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NEW APPROACH USING ARTIFICIAL NEURAL NETWORKS FOR MODELLING AND EVALUATION OF MAN-MACHINE-INTERACTION AT THE START-UP PROCESS IN PASSENGER CARS

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Abstract

This article describes a method using artificial neural networks (ANN) to predict subjective comfort ratings of average consumers at vehicle start-up from data measured in drive tests. The method is being developed in order to become an element of a product development process for power trains, allowing to integrate the customer's view during an early stage.

Similarly to the way a person makes his evaluation, an ANN is used to interconnect input data (sensation) with output data (comfort rating) by "learned" connections. After recording the transverse acceleration signal in drive tests, input data for an ANN are derived in time and frequency domain. The corresponding subjective ratings are determined on a scale from "bad" to "excellent". In the training stage, input and output data of a series of start-up tests are randomly presented to the ANN as teacher signals. This way it is trained to connect objective data with the corresponding subjective rating. The trained ANN is then used in the application stage to interpret input data, which has the same structure as the teacher signals but was not used for training. A comparison of the calculated comfort values and the comfort ratings actually given by a person shows that the prediction is possible and consequently that the applied method works.

Keywords: User evaluation, man-machine interaction, optimisation techniques, simulation

1 Introduction and objective

The comfort sensation and consequently the demand for comfort of every person are individual. In general, customers demand an easily controllable starting element – or for automated systems excellent adjustment of the drive torque – with consideration of the particular driving situation (e.g. plane, hill, trailer… etc.). An additional demand is the prevention of disturbance in terms of noise, vibration or traction discontinuance.

During the product development process, the dynamic features of vehicles are determined in drive tests. From these results, in order to adjust the characteristics of vehicles to customer demands and therefore to achieve good customer satisfaction, objectives are derived. However, as comfort quality produces subjective impressions, it is difficult to rate because a person connects the presented sensation with his individual experiences and demands. Because tests with customers are expensive, a test engineer assumes the evaluation function of customers at vehicle set-up and represents the according customer group. Usually, a rating system similar to the 10-digit rating system shown in table 1 is used, where a rating index as number is assigned to the adjectives for description of noise and vibration disturbance as well as the degree of detection by customers [1].

Table 1. Comfort rating system with a 10-digit scale following [1]

	unacceptable				border case	acceptable				
rating index	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
noise, vibration	unacceptable			objection-able	improve-ment required	moderate	slight	very slight	traces	none
detected by	all customers	average customers			critical customers			skilled observers		indis-cernable

The range of 1 to 4 points represents the average customer; critical customers can be found on the scale up to 7 points. Usually, a rating index of at least 8 points is targeted because above this border even critical customers do not sense any negative influence. With regard to cost-effectiveness from the point of view of vehicle designers, an optimal vehicle has to be designed to just overcome the comfort threshold of a driver and consequently not influence his comfort sensation negatively. For certain, an expert can only partially manage this because it is difficult to adjust his individual rating pattern to the comfort threshold of a customer. Thus, sometimes an optimisation is carried out in areas and on levels, which are only sensed by few customers so that the emerging costs and the additionally required development time are possibly not justifiable.

Because of the situation described above, an important objective in vehicle development is to find correlations of customer rating and data measured in drive tests or calculated by means of simulation models. However, for the attempt of objective consideration of comfort, i.e. the examination of the connection of subjective comfort ratings with objectively measurable data, this expert is usually also modelled. Experiments with groups of laymen as evaluators have until now very often not led to the demanded results. One reason for this is that the individuality of the comfort expectation is not taken into account and the influence of person and vehicle is mixed [2]. A possibility to avoid this is to model every person individually and determine his individual comfort rating. Although “if the ultimate objective is to predict accurately the range of human responses by algorithmic analysis, we should recognise that this is unlikely in the short term” [3], the results presented in this article demonstrate that ANNs are tools that allow to generate individual comfort ratings from data measured in drive tests without too high an effort.

2 Method of comfort evaluation by means of an ANN

2.1 Data acquisition by drive tests

The described method in the current stage is restricted by the assumption that the person concerned makes his rating only based on the sensed transverse acceleration. To make sure that the data, which was processed in the ANN, contained the same information as the impression rated, it was necessary to avoid impressions on the rating person that were not captured objectively. Therefore, the rating person did not drive the vehicle himself but was on the front passenger seat, i.e. the start-up process and not the vehicle is examined. Additionally, the ability of hearing was limited by using hearing protection to minimise acoustic influence. The test person was also asked to close his eyes to avoid any influence by the environment.

The tests were accomplished by 21 persons with the same vehicle – a premium class limousine with manual transmission. Each person rated a series of 50 consecutive tests. To achieve a difference in start-up quality, diverse drivers were used and the characteristics of the start-up process were varied by variations in clutch and gas pedal operation. The test persons were average consumers without special training concerning comfort rating.

The subject of the study is the start-up process, i.e. the process of starting to drive from standstill and the following acceleration process until a constant driving speed is reached. Figure 1 shows an exemplary chart of engine speed, gear input speed and wheel speed.

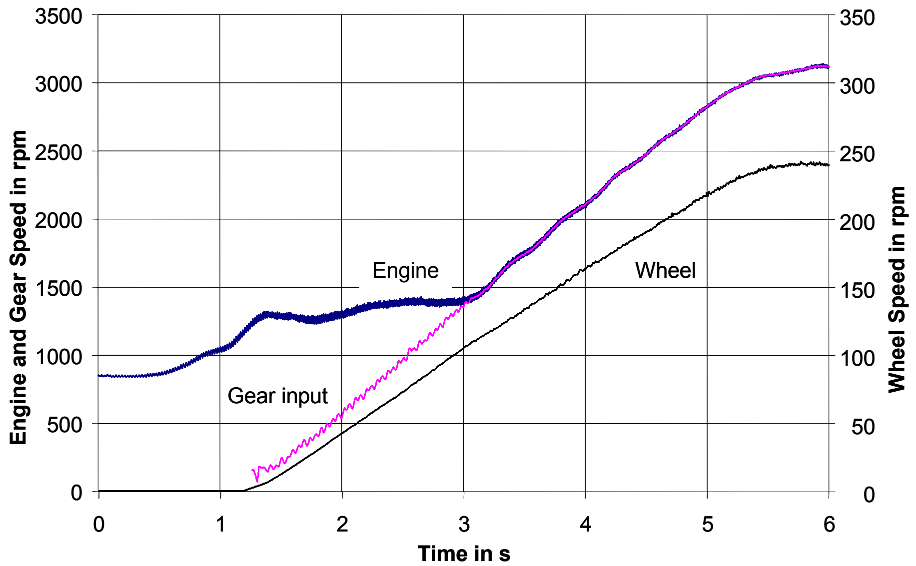

Figure 1. Speeds of engine, input gear-shaft and wheel during star-up process

2.2 Derivation of input data and output data

Of each test, the subjective comfort rating of the respective test person was noted. The comfort rating in the training stage (see 2.4) are supplied to the ANN as output.

The test person stated his comfort impression by a mark on a continuous scale with the subjective end points *„bad"* and *„excellent"*. There are intentionally no absolute formulations used for the extrema to enable every person to cover his individual comfort range. The relative position of the mark between 0 („bad") and 1 („excellent") is then interpreted as a value for the comfort rating as exemplarily shown in figure 2.

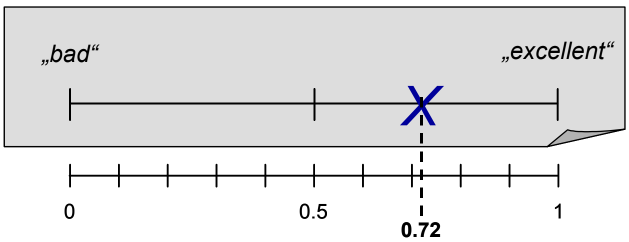

Figure 2. Subjective rating scale

During the test, the transverse acceleration in driving direction was captured at the seat rail. From this acceleration signal input values for the ANN are derived in time and frequency domain.

From the acceleration signal in time domain three values are derived as input data for the ANN. As indicated in figure 2 these values are the maximum a_{max} of the achieved acceleration, the relative time $t_{a,max}$ when maximal acceleration occurs and the duration T of the start-up process until a constant driving speed is reached.

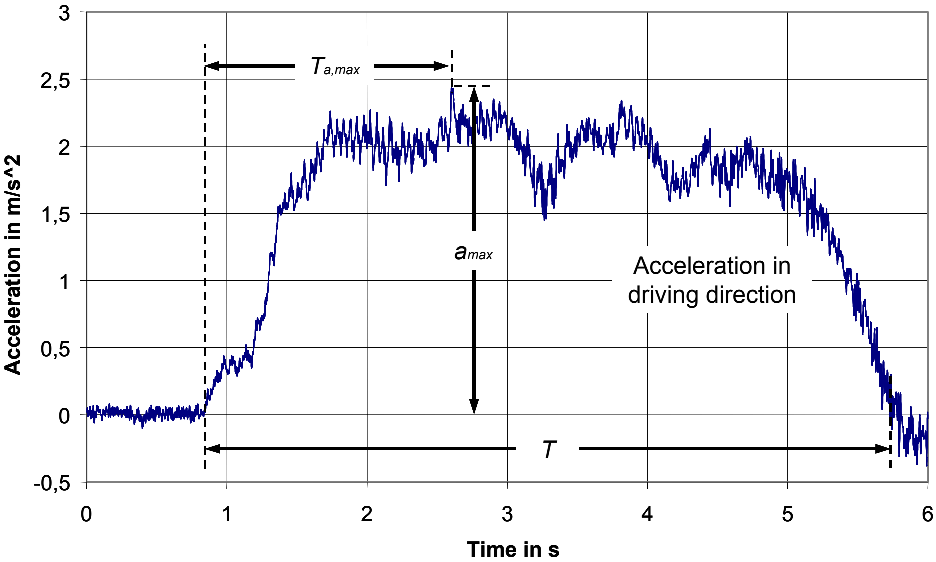

Figure 3. Input data derived from acceleration signal in time domain

The acceleration signal is transferred into frequency domain using a procedure similar to the calculation of the power spectral density (PSD) [4].

The basis of the PSD is the root-mean-square (rms) value of the vibration. Theoretically, the PSD of a function $a(t)$ with the real amplitude $\hat{a}(\omega)$ is determined according to:

$$\Phi_a(\omega) = \lim_{T \to \infty} \frac{4\pi}{T} [\hat{a}(\omega)]^2 \tag{1}$$

Instead of transforming the signal into frequency domain by using the Fourier transformation algorithm and determining the PSD according to the formula above, it can also be calculated by decomposing the time signal by band-pass filter with a filter range $\Delta\omega$ into harmonic oscillations and afterwards calculating the single rms values according to:

$$\Phi_a(\omega) = \lim_{\Delta\omega \to 0} \frac{1}{\Delta\omega} \left[\lim_{T \to \infty} \frac{1}{T} \int_0^T a^2(t, \omega, \Delta\omega) dt \right] \tag{2}$$

Furthermore, for a sufficiently small filter range $\Delta\omega$ the spectral density is approximately the square of the rms value divided by the filter frequency range.

$$\Phi_a(\omega) \approx \frac{a_{rms}^2(\omega, \Delta\omega)}{\Delta\omega} \tag{3}$$

For a constant filer frequency range, the square of the rms value is approximately equal to the discrete spectral density with the chosen filer frequency range. Because of this proportionality squaring is not necessary and the formula for a modified PSD can be given as:

$$\Phi_{a,mod}(\omega) = a_{rms}(\omega, \Delta\omega) = \frac{1}{T} \sqrt{\int_0^T a^2(\Delta\omega) dt} \tag{4}$$

Here with a filter frequency range of 0,25Hz, the calculation of the modified PSD delivers 400 values. A data reduction by determining average values in intervals following the perceptive faculty of humans as it is described in [4] results in 17 values. The size of the interval is therefore set to be small in areas of low frequency values and larger in areas of higher frequency. To be precise, there is a value each for the intervals 0-3Hz, 3-4Hz, 4-5Hz etc., and a value each for 10-19Hz, 20-29Hz, etc. up to 100Hz. Figure 4 exemplarily for the section from 3 to 30Hz shows how this procedure leads to 9 representative values.

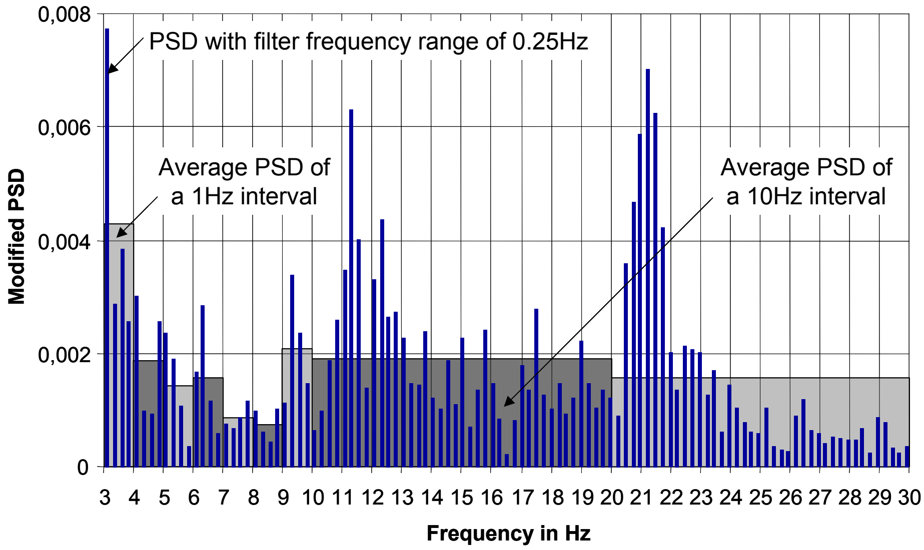

Figure 4. Input data derived from acceleration signal in frequency domain

As a result of the drive tests there are 50 sets of data available for each test person. The data sets are combined to a pattern file for processing in an ANN. Every set consist of three values derived from the acceleration signal in time domain, seventeen values derived in frequency domain representing the input signals and one value for the comfort rating representing the output value of the ANN.

2.3 The Artificial Neural Network

Artificial neural networks originally were developed as highly simplified copy of the human brain. However, the objective was not to exactly copy the biological example but to generate a model which accomplishes its main functional characteristics by a computer. Accordingly, neural networks are “information processing systems consisting of a large number of simple units (neurons) which dispatch information in form of activation of these units via directed connections. A fundamental feature of neural networks is their learning aptitude, the ability to independently learn a task, e.g. a classification problem, from training examples without the neural network being explicitly programmed” [5].

The artificial neuron, just as the biological neuron, consists of inputs (dendrites), connections (synapses), activations (cell body) and an output (axon). Figure 5 shows the components of a biological and an artificial neuron.

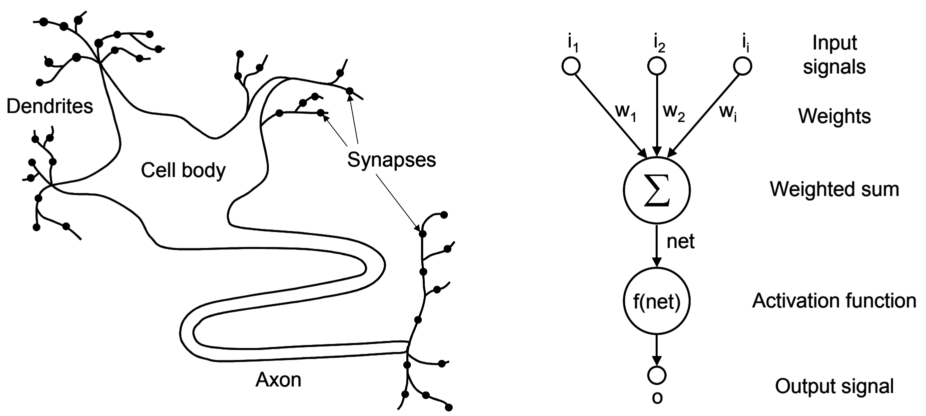

Figure 5. Components of a biological neuron (left) and artificial neuron (right) following [5]

The input signals i_i may originate from the environment or from the output of another neuron. Different network models allow different ranges of values with the real numbers of the interval [0,1] as the typical range.

A real number is assigned to every connection in an ANN as weight w_i to describe the strength of the connection.

The netto-input *net* corresponds to the weighted input signals:

$$net = \sum_i w_i \cdot i_i \qquad (5)$$

The activation function *f(net)* determines the output *o* according to the netto-input. This output, on the other hand, can be an input signal for another neuron or the output of the ANN.

The sigmoid function as described in figure 6 is used as activation function of the ANN used.

$$f(net) = \frac{1}{1+e^{-net}} \qquad (6)$$

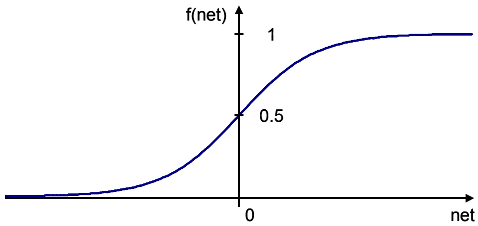

Figure 6. Function and plot of the sigmoid function

The operating principle of an artificial neuron can be described as follows: “The connections of a neuron accept activations i_i with definite boosts w_i, summarize them, and cause an activity at the output if a threshold is exceeded“ [6].

An ANN consists of several layers of neurons. The number of neurons in the input layer equals the number of input data. Similarly, each neuron in the output layer generates a value so that the number of neurons in this layer equals the number of output values. The number of hidden layers and the number of neurons in them depends on the problem to be solved by the ANN and affects the performance of the ANN. All neurons inside the hidden layer are connected. The topology of the ANN used is:

- Input layer: 20 neurons (20 input values describing the acceleration signal)
- Hidden layer: 100 neurons as a matrix of 10 x 10 neurons
- Output layer: 1 neuron (output value describing the comfort rating)

2.4 Training (learning) and application

The training method is characterised by the algorithm used to train the ANN for solving a special problem. The algorithm applied is the back-propagation algorithm. It works in two steps. In the feed forward step at the input, a pattern of teacher signals is presented and the output calculated with randomly chosen weights is determined. From the calculated output and the desired output teacher signals the error is calculated according to the error function. The error function used the square error *E*:

$$E = \sum_k (d_k - o_k)^2 \qquad (7)$$

During the back-propagation step, this error is then distributed to the weights in the layers starting from the output layer. This way, the weights w_i are modified to reduce the error. The back-propagation algorithm iteratively determines the minimum of the error function according to the gradient decent algorithm. By using the sigmoid function as activation function, the error function of the ANN becomes continuous and universally differentiable, which is required for minimum search. The sigmoid function (6) is very suitable to be used as activation function for processing by computer because its differentiation can be easily calculated as follows:

$$f`(x) = \frac{df}{dx}\left(\frac{1}{1+e^{-x}}\right) = \frac{e^{-x}}{(1+e^{-x})^2} = f(x)\cdot(1-f(x)) \tag{8}$$

The combination of weights which minimize the calculated error represents the solution to the given problem. The „knowledge“ of the ANN is then saved in the weights. After the training, the ANN has a definite structure and is ready for independent evaluation. Although training takes some time, the application works very fast.

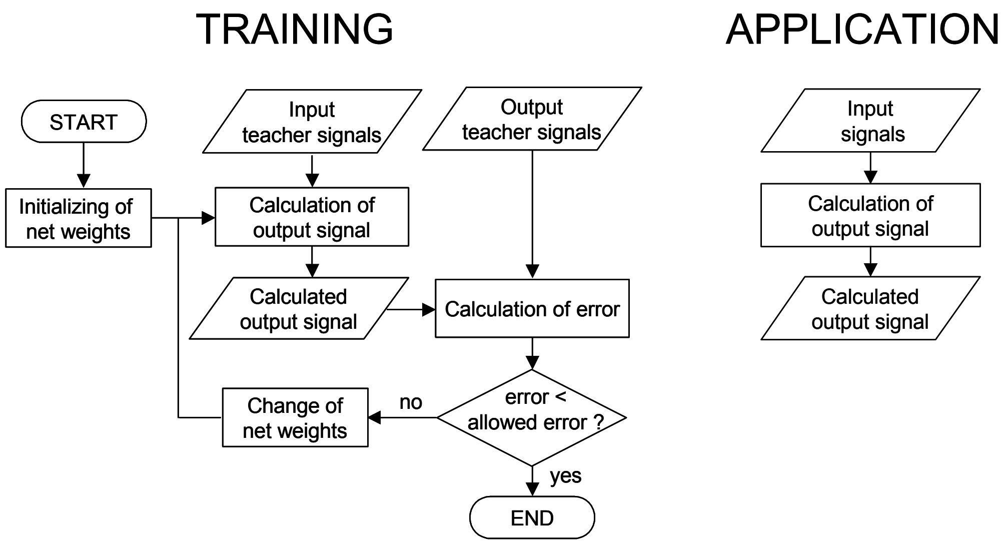

Figure 7. Training (left) and application (right) of an ANN

During training stage, the corresponding input and output teacher signals of 30 of the 50 start-up processes determined for every person are randomly presented to the ANN. To avoid “memorising” the input-output pairs instead of discovering the rule of connection, the training is stopped as soon as the net converges, which usually happens after 30.000 cycles.

During application stage, the remaining 20 input signals are presented to the trained ANN and the output signals are calculated.

3 Results

The evaluation of the results is carried out by comparing the predicted output value for the comfort rating of the ANN and the subjective rating actually given by the person in the corresponding drive test. Figure 8 shows the results of 80 drive tests by four persons – 20 tests per person – with the subjective comfort ratings on the ordinate and the calculated ANN output values on the abscissa. For each ANN, 30 sets of teacher data were used for training. There was no selection of data, i.e. the first 30 sets were used for training and the last 20 sets for verification.

If exact approximation was possible, all points would lie on the first bisecting line. In the diagrams, the area marked light grey represents a deviation from the exact value of +/-0.1, the area marked dark grey a deviation of +/-0.2. In comparison with table 1, the light grey area corresponds to a deviation from the exact value of +/-1 point for an average consumer who is able to differentiate a maximum of 5 points. For a critical customer with the ability to differentiate a maximum of 8 points it corresponds to a deviation of +/-1.6 points.

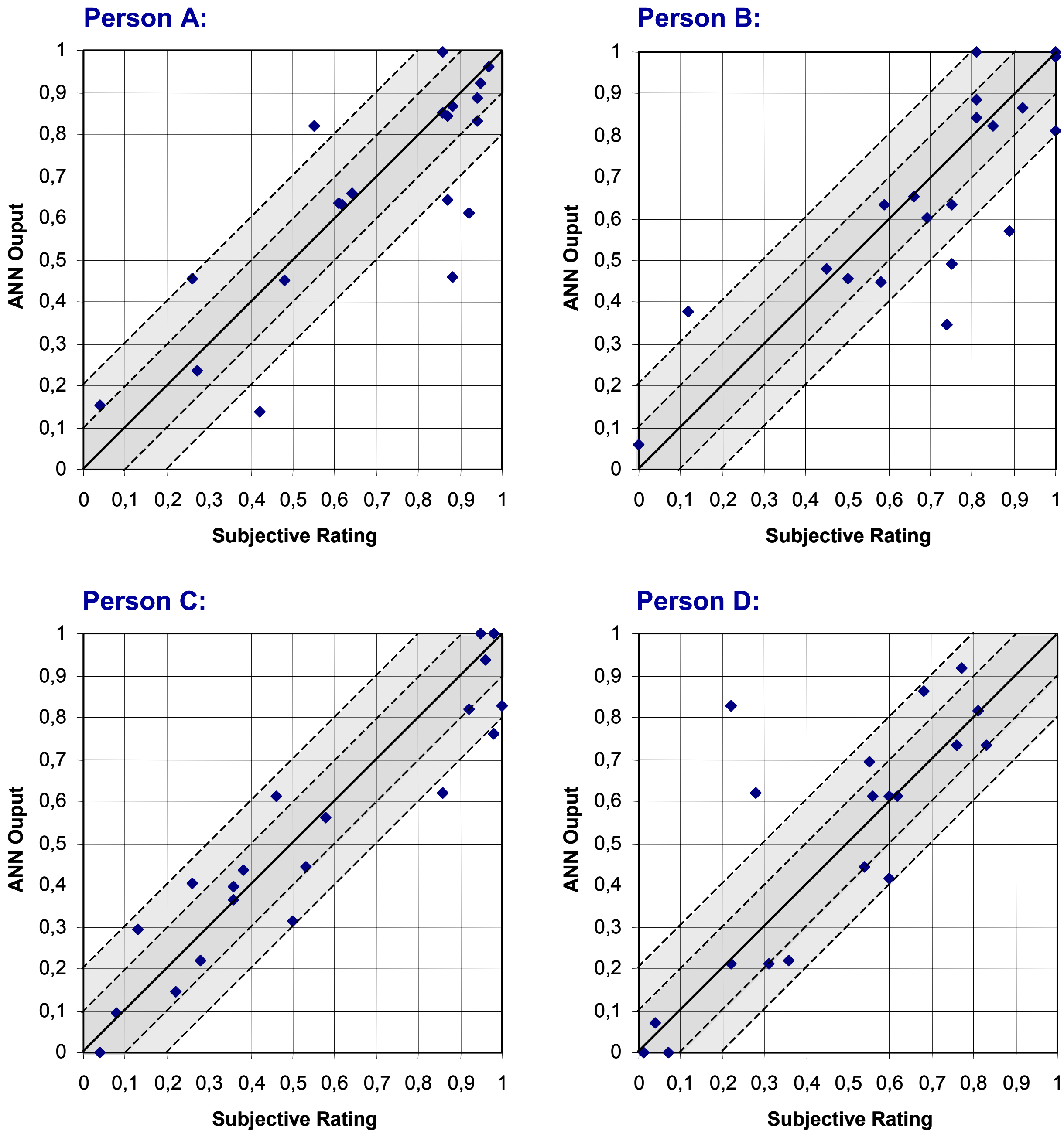

Figure 8: Comparison of subjective rating and ANN output

The deviation of the calculated ratings from the values actually determined in the tests is a criterion for the quality of the ANN. In statistics, the standard error $S_{y,x}$ is used to indicate the size of the error at the prediction of a y-value belonging to a certain x-value. It is calculated according to:

$$S_{y,x} = \sqrt{\left[\frac{1}{n(n-2)}\right] \cdot \left[n\sum y^2 - \left(\sum y\right)^2 - \frac{[n\sum xy - (\sum x)(\sum y)]^2}{n\sum x^2 (\sum x)^2}\right]} \tag{9}$$

The standard error of the ANN's output relating to the subjective rating is S_{yx} = 15.7 %. Compared to the rating precision of average consumers, this value is within a range of variation of subjective driver ratings by high experienced drivers [7].

4 Conclusions and Prospects

As demonstrated in the previous paragraph and in [8], the approximation of comfort ratings of average customers by means of ANNs is possible and consequently the practicality of the described method is proven. However, it turned out that the calculation did not show satisfactory results in all cases. Possible reasons for this are stated below. They are focus of further research at the Institute of Machine Design and Automotive Engineering.

Due to the fact that the participants of the drive tests were untrained laymen – which was an important factor of the investigation – it is likely to be assumed that not all of them were really capable of delivering reproducible testing results. From this point of view, it can be assumed that the respective ANN nevertheless modelled the evaluation pattern of the person according to the teacher signals. However, the comparison of calculated and actually determined ratings then had different results because the person rated randomly and the comfort ratings used for verification do not match to the learned pattern.

Furthermore, the investigation so far showed that it was hardly possible to use an ANN trained with teacher signals of a person "A" to calculate the ratings of a person "B". The attempt to train an ANN with teacher signals of all tests and then use this ANN to calculate ratings of single persons was not successful either. It is assumed that the reason for this is the subjective perception of comfort of individual persons.

One reason for unsatisfactory modelling may be that at least some of the test persons not only rated impressions which are to be put down to the transverse acceleration signal. For instance, in spite of the hearing protection, it is still possible to detect a certain amount of noise. In this case, the input data for the ANN does not contain all the information necessary for modelling.

In a next step, the test persons will be drivers instead of passengers. Then not only the transverse acceleration but also noise, accelerator pedal position, etc. are considered as input signals. Of course, the presented man-machine model, which is based on a test person at the front passenger seat and only considers data derived from the acceleration signal, can therefore not be applied to a driver as important input data like the accelerator pedal position are not taken into consideration. The driver expects the vehicle to react to his action and perceives a disturbance in terms of comfort, if this reaction is unexpected. On the other hand, he tolerates negative reactions, e.g. traction discontinuance, if they occur due to his operation.

In addition to the research topics mentioned above, the prediction of comfort ratings from test-bench data and numerical simulation data is a further challenge. ANNs are expected to be promising research tools for this [7]. Especially for optimisation and individualisation of automated systems like intelligent clutch systems [9] the method may serve a powerful tool. A further idea of application is to use the tool in research for the evaluation of test-bench or simulation quality. Which values does a test-bench have to deliver to allow the prediction of human sensation?

Generally, an increased number of tests used as teacher signals for every person will improve the modelling. The more independently input-output sets are presented to the ANN in the training stage, the better will be the approximation in the application stage, because the lower will be the effect of outliers.

The man-machine model, which is very simple in the current stage, will be improved step by step to become a further development tool that will help to improve the hardware-in-the-loop method in virtual product development and will complete the integrated product development environment of the Institute of Machine Design and Automotive Engineering at the University of Karlsruhe, Germany [10].

Nomenclature

$a(\omega)$	Acceleration function	o	Output signal
$\hat{a}(\omega)$	Real amplitude of $a(\omega)$	o_k	Calculated output of neuron of k-th layer
$a_{rms}(\omega,\Delta\omega)$	Root-mean-square value	$S_{y,x}$	Standard error
a_{max}	Maximum of the acceleration	T	Duration
$\Delta\omega$	Filter frequency range	$t_{a,max}$	Relative time till a_{max} is reached
E	Square Error	t_k	Desired output of neuron of k-th layer
$\Phi_a(\omega)$	Power spectral density	n	Number of values
$\Phi_{a,mod}(\omega)$	Modified spectral density	w_i	Weight of the i-th input
i_i	Input signal at the i-th input	ω	Angular frequency
net	Netto-input		

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