A neural network approach to quantification, modeling and prediction of driving comfort

Laura L. Lansing
Lehigh University

Follow this and additional works at: https://preserve.lehigh.edu/etd

Part of the Industrial Engineering Commons

Recommended Citation
https://preserve.lehigh.edu/etd/268

This Thesis is brought to you for free and open access by Lehigh Preserve. It has been accepted for inclusion in Theses and Dissertations by an authorized administrator of Lehigh Preserve. For more information, please contact preserve@lehigh.edu.
AUTHOR: Lansing, Laura L.

TITLE: A Neural Network Approach to Quantification, Modeling and Prediction of Driving Comfort

DATE: May 29, 1994
A Neural Network Approach to Quantification, Modeling and Prediction of Driving Comfort

by

Laura L. Lansing

A Thesis

Presented to the Graduate and Research Committee of Lehigh University in Candidacy for the Degree of Master of Science in Industrial Engineering

Lehigh University
March 30, 1994
This thesis is accepted in partial fulfillment of the requirements for the Master of Science.

May 10, 99

Date

Thesis Advisor

Chairperson of Department
ACKNOWLEDGEMENT

The author would like to express appreciation to the Chrysler Corporation which funded this research with a Chrysler Challenge Fund Grant. The author would also like to thank Dr. Robert Storer for his participation as a principle investigator on this research project and for his support in the preparation of this thesis. Dr. Ian Birky, Dr. Bruce Sharkin, and the Reverand Dr. Lloyd Steffen also offered their support, without which this thesis would not have reached completion. The author would also like to acknowledge the participation of Dr. Laura Burke as a principle investigator, as well as Charleen Achey and Seth Flanders for their contributions to the research.

Additionally, the author would like to thank her parents for their support over the years. Finally, the author would like to thank Drew, Dane, Dylan, Nathan, Will, Sam, Anna, Louisa, Rachel, and Nathan for their constant reminders that the little things in life are often the most important.
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abstract</td>
<td>1</td>
</tr>
<tr>
<td>Chapter 1 Introduction</td>
<td>2</td>
</tr>
<tr>
<td>Chapter 2 Literature Review</td>
<td>4</td>
</tr>
<tr>
<td>2.1 seat comfort: subjective assessments</td>
<td>4</td>
</tr>
<tr>
<td>2.2 seat comfort: objective assessments</td>
<td>5</td>
</tr>
<tr>
<td>2.3 automotive seating comfort</td>
<td>6</td>
</tr>
<tr>
<td>Chapter 3 Neural Network Background</td>
<td>8</td>
</tr>
<tr>
<td>3.1 the backpropagation network</td>
<td>8</td>
</tr>
<tr>
<td>3.2 issues in neural network training</td>
<td>10</td>
</tr>
<tr>
<td>3.3 alternatives to backpropagation</td>
<td>10</td>
</tr>
<tr>
<td>3.4 validation of neural network models</td>
<td>12</td>
</tr>
<tr>
<td>Chapter 4 Development of Experiment</td>
<td>15</td>
</tr>
<tr>
<td>4.1 phase one</td>
<td>15</td>
</tr>
<tr>
<td>4.2 phase two</td>
<td>16</td>
</tr>
<tr>
<td>4.3 experimental design</td>
<td>20</td>
</tr>
<tr>
<td>Chapter 5 Analysis and Results</td>
<td>23</td>
</tr>
<tr>
<td>5.1 preliminary statistical results</td>
<td>23</td>
</tr>
<tr>
<td>5.2 neural network analysis</td>
<td>25</td>
</tr>
<tr>
<td>5.3 a regression approach to prediction</td>
<td>30</td>
</tr>
<tr>
<td>Section</td>
<td>Title</td>
</tr>
<tr>
<td>---------</td>
<td>-------------------------------------------------</td>
</tr>
<tr>
<td>5.4</td>
<td>comparison of neural network and regression analyses</td>
</tr>
<tr>
<td>5.5</td>
<td>summary of forward model: the prediction of comfort</td>
</tr>
<tr>
<td>Chapter 6</td>
<td>Decision Support for Vehicle Design</td>
</tr>
<tr>
<td>6.1</td>
<td>the forward model</td>
</tr>
<tr>
<td>6.2</td>
<td>the inverse model: preliminary results</td>
</tr>
<tr>
<td>Chapter 7</td>
<td>Conclusions</td>
</tr>
<tr>
<td>Figures</td>
<td></td>
</tr>
<tr>
<td>References</td>
<td></td>
</tr>
<tr>
<td>Appendix A</td>
<td>Neural Network Algorithms</td>
</tr>
<tr>
<td>A.1</td>
<td>the backpropagation algorithm</td>
</tr>
<tr>
<td>A.2</td>
<td>radial basis function networks</td>
</tr>
<tr>
<td>Appendix B</td>
<td>Description of Physical Design</td>
</tr>
<tr>
<td>Appendix C</td>
<td>Fidget Counts</td>
</tr>
<tr>
<td>Vita</td>
<td></td>
</tr>
</tbody>
</table>
LIST OF TABLES

Table 1. Transformed Variables 25
Table 2. Results using Backpropagation on Holdout Set 27
Table 3. Results using Backpropagation - Jackknifing 30
Table 4. Summary of Regression Analysis 33
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Neural Network Structure</td>
<td>45</td>
</tr>
<tr>
<td>2</td>
<td>Platform B</td>
<td>46</td>
</tr>
<tr>
<td>3</td>
<td>Vertical 2&quot; x 4&quot; for Gas Pedal</td>
<td>47</td>
</tr>
<tr>
<td>4</td>
<td>Side View of Gas Pedal Apparatus</td>
<td>48</td>
</tr>
<tr>
<td>5</td>
<td>Vertical 2&quot; x 4&quot; for Gas Pedal</td>
<td>49</td>
</tr>
<tr>
<td>6</td>
<td>Horizontal 2&quot; x 4&quot; for Gas Pedal</td>
<td>50</td>
</tr>
<tr>
<td>7</td>
<td>Front View of Gas Pedal Apparatus</td>
<td>51</td>
</tr>
</tbody>
</table>
ABSTRACT

Designing a comfortable driving configuration has been a difficult problem confronting the automotive industry. Current practice involves expensive and time-consuming methods for addressing the relevant design issues. Studies have been conducted which consider the influence on comfort of the automotive seat alone; but, no work has been done involving the driver's configuration as a whole. In this study, the importance of considering the entire configuration in an investigation of driving comfort is shown. Specifically, neural networks are constructed both to predict comfort and to suggest design parameters.

Using a backpropagation network, successful models of comfort were constructed. These models were used to suggest comfortable design parameters as well as to predict comfort. Several interesting and practical insights were gained. Among these insights were gender differences in comfort assessment and several nonintuitive design suggestions.
CHAPTER 1

1.0 Introduction

More than ever, the competitive nature of the automotive industry dictates the need for a serious, systematic approach to designing driving configurations with comfort in mind. Current practice entails building a prototype of the proposed design, submitting it to tests where subjects rate its comfort, and then altering the design to meet a desired comfort rating. This approach has several undesirable features. First, rating comfort is by nature a subjective task, and thus large variation in subject evaluation due to individual characteristics and prejudices can be expected. This variation means that many subjects are required to obtain meaningful results. Since differences in people will affect their evaluation of comfort, the sample of subjects must be large enough to be representative of the population. Further, a prototype of the design must be built and subjects found in order to conduct the test. All aspects of such a procedure are costly in both time and dollars. Finally, in the absence of models linking design parameters to comfort, this expensive and time consuming process must be repeated for each design.

We propose a practical approach which involves constructing empirical models which, once built, can be used to evaluate comfort without the need for further testing. These models are able to relate design features directly to comfort and use subject attributes as additional inputs in the prediction of comfort. By using subject attributes, it will be possible to predict the distribution of subject response across the car buying population. These models also include the possibility of utilizing data
from physiological measurements when they are available. While this information will not be required for the models to work, the added information could improve the models' power when it is available.

Specifically, we formulate a neural network model which accepts as input, design features of a vehicle, subject attributes, and physiological measurements on a subject when available. The system then provides as output a rating of comfort for a particular input configuration. We also attempt to reverse this procedure and train a neural network to predict appropriate design features for a vehicle given human attributes, the desired comfort ratings, and a limited set of design constraints as input. As a preliminary investigation, we use data on vehicle comfort ratings found in consumer publications to create a neural network model as an attempt to relate design data to an objective panel's comfort rating.

The paper is organized as follows. Chapter 2 summarizes our findings in the literature related to seat and driving comfort. Chapter 3 provides background information on neural networks. The focus then turns to experimental descriptions in Chapter 4, with analysis and results appearing in Chapter 5. In Chapter 6, the practical significance of the model is examined through experimentation with both the "forward" and the "inverse" models.
CHAPTER 2

2.0 Literature Review

The literature relevant to automobile driving comfort consists primarily of studies of seat comfort. Various approaches have been taken to assessing this comfort; however, virtually no published investigations have attempted to study the effect on comfort of the entire driving configuration. Here we review the relevant literature uncovered in our search.

2.1 Seat Comfort: Subjective Assessments

The most common measure of comfort through subjective methods uses a ratings scale in order to let the subject decide where the perceived comfort sensation occurs. Such methods have been recognized by Shackel et al. (1969) as "somewhat crude measuring instruments". As a result, many experimenters use several ratings scales in order to try to obtain a better indication of the overall comfort of the subject.

An early example of measuring seat comfort using a rating scale is the forced choice method used by Allen and Bennett (1958). This research forced the subjects to choose from among several levels of comfort. Many researchers have instead decided to focus on the issue of discomfort. This rating is still questioned, as it is not certain that comfort is the absence of discomfort. Habsburg and Mittendorf (1980) directed subjects to focus on various areas and to ask the question "Is it for me/Not for me" which tends to focus the question response on how the comfort is felt at the time the
question is asked rather than in an overall manner.

Further work has been done in the area of a body part map which allows the subject to focus on the body part that is in question rather than giving the subject the opportunity to interpret general body area references subjectively. Corlett and Bishop (1976) were among the first to use this technique.

2.2 Seat Comfort: Objective Assessments

Since subjective measures are crude and often do not lead to any conclusive answers, many different types of objective measures have been attempted in order to determine if the movements or reactions of the body will provide some insight into comfort. These have ranged from an attempt to categorize the types of seating arrangements that an individual will assume (Branton and Grayson, 1967), to recording the image patterns left by displacements on a seat (Fleischer et al. 1987), to the measurement of the number of small movements, or "fidgets", that are made by the person in the seat (Bridger 1988). These methods have met with varying degrees of success.

Branton and Grayson had the best results by observing postural changes and making a postural map of movement directions for the British Railroad. The authors were only concerned with two different types of seats and because of this were able to find large differences. Fleischer analyzed six different seats but could not come up with differences among them, although the discussion of any analysis is not very complete. In that experiment, the displacement pattern of the movements of a seat
were measured through the torque that was exerted on the seat while subjects were engaged in the activity of moving chips about a table. In the Bridger experiment, fidgets were counted manually by examining the subjects and comparing the positions of adhesive tape that was placed on their bodies. The fidgets provided no discernible method for distinguishing seats.

2.3 Automotive Seating Comfort

There have been very few studies done on automotive seat comfort, and those have mostly concentrated on the comfort of the seat as a stand alone object. Jones (1969) conducted a study to determine data to be used in the design of automotive and other types of seats. The dimensions of each area of a driving mock-up were adjusted gradually and the subjects’ opinions were asked at each point. The range of the adjustments was such that some of the settings were in clearly unreasonable situations. Minimally comfortable limits were found for the population at large.

In Habsburg and Middendorf (1977), 32 different factors were surveyed over 20 different seats. The factors were taken from both physiological readings and the subject’s feelings of comfort. All data were correlated, and differences were found among the seats. In Reick (1969), a study was made to see if it was possible to differentiate between different types of automotive seats by counting fidgets. A survey questionnaire was given in parallel. The results of the survey indicated a difference between one type of seat and the other four, where as the fidget count was not helpful in differentiating among any of the five seats.
In Thomas (1988), the objective was to compare four seats, three automotive and one "posture seat," for differences in subjective comfort, performance on a driving simulator, and pressure measurements on the buttock-thigh area. Significant differences were found among the different types of seats that were tested in nearly all of the different areas.
3.0 Neural Network Background

We proposed the use of neural networks for relating driving configuration parameters to comfort assessments. As the literature indicates, even the problem of determining the comfort of a seat has eluded much analytical insight. An entire driving configuration consists of numerous parameters, each contributing to comfort and interacting with others. Moreover, although human subjects may be able to assess their comfort, they often find it quite difficult to articulate exactly what makes them comfortable. Neural networks offer an ideal empirical approach to constructing arbitrarily complex models relating high dimensional driving configuration data to comfort assessments.

Typically, we represent neural networks in graph form using nodes and connections. Nodes, which represent computational elements, compute from (respond to) local information; that is, they process information carried to them by way of the connections. Each connection is associated with a weight vector. The neural networks of interest here are adaptive networks. The most popular training algorithm for adaptive networks is backpropagation.

3.1 The Backpropagation Network

The structure of a network which can be trained by the backpropagation algorithm is shown in Figure 1. The network consists of processing units and connections between them. The processing units can be one of three types: input
layer units (or nodes) which accept patterns from the external world, output layer units which generate outputs to the external world, and hidden units which do not directly interact with the external world. The network performs pattern association tasks in which a pattern presented at the input layer of the network is associated with a pattern at the output layer. The output layer pattern is composed of the outputs of the nodes in the output layer. The presence of the hidden units allows the network to generate nonlinear associations between inputs and outputs. In this network, information propagates from the bottom to the top layer, with connections existing only between units in adjacent layers; however, more general structures allow connections to "skip" layers. The algorithm is easily extended to handle such cases. The weights on connections contain information and adapt according to externally provided "target responses" and the backpropagation learning algorithm.

During training, the patterns of a fixed training set are repeatedly presented to the network in order to associate patterns with "correct" responses and thereby reach convergence. As each pattern is presented, the network passes the information forward until the nodes at the output layer give the associated output pattern. Each output pattern is then compared to the desired response, and the network adapts the weights on its connections to reduce the difference between the two; that is, the error

\[ E = \sum_j \sum_i (t_{ij} - a_{ij})^2 \]  

(1)

where \( t_{ij} \) is the correct response of output node \( j \) to input pattern \( i \), and \( a_{ij} \) is node \( j \)’s
actual response to pattern i. Convergence is reached when E reaches a minimum.

When the training process has been completed, the network’s weights freeze. When a new pattern is presented to the input layer, the network computes forward until the output layer produces a final response. At this point, the network does not adapt any of its weights. A more detailed discussion of the backpropagation algorithm can be found in Appendix A.

3.2 Issues in Neural Network Training

While the algorithm described for backpropagation sounds relatively straightforward, its successive nature leads to a variety of training issues which do not lend themselves to easy resolution. First and foremost, neural network researchers must determine the specific architecture of a network: how many hidden units should it possess? Too many hidden units can hinder the network’s ability to generalize to data not seen during training by causing overfitting; too few can cripple its ability to learn the mapping at hand. Next, what learning rate should be chosen? Finally, how many cycles through the training set should the network use for training? Training for too long can also contribute to overfitting. We addressed these issues using various heuristics from both the neural network literature and conventional statistics, and most importantly by focusing on the validation of the network.

3.3 Alternatives to Backpropagation

Backpropagation is the most widely used learning algorithm in its neural
network class. Still, the discussion in section 3.2 indicated that successful application of the network may require trial and error. Also, the network may require an excessively long training period. Thus, a variety of modifications to the algorithm have emerged. In addition, alternative approaches have yielded algorithms with advantages over backpropagation, usually in terms of speed. Appendix A includes a discussion of an alternative network used in this investigation.

3.3.1 Variations on Backpropagation

The backpropagation algorithm described above can yield drastically varied results. Different learning rate choices and lengths of training can alter performance, and the choice of the number of hidden units can similarly influence results. Variants on the backpropagation algorithm have taken the approach, typically, of focusing on either parameter adaptation or hidden unit construction and destruction.

Parameter adaptation methods may allow different learning rates for each node or connection and adapt these learning rates according to the perceived steepness of the error surface (1) (Hertz, Krogh and Palmer, 1992). Such methods may speed learning but may also lead to instability. In our practical experience with the delta-bar-delta variant (Jacobs, 1991), the instability problem prevailed over any speed advantage.

Methods which aid in determining an optimal structure often gradually eliminate unnecessary weights or units. These methods may prove particularly useful for improving generalization without excessive data. Unfortunately, such weight
elimination techniques require additional parameters, the choice and adaptation of which can again dictate the degree of success. As part of this investigation, software for the weight elimination variant of backpropagation was constructed.

3.4 Validation of Neural Network Models

One of the most difficult issues with regard to neural networks is that of validation. The "traditional" approach to validation is the split sets approach. In addition to this approach, we attempted to employ jackknifing. Finally, in section 6 we describe the sensitivity of the network to small changes in various parameters. The results aid us in further validating the "common sense" level of the network as well as its unexpected insights.

3.4.1 Split sets

Traditionally, neural network validation has used the idea of splitting the data set into a training set, used for updating the weight values (i.e., finding the model) and a test set, used to gauge the net's performance on "holdout" data. The sum of squared errors on the test set, SSE, can be used to find a coefficient of determination,

\[ R^2 = 1 - \frac{\text{SSE}}{\text{SSTO}} \]  \hfill (2)

where

\[ \text{SSE} = \sum_{j=1}^{P} (y_j - y')^2 \]  \hfill (3)

\[ \text{SSTO} = \sum_{j=1}^{P} (y_j - \bar{y})^2 \]  \hfill (4)
$y_j$ is the correct output for input pattern $j$; $y'_j$ is the model (neural network) output for input pattern $j$; and $y_{bar}$ is the mean $y$ value over all $P$ patterns in the holdout set.

This method of validation has the advantage of sidestepping the issue of the effective number of parameters in the model. If we were to assess $R^2$ for the error on the training set, we would need to normalize with the number of parameters; however, the apparent parameters of neural networks, the weights, do not correspond in a one-to-one fashion with the effective parameters of the model (Moody, 1992).

Even with the split sets approach, a misrepresentation of the generalization ability of the network can result. The more effective split set method uses a second training set to monitor progress (not to update weights) (Weigend et al 1990). When training error on this second set appears to level out or to begin to rise again, training should be stopped. A final validation set would then provide an estimate of the network's ability to generalize. The primary disadvantage of such an approach is that it requires a large amount of data.

3.4.2 Jackknifing

The use of jackknifing in neural networks applications is particularly novel; we know of only one other application which employed the technique, and it is not yet published (Wang et al, 1992). For problems in which data is relatively scarce, jackknifing offers particular appeal since more data can be used to train the network. The idea, quite simply, is that $(N-1)$ of a total of $N$ patterns are used for training; the error for the network's response to the single pattern test set is then computed. The
procedure is repeated \( N \) times, each time holding out a different pattern. The average error may then be used as an estimate of the network's error. Still, the neural network implementation of jackknifing poses problems analogous to those for splitting sets. The questions of how long to train the network and how many nodes it should have still plague the user. We addressed these issues heuristically and experimentally, as we describe in section 5.2.2.
CHAPTER 4

4.0 Development of Experiment

Two studies were conducted to demonstrate the feasibility of neural networks for this application. The first approach establishes the feasibility of developing a neural network model to predict automotive comfort based on design parameters only. The second approach establishes the potential for neural networks to receive data on relevant design features and human attributes, and relate them to a comfort rating or ratings.

4.1 Phase One

To conduct the first approach, automotive design feature data and comfort ratings were collected from trade magazines, primarily Consumer Reports. The data, which were taken from over a four year period, provided 93 patterns for a backpropagation network. From this data, six design related features provided the inputs to the network, and four comfort related ratings provided the outputs. We were able to employ a variety of neural network approaches.

The best neural network found (using backpropagation) was able to explain 15.5% of the variance (on a "holdout" test set). While this may appear to be disappointing, it is actually rather encouraging because it led us to believe that the addition of human attributes, which were not available for this data, would improve results. Given no information on the subjects who rated the cars and no control over the experiment in which the rating was obtained, the result is almost surprising. As
we discuss later, the comfort ratings we obtained proved virtually impossible to model effectively, even with subject data at hand. In retrospect, one wonders how we could do as well as we did with such limited data. It is possible that the determining factor was the source of the data. The Consumer Reports panel is trained to rate automotive comfort; the members of the panel, which are the same from vehicle to vehicle, have a specific, detailed list of items to survey. We reasoned that this would tend to reduce the overall variance.

This preliminary phase established the feasibility of neural network models of comfort and the need for subject data to be included in the model. It also foreshadowed the difficulty we might have with using comfort ratings from subjects.

4.2 Phase Two

To conduct the second approach, we built a prototype driver configuration and used human subjects to rate overall and specific body part comforts (Appendix B describes in detail the prototype configuration). Given that our configuration was of necessity somewhat rudimentary, we focused on selected design features only. Any combination of the selected parameters at fixed values was considered to be a design. The ability to adjust all of our parameters made it possible to generate a large number of different designs relatively easily.

The subjects were asked to record several body measurements and then to position themselves in the mock up and simulate a driving trip for forty minutes. After the simulation, which consisted of playing a computer driving game, the
subjects were asked to complete a survey regarding various aspects of their comfort.

4.2.1 Selection of Design Parameters

The initial step in the design of the driving configuration was to select a set of parameters whose influence upon driving comfort appeared to be measurable, constructable, and relevant. Selections were made by listing all possible parameters and then keeping only those that best met the above criteria. The seat back angle and distance between the pedals and seat were, for example, parameters that were excluded because they are currently adjustable in automobiles. That level of adjustment was maintained, but it wasn’t utilized as one of the design parameters. The parameters selected as those to be varied in the configuration were: headroom, location of the pedals with respect to each other and the steering wheel, pedal distance from the floor, seat pan height, length, and angle with respect to the floor, and the height of the steering wheel with respect to the floor and seat. The parameters selected were among those not currently adjustable in (most) automobiles because common sense indicates that those aspects of a driving configuration which are not adjustable are more pertinent to overall comfort than those that the driver is at liberty to alter at any time to suit his specific needs.

4.2.2 Subject Characteristics

Essentially the same method was employed to determine which subject characteristics to include in the experiment as was used in determining the
experimental parameters for the mock up. A list of all reasonable possibilities was made and then narrowed down to those characteristics which were easily measured by the individuals themselves and which were believed to be related to the comfort issue. The attributes selected were: height, weight, age, and sex. The body measurements chosen were: heel to knee, knee to hip, hip to shoulder, shoulder to wrist, and hip circumference. A short questionnaire which the subjects completed as the first step in their participation was developed as a simple means of recording the information. We also asked about the presence of other possible health considerations, such as a bad back, which could influence comfort.

4.2.3 Game Scores and Fidget Counts

In an attempt to include an objective comfort measurement, we counted small body movements, or fidgets. Rather than taking direct or indirect physical counts by means of direct observation or videos, a dynamometer was embedded in the driver configuration to measure all body motion in the X, Y, and Z axes in half second intervals. Since the dynamometer would record all movement, including that of steering and use of the gas and brake pedals through which the driving simulator was run, a running record of the time, the positions of the gas and brake pedals, the position of the steering wheel, distance traveled, points scored, and the number of speeding tickets received was kept by recording these items through the game software. By using this information, the effects of driving could be removed from the dynamometer data, thus leaving a fidget count.
As noted in the literature, past attempts at using fidget counts as a measure of comfort have not been successful; however, the personal experiences of the authors and others indicate that people do tend to fidget more when they are not comfortable. We believed our method to be more reliable than that of previous methods tried because it did not rely on human observation. We hoped to attain more accurate information using technological means.

At present, the fidget counts have not been utilized; however, we believe that there is valuable information in them. We intend to use these as a comfort measure in our future study. If successful, we will then have an objective means of evaluating comfort which would help to identify and compensate for inconsistencies between subjective human ratings. Appendix C describes in detail the steps involved in processing the fidget data.

4.2.4 Subject Ratings

After their driving simulation, subjects were asked to complete a comfort survey. We requested that the subjects remain in the configuration while completing the survey to assist them in making accurate responses. The survey required subjects to rate on a one to five scale their overall comfort as well as their neck, shoulder, lower back, buttock, hip, thigh, lower leg, foot, and arm comforts. A rating of one indicated low comfort, and a rating of five indicated high comfort.

Additionally, the subjects were asked how they would, if given the opportunity, improve the design in which they "drove." Each experimental parameter
was identified, and the subjects were to respond in one of three ways - less, same, or more. A response of less indicated that a smaller amount (distance or angle) of that parameter would be better. For instance, less seat pan angle would indicate that the subject would prefer that the seat pan be less slanted, or more nearly horizontal. A response of more in this case meant that the subject would have found a seat pan with more tilt desirable. A response of same indicated that the subject found the arrangement comfortable as it was. Given that two seats were used in the experiment, improvement in the seat padding, which was not identical in the seats, was surveyed as well. An improvement rating on the fixed portion of the seat to pedal distance was also sought to avoid the assumption that the standard distances found in vehicles are optimal.

Finally, subjects were asked to evaluate the design in their own words and make any additional suggestions or complaints not covered in the earlier questions. The subjects were also encouraged to critique the survey at this point.

4.3 Experimental Design

To design the experiment, the dimensions of an actual automobile were needed. There is, however, a great deal of variation in automotive designs. To overcome this variation, several vehicles were measured. These dimensions were then used to construct both the mock up and the overall experiment.

A wide variety of automobiles, twelve in all, were measured. They included designs from full sized, mid sized, luxury, sports, compact, subcompact, and all
terrain vehicles. The dimensions of interest for the construction and adjustment of the configuration were: the seat angle and height, the seat pan length, the wheel to brake, floor, and seat distances, headroom, the pedal distances apart, the brake location with respect to the steering column, the distance from the pedals to the seat track, and the gas pedal pressure.

The mean of each design feature was calculated, and this became the x-bar design. Since a conservative estimate of the variance for each feature was desired, the deviation from the mean was calculated using two methods, and the two resultant values were averaged to get the final deviation figure. The first deviation calculation was the sum of the squared differences from the mean divided by the degrees of freedom. The second calculation was based on the range of values rather than their mean. If R is the range of the measurements for a particular feature, then the estimate of the deviation is $R/d_2$ where $d_2$ depends on the sample size and is the mean of the random variable known as the relative range.

It was important to keep all of the designs used in the experiment within the realm of reality while at the same time spanning that space. Consequently, the experiment was partitioned into three segments known as a "central composite" experimental design. Eight experiments were run with all design parameters set at their x-bar values. The remainder of the seventy-two experiments were divided into a $2^{9-4}$ factorial design and a star design, each with thirty-two runs. The factorial experiments were run by varying the parameters by plus or minus one and a half deviations from their means. The star design was conducted by leaving all but one
parameter at their x-bar values for each run. The one varied parameter was then moved as far away, in both the positive and negative directions, from its x-bar position as possible while remaining within reality and the physical limitations of the apparatus. The three experiments were run as separate units, but subjects were assigned designs randomly.
CHAPTER 5

5.0 Analysis and Results

The data collected by the surveys, dynamometer, and game were compiled and arranged into several datafiles. The datafiles were of two types - those which consisted of the raw variables and those which were made up of ten transformed variables to be discussed in section 5.1. The independent variables for each file consisted of some combination of design features and human attributes. The dependent variable(s) was either the overall comfort rating, a specific body part comfort rating, or the total number of design improvements suggested by the subject. These files were then used to do both classical statistical and neural network analyses.

The division of the data into training and testing sets to be used in the neural network analysis was done by putting two thirds of the data points, or patterns, in the training set and the remainder in the test set. Specifically, two thirds of each type of experiment, x-bar, factorial, and star design, were in the training set, and one third of each type were in the test set. The patterns were divided into one third and two third segments within each experiment randomly.

5.1 Preliminary Statistical Analysis

A preliminary conventional statistical analysis of the data was conducted to see if any insights could be gained by conventional analysis techniques. The first analysis performed was that of computing the correlation matrix of all the variables. This matrix was large (44x44), but it contained a few interesting and reassuring
discoveries. First, the overall comfort rating was found to be correlated with the other nine comfort ratings which implied that people did not pick the comfort ratings randomly, but were consistent within themselves. There were also correlations between connected body part ratings; that is, if the neck was uncomfortable, the shoulders were uncomfortable, or if the lower leg was uncomfortable, the feet were uncomfortable. The correlation matrix contained intuitive body attribute correlations (sex to height and weight, height to weight, etc.) as well as a few correlations between the improvements recommended and the comfort of various body parts. For example, headroom improvement was correlated to neck and shoulder comforts.

What was not found was a clear correlation between the design parameters and the comfort ratings or the improvement values.

A fractional factorial analysis was performed on the $2^{9-4}$ factorial experiment to determine if there were any two way interactions present. The analysis was done in a standard manner using StatGraphics, and the results showed that while there appeared to be several significant interactions present, none of these could be used to construct a model that would adequately explain any comfort rating. When first order multiple regression was performed, none of the individual elements came forward as having a significant effect on the final comfort ratings.

Having failed to construct adequate explanations for comfort from the raw data, we constructed new variables that were based on the mock-up configuration and the physical attributes of the subjects. Ten new variables were developed and are listed in Table 1. These new measurements were run through the same battery of
tests to which the raw data were subjected with only slightly improved results; however, the new variables proved to be important to the neural analysis.

5.2 Neural Network Analysis

Two different paradigms, backpropagation using NeuralWare Professional II Plus and radial basis functions using software written by one of the authors of this paper, were used in the neural analysis. Several experiments were conducted; and, wherever possible experiments were done using both types of network. Here, we report results using backpropagation since it performed best overall.

Table 1. Transformed Variables

<table>
<thead>
<tr>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Headroom - (Height - Heel2hip)</td>
</tr>
<tr>
<td>AdjustedSeatPosition - WheelPedalDistance</td>
</tr>
<tr>
<td>SeatPanAngle + SeatBackAngle</td>
</tr>
<tr>
<td>Heel2Hip - AdjustedSeatPosition</td>
</tr>
<tr>
<td>PedalDistanceApart + BrakePosition</td>
</tr>
<tr>
<td>WheelFloor - WheelSeat</td>
</tr>
<tr>
<td>Weight to Height ratio</td>
</tr>
<tr>
<td>Armlength - (AdjustedSeatPosition + 17.5)</td>
</tr>
<tr>
<td>Knee Angle</td>
</tr>
<tr>
<td>Body Angle</td>
</tr>
</tbody>
</table>

5.2.1 Backpropagation Results

Initially, backpropagation was used on the raw data. Nine design features and
four human attributes were given to the network as input with overall comfort as the output. Several different models were tried, each with a different number of hidden units. (The selection of the range of the number of hidden units was based on the discussion in Zurada, 1992, on pages 216-218). The best results were found with three nodes in the hidden layer. Since the results were not promising, another hidden layer was added in an attempt to scale the data. Using five nodes in the additional layer, there was a substantial improvement. This resulted in a 13-3-5-1 network. The network was then trained again for each of the specific comfort ratings as well.

The comfort ratings provided, unfortunately, little information. When a subject is asked to rate comfort, many subjective and uncontrollable factors come into play. Perhaps more significantly, comfort is relative, and therefore each subject's "comfort scale" is different. The end result is a high degree of variation in the overall comfort rating.

By more directly asking the subjects about how changes in the design parameters will affect comfort, much of the subjectivity and relativity can be removed. Subjects will certainly have difficulty determining if a certain driving configuration is a "3" or a "4" on an "overall comfort" scale of 1 to 5. On the other hand, deciding if the pedals are too close, too far away, or just about right can be answered in much more concrete terms. This intuitive observation was borne out by our results which indicate "overall comfort" is virtually impossible to predict, whereas the number of improvements provides significantly more useful information.

In this spirit, we turned to the information we had collected by asking subjects
what they would change about the design in which they drove. We reasoned that a
subject who chooses to change several parameters is reflecting lower comfort than a
subject who would change fewer parameters; thus, the total number of improvements
suggested was used as an estimate of comfort. In addition, the transformed variables
were used as inputs for two reasons: (1) it is generally recommended to provide
variables which are as informative as possible to a neural network, and (2) the
transformed variables led to a reduced input dimension. A reduction in input
dimension leads directly to a reduction in network parameters; and hopefully
therefore, to better generalization (see section 3.3).

Initially, only the first six variables in Table 1 were considered. We continued
to use three units in the hidden layer. We also scaled the data to between zero and
one to avoid resorting to the use of a second hidden layer and to further suppress
noise in the data. In addition, two networks were trained using noisy input data to
see if that would further improve generalization (Matsuoka, 1992). A normal random
number generator was used to create the noise, and the range of the numbers
generated was from (-.1, .1) to (-.25, .25). A summary of the results are shown in
Table 2.

Table 2. Results using Backpropagation on Holdout Set.

<table>
<thead>
<tr>
<th>range of noise</th>
<th>no. of cycles</th>
<th>SSE (test set)</th>
<th>SSTO</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>none</td>
<td>235</td>
<td>39.06</td>
<td>76.87</td>
<td>.49</td>
</tr>
<tr>
<td>(-0.1, 0.1)</td>
<td>400</td>
<td>54.36</td>
<td>76.87</td>
<td>.40</td>
</tr>
</tbody>
</table>
Clearly, the best result was the first; but, in all three cases we were able to predict comfort quite well. Since the errors listed reflect test set error, we can find the coefficient of determination from

$$R^2 = 1 - \frac{\text{SSE}}{\text{SSTO}} = 1 - \frac{39.06}{76.87} = .49$$

for the model trained without noise. While the number appears low for an engineering application, it reflects a fairly high $R^2$ for an experiment conducted to predict human assessments.

Injection of noise into the training set worsened results, which may seem surprising. However, as Matsuoka points out, the use of noise injection is helpful when training data consist of a large amount of similar data points. In our case, the opposite held. Each data point differed in subject attribute information, and 64 out of the 72 data points differed in design information.

5.2.2 Jackknifing for Model Validation

By testing the network on a set of "holdout data," we attempted to validate its performance; however, the issue of validation is a complex one in neural networks (see section 3.4). We employed, in addition to the holdout set method, an alternative which has only just begun to surface in neural network research. The technique employed was jackknifing. Rather than the previously used training and test sets, the model was trained on all but one of the seventy-two patterns and then tested on the
omitted pattern. This was done seventy-two times, each time omitting a different pattern. This procedure was used on networks with up to five hidden units. As indicated in Table 3, the best result was reached using four hidden units. Since it was not at all clear that the choice of ten cycles for training was optimal, several other trials were run with other training schedules. Ten cycles gave the best results, so all further jackknifing trials were run by training for ten cycles.

While jackknifing did produce favorable results, we believed that we could do better if we jackknifed on a partially trained network. Backpropagation is essentially a gradient descent procedure. The idea was that if the process began in the neighborhood of the solution, jackknifing would do better. This would prove particularly useful if, as expected, the function surface is nonconvex (Wang et al, 1992, used the same approach). Consequently, a network was trained with all seventy-two patterns, and then the resultant network was used as a starting point for jackknifing. The results for this experiment are also summarized in Table 3.

When the pretraining was allowed to go further than 350 cycles, the total error for the resultant network increased, making the jackknifing process unnecessary since jackknifing further raises the error.

The results in Table 3 would seem to indicate that the best design is actually a four hidden unit design. It is interesting to note that, using holdout set validation, virtually identical results were obtained for the 6-4-1 structure as for the 6-3-1 structure as given in Table 2. Since a network with fewer hidden nodes is generally preferable whenever possible, our choice of three hidden units stands. In addition,
note that the $R^2$ for the best structure as indicated by jackknifing (.46) matches relatively closely the $R^2$ obtained using split sets. Again, the results further validate the structure.

Table 3. Results using Backpropagation - Jackknifing

<table>
<thead>
<tr>
<th>No. of hidden units</th>
<th>No. of cycles in pretraining</th>
<th>No. of training cycles</th>
<th>Training Set SSE</th>
<th>Jackknife SSE</th>
<th>SSTO</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>10</td>
<td>--</td>
<td>293.24</td>
<td>281.99</td>
<td>--</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>10</td>
<td>--</td>
<td>283.64</td>
<td>281.99</td>
<td>--</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>10</td>
<td>--</td>
<td>270.42</td>
<td>281.99</td>
<td>.04</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>10</td>
<td>--</td>
<td>260.86</td>
<td>281.99</td>
<td>.07</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>10</td>
<td>--</td>
<td>285.50</td>
<td>281.99</td>
<td>--</td>
</tr>
<tr>
<td>4</td>
<td>200</td>
<td>10</td>
<td>123.98</td>
<td>156.48</td>
<td>281.99</td>
<td>.45</td>
</tr>
<tr>
<td>4</td>
<td>250</td>
<td>10</td>
<td>122.14</td>
<td>160.23</td>
<td>281.99</td>
<td>.43</td>
</tr>
<tr>
<td>4</td>
<td>300</td>
<td>10</td>
<td>118.58</td>
<td>152.17</td>
<td>281.99</td>
<td>.46</td>
</tr>
<tr>
<td>4</td>
<td>350</td>
<td>10</td>
<td>116.98</td>
<td>150.98</td>
<td>281.99</td>
<td>.46</td>
</tr>
</tbody>
</table>

5.3 A Regression Approach to Prediction

To establish a baseline to which the neural network results could be compared, multiple regression was used to build models to predict comfort and the number of improvements suggested. Modeling efforts were undertaken for three separate cases. The first case had the total number of improvements as the dependent variable and included the six transformed measures as independent variables. The second case again attempted to predict the total number of improvements but included four additional independent variables. The final case had the overall comfort rating as the
dependent variable and used the same ten independent variables as the second model.

A summary of the variables used in the three analyses appears below. The individual variables were discussed in detail in section 5.1.

Model 1.

Dependent: Number of Improvements.

Independent: X1 = Headroom - (Height - HeeltoHip)

\[
\begin{align*}
X2 &= \text{AdjustedSeatPosition} - \text{WheelPedalDistance} \\
X3 &= \text{SeatPanAngle} + \text{SeatBackAngle} \\
X4 &= \text{HeelToHip} - \text{AdjustedSeatPosition} \\
X5 &= \text{PedalDistanceApart} + \text{BrakePosition} \\
X6 &= \text{WheelFloor} - \text{WheelSeat}
\end{align*}
\]

Model 2.

Dependent: Number of Improvements.

Independent: X1 to X6 as above plus the following four variables

\[
\begin{align*}
X7 &= \text{ArmLength} - (\text{AdjustedSeatPosition} + 17.5) \\
X8 &= \text{Height to Weight Ratio} \\
X9 &= \text{Knee Angle} \\
X10 &= \text{Body Angle}
\end{align*}
\]

Model 3.

Dependent: Overall Comfort Rating.

Independent: X1 to X10 as above
A central composite design in the original design parameters was used in this experiment as discussed in section 4.3. The central composite design is conducive to fitting quadratic models; and, since the variables used in models 1, 2, and 3 rely heavily on the original design variables, quadratic models were also used in the present analysis. A full quadratic model in p variables includes the following terms:

\[ k = \frac{p^2 + 3p}{2} \]

- Linear terms: \( X_1, X_2, \ldots, X_p \)
- Quadratic terms: \( X_1^2, X_2^2, \ldots, X_p^2 \)
- Cross product terms: \( X_iX_j \) for \( i = 1, \ldots, p \) and \( j = i+1, \ldots, p \)

For each of the three models, a version of stepwise regression was used for model selection. Specifically, the MAXR option of the stepwise procedure in SAS was used. This procedure provides k models from which to choose by attempting to build the best one variable model, the best two variable model, and so on up to the full k variable model. It is similar to an all possible regressions procedure but is more efficient computationally. In order to further select final models, we followed standard procedure and examined the mean squared error and Mallow's \( C_p \) statistic for each fitted model. Based on these criteria, two or three potential models were identified for each of the three cases. The final step was to apply the SAS REG procedure to each of the final selected models in order to obtain additional necessary statistics. In particular, the REG procedure calculates studentized residuals and
Cook's distance so that high leverage points may be identified. Additionally, the REG procedure calculates the prediction error sum of squares (PRESS) statistic, which is equivalent to jackknife sum of squares. PRESS will be used for direct comparisons between the regression and neural network models.

5.3.1 Regression Results

Table 4 summarizes the results:

Table 4. Summary of Regression Analysis

<table>
<thead>
<tr>
<th>Case</th>
<th>Number of Variables</th>
<th>SSTO</th>
<th>MSE</th>
<th>SSE</th>
<th>PRESS</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12</td>
<td>282.0</td>
<td>2.19</td>
<td>129.1</td>
<td>207.4</td>
<td>.54</td>
</tr>
<tr>
<td>1</td>
<td>19</td>
<td>282.0</td>
<td>1.99</td>
<td>115.7</td>
<td>200.1</td>
<td>.59</td>
</tr>
<tr>
<td>2</td>
<td>6</td>
<td>282.0</td>
<td>2.44</td>
<td>158.9</td>
<td>194.5</td>
<td>.44</td>
</tr>
<tr>
<td>2</td>
<td>15</td>
<td>282.0</td>
<td>1.70</td>
<td>95.0</td>
<td>144.8</td>
<td>.66</td>
</tr>
<tr>
<td>2</td>
<td>28</td>
<td>282.0</td>
<td>0.99</td>
<td>42.6</td>
<td>122.6</td>
<td>.85</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>99.8</td>
<td>1.11</td>
<td>72.1</td>
<td>87.3</td>
<td>.28</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>99.8</td>
<td>0.95</td>
<td>53.3</td>
<td>80.6</td>
<td>.47</td>
</tr>
<tr>
<td>3</td>
<td>25</td>
<td>99.8</td>
<td>0.85</td>
<td>39.0</td>
<td>80.6</td>
<td>.61</td>
</tr>
</tbody>
</table>

The regression analysis reveals an apparent difficulty in explaining the overall comfort rating results. Comparison of the total sum of squares (SSTO) and PRESS for this dependent variable indicates that only about 20% of the variation is predictable (i.e. 1 - PRESS/SSTO = 0.20). Somewhat better results appear possible when predicting the total number of improvements in that roughly 57% of the variation is predictable.
The regression results can be used as a basis of comparison for the neural network models. The SSTO represents the sum of squared error when the mean of the dependent variable is used as a predictor. The error sum of squares (SSE) reflects error variation from the fitted model and thus is comparable to squared error results from the training set in the neural network models. The PRESS values represent jackknife error sum of squares and are comparable to the jackknife squared error computed for the neural networks.

5.4 Comparison of Neural Network and Regression Analyses

To compare the regression and neural network models, we should use the jackknife error - the sum of squared errors on the individual holdout sets. Moreover, the model’s generalizability is questionable if there exists a very large difference between the SSE for the training set and the jackknife error. The best regression model, in terms of jackknife error, appears to be the 28 term model with an SSE of 42.6 and a jackknife error of 122.6. On the other hand, the model with 15 variables gave an SSE of 95.0 and a jackknife error of 144.8, which suggests a potentially better model in terms of generalizability. While the jackknife error for backpropagation (151) exceeds that of either of these regression models, the SSE for backpropagation was 117; thus, the fact that the difference between the two is relatively small suggests that the model possesses good generalizability.
5.5 Summary of Forward Model: The Prediction of Comfort

The best neural network results for the prediction of comfort were found using backpropagation with scaled transformed variables as input, a comfort estimate based on the total number of improvement suggestions, and a 6-3-1 or 6-4-1 architecture. The first six transformed variables in Table 1 were the input to the network. In common sense terms these variables describe headroom from the top of the driver’s head to the ceiling of the vehicle, the horizontal distance from the front of the seat to the steering wheel, the total body angle of the driver with respect to the horizontal, legroom as a function of how straight the driver’s legs are, the distance from the left wall of the vehicle to the gas pedal, and the seat pan height. What remained was the issue of the practical significance of the model.
6.0 Decision Support for Vehicle Design

To aid us in explaining and validating the relationships the network was discovering and to demonstrate the use of the network for making design decisions, we independently changed the value of each input by five percent and looked at the resultant changes in the network output. The choice of five percent was arbitrary; the purpose was to vary inputs by a small but realistically feasible amount to see if comfort would be influenced, and if so, how. To obtain conclusive evidence to support the trends found would require further research, but several interesting design preferences did begin to surface.

6.1 The Forward Model

When the input value for headroom was increased by a small amount, the output value decreased by an average of 12%. This indicates that as headroom is increased, the total number of improvements suggested decreases. In practical terms, this means that an increase in headroom enhances driving comfort. This was encouraging because it showed that the network was picking up on what we attribute to common sense. Given that, perhaps the network was also discovering trends that are not so apparent to human intuition.

An increase in the horizontal seat to wheel distance produced an average increase of 30% in the output value. This translates into the suggestion that comfort decreases as the seat is moved away from the wheel. This makes sense according to
Dr. Zigman Strylecki, an orthopedic surgeon, because sitting with the knees higher than the hips decreases lumbar strain and intradiscal pressure (Strylecki, personal communication). Sitting too close to the wheel does pose a problem, though. As the seat moves up, the steering wheel interferes with the driver's legs. Men and women appear to have resolved this conflict differently, as will be shown in the next section. Men tend to sit with their legs apart and feet resting on the outer part of the heel, while women tend to sit with their knees together and feet resting on the inner part of the heel. This tendency could be due to a number of influences, the most probable of which appear to be anatomical differences between the sexes, cultural conditioning, and manner of dress. Additionally, the preference for a short distance between the wheel and seat implies that arm comfort is improved when the driver is not forced to reach for the wheel.

The results for varying the total body angle are somewhat more complex. The network indicates that as the total body angle with respect to the horizontal is increased by five percent, comfort also increases by an average of 20%. The subject surveys and experimental data suggest that as the seat pan angle is decreased, or made more nearly horizontal, people tend to adjust the seat back to have a smaller angle. When seated in a configuration with a greater seat pan angle, drivers tend to adjust the seat back to have a larger angle. Given the network result, it appears that a larger seat pan angle improves overall comfort. Again, this shows the network's ability to recognize that comfort increases when the angle of the seat pan elevates the knees slightly above the hips.
Increasing the legroom tended to decrease comfort ratings by seven percent, on average. The implication is that when a driver is forced to reach for the pedals, and consequently drive with legs straight, comfort decreases. Considering the apparent preference for a short horizontal wheel to seat distance, this result implies that drivers also like the horizontal wheel to pedal distance short enough that they are not forced to reach for the pedals. This is clearly a particularly relevant feature for shorter individuals.

A mean increase in comfort of 12% was found when the distance of the gas pedal to the left wall of the vehicle was increased. This indicates that comfort is increased as the gas pedal is moved to the right by a small amount. This may be related to the preferences for having the seat and pedals close to the wheel. In such a design, there again tends to be a gender difference as shown in section 6.2. For both men and women, the preferred sitting stance forces the driver's feet to the right; and hence, a gas pedal a bit further to the right would become more comfortable. This result does not, however, imply anything about the brake position or the relative positions of the pedals.

Finally, as the seat pan height is increased, an average decrease in comfort of seven percent was found. This appears to imply more about related comforts than about seat pan height itself because this design feature affects several others. For instance, as the seat pan is raised, headroom and the vertical wheel to seat distance are reduced. Since people tend to prefer support for their thighs to reduce fatigue, it would appear that a higher seat pan should be advantageous provided that other
parameters are adjusted accordingly; however, as mentioned, further study is required to substantiate this suggestion.

6.2 The Inverse Model: Preliminary Results

As a final experiment, an attempt was made to reverse the training procedure with backpropagation by creating several networks to predict design parameters. The networks used four human attributes, either the total or individual improvement counts, and three design constraints as input and a designated design feature as an output. We decided to focus on the prediction of the distance between the gas and brake pedals and the vertical wheel to seat distance. These particular design features were chosen because they are both critical to the comfort issue and virtually always fixed. As discussed in the previous section, we suggested that a gas pedal moved further to the right increases comfort. As this has no implications for the brake pedal position, we decided to try to get a better understanding of that by looking at the distances between the pedals. Additionally, the above discussion suggesting a short horizontal wheel to seat distance led us to wonder what a neural network might discover regarding the vertical wheel to seat distance because the two measures are interdependent.

Two different networks were developed, one to predict each design parameter. The networks were trained with the split set approach, and a fair amount of the variance was explained. For the vertical wheel to seat predictor the test error was 10.58 which results in an $R^2$ of .882. The pedal distance predictor had a test error of
21.08 giving an $R^2$ of .052.

To better understand the relationships the networks were finding, we created a new test set consisting of six hypothetical people, three men and three women. The ages, heights, and weights of these individuals were taken from our data in such a manner as to create subjects who would represent both extreme and average cases; for instance, a very short, light weight man or a young woman with a medium build. Each pattern was also associated with a perfect comfort rating represented by no improvements suggested. These new test patterns were then presented to the networks to see what they would suggest for the two parameters in question.

The wheel to seat predictor suggested that women prefer a slightly greater vertical wheel to seat distance than men; although, the distances suggested by the neural network varied little between the subjects (variance = .0002). The difference manifested may, in part, be due to the sitting preferences discussed in section 6.1. Sitting with one’s knees together could cause interference with the steering wheel unless there is sufficient distance between the wheel and seat. At the same time, women tend to have shorter legs than men, so the extra room required may be rather small. It should be remembered, however, that this insight is inconclusive, and more work is required before any conclusions can be reached.

The pedal distance predictor indicated that women prefer more distance between the gas and brake pedals than men do. This insight may also be due to the sitting preferences discussed. In this case, the insights were more clear cut; although again, the variance among subjects was small (.0184). Again, more research is
needed.

As a final attempt to make practical sense of the inverse models, we independently varied the inputs to the networks to see what influence each input had on the design features in question. In both cases, the four human attributes (sex, age, height, and weight) were selected to be varied in the same manner as was done with the forward model in section 6.1. The relationships found all agreed with the findings from the forward model which we found encouraging because it showed a consistency between the several networks.
CHAPTER 7

7.0 Conclusions

This project illustrated the feasibility of a neural network approach to predicting the comfort of automotive designs. A neural network can successfully learn the relationships between design features, human attributes, and comfort measures. This relationship can be learned in two ways. The network can predict comfort based on design features and human attributes; or, it can aid in design decisions by suggesting design features given human attributes, desired comfort measures, and a minimal set of design constraints as inputs.

The relationship between comfort, design parameters, and subject attributes is nonlinear, and that makes it an ideal application for neural networks. We found first order regression models inadequate to explain comfort; although, using quadratic models, we were able to produce results comparable to those of the neural networks. The advantages of the neural approach should become apparent as the input space increases. In our investigation, the backpropagation network produced the most promising insights as expected, since backpropagation is essentially an efficient means of performing nonlinear regression.

While training the neural network to learn the appropriate responses, whether for the prediction of comfort or as a decision aid, was fruitful, the most interesting insights were found in our attempts to translate the relationships discovered by the network into practical information for the automotive industry. Probably the most useful discovery was that men and women have separate agendas where comfort is
concerned. As stated in *The Ann Arbor News* (Sunday, August 23, 1992), automobiles are currently designed for the "50th percentile male;" yet, when a vehicle is designed for women, everyone benefits.

A second interesting discovery was that more legroom does not necessarily translate into improved comfort. In fact, most drivers prefer not to drive with their legs stretched out because that position results in leg fatigue. Rather than more legroom, drivers would appear to prefer an adjustable steering wheel which can be moved closer to or further from the dashboard according to the height of the driver. The critical measurement appears to be the horizontal wheel to pedal distance and not the seat to pedal distance.

Finally, this study made it apparent that driving comfort can not be measured in terms of the seat alone. The entire driving configuration must be considered because each element is dependent on all of the others.

Much has been learned in addition to the feasibility of using neural networks and the insights provided by them. As anticipated, subject ratings of comfort are difficult to use. While comfort may be a universal concept, people are not the same. Consequently, people do not rate comfort uniformly. A rating of four on a one to five scale will mean different things to different people. Additionally, everyone wants such things as "sufficient" legroom, but "sufficient" to someone who is six feet tall is frustrating to someone who is five feet tall.

Further, to be truly useful, a written survey should be more detailed and explicit than the one used. There should be less room for interpretation. We found
that subject ratings are too individual specific to be useful as a measure of comfort. Our use of improvement counts served to remove much of the subjectivity found in the ratings.

Objective methods of measuring comfort should help to identify the differences and inconsistencies among human comfort ratings. We hope to be able to use fidget counts for this purpose in future work. Our techniques for measuring fidgets should prove to be better than previous efforts because we do not rely on human observation. There is still much to do in this line of research. With more time, neural networks could be found which would predict comfort or design features with even greater accuracy.
Figure 1. Neural Network Structure
Figure 2. Platform B
Figure 3. Vertical 2" x 4" for Gas Pedal
Figure 4. Side View of Gas Apparatus
Figure 5. Vertical 2" x 4" for Gas Pedal
Figure 6. Horizontal 2" x 4" for Gas Pedal
Figure 7. Front View of Gas Apparatus
References


A.1 The Backpropagation Algorithm

Backpropagation is the most popular algorithm for training networks to perform pattern association tasks. In such training, input patterns are repeatedly presented to the network; the network is allowed to produce an associated output pattern; the correct response is presented to the network; and then the network adapts its parameters (the weights on the connections) so that the network’s response more closely resembles the correct one. When the network has "learned" to associate patterns with appropriate responses, its weights are fixed.

During training with the backpropagation algorithm, input patterns consisting of vectors from a fixed training set are presented to the net repeatedly until convergence (input patterns should appear in random order). When an input pattern, \( \mathbf{x} \), enters the system, the net passes the information forward. Let:

\[
\begin{align*}
  w_{i,j,k} & = \text{the weight representing connection strengths from node } j \text{ in (k-1)st } \text{layer to node } i \text{ in kth layer} \\
  \text{net}_{i,k} & = \text{input to node } i \text{ in kth layer.} \\
  \text{out}_{i,k} & = \text{output to ith node in the kth layer} \\
  \Theta_{i,k} & = \text{threshold associated with node } i \text{ in kth layer}
\end{align*}
\]

The input to a node \( i \) in the \( k \)th layer is given by

\[
\text{net}_{i,k} = \left[ \Sigma_j w_{i,j,k} \text{out}_{j,k-1} \right] + \Theta_{i,k}
\]  \hspace{1cm} (1)
The output of the node is given by a sigmoid activation function,

\[ f(\text{net}_{i,k}) = \frac{1}{1 + e^{-\text{net}_{i,k}}} \]  

(2)
or another nonlinear, continuously differentiable function.

The activations of the node or nodes at the output layer give the output of the network. For instance, for a classification task, a single output node may give a value between 0 and 1 in response to input pattern \( x \). If the "desired" response was 0 (\( x \) belongs to class 1) and the output node responded otherwise (e.g., \( \text{out}_{i,f} = 1 \) where \( f \) is the final or output layer), the weights of the network should be modified in order to correct the mistake. Backpropagation modifies the weights in order to minimize the squared error between the actual and desired output of the network:

\[ \text{Error} = E = \frac{1}{2} \Sigma_i (t_i - \text{out}_{i,f})^2, \quad i=1,2,\ldots,N \]  

(3)

where \( N \) is the number of output nodes, \( t_i \) is the desired, or target, response for output node \( i \), and \( \text{out}_{i,f} \) is the actual activation of output node \( i \). The error is calculated for every pattern in the training set.

Given a final output in response to an input pattern and current weight vectors, the weight update equation derives from the goal of minimizing the error function (3).

Thus,

\[ w_{i,j,k} = -\mu \frac{\delta E}{\delta w_{i,j,k}} \]  

\[ \Theta_{i,k} = -\beta \frac{\delta E}{\delta \Theta_{i,k}} \]  

(4)
where $\mu$ and $\beta$ are fractional learning rates. The algebraic form of the update, which can be found in Rumelhart and McClelland (1986) leads to successive approximation of gradient descent minimization, so numerous passes through the training set are required.

The function of the network during training is to adapt its learning parameters, the weights and thresholds, in order to learn to associate patterns with "correct" responses. It learns via supervision; that is, environmental feedback as given by the target response. The network adapts its internal parameters, the weights on its connections, to improve its performance with respect to the error criterion, (3). In order to satisfy theoretical stability conditions, the weight update in (4) should be computed in a "batch" manner at the end of a pass through the entire training set, and the learning rate should be arbitrarily near zero; however, research indicates that variations on these rules may yield improved results.

When training has finished, the network's weights freeze, and the network then computes only in a forward manner. When a new pattern, similar to but different from the patterns which trained the network, is presented to the input layer, the network's nodes compute their activations and feed those signals forward until the output layer gives a final response.

A.2 Radial Basis Function Networks

Radial basis function networks (RBFs) provide an alternative to backpropagation-trained supervised networks. Computation proceeds in a two stage
manner. First, the centers and widths of "receptive fields" in input space must be identified. The k-means clustering method, or similar approach, can find centers. The clusters identified by the method define, in part, the receptive fields, and the centroids of those clusters provide the corresponding field centers. To identify widths, several heuristic methods can be employed. If K fields with centers $c_1, \ldots, c_k$ and respective widths $\sigma_1, \ldots, \sigma_k$ result, then supervised learning takes place as follows. When an input pattern, $x$, enters the system, the activations of K receptive field nodes are computed as:

$$a_i = \exp - \left\{ \frac{|x-c_i|^2}{|\sigma_i|^2} \right\} \quad (5)$$

The output layer nodes then receive as input the weighted sum of activations of all connected nodes, as in (1) with the vector $x$ replaced by $a$. Now, however, the activations of the output nodes result from a linear function, and a greatly simplified learning algorithm can be applied to the single layer of adaptive weights. However, the determination of widths plays a critical role in training and generalization.
Appendix B: Description of Physical Design

The floor of the set-up consists of three levels. The bottom level, platform A, is two pieces of 1/2" press board 4' x 6' in dimension nailed together. Platform A is raised by placing 2" x 4" boards underneath. The dynamometer is bolted to this platform in two places. It is bolted 9 1/2" in from the front and 18 1/2" in from either side.

The middle platform, platform B, is oddly shaped as shown in Figure 2. Since the dynamometer is placed on platform A, platform B must be raised to its height of 6 3/4" allowing the platform to rest on top of the dynamometer. This is done by stacking three 2" x 4" and a 1" x 6" under the back of the platform and bolting them through to platform A. Boards were also placed along either side of the 2'8" x 2'10" rectangle. The platform is just resting on these boards.

The top platform, platform C, the floor to the driver, consists of a 38" x 32" x 1/2" piece of plywood supported by five pieces of 2" x 4". Two 32" long pieces are placed along the edges parallel to the 32" side. Three 30" long pieces are placed parallel to the 38" side. One piece is placed 4" in from the edge on either side and the remaining piece is centered 6" in from these (14" in from either edge). This platform is then raised by using four 12" bolts. These bolts go through the platform 3" in from the edge on either side at 5 1/2" and 23" from the front. The other end of the bolts go through a 38" piece of 2" x 4" at 5 1/2" and 23". A-nut and washer are placed on either side of the platform and on the top side of the 2" x 4". These bolts were chosen to ease the raising and lowering of the platform needed to keep platform
C in line with the seat platform, which will be discussed later. On both sides of the platform at 16 1/2" in from the front there is a 1" wide by 4" deep notch. This notch allows platform C to be clamped to platform B and therefore enabling it to be moved instead of remaining stationary.

Although there were two different seats used in the experiment, they were both set up and attached to platform B in the same way. The seats remained on their tracks so the subject could adjust the seat to pedal distance as can be done in a real car. In addition, the subject could adjust the back angle. A piece of tape was placed along the side of the seat pan and up the back to enable easy reading of the adjusted seat back angle. The seats were bolted to the middle of a 2’ x 2’ platform constructed from two pieces of 1/2" plywood nailed together. This seat platform is constructed similarly to platform C. Four bolts were placed at each corner 2 3/4" from the edge and 3 1/2" in from the front or back of the seat platform. The bolts go through to two 2’ long pieces of 2" x 4" at 3 1/2" from the front and back. These bolts enable the changing of the wheel to seat distance and the seat pan angle. The seat is held at the correct height by placing a nut and washer on either side of the seat platform and on top of the 2" x 4". On either side of the seat platform 12" back from the front there is a 1" wide by 4" deep notch. Like the ones on platform C, these notches are to enable the seat configuration to be clamped to platform B. The seat is positioned for the correct pedal to seat distance and then clamped to platform B. After this, platform C is moved until it comes in contact with the front of the seat platform and is then clamped down. The table top is constructed of four 42" x 2" x
6" boards. These boards are attached by nailing two 22" long pieces of 2" x 4" at the edges of the table top. This is the whole depth of the table top. The legs are 36" x 2" x 4" and are attached at the corners. The front legs are attached by being nailed to the table top and the front posts for extra support. The back legs are two pieces of 2" x 4" nailed together and to the table top. Then there is a corner edge attached to the underside of the table top and to the back legs for support. All of the table legs, and the front posts, have a 2' x 2" x 4" nailed to the bottom. The board is flush with the front of the post and continues to the back leg. Another 2' x 2" x 4" is attached to platform A along each outer edge flush with the front. These two boards are nailed together, thus attaching the table and the front posts to platform A. At 20 3/4" up the table legs there is a 24" x 2" x 4" attached between the front and back legs on both sides. These boards will be used to suspend the pedals. Muslin was tacked around the table to obstruct the subject's view under the table.

The steering column is attached underneath the table top and to a board placed between the front posts. The column has two holes toward the front that are used to bolt the column to the table top at 7 1/2" back from the front and 18 1/4" from the sides. Here two corner edges were bent into a shape similar to 3/4 of a square. To keep from creating too large of a moment, the back of the column is attached to the board between the front posts. A straight bracket is slightly bent, just enough to fit around the materials between the board and the column. A potentiometer is connected to the steering column to enable the subject to use the steering wheel while playing the game. On the side of the column not attached to the board, a bracket is
held to the column by wrapping wire around both the column and the bracket. A piece of metal cut from a bookend is held at one end to the last hole in the bracket with a screw and nut. The other end of the metal is attached to the head of the potentiometer to hold it steady. The post of the potentiometer is put in a piece of cork and then placed into the end of the steering column. The cork causes the post to fit snugly into the steering column, thus turning the post when the wheel is turned.

The pedals are attached to a 42" long L shaped bar. The bar is clamped to the 2" x 4" between the front and back legs of the table at 20 3/4". Since the bar is only clamped to the boards, pieces of wood may be placed between the bar and the board to raise and lower the pedals. The brake pedal had to be cut into two pieces because of the position of the steering column. The two pieces were reconnected with the use of a bracket that was bent on both ends and then bolted into the two pieces of the brake. The brake was bolted onto a 5 1/2" long 2" x 4". Then the 2" x 4" was bolted into the "L" bar. A potentiometer was connected to the brake so the brake could be used with the game. A piece of metal bookend was screwed into the top of the brake's 2" x 4", and then this was attached to the head of the potentiometer for stability. The post is placed in a small piece of cork and then snugly fit into the hollowed out end of the bolt, thus allowing the post to move when the brake was used.

The gas pedal is bolted in three places to a 7 1/2" long 2" x 4" held vertically. This vertical board is then attached to a 6" long 2" x 4" and laid horizontally on the "L" bar using two corner edges. The horizontal board has a 2" long by 2 1/2" wide
notch along one corner to allow the gas pedal to be placed here. Otherwise the horizontal board would be in the way. These boards are then clamped to the bar. Since the brake is bolted into the bar, the gas pedal must be able to be moved along the bar to change the pedal distance. A corner edge is screwed into the top of the vertical 2" x 4" horizontally so it sticks out away from the pedal. A spring is attached to the corner edge through the hole furthest from the pedal, and the other end is attached to the bolt hole on the top of the pedal enabling the tension of the pedal to be changed. A potentiometer is connected to enable the subject to use the pedal while playing the game. A piece of metal bookend is screwed into the lower edge of the vertical 2" x 4". The other end holds the potentiometer head stationary. The post fits snugly into a bolt hole in the gas pedal so that the post moves with the pedal. (see Figures 3 through 7)

The back wall is a 4' wide by 6' long flat. First a 4' x 6' frame was made from two 6' long and three 43" long pieces of 1" x 3" and six plywood triangles. The two 6' long and two of the 43" long were connected to form a 4' x 6' rectangle by nailing the triangles into the corners of the adjoining pieces of wood. Then the last 43" long piece is placed across the center at 3' high and attached using the last two triangles. The plywood is then nailed to the frame. The bottom of the back wall is nailed to platform A and support is given by a 30" long 2" x 4" which has angled ends. The board has angled ends so it can be attached diagonally from the back wall to platform A. One end is bolted into the back wall and the other is nailed into platform A. Along both vertical edges of the back wall there are four holes drilled.
These holes are there so the roof can be attached (bolted) to the back wall. The holes are placed 3" in from the edges starting 1" from the top and being spaced 3 1/2", 4 1/2", and 5" apart.

The front posts consist of two 7' tall 2" x 4". The posts are nailed to the front legs of the table for support. The front posts are attached to platform A in the same way, to the same boards, as was the table. At 3' on the front posts and at the very top there is a 2" x 4" nailed across the two boards to keep them steady. Starting at 53" up on the posts four holes are drilled. Working your way up from the 53" point they are 5", 4 1/2", and 3 1/2" apart.

There are four 20" long 1" x 3". A set of two are attached by two 78" long piece of wire. The wires are attached by hooks 2" from the top and bottom of the boards. The bottom wires of the boards have a piece of muslin laid across them, folded over and then sown to produce a lightweight flexible roof. There are five pieces of wire attached every 12" to the upper and lower wires to insure the wires do not become more than 6" apart. There are also thin wooden rods placed between the bottom wires of the two sides, over the muslin roof. There are small notches placed in the ends of the rods just large enough as to allow the small pieces of wire to fit. The rods are then placed between the small wires on either side of the roof. These rods keep the edges about 40" apart. Each board has eight holes drilled into it starting at 9" up the board and placed 1" apart. These holes are there to bolt the roof into the back wall and the front posts. The large number of holes allow the roof to be raised or lowered to the specified headroom.
The potentiometer is used in this experiment to enable the steering wheel, brake, and gas pedal to be used with the game. The head of the potentiometer must be held stationary and the post must be allowed to rotate. When the post rotates the resistance varies. There are two wires connected to the potentiometer. One of these wires is connected to an outside prong and the other is attached to the middle prong located on the head of the potentiometer. These wires are then attached to the game card. The GameCard 111 Plus is plugged into any of the available expansion slots and secured by retaining the bracket screw. The outside wires are attached to pins 1, 8, and 9 and the middle wires are attached to pins 3, 6, and 11. The computer puts out a constant voltage through pins 1, 8, and 9 and reads the current coming back into it, by way of the potentiometer, through pins 3, 6, and 11, thus reading the resistance.
Appendix C: Fidget Counts

To determine the fidget count, data collected by the dynamometer and the driving game were placed into files that were ordered and labeled by subject number. The driving game data were not able to be accurately collected every half second due to software limitations, but were instead collected approximately every seven tenths of a second. Since the data collected were too large to be analyzed by any available PC based software package, both datafiles were uploaded to a VAX mainframe to use SAS for analysis.

First, a data transformation was run on the driving game data to ensure that the data would correspond to the one-half second intervals that were produced in the dynamometer data. After this, a regression was run using the equation:

\[
F_y = b_0 + (\text{BrakePosition})b_1 + (\text{GasPosition})b_2 + (\text{WheelPosition})b_3 + (\text{Time})b_4
\]

The inclusion of the time variable in this equation was based on the assumption that as the driving simulation progressed, the variation in a person’s movements would increase. We wished to take out the merely exaggerated movements of a tired individual and only include that data which would be relevant to fidgets.

The residuals to the regression were then downloaded to the base PC. These data were analyzed using a form of quality control x-bar chart. That is, the residuals were plotted against time, and all points that plotted outside of 3-sigma limits were counted as fidgets.
At present, the fidget counts have not been utilized; however, we believe that there is valuable information in them. We intend to use these as a comfort measure in our future study. If successful, we will then have an objective means of evaluating comfort which would help to identify and compensate for inconsistencies between subjective human ratings.
Laura L. Lansing received her Bachelor of Arts degrees in Philosophy and Mathematics from Rockford College, Rockford, Illinois in 1982 and 1986, respectively. She received a Master of Science in Mathematics with a major in Operations Research from The College of William and Mary in Virginia, Williamsburg, Virginia in 1989.
END
OF
TITLE