An Overview Of Driver Seat Comfort: Objective and Subjective Measures and Its Neural Network Modeling

Shohreh Omidi Varmazani *somidiva@trinity.edu*
Department of Engineering Science
Trinity University
San Antonio, Texas, 78212, USA

Farzan Aminian *faminian@trinity.edu*
Department of Engineering Science
Trinity University
San Antonio, Texas, 78212, USA

Mehran Aminian *maminian@stmarytx.edu*
Department of Engineering Science
St. Mary's University
San Antonio, Texas, 78228 USA

Reza Omidi Varmezani *reza.omidi@ksb.ch*
Department of Diagnostic and Interventional Radiology,
Baden, 5404, Switzerland

Eddie Kirby *ekirby@stmarystx.edu*
Department of Engineering Science
St. Mary's University, San Antonio, Texas, 78212, USA

Abstract

The purpose of this work is to investigate driver seat comfort and discuss some of the subjective and objective factors that impact it. Comfort describes the nature of the interaction between a human being and a specific environment and is characterized as a feeling of pleasure and satisfaction or discontent and pain. Driver seat design for comfort is complex and challenging because it is somewhat subjective in nature (e.g. mood, culture & car brand). However, there are certain aspects of a seat comfort, which are objective (e.g. anthropometrics, pressure distribution on seat) and can be modeled mathematically. This paper discuses some of the objective and subjective measures which influence seat comfort. In addition, it provides a mathematical model of seat comfort index based on neural networks in terms of some of the objective measures, which influence it. The results of this work show that the objective measures included lead to a correlation of 0.794 to the overall comfort index identified by twelve drivers testing five different types of seats. This implies that our selected objective measures/inputs can capture about 80% of the comfort index identified by test drivers. The remaining 20% variation in comfort index not captured by the model utilized in this work can be attributed to subjective measures and/or additional objective measures which can be added as inputs to the neural network.

A comparison of this study to a previously published work [1] which also utilizes neural networks to model seat comfort index reveals important facts. This previous study uses a very large neural network with a significant number of adjustable parameters to model seat comfort. As a result, their neural network is very prone to memorizing the data associated with seat comfort index without capturing the underlying mathematical behavior. The neural network proposed in this work, however, has an optimal architecture, which captures the mathematical model describing comfort index accurately, and is not prone to memorizing the seat comfort data.

Keywords: Seat Comfort Index, Artificial Neural Networks, Seat Comfort Modeling.

1. INTRODUCTION

1.1.Seat Comfort Definition and Modeling

Comfort is defined as a pleasant state of psychological, physiological and physical harmony between a human being and his/her environment [2]. Another definition used in the literature describes comfort as a pleasant experience while using a product [3]. Discomfort can lead to back, neck, arm and musculoskeletal problems, which cost patients, and insurance companies a lot of money every year. There are studies that suggest a large number of sick leaves are attributed to back and neck pain and musculoskeletal injuries [2]. Everybody pays attention to comfort in the household, at work and while commuting. As a result, manufacturers of cars, airplanes, mattresses and chairs pay particular attention to comfort so that they can attract customers. A product is not judged as being comfortable in itself but is described as comfortable or uncomfortable after it has been tested by an end user. Comfort is a complex theory and emerges from a chain of interrelationships between the driver and several elements of the system. This interaction can lead to a high level of comfort associated with a feeling of pleasure and satisfaction or it can lead to discomfort, pain and stress. Obviously, comfort is not the only factor that plays a role in design of any product but its consideration as a key element is important in good engineering practice [2,4]. The reason comfort plays an important role in our daily activities is that our optimal human performance can only be achieved in an environment which reduces discomfort and physical stress. Given the importance of comfort, its inclusion in design process plays a key role in providing high quality driver seats.

What makes design for comfort challenging is that comfort is a somewhat subjective matter. For instance, for a passenger on a long drive, back problems could be a major issue while other drivers may prefer a reduction in noise or more space. Hence there are no comfort design process nor comfort models available to fully describe it objectively [2]. However, there is some knowledge of comfort that can be generalized and some predictions of comfort level can be made. For instance, passengers on a car seat can be surveyed to measure the seat comfort level and identify which features lead to higher comfort level. As a result, it is now evident that even though a fully quantitative comfort model may not exist, the design process would clearly benefit from the participation of the end users in studies that evaluate the comfort level of the final product. There is no doubt that their expertise in specification of the aspects of comfort that need improvement would be very beneficial in seat comfort studies.

In summary, it is possible to model some aspects of seat comfort. What is required is to consider tangible factors that can impact a driver’s experience of comfort thus separating what is observable and unobservable. This allows the field of ergonomics to model some aspects of seat comfort, which are observable and objective. Some elements of seat comfort, which for instance cannot be modeled, include studies that suggest men and women have different perceptions of seat comfort [5]. For instance, men and women weigh differently the discomfort resulting from noise and vibration. Men experience more discomfort from noise while women are more discomforted by vibration.

1.2.Seat Comfort Factors

Studies of seat comfort rely on measurement of pressure on the interface between the seat and human subject [6]. These types of measurements, conducted through tactile sensors, provide valuable data to model seat comfort. For instance, a greater uniformity on the distribution of pressure, a lower peak of pressure and a wider and more symmetric contact surface lead to improved comfort seat. Other studies [7] have shown that lower rates of pressure on the buttocks and higher on the back together with balanced pressure among buttocks, upper part and lower body lead to better seat comfort. Kolich and Tabourn [1] have studied seat comfort in terms of factors including characteristics of pressure on the seat interface, passengers’ anthropometrics and demography and perception of seat appearance. Such studies can help identify the degree to which seat comfort can be attributed to subjective and objective factors.

Apart from the actual causes of discomfort discussed here, our perception also plays an important role. We are influenced by our mood, culture, car brand, and age group in judging the comfort level of a car seat. For instance, our mood could be excited, relaxed or stressed which can influence our perception of comfort. According to Kolich [1], seat comfort has been described in terms of vehicle/package, social, individual and seat factors. The contribution of the vehicle/package factor includes seat height, the field of vision, pedals, space for the knees and type of transmission. The social factors include the vehicle nameplate and purchase price. The individual factor encompasses demography, anthropometrics and culture. For instance, Western Europeans prefer firmer seats compared to North Americans [8]. Finally, the seat factor entails rigidity, geometry, shape, breathability and styling. Rigidity refers to the seat system resistance, geometry defines the seat shape in terms of width, length, and height, and shape defines the profile of the seating surface. Breathability relates to a soft finishing, which can affect driver comfort in extreme weather condition, and style refers to aesthetic quality, which can impact the perception of comfort [9].

Some of the factors influencing comfort can be further broken down to more basic elements. This is an important step to fully understand these factors and their importance in modeling seat comfort mathematically. For instance, the physical and social factors have been described in the literature as follows: Posture [6,9,10,11,12,13], anthropometrics [5,6,9,12,14] demography [1,9.12], fatigue [13,15], distribution of pressure on the seat [6,16], physiological degradation [15], muscle activity [13], body region [5,17], contracture [17], and age [9].

2. SEAT COMFORT EVALUATION (TRIAL and ERROR APPROCH)

The typical approach to improving seat comfort involves the use of a currently available seat as benchmark. Test drivers are asked to ride the car over an extended period of time and fill out a highly structured survey, which requires them to address feeling of discomfort in specific regions of the seat. The subjective nature of such surveys and their evaluations require a large number of test drivers of various backgrounds to extract as much objectivity as possible in describing seat comfort. These surveys must reflect precisely what the design team intends to measure thus requiring special emphasis on the wording of the survey items. The resulting feedback which describes the likes and dislikes attributable to seat comfort lead to future modification of the seat to improve its overall comfort. Normally, the surveys are reduced and mapped to a single digit called Overall Comfort Index (OCI), which tries to minimize biases such as car brand [1,2,4,9]. Based on the feedback received from surveys, prototypes are built and evaluated for comfort. If the prototype seat receives better rating than the benchmark, the study has been successful. Normally up to 15 separate evaluations of prototypes are conducted to improve the seat comfort, which can take three to four years. There is no doubt that improving seat comfort based on trial and error approach is a lengthy process.

In spite of its value, the trial and error approach alone to improve seat comfort is time-consuming, inefficient and costly [1]. As a result, there has been a need to combine the trial and error process with a more efficient approach. An appropriate candidate to be added to the design process is a mathematical modeling of seat comfort, which can capture how objective factors contribute to design for comfort. These mathematical models can reduce the amount of trial and errors required by identifying objective features that contribute significantly to the overall seat comfort. This approach allows the objective factors contributing to seat comfort to be optimized through mathematical models while subjective measures can be addressed through surveys.

3. SEAT COMFORT MATHEMATICAL MODELING

In modeling seat comfort, a subset of seat-interface pressure readings, anthropometric measures, demographic information and perceptions of seat appearance are used as inputs to determine how well they can describe OCI as an output [1]. The OCI is usually described as a single digit score between 0 and a maximum. This type of mathematical modeling sheds light on how much of the overall comfort index is related to objective measures such as pressure on different parts of the body. As a result, one can identify the degree to which overall comfort index in subjective and biased by factors such as gender, mood and culture. If one can find a high correlation between the overall comfort index and objective factors, the results can help improve seat comfort while reducing the amount of necessary and costly trial and error practices.

In order to develop a mathematical model for seat comfort, one needs to identify the inputs and output. The work by Kolich [1] shows that pressure measurements at the occupant – seat interface are effective measures that have significant contribution to seat comfort. This implies that perception of comfort is objectively related to pressure distribution characteristics exhibited in such measurements. As indicated before, the output of interest in such models is the overall comfort index, which is a single digit, obtained from a survey of test drivers.

To model seat comfort index in terms of inputs, one can use linear or non-linear regressions. Among these two approaches, non-linear regression is the most popular [1]. Even though a neural network approach to model overall seat comfort index is a non-linear regression technique, many studies [1] consider it to be a separate approach. The main idea behind these approaches is to capture how much of the overall comfort index can be described by pressure measurements at the occupant-seat interface. This is accomplished by calculating the correlation coefficient between the output of the mathematical model predicting the overall comfort index and the actual values obtained from the surveys of test divers. A correlation coefficient of 1 implies that the seat comfort index can be fully described by the pressure measurements while a correlation coefficient of 0 implies that these measurements have no influence on the overall comfort index obtained from test drivers. In the latter case, the implication is that the overall comfort index is mostly a random, subjective number expressed by test drivers with no attention to the pressure they feel on different part of their bodies. In practice, one expects the correlation coefficient to be between 0 and 1 with numbers closer to 1 proving that these pressure measurements are of significance in the comfort level of test drivers.

Our approach in this paper is to model overall comfort index in terms of neural networks and develop a non-linear model capturing the relationship between objective factors as inputs and OCI as output. The rest of this paper is organized as follows. In the next section, we describe the inputs and output used for modeling seat comfort in this study. Next, we provide a brief description of data normalization used to generate an optimal set of inputs for our mathematical modeling problem. Finally, we provide a brief introduction to neural networks used in this paper to model the overall comfort index in terms of the 9 input variables discussed later in this work.

4. INPUTS AND OUTPUT DESCRIPTION OF THE SEAT COMFORT MODEL

The data describing the relationship between pressure measurements at the occupant-seat interface and the overall comfort index is generally proprietary and hard to obtain. In this work, we have used the data published by M. Kolich et al. [1]. In their study, five different driver seats ranging from bad to good (based on seat comfort ratings provided by J.D. Power & Associates (1997)) were tested leading to a broad range of overall comfort index. Only seats from compact car category were selected. Making sure all seats came from the same type of car (compact car in this case) is important to make sure seat size and leg rooms for different categories of car do not bias the data. All cars were white, 1997 model from different manufacturers with gray interior to minimize the effect of color preferences. Demographics and anthropometry were held constant by using the same 12 drivers to test all five seats.

Pressure measurements at the occupant-seat interface were conducted using thin, flexible sensor arrays manufactured by Tekscan. The occupant-seat interface was divided to 48 columns and 44 rows for a total of 2112 grids. At the center of each grid, a sensor was placed. Scanning the grids and measuring the electrical resistance at the center of each grid can calculate the pressure distribution on the sensors' surface. A system software then calculated the following objectives measures, which served as inputs to any mathematical model.

- Cushion contact area (cm^2) – CCA
- Cushion total force (N) – CTF
- Cushion load at the center of force (N/cm^2) – CCF
- Cushion peak pressure (n/cm^2) – CPP
- Seatback contact area (cm^2) – BCA
- Seatback total force (N) – BTF
- Seatback load at the center of force (N/cm^2) – BCF
- Seatback peak pressure (N/cm^2) – BPP

In addition to these inputs, each driver was asked to rate the appearance of each seat (AR) as well on a scale from 0 to 5 with 5 being the best. All drivers were asked to remove their wallet and belts to avoid false pressure readings at the seat interface. The twelve drivers were chosen to be half male and half female to remove gender bias. Each driver was allowed to adjust the track position and the seatback angle to his/her preferred setting. Given that the same twelve drivers and five car seats were used in the study, it was expected that the preferred seating positon would be similar for all drivers among seats. This would not have been the case if the test cars were chosen from different categories such as compact and sport cars.

To obtain the overall index comfort for each seat, the twelve test drivers were asked to rate the following factors on a scale from -3 to +3.

Seatback:

- Amount of lumbar support
- Lumbar comfort
- Amount of mid-back support
- Mid-back comfort
- Amount of back lateral support
- Back lateral support
- Seat back feel/firmness

Cushion:

- Ischial/buttocks comfort
- Thigh comfort
- Cushion lateral comfort

A score of -3 corresponded to too little support and a score of +3 represented too much support. A score of 0 corresponded to a support, which is just right. Since both positive and negative deviations from a score of 0 were undesirable, the absolute value of all deviations from 0 for the ten rubrics stated above were added to obtain a single digit value for overall comfort index. As a result, the overall comfort index took a value between 0 and 30 with a score of 0 representing the most comfortable seat. The worst-case score of 30 corresponded to a very uncomfortable seat. With twelve drivers and five car seats, sixty data points were generated to relate the inputs indicated above (AR, CCA, CTF, CCF, CPP, BCA, BTF, BCF and BPP) to the overall comfort index (OCI). Table 1 shows the mean, standard deviation, minimum and maximum values for each of the nine inputs and output for five seat types. Please note that the 5 seats tested in this study have been labeled as A, B, C, D, and E.

5. DATA NORMALIZATION FOR INPUT PROCESSING

The first stage in our neural network modeling is data normalization for the purpose of enhancing the features in our data set. Data normalization is a scaling of the input features to avoid large dynamic ranges in one or more dimensions [18]. There are many applications in which two or more input features may differ by several orders of magnitude. These large variations in feature sizes can dominate more important but smaller trends in the data and should be removed through normalization. In this study, all nine inputs generated from table I have been normalized to have a norm of 1. For instance, after 500 samples from the normal distribution of AR are generated according to the specifications in table I, the resulting column vector of size 500 has been normalized to have a length of 1.

6. AN OVERVIEW OF NEURAL NETWORKS

Neural networks are discussed in detail in Bishop [18] and Hagan [19]. In this section, we briefly discuss neural networks and their characteristics relevant to our study. The mathematical model of a single neuron used in neural networks is shown in Fig. 1. The input-output mapping function associated with this neuron is given by $\tilde{y}(\mathbf{x}, \mathbf{r}) = a = F(n)$. As discussed later in this section, the vector **x** represents the inputs to the neuron and the vector **r** represents the adjustable parameters. If $a = F(n) = n$, the single neuron behaves linearly while $a = F(n) \neq n$ represents a nonlinear neuron. The common choice for the transfer function $a = F(n)$ is the hyperbolic tangent sigmoid $(\tan sig)$ given by $a = F(n) = \dfrac{e^n - e^{-n}}{e^n + e^{-n}} = \tan sig(n)$ and shown in Fig. 2.

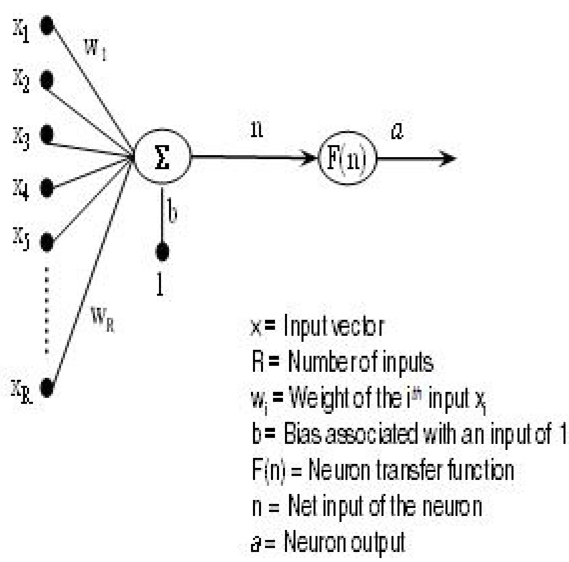

FIGURE 1: A Neural Network Architecture Containing One Neuron with Transfer. function a = F (n). When a = F (n) = n this model represents a linear architecture.

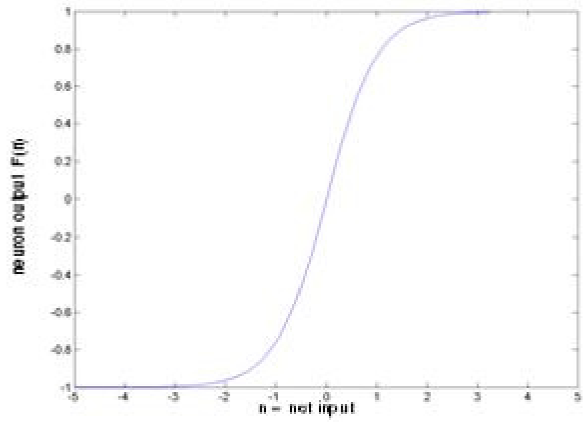

FIGURE 2: Transfer Function of A Nonlinear Neuron using the Hyperbolic.

tangent sigmoid (tansig) represented by $F(n) = \dfrac{e^{n} - e^{-n}}{e^{n} + e^{-n}}$

Neurons are the building blocks for generating neural networks, which can model complex systems. A neural network may consist of several layers of neurons interconnected with other neurons in the same or different layers through adjustable weights. A neuron's connection topology to other neurons, number of layers, number of neurons in each layer and the choice of each neuron's transfer function collectively define the neural network's architecture. Figure 3 shows typical neural network architecture.

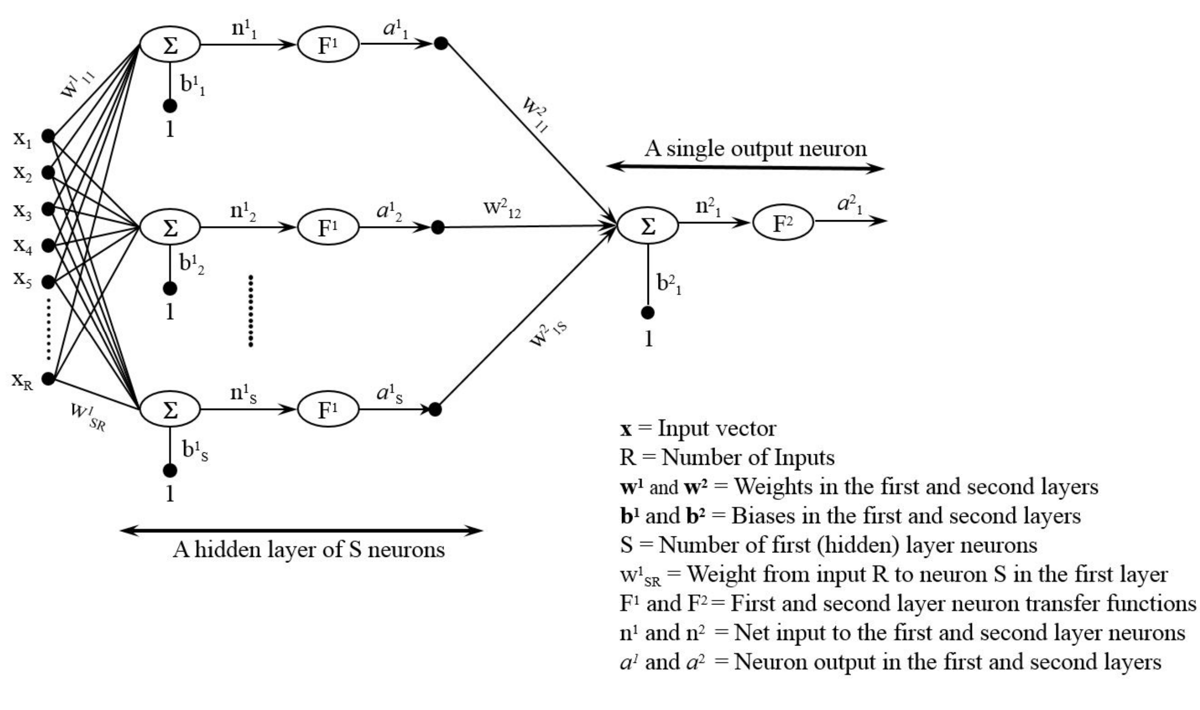

FIGURE 3: The architecture of a two-layer neural network widely used in modeling data sets.

Neural networks have emerged as an important tool to study complex problems in science and engineering. One problem of interest is data modeling and forecasting in which a data set of size

N denoted by $(\mathbf{x_1}, y_1)$, $(\mathbf{x}_2, y_2) \ldots (\mathbf{x}_N, y_N)$ is available, but the underlying mapping function from the inputs $\mathbf{x_i}$ to the outputs y_i $(i = 1, N)$ is unknown. In general, $\mathbf{x}$ can be a vector of size R $(\mathbf{x} = x_1, x_2, \ldots x_R)$ to represent cases where the output y depends on several inputs. A neural network tries to find an approximate model $\tilde{y}(\mathbf{x}, \mathbf{r})$ to actual $y(\mathbf{x})$ by adjusting its free parameters $\mathbf{r} = (\mathbf{w}, \mathbf{b})$ to learn the desired input-output relationship described by the data set. In this notation, $\mathbf{w}$ and $\mathbf{b}$ represent the set of weights and biases in the network, respectively. To achieve this goal, a neural network minimizes the mean square error (mse) or performance function given by

$$mse = E(\mathbf{r}) = \frac{1}{N}\sum_{i=1}^{N}\{y(\mathbf{x}_i) - \tilde{y}(\mathbf{x}_i, \mathbf{r})\}^2. \qquad (1)$$

The values of $r_1, r_2, \ldots, r_M$ that minimize $E(\mathbf{r})$ represent the optimum parameter values associated with the neural network model. The input-output mapping function defined by a neural network can be modified by changing either the number of neurons in any layer or their transfer functions.

The process of employing a neural network to model a dataset is as follows. The available data is first divided into training and testing sets. The input-output pairs associated with the training set are then presented to the network, which adjusts its weights and biases to minimize the error function expressed in eq. 1. This is called the training phase of the neural network. Once the error goal is minimized (i.e. the neural network weights and biases are determined), the neural network's ability to generalize is evaluated. During this testing or generalization phase, the network is presented with inputs from the testing set, which it has not seen before, and its predicted outputs are compared to the target outputs. The purpose of this phase is to assess the knowledge acquired during the training phase and determine if the underlying mapping function describing the behavior of the dataset has been captured by the neural network.

7. ANALYSIS OF RESULTS

The goal of our mathematical model is to obtain the relationship between the nine inputs presented in Table I and the output (overall comfort index). In this study, we use a neural network to obtain a model. Once the neural network model is developed, we can compare its actual output to the target OCI output values obtained from test drivers. This allows us to calculate the correlation between the actual OCI obtained from test drivers and calculated values obtained from the neural network model. This correlation coefficient can then determine the degree to which the specified inputs impact the overall comfort index. Any discrepancy between the calculated and actual OCI values can be attributed to the subjectivity of the OCI described by test drivers. In addition, we will compare our results to previously published work to model OCI using neural networks [1] and discuss our important contributions.

To train and test the neural network, we start by generating input data for each seat type A, B, C, D, and E as specified in Table I. For each seat type, the 9 inputs, which characterize it, are generated from a normal distribution with the specified mean and standard deviation shown in this table. For instance, for seat type A, we generate 100 input data points from the normal distributions for AR, CCA, CTF, CCF, CPP, BCA, BTF, BCF, and BPP. These input data points of size 100x9 are paired with 100 appropriate OCI output values, which are also generated from a normal distribution as specified in Table I. This process is repeated for seat types B, C, D and E. The neural network model would then find the best fit to describe the relationship between the output OCI and the inputs as shown below:

$$OCI = F(AR, CCA, CTF, CCF, CPP, BCA, BTF, BCF, BPP).$$

The mapping function F selected by the neural network is optimized to capture the input-output behavior depicted by the sampled data generated above. For each seat type, 85 data points are set aside for training and the remaining 15 points are used to test the neural network. As discussed before, the neural network has adjustable parameters, which are optimized to describe the training data accurately.

Figure 4 summarizes the results of our neural network model for the seat comfort index. The neural network is trained to minimize the error between its predicted and target OCI values over the training data. The complete training data has a size of 425 by 9 over all five seat types. At the end of the training phase, neural network determines the optimal values of its adjustable parameters. After the neural network is trained, its predicted output on test data (i.e. data it has not seen before) is calculated. The mean of the resulting 15 outputs for each seat type is calculated and plotted against the target mean provided by the 12 test drivers and shown in Table I under OCI column. The overall correlation coefficient between these two outputs (i.e. neural network output and actual OCI obtained from test drivers) is 0.794. This shows that our neural network model can capture about 80% of the variation in OCI expressed by test drivers. The remaining 20% variation in OCI described by test drivers is due to subjective matters discussed earlier. It is also possible to identify additional objective inputs, which may lead to higher correlation coefficient between the neural network and target OCI values.

Examination of Figure 4 reveals interesting facts. For the seat types with the best and worst comfort indices, neural network model had the worst performance in forecasting them. However, the neural network output for seats in the middle of the OCI range is very accurate. This is an indication of the fact that for the best and worst seats, subjective measures and biases play the most important role. It is also important to note that the test drivers found a significant correlation between seat comfort index and its appearance. The three most comfortable seats (i.e., seats C, A, D) also have the highest appearance rating.

A										
Mean	3.8	1717	598	0.3	1.1	1318	273	0.3	0.7	6.0
STD	0.7	113	160	0.2	0.3	191	74	0.2	0.3	2.2
Min	2.5	1585	377	0.0	0.7	1086	192	0.0	0.5	2
Max	4.5	1967	1010	0.7	1.6	1653	422	0.5	1.3	11
B										
Mean	2.8	1699	588	0.3	1.2	1338	240	0.2	0.7	10.3
STD	0.6	122	194	0.1	0.5	248	74	0.1	0.2	1.9
Min	2.0	1494	367	0.0	0.6	990	137	0.0	0.4	7
Max	4.0	1964	1066	0.4	2.4	1896	363	0.4	1.0	13
C										
Mean	4.4	1746	697	0.2	1.5	1342	277	0.2	1.1	2.3
STD	0.6	112	172	0.2	0.7	281	108	0.1	0.9	1.1
Min	3.0	1623	537	0.0	0.6	850	140	0.0	0.4	1
Max	5.0	2002	1186	0.5	3.4	1908	518	0.4	2.9	4
D										
Mean	3.8	1630	564	0.3	1.1	1219	250	0.3	0.7	8.6
STD	1	119	155	0.2	0.3	183	88	0.1	0.2	1.3
Min		1494	359	0.1	0.6	1005	126	0.1	0.5	6

Max	2.	1917	958	0.5	1.7	1711	451	0.5	1.0	10
	5									
	5.									
	0									
E										
Mean	3.	1725	579	0.2	0.9	1358	322	0.4	0.7	12.8
STD	2	117	149	0.1	0.3	254	116	0.1	0.2	1.4
Min	0.	1494	424	0.0	0.5	953	154	0.1	0.5	10
Max	7	1948	970	0.4	1.6	1978	557	0.6	1.1	15
	2.									
	0									
	4.									
	5									

TABLE 1: mean, standard deviation, minimum and maximum values of the nine inputs and the output overall comfort index) for five seat types (A, B, C, D, E) used in this paper. All the values shown here are calculated from a sample of twelve drivers.

8. COMPARISON TO PREVIEUS WORK AND NEW CONTRIBUTIONS

Kolich (2004) has also conducted a mathematical modeling of overall seat comfort based on neural networks. Their model uses the same inputs shown in Table I and three additional inputs, which are drivers' height, weight and gender. They report a correlation coefficient of 0.832, which is close to our value of 0.794. Their neural network contains 31 hidden neurons compared to 1 hidden neurons used in this study. It is very difficult to access any data, which includes gender, weight and height information to include in mathematical models because such data are considered to be proprietary. However, the close correlation coefficients between the two studies indicate that these three additional inputs do not play a significant role in determining the overall comfort index. What is alarming about their study is the large number of hidden neurons used in their mathematical modeling. The use of 31 hidden neurons implies that they are using between 300 to 400 adjustable parameters in their model compared to 10 used in this study.

According to their paper, they have used 60 data points (12 occupants times 5 seats), divided to 45 training and 15 testing data, to develop and test their neural network model. There are significant problems with their neural network, which this work addresses effectively as discussed next. Their small size of training data does not allow for such a large number of adjustable parameters in the neural network model to be optimized accurately. In fact, their neural network is prone to overfit (i.e., memorize) the training data without developing a valid model that describes the relationship between comfort index and the inputs. It is common practice to keep the number of neural network's adjustable parameters well below the size of the training data [18]. This ensures that the neural network doesn't merely memorize the training data without capturing the underlying mapping function from inputs to output. This requirement has not been met in their study.

The result of this work clearly shows that a small neural network architecture with 10 adjustable parameters can model the seat comfort index. The work of Kolich, et.al, on the other hand, uses an extremely large architecture with a significant number of adjustable parameters and a small set of training data to model this problem. The results reported in their work rely on a neural network which is unnecessarily too large to learn the mathematical model of seat comfort and opts for memorizing the training data.

The simulation of a neural network with similar architecture to their work (i.e., 31 hidden neurons) to model seat comfort index is quite informative and is conducted in this study. Even with 425 training data, the correlation coefficient achieved on 75 test data is around 0.55. On the training data, which the large neural network tends to memorize, the correlation coefficient obtained is about 0.8. This shows that their reported correlation coefficient of 0.832 was most likely associated with the training data. The neural network model utilized in this study leads to a correlation coefficient of 0.794 and is obtained by using the test data only.

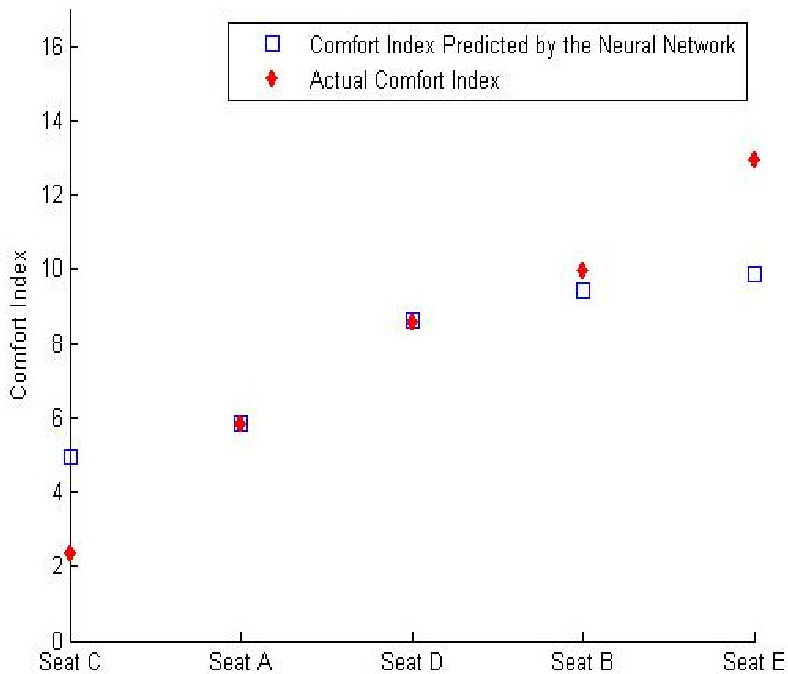

FIGURE 4: A comparison of overall comfort index described by test drivers and calculated from neural network model.

9. CONCLUSION

In this paper, we have studies the objective and subjective factors, which contribute to driver seat comfort. Comfort generally describes the state of physiological, psychological, and physical harmony between a driver and a car seat. Modeling seat comfort is challenging and complex due to subjective matters, which cannot be formulated and captured, in a mathematical model. It is common practice to distinguish between a driver's experience of observable and unobservable factors contributing to seat comfort. For instance, objective factors such as anthropometrics and pressure distribution on car seat can be modeled mathematically. However, mood, culture, car brand and demographic information are subjective in nature and do not lead to a collective pattern over a large and diverse number of drivers which can be captured by a mathematical model. In this paper, we have developed a neural network model for some of the objective measures which influence seat comfort. This model has a correlation of 0.798 with the overall comfort index provided by twelve test drivers for five different types of car seats. As a result, the model utilized in this work can capture about 80% of the behavior of the comfort index expressed by test drivers. Since the resulting correlation is less than 1.0, the conclusion is that there are subjective factors which impact seat comfort. It is possible that through introduction of additional inputs, one can increase the correlation between the neural network output and the actual comfort index. However, this correlation will always be less than 1.0, as unobservable factors are not captured in mathematical models.

The work presented here demonstrates that the previous work by Kolich (2004) suffers from an extremely large neural network architecture trained and tested on a very small dataset. As a result, their neural network is very prone to memorizing the training data and fails to capture an accurate mathematical model describing seat comfort index. Based on the results presented here, it is evident that a very small neuron network with 10 adjustable parameters can be trained and tested effectively to model seat comfort with respect to desired inputs.

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