous layers along temporal sequence. This leads to the possibility of taking into account the results of the transformation of information by the neural network in the previous phase for processing the input vector in the next phase of network operation. Recurring networks can be used to solve forecasting and control problems.

Typically, traditional deep learning algorithms are used for ordinal or temporal problems, such as language translation [21], natural language processing [22], speech recognition [23], and image captioning [24]. Our data have a temporal character (the seat-head system oscillates over time and every movement is recorded), which is why we decided on this approach.

There are three types of RNN: the simple, gated recurrent unit and long short term memory unit (LSTM). Long-term memory is a type of recurrent neural network dating back to 1997 designed by Sepp Hochreiterand Jürgen Schmidhuber [25]. This type of network is designed to have no problem with the gradient disappearing, so it is currently the most popular type of network neuron. In this paper, LSTM cells were used for the time-series modelling. Standard RNNs have problems with the disappearance and explosion of the gradient, because of that reason it is difficult to train the RNN to solve problems that require learning long-term time dependencies. On the other side, LSTMs deal with these problems by introducing new gates, i. e. input, output and forget gates. In this way, unlike RNN, LSTM can use information from memory for a much longer period of time. Compared to LSTMs, gated recurrent network represents a similar type of recurrent network but with simplified structures [26].

3 RESULTS

The first part of the results section shows the results of the frequency response functions of 20 subjects exposed to fore-and-aft vibrations for three seating angles and two different excitation amplitudes. Due to the large number of obtained diagrams, all results of laboratory measurements were organized so the most relevant ones were presented in a smaller number of figures. The second part of this section presented the results obtained by applying artificial neural networks in predicting STHT magnitude.

Fig. 2 shows fore-and-aft STHT modulus of 20 subjects for 90° degree backrest angle and vibration magnitude of 1.1 m/s^{2}r.m.s. Despite the scatter between the STHT magnitude responses of different subjects, the peak module of STHT in fore-and-aft axis occurs around 3 to 4.5 Hz frequency range for all subjects, often referred to as the primary resonant frequency of the seated body [27-29]. The mean value (Fig. 2 black bolded line) of the STHT function has an amplitude of 2.1, at a frequency of 4.1 Hz.

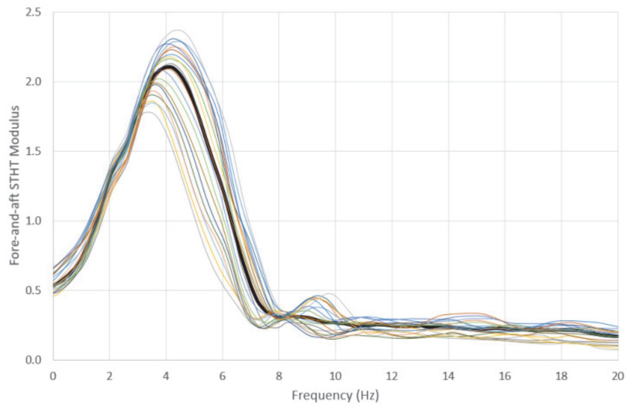

Figure 2 Inter-subject variability in fore-and-aft STHT measured at 1.1 m/s^2 with 90° degree backrest angle

Similar degree of scatter and consistent trend in the data was also observed for vertical STHT modulus, Fig. 3. The peak module of STHT in vertical axis occurs around 3.8 to 5.3 Hz frequency range for all subjects. In contrast to the results of Fig. 2, Fig. 3 shows a significant scattering of the results after 8 Hz. The amplitude of the mean value of the STHT function has an amplitude of 1.48, and was slightly shifted to the right, at a frequency of 4.81 Hz. It was noticed that the weight of the subjects has the greatest effect on the appearance of peaks and their frequency value. Heavier subjects do not allow too much movement and thus have lower values of STHT amplitude and lower frequency.

Fig. 4 shows how changes in seating angle and excitation amplitude affect STHT values. In the case of fore-and-aft STHT functions, it was observed that an increase in the seating angle, from 90° to 110°, leads to a decrease in the peak STHT amplitude and shifts it to the left, to lower frequencies, while at higher frequencies, above 12 Hz, STHT functions of larger seating angle have higher values, compared to STHT functions obtained for 90° seating angle. The values of the resonant frequency peaks for excitation 0.45 m/s^2 were 3.94 Hz (110°), 4.29 Hz (100°) and 4.52 Hz (90°).

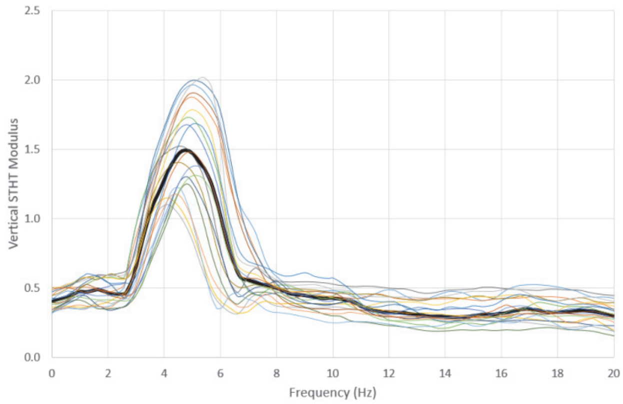

Figure 3 Inter-subject variability in vertical STHT measured at 1.1 m/s^2 with 90° degree backrest angle

Compared to the excitation of 0.45 m/s^2, the excitations of 0.8 m/s^2 and 1.1 m/s^2 result in higher amplitudes of STHT functions, and thus further shift them to the left. In the areas of higher frequencies, a new difference was observed. The STHT functions of 100° and 110° degree seating angles have much higher values as opposed to 90° degree seating angles. The reason for this was precisely the larger seating angle, which tends to reduce the primary frequency and cause the appearance of secondary ones. The values of the primary resonant frequency peaks for excitation 1.1 m/s^2 are 3.43 Hz (110°), 3.6 Hz (100°) and 3.83 Hz (90°).

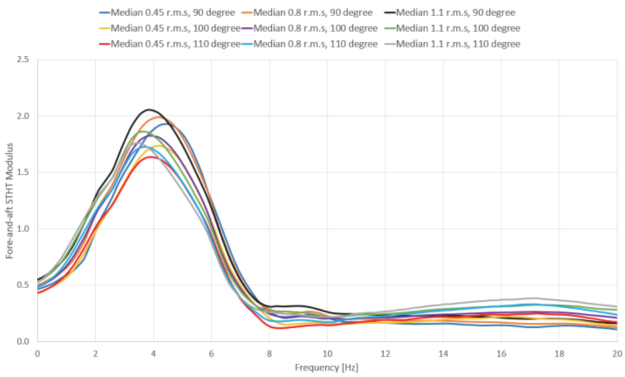

Figure 4 Mean fore-and-aft STHT values for the three sitting angles of 90°, 100° and 110°, 0.45 m/s^2, 0.8 m/s^2, 1.1 m/s^2

In the case of vertical STHT functions, Fig. 5 also shows that an increase in the seating angle leads to a decrease in the peak STHT amplitude and shifts it to the left. It has also been observed that increasing the excitation amplitude affects the value of the resonance peaks by moving them to the lower ones. Here, the appearance of secondary resonances was now clearly seen as a consequence of the increase in the mass of contact between the examinee and the seat. The values of the primary peaks range from 4.56 Hz (1.1 m/s^2, 110°) to 5.27 Hz (0.45 m/s^2, 90°), and the secondary from 13.49 Hz (0.45 m/s^2, 110°) to 13.98 Hz (0.8 m/s^2, 110°).

Second part of this paper was dedicated to testing three approaches in order to predict the seat-to-head transmissibility magnitude. First, we started from the traditional approach, such as ARIMA (Auto Regressive Integrated Moving Average) [27]. It is a generalization of the simpler Auto Regressive Moving Average and adds the notion of integration. However, this model resulted in very poor prediction results, so further it was not considered at all. After that, two more advanced approaches were tested, Facebook Prophet [28] and Recurrent Neural Networks (LSTM) [29].

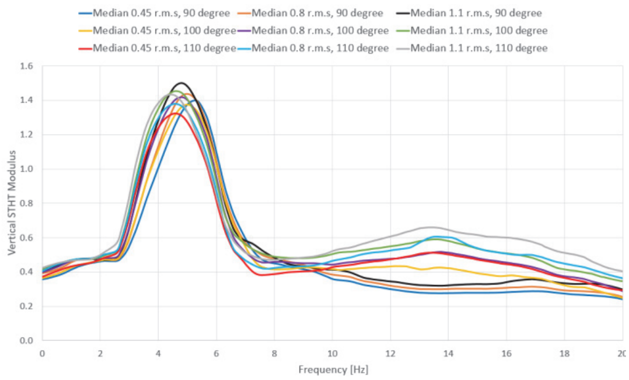

Figure 5 Mean vertical STHT values for the three sitting angles of 90°, 100° and 110°, 0.45 m/s^2, 0.8 m/s^2, 1.1 m/s^2

In order to test robustness of the models, dataset was split into training, validation and test sets, where eighteen randomly selected subjects were used for training, one for validation and one for the test phase. We decided on this division of training data on the basis of recommendations for working with large databases [30]. For each subject, his personal data (height, weight, seating height, years and BMI) were combined with the three considered amplitudes and three seating angles.

The first step was to prepare the experimental dataset for the LSTM. This involves framing the dataset as a supervised learning problem and normalizing the input variables. The same variables used by the Facebook Prophet algorithm are used here as well. The supervised learning problem was framed as predicting the frequency response function seat-to-head at the current moment (t) given the STHT measurement and personal data at the prior time step. After this transformation step, the nine input variables (input series) and one output variable (STHT value at the current moment), which was in the 9th position.

$$var1(t-1),\ var1(t),\ \dots,\ var9(t-1),\ var9(t) \tag{2}$$

where *var*1 is Height (cm), *var*2 is Weight (kg), *var*3 is BMI (kg/m^2), *var*4 is Seating heights (cm), *var*5 is Years, *var*6 is Amplitude, *var*7 is Seating angle 110°, *var*8 is Seating angle 90°, *var*9 is Output. Variables *var*7 and *var*8 represent the dummy variables created by dummy encoding technique for treating categorical variables. The column corresponding to the seating angle of 100° is omitted, because dummy encoding uses $N - 1$ features to represent N labels/categories.

The LSTM with 30 neurons were defined in the first hidden layer and one neuron in the output layer for predicting STHT for the selected subject. The input shape was one time step with 10 features. The Mean Absolute Error (MAE) was used as loss function and the efficient Adam version of stochastic gradient descent. The model was fit for 50 training epochs with a batch size of 20.

Finally, track of both the training and validation loss during training phase was kept. The resulting loss curves during the training and validation phases, for STHT, are shown in Fig. 6.

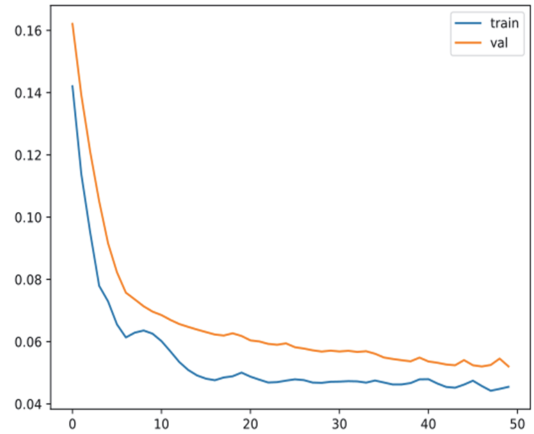

Figure 6 Loss function

The regression in training, validation and test are over 98% (Tab. 1). This shows that the accuracy of the model was in acceptable range.

Table 1 R correlation coefficient between output of model and target values

R correlation coefficient	Train	Validation	Test
LSTM	0.98	0.99	0.98
Facebook Prophet	0.57	0.6	0.7

Time-series forecasts on test set, in this case it was the frequency response function seat-to-head, for each frequency and angle separately, are shown in Fig. 7. Actually, the original and predicted values of STHT for one user are shown. Nine predictions are obtained for each potential combination of amplitude we used for the seat (0.45 m/s^2, 0.8 m/s^2, 1.1 m/s^2) and three seating angles 90°, 100° and 110° degrees of inclination with respect to the *z* axis.

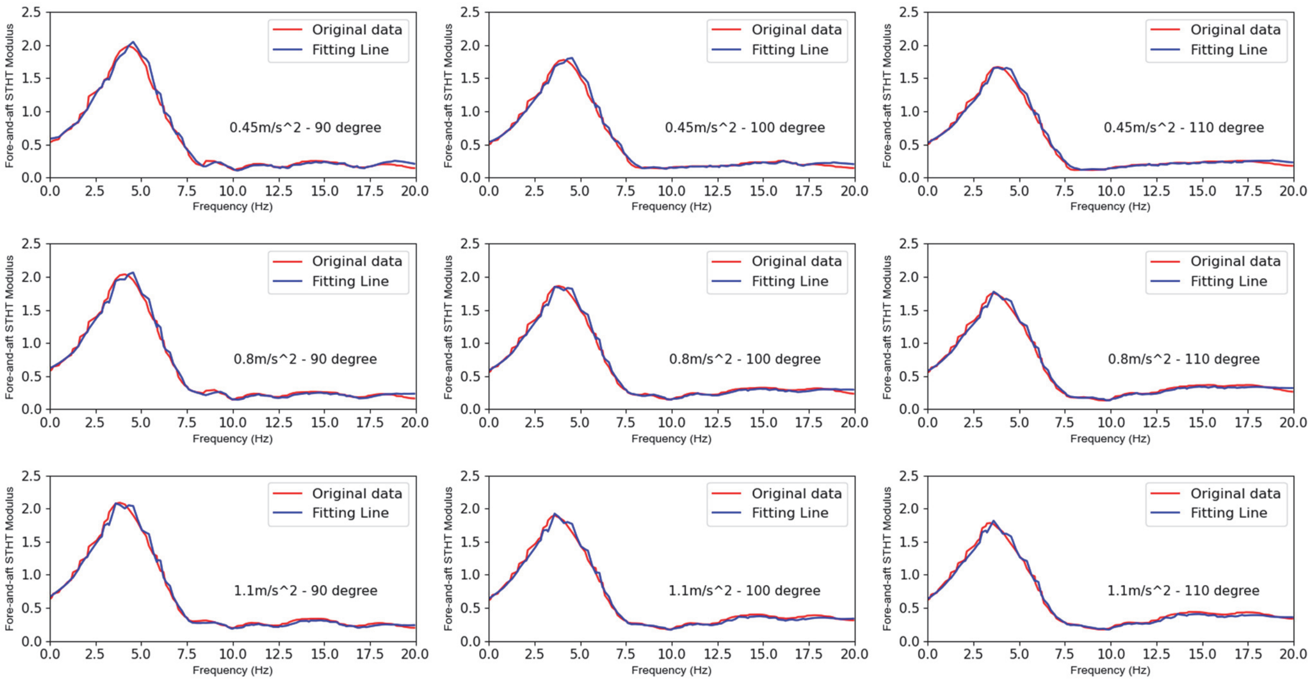

Figure 7 Original and predicted values for one user, for each combination of frequency and angle

The Root Mean Square Error (RMSE) for these nine combinations for the LSTM model was 0.05, which shows very high accuracy of the trained model. On the other side, Facebook Prophet achieved much worse results when compared to the LSTM model, and its RMSE was equal to 0.15 on the same set. It could be seen that machine learning applied to time series data, in this case RNN, is an efficient and effective way to analyse the data.

4 CONCLUSIONS

In the first part of this paper, an experimental study of the change in seat-head frequency response function for three different vibration magnitudes and three different seating angles was conducted. When the magnitude of vibration increases, whether observed fore-and-aft or the vertical modulus of the STHT function, there is an increase in the peak of the function and a slight decrease in the frequency of its occurrence. Increase of the sitting angle has an impact on the value of the first peak in the form of a decrease in the value of the frequency response function and a decrease in the frequency at which it occurs. In the case of mean fore-and-aft STHT values, the values of the primary resonant frequency peaks for excitation 1.1 m/s^{2}r.m.s were 3.43 Hz (110°), 3.6 Hz (100°) and 3.83 Hz (90°). Another conclusion that can be observed was that increasing the angle of the backrest in frequency zones greater than 12 Hz leads to the appearance of a second, secondary peak that increases with each increase in seating inclination due to the larger contact area between the subject and the seat back.

The second part of the research is dedicated to the introduction of artificial neural networks in order to predict the behaviour of subjects on the seat after training the network with measured experimental values. Two advanced approaches were tested, Facebook Prophet and

Recurrent Neural Networks (LSTM). The LSTM were defined with 30 neurons in the first hidden layer and one neuron in the output layer for predicting STHT for the selected subject. The results show that the regression in training, validation and test is over 98%.The Root Mean Square Error for nine combinations (three magnitude and three seat back angle) for the LSTM model was 0.05, which shows very high accuracy of the trained model. ARIMA and Facebook Prophet approaches were not capable of providing highly accurate models that could reliably predict the STHT outcome.

The mentioned neural network model has a limitation in terms of determining the transfer functions of only uniaxial excitation in the fore-and-aft direction. Future research will go in the direction of determining the influence of multiaxial vibrations on the transmission of vibrations through the human body, so the plan is to make a neural network model that will have the ability to determine the transfer functions of both uniaxial and multiaxial stimuli at the seat.

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