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Original Article

Predictive modelling of whole-body vibration transmission through strategic locations of human body using artificial neural networks

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ABSTRACT

Introduction: Modelling the seated human body's response to whole-body vibration poses a formidable challenge due to its intricate reliance on factors encompassing anthropometry, postures, and vibration characteristics. While lumped parameter models are prevalent in this domain, their fixed weight necessitates modifications. Hence, a novel biodynamic model utilizing artificial neural network methodology was devised to simulate transmitted vibrations across strategic locations of body segments in seated individuals, facilitated by field vibration data.

Methods: Employing a multilayer feed-forward neural network integrated with the back propagation algorithm, an optimal setup was explored. Data were collected from 52 adult male subjects. Mean square error (MSE) values were evaluated during the training, validation and testing phases to assess the performance of the model. The study also compared the model-predicted values to the actual values using four unseen datasets, which were reserved for evaluating the model's generalization performance.

Results: The neural network model achieved mean square error (MSE) values of 0.0015, 0.0030, and 0.0015, accompanied by regression (R) values of 0.992, 0.990, and 0.991 in training, validation, and testing, respectively. Comparison shows high accuracy between the model-predicted values and the actual values.

Conclusion: The well-trained artificial neural network demonstrated proficiency in forecasting vibration transmission along the vertical direction through different body parts of a seated human, based on parameters such as age, body mass index, posture, experience, seat-buttock interface clothing layer, frequency, and vibration intensity. The comparison between the model-predicted results and the experimental value affirmed high accuracy and reliability of the developed model.

Keywords: Artificial Neural Network, Predictive Model, Seated Human Body, Vibration Transmissibility, Whole Body Vibration

Introduction

Research has consistently shown that musculoskeletal disorders (MSDs) predominantly impact the human body's neck, shoulders, upper back, lower back, abdomen, pelvis, and knees.[1,2] In their systematic review, where 51 scientific articles analyzed and identified significant causative and risk factors of Work-related musculoskeletal disorders (WRMSDs), exposure to whole-body vibration (WBV) is the leading factor, followed by posture, repetitive movement, lifting tasks, force/load applied, and demographic factors such as age, BMI, experience and gender.[3] Exposure to low-frequency, high-magnitude WBV in occupational settings, especially for off-road vehicle operators, has been associated with decreased performance, increased discomfort, and a range of spinal disorders among seated operators.[4] Study also confirmed that WBV exposure dominates along the vertical direction (z-axis) when measured over the seat surface.[5,6] Another study investigates whole-body vibration (WBV) and shock exposure among 10 bus and 10 truck drivers in Northern India, identified personal and vehicle/road-related factors influencing WBV, with univariate and multiple regression analyses highlighting driver age, driving experience, vehicle speed, and road roughness as key contributors to elevated WBV, particularly along the vertical axis, exceeding ISO 2631-1 limits for 25% of drivers.[7] This exposure influences the biodynamic response of the seated body to whole-body vibration, which is quantified as vibration transmissibility and is often measured as a function of frequency to evaluate the amplification or attenuation of vibration transmitted through the body.[8,9] This transmissibility shows a highly complex dependency on factors including age, weight, height, experience, posture, and the nature of vibration.[10,11]

In the context of biomechanics and occupational ergonomics in India, few studies have been conducted that focus on applying Artificial Neural Networks (ANN) and other machine learning algorithms. One study investigates tractor drivers' responses to whole-body vibrations (WBV) during loader operation, analyzing seat-to-head transmissibility (STHT) across three translational axes using IoT-enabled data collection and metrics like A_w, A(8), signal-to-noise ratios, and power spectral density (PSD), highlighting dominant vertical vibrations, in the 4–7 Hz and 8–12 Hz frequency bands, respectively. STHT showed primary and secondary resonance.[12] Another study investigates the effects of whole-body vibrations on a 76 kg Indian male (95th percentile) during tractor disc harrowing at varying RPMs (1500, 2000, 2500) and accelerations (0.5, 1.0, 1.5 m/s^2), using a 4-layer finite element CAD model to analyze the impact of vibrations influenced by tractor suspension, soil, posture, and external conditions.[13] Various mathematical models, including lumped-parameter, finite element (FE), and multi-body models, have been developed to describe biodynamic responses. Lumped-parameter models simplify analysis but are limited to one-directional analysis and the subjects' weight. FE models utilize finite elements derived from experiments on human corpses, enabling biodynamic response and injury assessment with accurate input of human properties. Multi-body models, interconnected rigid bodies with pin or ball and socket joints, facilitate kinetic and kinematic analyses, such as in vehicle crashes.[14] Another Indian study presents a lumped parameter model for biodynamic responses of a seated 54-kg Indian male without backrest support, incorporating interconnecting spring masses, and demonstrates closer eigenvalues to literature, decoupling vertical and fore-and-aft oscillations.[15]

The nonlinear effects of various factors, such as anthropometric dimensions, experience, postures, and vibration characteristics, hinder the success of biodynamic models of the seated body.[16] Consequently, these models cannot be universally applied across different populations of drivers or operators, as well as various vibrations and sitting postures encountered during vehicle driving. Alternate modeling approaches capable of incorporating nonlinear dependence on various factors are thus necessary to enhance these models' general applicability and make robust assessments of exposure risks.

Artificial neural networks (ANNs) have shown promise in modeling complex systems, such as optimization approaches for predicting soil compaction in soil bin facilities.[17] With the potential of ANN, few attempts have been made to characterize the human body's response to vibration using this approach. An Artificial Neural Network (ANN) model was developed to predict seat-to-head and seat-to-spine vibration acceleration transmissibility using data from only five adult male subjects tested in a laboratory setting with a straight-back posture only.[18,19] Similarly, another ANN was proposed to estimate the apparent mass of a seated body at different vibration excitations ranging from 0.5 to 20 Hz frequency.[20] In a study, MSD prediction at different body regions was made using an ANN-based model.[21] It is widely recognized that biodynamic models of the human body must encompass diverse factors such as age, body mass index (BMI), experience, posture, and vibration conditions to accurately predict behavior and understand injury mechanisms, ultimately leading to viable dose-response relationships.[22,23] The current study addresses the limitations of existing biodynamic models, which are often constrained by complex, nonlinear dependencies on input parameters. The study proposes using ANN modeling to predict the vibration transmissibility responses across a broader spectrum of ages, BMI, experience, postures, seat-buttock clothing layers, and vibration-related factors (frequency and acceleration).

To the best of the authors' knowledge, the application of the novel ANN method for predicting body segmental vibration transmissibility through biodynamic modeling of the seated operators under varying conditions such as age, height, weight, experience, posture, seat-buttock interface clothing layers, frequency, and acceleration, under field experimental conditions, has not been previously attempted. This study aims to fill this gap by introducing ANN modeling to predict the vibration transmissibility responses at strategic locations of seated shuttle car operators over a broader range of influencing factors.

Methods

A data acquisition system is prepared to collect the vibration data at six different body locations and over the seat surface (Figure 1). The system utilizes seven ADXL-345 accelerometers to capture the WBV data at seven strategic locations, enabling a detailed investigation of vibration transmission across different body regions (Figures 2 and 3). The data is stored on an SD card via an SD card module, facilitating a comprehensive understanding of WBV exposure patterns.

Specification of data acquisition system:

- Transducer: Adafruit ADXL-345 Accelerometer.
- Micro Controller: Arduino Uno
- Time Record: Real Time Clock (RTC) Module.
- Data storage: SD card and SD card module
- Parameters: Time, acceleration.
- Measuring range: Frequency 3200Hz, Acceleration unpowered 10000g, Powered 10000g (any axis).
- Accuracy: ± 4.6%.
- Operating condition: operating voltage 2 to 4.5V, operating temperature -40^{0} C to +85^{0} C.
- Power supply: +5V.

Design:

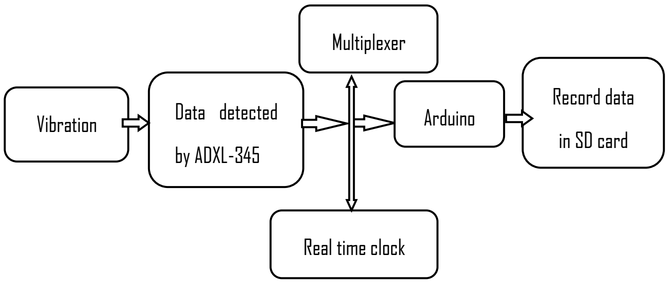

Figure 1: The flow for the data acquisition system of the model

Field test and data collection

This biodynamic model considers the human body as a system in which seat vibration value is input, and six other strategic body segments are output. The six locations (pelvis, lumber spine, abdomen, thoracic spine, shoulder, and neck) get output vibration when the body is subjected to vibration excitation as the vehicle (shuttle car) starts its operation (Figure 1). ANN model requires some examples for learning and can learn the relationship between inputs and outputs. To achieve this and build a realizing a reliable model, the field data is acquired from 54 seated shuttle car operators from five different underground coal mines in eastern India (details shown in Table 2) under different vibration and sitting conditions (back supported, back not supported), apart from subjects of different ages, body mass, height, experience, seat-pelvis interface clothing layers. All the measurements are conducted in actual underground mine working conditions with real machine (shuttle car) operators. An Arduino-based multi-sensor device is used to collect the vibration data. The ADXL-345 vibration sensors were placed at seven different strategic locations: one sensor over the seat (as input), and the rest of the six sensors were placed at the pelvis, lumber spine, abdomen, thoracic spine, shoulder, and neck (as output) as shown in figure 2 and figure 4. The data during each measurement was acquired for one cycle of operation, ranging from six to eight minutes, and each measurement was repeated twice for two different postures (back supported and without back support). The acquired data were analyzed in MATLAB 2023b.[24] The time domain acceleration data is converted into the frequency domain, used for the ANN model's learning purpose (input and output values). This whole-body vibration data collected by ADXL-345 sensors is not the absolute value; instead, these vibration values are used to train the ANN model and to know the vibration transmissibility characteristics through the said strategic locations of the seated human body.

In this biodynamic model, vibration intensities measured at the pelvis, lumbar spine, abdomen, thoracic spine, shoulder, and neck were considered as if they had been computed through a transfer function. The input parameters were age, BMI, experience, posture, clothing layers at the seat-pelvis interface, acceleration, and respective frequency. This strategy trained an ANN model by examples, which were finally achieved in dynamic experimental results. This study uses the body segmental vibration transmissibility response data from 54 adult subjects.

Inclusion criteria for recruitment of subjects

1. Only underground shuttle car operators were included in the study.
2. Only full-time or full-shift operators are considered.
3. Subjects above 18 years old (as per statutory restriction, only those above 18 are allowed to work in Indian mines).
4. Experience more than 1 year (The first one-year service is a training period; operators do multiple tasks).
5. Free from any past injuries or accidents.

Table 1 details the participants' demographic and anthropometric characteristics and presents the minimum, maximum, mean, and standard deviation values.

Before commencing the vibration measurements, the experimental procedures and safety guidelines were thoroughly explained to each participant. Informed consent was obtained from all subjects following the protocol approved by the Ethics Committee of the Indian Institute of Technology, Kharagpur, via Approval No.: IIT/SRIC/DEAN/2024/Revised, dated 08.01.2024.

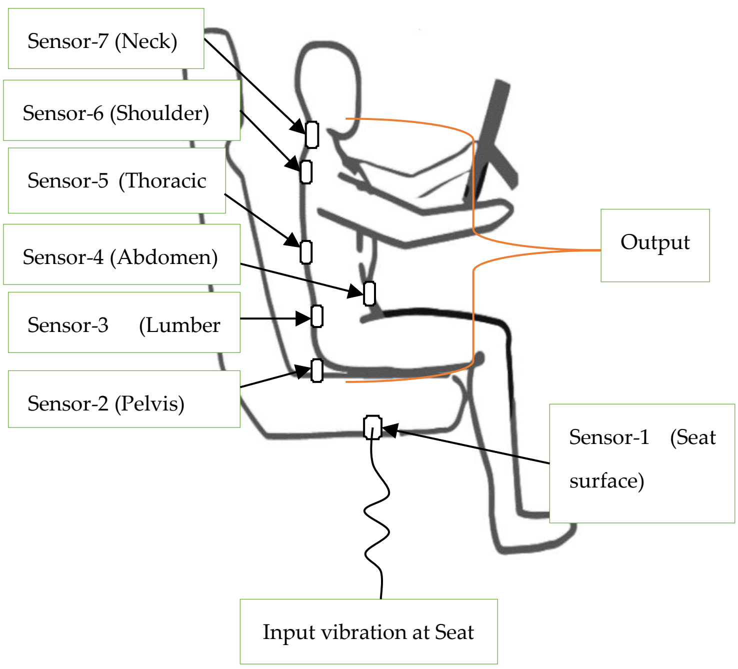

Figure 2: Schematic diagram of shuttle car operator with sensors placed at the strategic locations

Artificial Neural Network Modelling

The artificial neural network architecture is formulated based on data gathered from 54 adult subjects with varying ages, body masses, heights, experiences, two levels of sitting postures, seat-buttock interface clothing layers, input frequencies, and acceleration excitations. A total of 108 datasets were available, each corresponding to a subject and posture combination acquired. Within the 0.5 to 20 Hz frequency range, with one-third octave band central frequencies, resulting in 17 data points per set. To ensure the robustness and good performance of the model, 104 datasets were used for training (64 sets), testing (20 sets), and validation (20 sets). The remaining four data sets were reserved for evaluating the model's generalization performance over unseen data. This provided 1768 (104 X 17) body segmental vibration transmissibility responses magnitude data points.

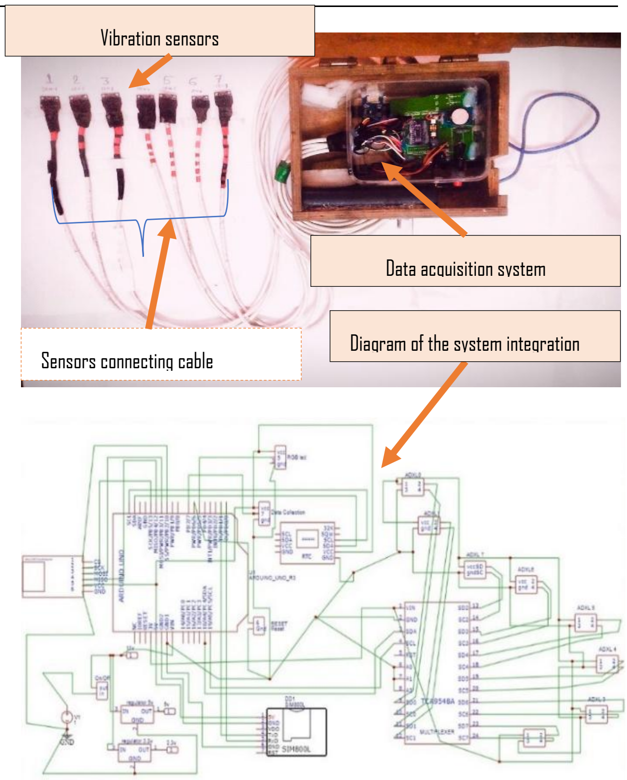

Figure 3: Data acquisition system with the vibration sensors

Table 1: The maximum, minimum, mean and standard deviation values of personal details of the participants

Parameters	Minimum value	Maximum value	Mean ± Standard deviation
Age (yrs.)	25	48	34.5 ± 3.53
Weight (kg)	59	85	68.88 ± 1.41
Height (m)	1.58	1.74	164.32 ± 1.41
BMI (kg/m^2)	20.76	30.84	24.64 ± 0.94
Experience(yrs.)	5	15	9.64 ± 0.71

Table 2: Details of the underground work place conditions in different mines

Name of the mine	Depth	Air velocity (m/s)	WBT	DBT	Relative Humidity
Mine 1	220m	0.50±0.04	30.10±0.65	31.50±0.45	90.2%
Mine 2	130m	0.42±0.03	27.50±0.55	29.50±0.62	85.7%
Mine 3	165m	0.46±0.05	27.40±0.50	29.0±0.66	84.5%
Mine 4	170m	0.55±0.04	27.50±0.50	29.50±0.60	88.4%
Mine 5	190m	0.54±0.03	29.00±0.60	30.50±0.40	89.4%

Figure 4: Data collection of the Shuttle car operators at two different postures

The model incorporated input factors influencing the vibration transmissibility responses, such as age, body mass index (BMI), experiences, seat-buttock interface clothing layers, back support condition, frequency, and magnitude of vibration excitation. Consequently, an input matrix of 1768 × 7 was generated. A multilayer feed-forward neural network with a backpropagation algorithm was employed, consisting of one input layer, one output layer, and three hidden layers, to account for the complex dependencies among factors.

Developing the ANN model involved, identifying the optimal number of neurons and hidden layers, training algorithms, and transfer functions. Preliminary simulations with a single hidden layer yielded poor predictions, prompting the use of an MLP neural network with three hidden layers, where the number of neurons ranged from 1 to 20. The final neural network with 3 hidden layers, having 18 neurons in the first layer, 12 neurons in the second layer, and 8 neurons in the third layer, showed the best configuration of the model. The schematic picture of the ANN architecture is illustrated in Figures 5 and 6.

This architecture exhibited improved convergence regarding mean squared error (MSE) without overfitting, ensuring smooth learning and good correlations between predicted and measured responses during cross-validation.

The qualitative inputs, sitting posture, and seat-pelvis clothing layers were introduced as model inputs described by 0 as sitting without back support and 1 representing with a back support. Also, 2 or 3 values represent the number of clothing layers the subjects had worn. The sigmoid transfer function was selected for its compatibility with the normalization range of input variables and enhanced learning performance. The backpropagation (BP) training algorithm employed iterative-based gradient descent optimization to minimize MSE.

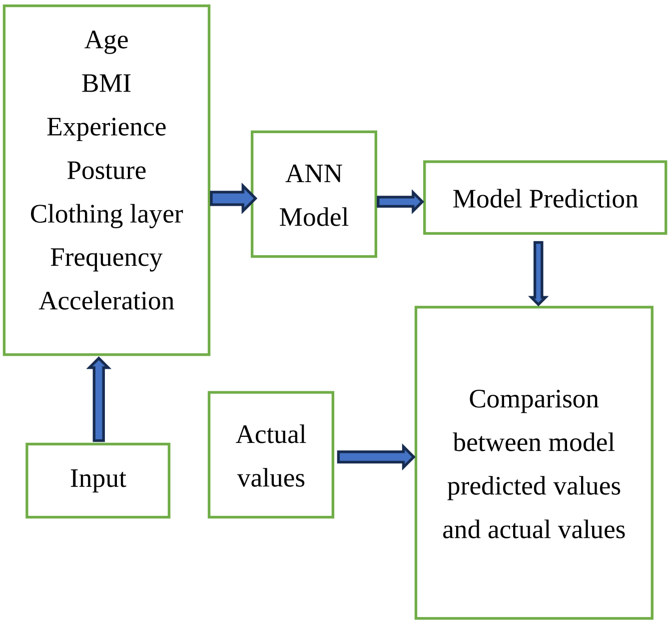

Figure 5: The flow chart of ANN-based prediction model

The Levenberg-Marquardt training algorithm ('trainlm') was chosen for its rapid convergence and updating of weights and biases according to the Levenberg-Marquardt (LM) optimization approach. The ANN performance is evaluated by utilizing the mean square error (MSE) and the regression ratios, the R-value of the target, and output body segmental vibration transmissibility magnitudes.

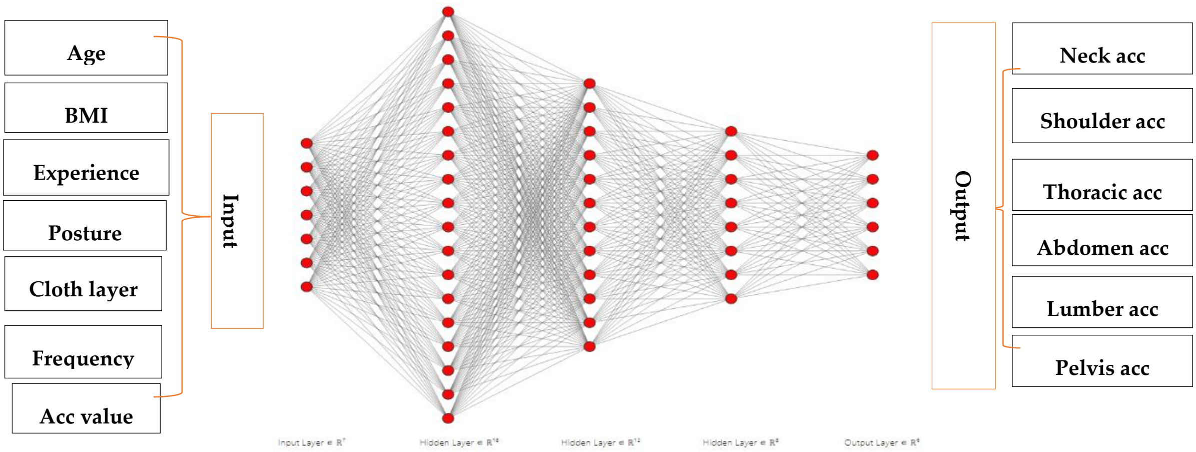

Figure 6: The schematic diagram of ANN architecture

Results

The final neural network with 3 hidden layers, having 18 neurons in the first layer, 12 neurons in the second layer and 8 neurons in the third layer, showed the best correlation ratio. The Levenberg-Marquardt training algorithm ('trainlm') and sigmoid function ('logsig') were selected in final model architecture as the learning function and transfer function.

The correlation coefficient, R-value in training, validation, test, and overall are 99.24%, 99.08%, 98.17%, and 99.12%, respectively. This shows that the model's accuracy is in the acceptable range.

In the generalization performance evaluation step, four input acceleration datasets of 2 subjects (with varying input parameters) were entered into the achieved ANN model to simulate their output. Figures 7 to 10 compare actual body segmental acceleration values and acceleration predicted by the ANN model in the frequency domain.

Discussion

The outcome of this Artificial Neural Network (ANN) model represents good agreement (R = 0.9912) between approximated vibration values and actual values compared to (R = 0.9817) a similar previous laboratory experimental study conducted by Gohari et al. (2014).[19] Figures 7 to 10 illustrate the actual and predicted output values for six strategic body locations. The ANN model exhibited robust performance within the evaluated input data range. Notably, in the critical frequency range of 3 to 8 Hz, the model's predicted acceleration values are closely aligned with the measured values (Figures 7 to 10). This frequency band is particularly significant, as the human body is susceptible to vibrations within this range. Vibrations between 3 Hz and 8 Hz can induce discomfort and pose health risks due to resonance with the body's internal organs and structures.[25] This study focused exclusively on male operators, as female operators were not available in the field during data collection for this study.

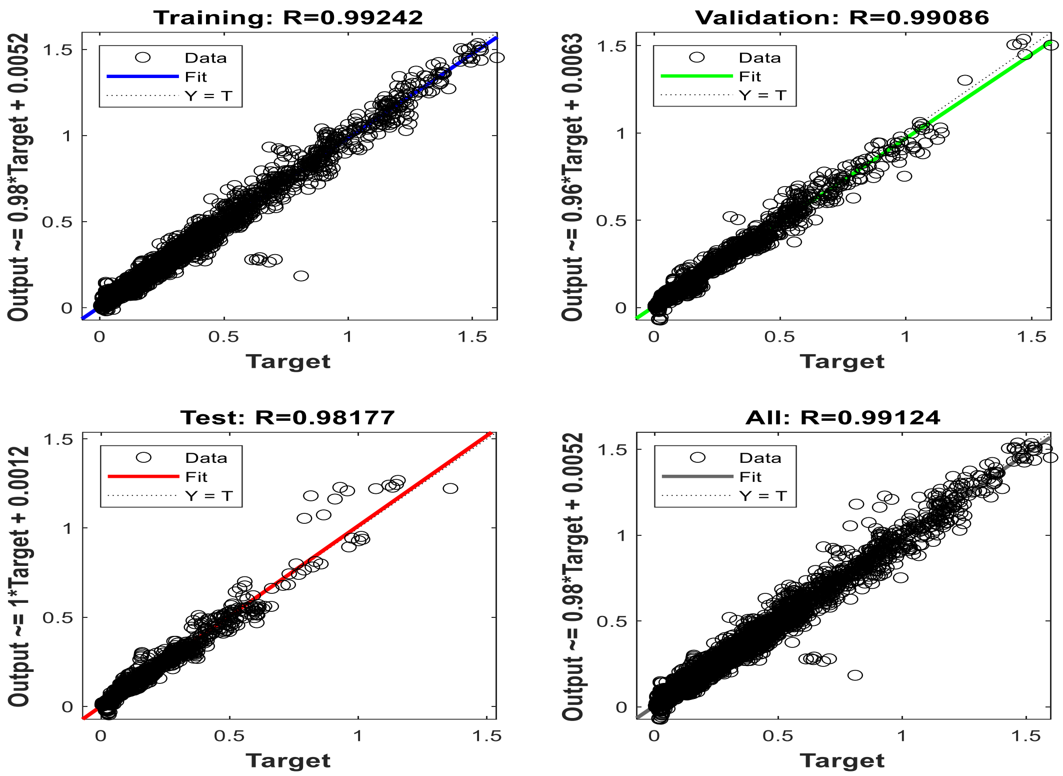

Figure 7: The regression between output and target in training, validation, test steps and in overall, respectively

**(T=target values; Y=predicted output; and R=correlation coefficient between output of model and target values).*

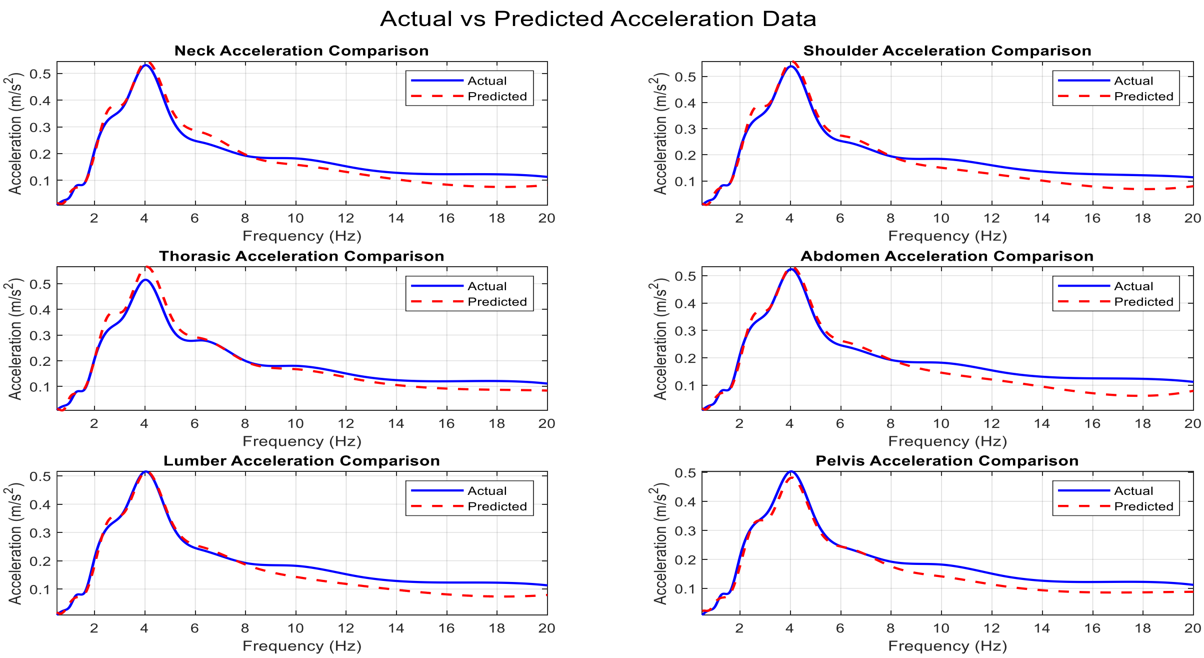

Figure 8: The whole-body vibration response comparison between actual and ANN model predicted values

**(Subject having age 36yrs, experience 11 years, BMI 27.28 kg/m², posture-back supported (code 1), seat buttock interface clothing layer 3).*

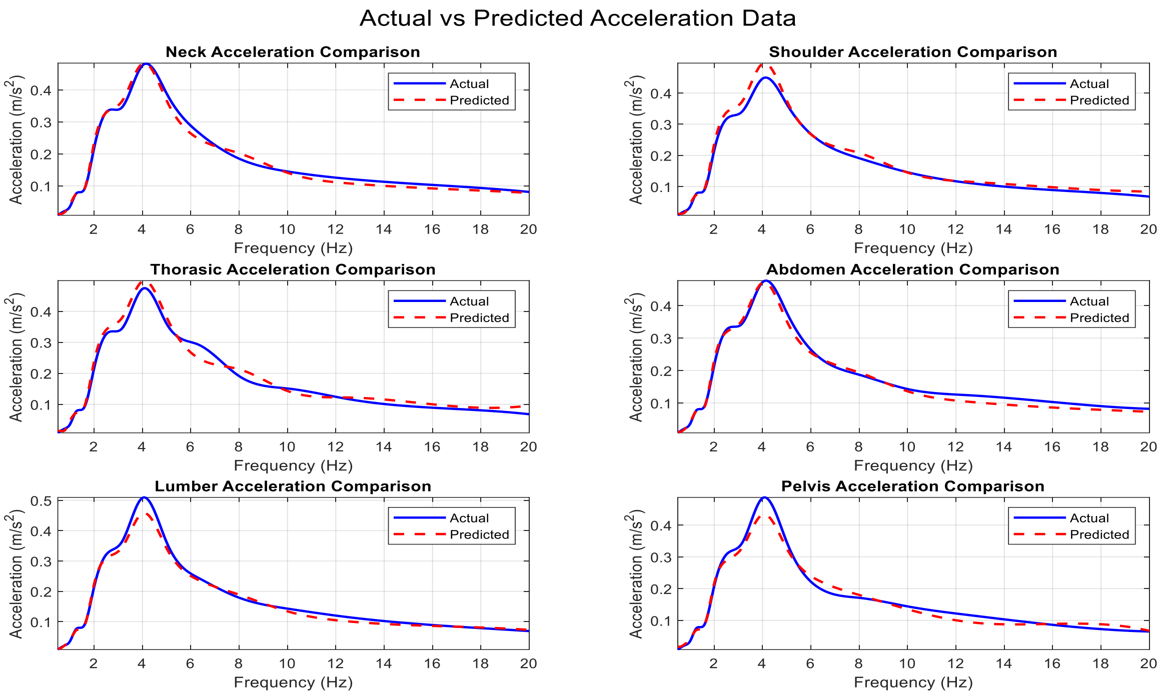

Figure 9: The whole-body vibration response comparison between actual and ANN model predicted values

(Subject having age 36yrs, experience 11 years, BMI 27.28 kg/m², posture-No back support (code 0), seat buttock interface clothing layer 3).

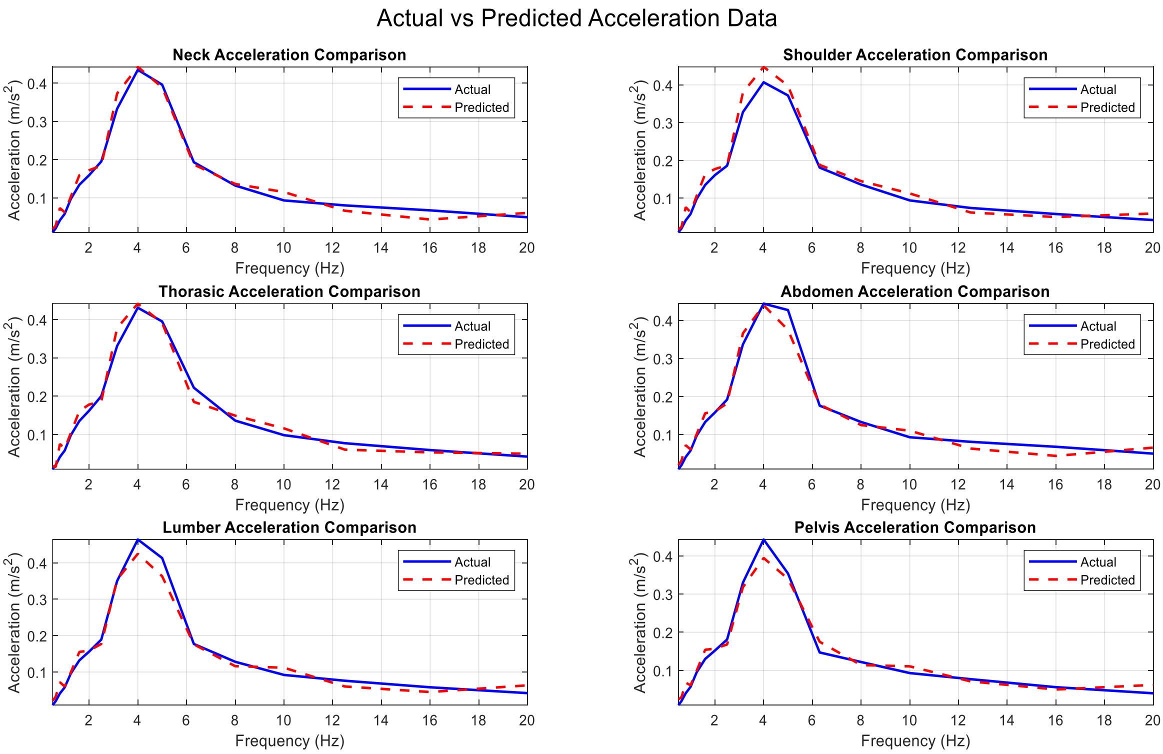

Figure 10: The whole-body vibration response comparison between actual and ANN model predicted values

(Subject having age 43yrs, experience 13 years, BMI 25 kg/m², posture-back supported (code 1), seat buttock interface clothing layer is 2).

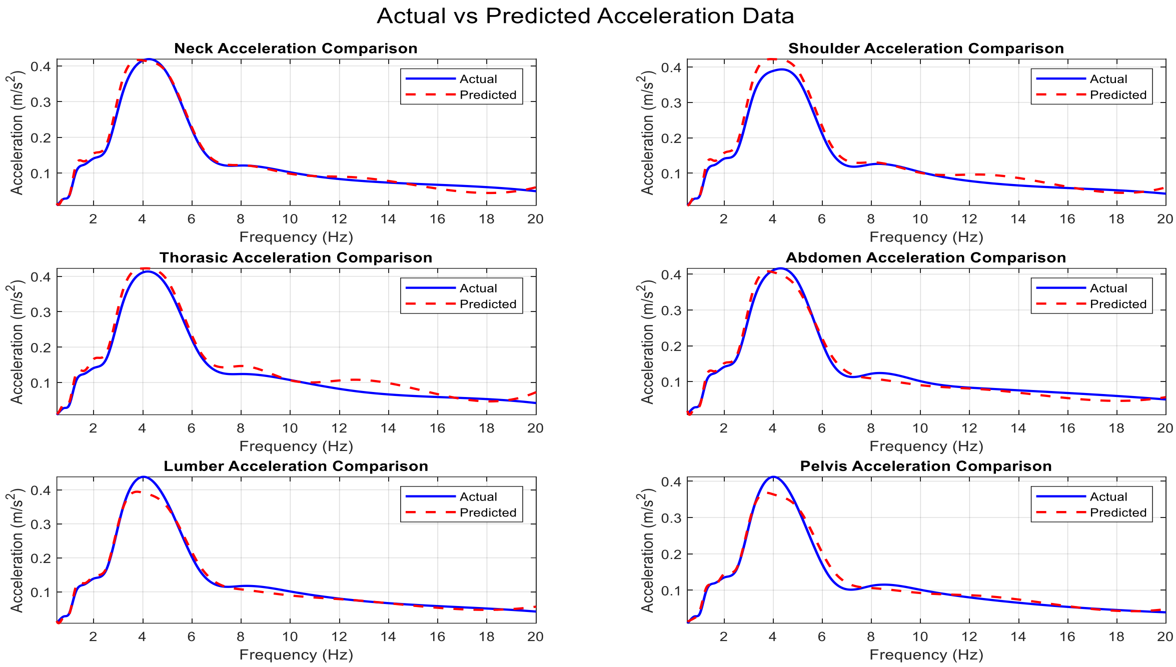

Figure 11: The whole-body vibration response comparison between actual and ANN model predicted values

**(Subject having age 43yrs, experience 13 years, BMI 25 kg/m², posture-No back support (code 0), seat buttock interface clothing layer is 2).*

Limitations

While the model performed well within the specified range, caution must be exercised when extrapolating beyond these frequencies. The accuracy of predicted whole-body vibration transmissibility responses may diminish outside this range, due to the inherent limitations of ANN models in handling data that diverges significantly from the training set. The subjects in the study are underground shuttle car operators; future studies can be performed, including data from varying occupational settings with variations of the input parameters.

Conclusion

The limitations of lumped parameter models in predicting human body vibration response prompted the development of an Artificial Neural Network (ANN) model. This innovative biodynamic ANN model demonstrates exceptional accuracy with MSE values of 0.0015, 0.0030, and 0.0015, accompanied by regression (R) values of 0.992, 0.990, and 0.991 in training, validation, and testing phases, respectively, in predicting body segmental vibration acceleration originating from the seat surface of seated occupants. Notably, it incorporates crucial input factors such as age, weight & height (BMI), experience, seated posture (back supported/not supported), and seat-pelvic interface clothing layer, which were previously overlooked in existing models. Our investigation into the predictive capabilities of artificial neural networks focused on modeling vibration transmission at different body parts from the seat surface of seated operators under vertical whole-body vibration exposure. The proposed model's properties render it suitable for assessing the risk of musculoskeletal disorders in different body parts among seated operators exposed to whole-body vibration. Moreover, it holds promise for optimizing seat suspension systems and implementing active seat suspension control mechanisms. This research represents a significant step forward for predicting WRMSDs at different body segments among seated individuals exposed to vibration in various occupational settings.

References

1. Kheterpal AB, Palmer WE, Bredella MA. Musculotendinous disorders of the abdomen and pelvis. Seminars in Musculoskeletal Radiology. 2017;21(4):403-14. Available from: https://doi.org/10.1055/s-0037-1604004
2. Demissie B, Bayih ET, Demmelash AA. A systematic review of work-related musculoskeletal disorders and risk factors among computer users. Heliyon. 2024 Jan 22;10(3):e2507. Available from: https://doi.org/10.1016/j.heliyon.2024.e25075
3. Shaikh AM, Mandal BB, Mangalavalli SM. Causative and risk factors of musculoskeletal disorders among mine workers: A systematic review and meta-analysis. Safety Science. 2022 Nov 1;155:105868. Available from: https://doi.org/10.1016/j.ssci.2022.105868
4. Burström L, Aminoff A, Björ B, Mänttäri S, Nilsson T, Pettersson H, et al. Musculoskeletal symptoms and exposure to whole-body vibration among open-pit mine workers in the Arctic. International Journal of Occupational Medicine and Environmental Health. 2017;30(4):553-64. Available from: https://doi.org/10.13075/ijomeh.1896.00975
5. Jack RJ, Eger T. The effects of posture on seat-to-head whole-body vibration transmission. Journal of Low Frequency Noise, Vibration and Active Control. 2008 Dec;27(4):309-25. Available from: https://doi.org/10.1260/026309208786926831
6. Mandal BB, Srivastava AK. Musculoskeletal disorders in dumper operators exposed to whole body vibration at Indian mines. International Journal of Mining, Reclamation and Environment. 2010 Sep 1;24(3):233-43. Available from: https://doi.org/10.1080/17480930903526227
7. Kumar R, Sharma R, Kumar V, Khan AA. Predictors of whole-body vibration exposure among Indian bus and truck drivers. Journal of Physics: Conference. 2021;1854:012033 Available from: https://doi.org/10.1088/1742-6596/1854/1/012033
8. Zagorski J, Jakubowski R, Solecki L, Sadlo A, Kasperek W. Studies on the transmission of vibrations in human organism exposed to low-frequency whole-body vibration. Acta Physiologica Polonica. 1976 Jul 1;27(4):347-54. Available from: https://europepmc.org/article/med/983715
9. Lam FM, Tang CY, Kwok TC, Pang MY. Transmissibility and waveform purity of whole-body vibrations in older adults. Clinical Biomechanics. 2018 Jan 1;51:82-90. Available from: https://doi.org/10.1016/j.clinbiomech.2017.12.007
10. Mansfield, N. J. Human response to vibration. 1st edition. CRC press; 2004. Available from: https://doi.org/10.1201/b12481
11. Griffin, M. J. Handbook of human vibration. Academic press. 2012. Available from: https://www.perlego.com/book/1896322/handbook-of-human-vibration-pdf
12. Singh A, Samuel S, Dhabi YK, Singh H. Whole-body vibration: Characterization of seat-to-head transmissibility for agricultural tractor drivers during loader operation. Smart Agricultural Technology. 2023 Aug 1;4:100164. Available from: https://doi.org/10.1016/j.atech.2022.100164
13. Bhatia A, Kalsi S, Sehgal AK, Singh J, Singh I. Evaluation of Whole-Body Vibrations Effect on Tractor Driver in Indian Agricultural Conditions Using 4-Layered CAD Model. Journal of The Institution of Engineers (India): Series C. 2023 Jun;104(3):503-12. Available from: https://doi.org/10.1007/s40032-023-00933-0
14. Liang CC, Chiang CF. A study on biodynamic models of seated human subjects exposed to vertical vibration. International Journal of

Industrial Ergonomics. 2006 Oct 1;36(10):869-90. Available from: https://doi.org/10.1016/j.ergon.2006.06.008

15. Singh I, Nigam SP, Saran VH. Modal analysis of human body vibration model for Indian subjects under sitting posture. Ergonomics. 2015 Jul 3;58(7):1117-32. Available from: http://dx.doi.org/10.1080/00140139.2014.961567
16. Mandapuram S, Rakheja S, Boileau PÉ, Maeda S. Apparent mass and head vibration transmission responses of seated body to three translational axis vibration. International Journal of Industrial Ergonomics. 2012 May 1;42(3):268-77. Available from: https://doi.org/10.1016/j.ergon.2012.02.002
17. Taghavifar H, Mardani A, Taghavifar L. A hybridized artificial neural network and imperialist competitive algorithm optimization approach for prediction of soil compaction in soil bin facility. Measurement. 2013 Oct 1;46(8):2288-99. Available from: https://doi.org/10.1016/j.measurement.2013.04.077
18. Gohari M, Rahman RA, Raja RI, Tahmasebi M. A novel artificial neural network biodynamic model for prediction seated human body head acceleration in vertical direction. Journal of Low Frequency Noise, Vibration and Active Control. 2012 Sep;31(3):205-16. Available from: https://doi.org/10.1260/0263-0923.31.3.205
19. Gohari M, Rahman RA, Tahmasebi M, Nejat P. Off-road vehicle seat suspension optimization, part I: derivation of an artificial neural network model to predict seated human spine acceleration in vertical vibration. Journal of Low Frequency Noise, Vibration and Active Control. 2014 Dec;33(4):429-41. Available from: https://doi.org/10.1260/0263-0923.33.4.429
20. Taghavifar H, Rakheja S. Supervised ANN-assisted modeling of seated body apparent mass under vertical whole-body vibration. Measurement. 2018 Oct 1;127:78-88. Available from: https://doi.org/10.1016/j.measurement.2018.05.092
21. Shaikh, A. M., & Mandal, B. B. (2025). Predictive Modeling of Work-Related Musculoskeletal Disorders among Shuttle Car Operators Using Artificial Neural Network. Journal of Mines, Metals and Fuels. 2025;*73*(1):65–74. Available from: https://doi.org/10.18311/jmmf/2025/45937
22. Hinz B, Seidel H, Menzel G, Blüthner R. Effects related to random whole-body vibration and posture on a suspended seat with and without backrest. Journal of Sound and Vibration. 2002 May 23;253(1):265-82. Available from: https://doi.org/10.1006/jsvi.2001.4259
23. Seidel H. On the relationship between whole-body vibration exposure and spinal health risk. Industrial health. 2005;43(3):361-77. Available from: https://doi.org/10.2486/indhealth.43.361
24. MathWorks. Artificial neural network toolbox user's guide, for the use of MATLAB. Available from: www.mathworks.com
25. Yau HK, Luk BL, Chan SS. Evaluation of Human Response under Vibration Condition. Proceedings of the International Multiconference of Engineers and Computer Scientists. 2012;2:1439-42. Available from: https://www.iaeng.org/publication/IMECS2012/IMECS2012_pp1439-1442.pdf