Correlation of Subjective and Objective Handling of Vehicle Behaviour

by

Howard Alan Simon Ash MEng (Hons)

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The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others.

Abstract

This thesis presents the results of a research project which sought to find links between driver subjective ratings and objective measures of vehicle handling. The experimental data used in this project has been made available from a previous research project. The experimental data was collected using a prototype vehicle which was used in 16 different configurations. Objective data was collected based around the ISO defined steady state, step input, and frequency response tests. Subjective assessments were collected from eight trained test drivers using a numerical rating

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scale to a questionnaire covering various aspects of vehicle handling.

Analysis of the subjective assessments has been done to identify any shortcomings that may affect any subsequent analysis.

From the literature review, an approach that claims to relate four simple objective metrics to subjective measures of vehicle handling has been developed in two new ways. Firstly, the proposal was tested [1] with the large amount of subjective data available to see if good levels of correlation could be found between the proposed metrics and driver subjective ratings to specific handling questions. Secondly, the

method was extended to include further simple metrics to try and improve links between the subjective and objective data [2].

Non-linear relationships in the correlation of subjective vs. objective data have been investigated for the first time [3] using non-linear genetic algorithms, which, in addition have not previously been used to correlate driver subjective ratings with objective measures that describe vehicle handling.

From the results, it has been possible to specify ranges of preferred values of objective metrics in order to produce a subjectively satisfying vehicle.

Finally, the work discusses how the results obtained can be used by engineers to aid

the vehicle design and development process.

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1. Introduction

The term vehicle handling can be defined as the dynamic response of a vehicle to driver inputs. Although it is probably the most widely discussed aspect of vehicle performance, it is not so well understood due to the reliance on subjective judgements. Vehicle handling can be analysed in three particular ways: i) subjective driver feedback, ii) measured objective data and iii) mathematical predictions. The relationships between these three is shown diagrammatically in figure 1-1.

Figure 1-1: The three approaches to vehicle design

Good levels of correlation exist between measured objective metrics and predicted objective metrics. However there is uncertainty in the links between subjective assessments and measured objective metrics, hence the use of mathematical predictions has been limited in the automotive design and development cycle. This has meant that development engineers have had a lack of design aids to assist in producing an acceptable solution. Thus, a great deal of development work still focuses on prototype vehicles, which is a lengthy and costly process. If models used in the early design process can accurately predict subjective and objective assessments of the final product, then the automotive industry will see increased efficiency and

reduced costs by reducing the amount of prototype development.

A previous linked research project [4] between the University of Leeds and the Motor Industry Research Association (MIRA) contributed to the subjective-objective correlation debate and has resulted in the collection of substantial test data available for this project. All subjective and objective data used in this project has been inherited from this previous project.

1.1 Definition of Subjective and Objective Handling

Vehicle handling qualities describe the behaviour of driver-vehicle combinations in actual driving. The handling qualities consist of vehicle directional response properties to steering, brake and throttle inputs. In general, the overall theme of handling comes down to the driver's control of the vehicle, which can be assessed in two main ways; subjective assessments made by the driver and objective measurements taken from the dynamic response of the vehicle.

Objective handling properties are more easily defined than subjective handling properties. Typically, measurements are recorded using transducers fitted to a vehicle whilst a specified manoeuvre is being conducted. The outputs from transducers can be calibrated and thus measurements taken from them are valid and easily repeatable, which makes such measurements the preferable way of assessing vehicle

In subjective handling, driver perceptions are used as the critique for evaluation. These opinions can be best described by words, although in vehicle development expressing the evaluation in a numerical scale is common practice for subjective evaluators.

- Firstly analyse the existing subjective data set to check for reliability.
- To further investigate links between subjective evaluation and objective vehicle behaviour by extending the use of the available data set by applying new methods for analysing the subjective vs. objective correlation.

characteristics.

It can be seen that the two methods of describing vehicle handling are quite different, not least because of the driver dependence of subjective ratings. By bridging these two aspects of handling together, vehicle designers can produce a vehicle with satisfactory subjective handling using objective measurements, which can be predicted using computer models.

1.2 Research Aim and Objectives

The overall aim of this project is to investigate the links between driver subjective opinions with objectively measurable vehicle responses. To enable this a set of

objectives has been set out, they are:

• On the basis of new results, the methods shall be extended to include further metrics to investigate other approaches to improving the understanding of subjective vs. objective correlation in vehicle handling. This shall be done using the existing data.

9 Investigate other methods to try and establish links that may exist between the subjective and objective data sets.

• The final objective is to propose how such improved understanding of subjective /

objective assessments can be used in the modelling and simulation procedures

used early in a vehicle design program. Achieving these objectives would allow

the predictive use of computer models to achieve better handling vehicles in the

design and development stage.

2. Literature Review

2.1 Introduction

This chapter reviews the various methods that have been used in previous handling evaluation studies. In particular, objective measurement techniques, subjective evaluation methods, mathematical models and data analysis methods used are reviewed.

2.2 Objective Measurement Techniques

By using these tests it is possible to measure properties relating to both steady state and transient behaviour in both the linear and non-linear range. The differentiation between linear and non-linear handling are normally delineated by lateral accelerations of approximately 0.3g. The steady state circular test [5] is used to define the steady state behaviour conducted on a steering pad. The frequency response test [6] is used to find the transient behaviour using either a pseudo random steer input or an impulse steer input. In cases where the vehicle is to be evaluated close to or at its limit condition, the step input test [6] is used to measure behaviour not provided by the frequency response data from the pseudo random steer and impulse steer tests.

Test procedures for characterising the performance of a vehicle are well documented in a number of International Standards Organisation (ISO) standards or technical reports. The four tests listed below are of most interest in vehicle handling development:

i) The steady state circular test, ISO 4138: 1982 (E) [5]

ii) Frequency response test, ISO 7401: 1988 (E) [6]

iii) The step input test, ISO 7401: 1988 (E) [6]

iv) Severe lane change, ISO Technical Report 3888: 1975 [7]

A human driver performs each of the tests and so to ensure validity and repeatability the vehicle inputs are carefully controlled by mechanical stops making the test open loop. *i.e.* the driver does not close the control loop between external demands and control outputs by correcting errors. This ensures the measurement of vehicle output as a function of inputs which are not superimposed with driver control outputs. Hence the severe lane change test [7] is not suitable for subjective- objective correlation due

to the closed loop nature of the test. Data recorded during the tests is then normally checked to ensure that it is of sufficient quality to be used in analysis. Typical measures are:

- Lateral acceleration
- " Roll angle
- Yaw angle
- Roadwheel steer angle
- Handwheel steer angle
- Handwheel torque

2.3 Subjective Evaluation of Vehicle Handling

Unlike the collection of objective measures to describe vehicle behaviour, no standards detailing procedures for subjectively characterising the handling performance of a vehicle have been found, despite the fact that every vehicle manufacturer uses subjective assessments as part of their development work. As such,

vehicle manufacturers and specialist consultancies use their own techniques to

evaluate subjective vehicle handling properties.

2.3.1 Subjective Evaluation Techniques

Before a new vehicle goes into production, the vehicle must be accepted by the vehicle development engineers from a handling viewpoint, based on subjective assessments [8]. The techniques used by manufacturers for subjective evaluations are well kept secrets, and as such are not in the public domain, thus can not be included in the review. During the completion of previous work, Chen [4] commented on how subjective evaluation was conducted at the MIRA proving ground, used by manufacturers and consulting companies. The following summarises how subjective

handling evaluations are conducted at MIRA.

Experienced test drivers with specialist training in evaluating vehicles or engineers familiar with the particular vehicle are used in subjective evaluation during vehicle development. Although from different backgrounds, both types of drivers have overlapping skills and knowledge enabling them to communicate with each other.

- Steering pad, used for steady state evaluation.
- General durability circuit, used to investigate straight-line running characteristics and moderately severe cornering manoeuvres.
- Closed handling circuit, used for conducting more aggressive manoeuvres such as

During an overall evaluation of a new vehicle, several different manoeuvres are conducted on the different circuits available at the proving ground, they are:

a severe lane-change and sudden braking into a corner.

- Ride and handling circuit, which features discrete features such as potholes, cambers and ridges etc. The response to these disturbances often plays an important role in the driver's overall assessment.
- High speed oval, which is suitable for assessing stability at high speeds.

From the multitude of driving tasks conducted at the proving grounds, the drivers note the feedback and response of the vehicle in terms of:

- Hand wheel torque feedback
- Lateral acceleration, yaw rate, roll rate, roll angle
- Pitching motion
- Hand wheel kickback due to suspension movement

The summary shows typically how subjective handling evaluations are conducted. It is important to note that drivers are free to assess the vehicle over manoeuvres of their choice and that they focus their opinions on a variety of vehicle feedback and responses.

2.3.2 Subjective Rating Scales

There are a number of methods that people can use to obtain subjective assessments.

Two particular methods can be readily used to assess the various aspects of handling, including steady state cornering, transient responses, straight line cornering and lane changing. They are the rating scale method and the ranking method.

In the first method, an arbitrary scale is constructed which describes various degrees of the quality of the object which is to be measured. Each evaluator rates each object in accordance with the scale, marking off on the scale the degree of the described

quality which he/ she considers most suitably describes the quality of the object under assessment. This opinion can then be converted to a numerical quantity and from these the average rating from a group of observers can be calculated. The sensitivity of this method depends on the proper choice of the values on the scale.

The second method is that of ranking. Several types of ranking method have been devised, with the simplest being that of simple comparison. Here, observers compare the objects under consideration with each other, so that the objects can be placed in rank order of the property under assessment. This offers the advantage that observers only have to state better or worse which is a relatively easy subjective task. In this case very small differences between vehicles can be detected, however the method does not give direct indication of the extent of the differences between them. A problem associated with ranking several objects at once is that it puts a considerable strain on the evaluator's memory when dealing with a large number of objects. Other ranking methods have been devised to overcome this problem, in particular the method of paired comparisons and of triads.

The method of paired comparisons allows the observer to evaluate separately all

possible pairs of objects being assessed. A benefit of using this method is that it is a more sensitive and discerning method of subjective measurement. An associated problem of using the paired comparison method is that it is time consuming since

from 'n' objects, $\frac{n(n-1)}{2}$ $\frac{1}{2}$ pairs can be obtained, all of which have to be assessed by

the evaluators, which tends to become long and tedious. Work done at MIRA [9,10] addressed this problem by employing a similar method, but now the evaluators ranked three vehicles in one session, thus the method of `triads'. This method by which rankings can be obtained is still simple, reduces the time necessary by ordering three items at a time. However, the method is only suitable for either 3,4,7, or multiples of

7 objects. Aspinall [9,10] considered this method to be a good compromise between the method of paired comparisons and the formal ranking method.

The benefits of using a ranking method are that it is relatively easy for the evaluator to

order the items of interest. Unfortunately ranking experiments give a unique scale to each group of assessments, and the scales from different sets of experiments cannot be compared with each other.

Using the rating scale method requires more mental effort from the evaluators and as such is best suited to skilled drivers. Less skilled drivers would have a higher mental load from driving and hence less able to concentrate on the more subtle aspects of vehicle handling to produce a subjective evaluation. The benefit of using a rating scale is that a numerical value can be used to describe the absolute behaviour of an aspect of handling under investigation, which is useful in correlation analysis where objective vehicle measurements are linked to subjective assessments. For these

The time line in figure 2-1 shows the main contributors to the rating scale development over the last thirty years. There follows a brief description about the scales, highlighting the problems, and the ways in which they have been improved.

reasons rating scales have been mostly used in subjective- objective research.

Aircraft Automotive

Figure 2-1: Key contributors to the rating scale development

Early work done by Bergman [11] and Weir & DiMarco [12] used derivatives of the SAE ratings scale shown in figure 2-2:

Figure 2-2: Society of Automotive Engineers (SAE) ratings scale

It is a ten point, continuous, bipolar scale which neither defines a question nor the dimension to be rated. The scale only has one verbal terminal anchor, 'excellent'. Another criticism is that `very poor' is not counterbalanced by having `very good'. Both points mentioned result in a scale that has non-symmetry. Handling qualities of vehicles on the market today hardly cover `borderline' rated vehicles so only the `good' half of the scale is used. Since the extreme end of the scale is rarely used, the

usable, or effective scale length is reduced to four points (6-9). Bergman [11] states that rating standard deviations (SD) of two points are common on this four point effective scale even with highly trained drivers. The problem this causes is difficulty in discriminating just noticeable differences in handling.

Later work by Matsushita [13] used an improved version of the SAE scale as shown in figure 2-3.

Figure 2-3: Subjective rating scale, Matsushita [13]

region marked by 'fair'. The sensitivity and discrimination of experimental variables seems not to be better than in the original SAE scale.

The scale uses ten points and has no anchors or rating descriptors. Values between one and ten maybe returned although this is unlikely to be greater than six for reasons discussed earlier, leading to a scale that has a short effective scale length. During evaluation, drivers were told to treat the scale as continuous, however ratings had to be written as opposed to marking the scale along the line resulting in 'n' or 'n.5' type

The most obvious change from the scale shown in figure 2-2 is the removal of the sector description set. To improve the language balance, 'very poor' has been replaced by `bad'. However, asymmetry still exists because there is no centre point using an even number of scale points. The previous problem of having a short effective scale length exists in this scale by having low sensitivity in the middle

A derivative of the Weir & DiMarco [12] rating scale was used by Sano [14] in

evaluation using a lateral motion simulator, see figure 2-4.

Figure 2-4: Subjective rating scale, Sano [14]

ratings. Despite this weakness, variance in driver ratings was generally found to be less than one. A reason for this can be attributed to the fact that using a simulator allows good test condition reproducibility hence improved reliability.

Away from the automotive field, a rating scale developed by the National Aeronautical and Space Administration (NASA) for the evaluation of aircraft prototype handling qualities has been used successfully, known as the Cooper-Harper scale [15] shown in figure 2-5.

Figure 2-5: Cooper-Harper aircraft handling qualities rating scale [15]

For over thirty years this scale has been used to document and legislate safe flying characteristics for aircraft throughout their operating manoeuvres. The scale has ten categories with numbers and a detailed description at each point. Questions and instructions are integrated into the scale, using language understandable for highly trained aircraft pilots. Each rating point has a three level descriptor which identifies the aircraft characteristics, the handling performance and the compensation required in the execution of a defined task. The scale user guidance is useful for the user and because of the category like boxes containing the numbers, only ordinal data maybe obtained. Käppler [16] stated that communication with the development and user group of Harper at Calspan, U.S.A., revealed that mostly points one to three are used. Despite the multi-level approach and descriptive text, discrimination with this scale is

hardly better than with the SAE scale shown in figure 2-2. The success of the Cooper-Harper scale can be put down to a combination of the descriptive text, highly trained pilots, specific training with the scale and the highly defined flight manoeuvres. Käppler [16] suggests it is problems with one or more of these reasons that adaptations of the Cooper-Harper scale to automotive handling have not been successful.

Käppler [16] recognised the shortcomings with the rating scales already in use and

addressed the problems of i) reliability, and ii) sensitivity problems, that could have resulted in a lack of discrimination of experimental variables. Figure 2-6 shows the rating scale developed by Käppler [16,17,18] and the TNO Institute for Perception and Road Vehicles Research in the Netherlands.

Figure 2-6: Two level sequential judgement scale, Käppler [16]

The scale is continuous rather than ordinal to improve reliability, due to errors introduced by grouping data into category boundaries. Similarly, to improve reliability the scale descriptors are psychologically balanced and successively ordered with equally spaced perceptual variation between rating points. This allows parametric statistical methods to be used. Scale length is large by having as many

anchors as the number of descriptors permits, in order to increase sensitivity. The number of scale anchors is uneven in order to provide a neutral point that may be used when evaluators perceive the vehicle response to be as they expected. The scale includes both instructions and questions into the design and uses a simple qualifier to graphically direct the user to the relevant section of the continuous scale. With this design, evaluators do not have to deal with more than four points. As a result, their ratings can be made with the workload of two short scales, but with the

precision of a long one. Although many of the problems of other handling evaluation ratings have been addressed, this scale does not have the same versatility of the other scales. Evaluations conducted using this scale claim a marked improvement in both effective scale length and similarly for reliability and sensitivity.

In more recent research, Chen [4] used a seven point relative rating scale for quantifying responses to questions as shown in figure 2-7. Three descriptive anchors, worse, same, and better were used to label the 1, 4 and 7 points respectively on the scale. In addition, an option of "don't know" was added, recognising that a driver might genuinely not be able to provide a rating, thus not forcing a driver to guess,

which would cause random points to be collected. This gives a balanced scale that is

both simple and easy to use. Despite the small number of points on the scale, the effective scale length is still good due to the rating being relative and not representative of the absolute behaviour of the vehicle as in scales mentioned earlier.

Figure 2-7: Relative subjective rating scale, Chen [4]

2.3.3 Drivers

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Whether or not to use drivers trained to do subjective appraisals or ordinary drivers for research is an area that is split in opinion. The concern is that drivers not trained to do subjective appraisals may be influenced by things such as, vehicle appearances, thus not basing their ratings on the vehicle's handling. Using trained drivers should alleviate this problem because they are able to focus on the actual performance of the vehicle. It was stated earlier that the vehicle development process is restricted to

development engineers and trained drivers who have specialist knowledge about test driving. However, Matsushita [13] argues that although trained drivers are highly skilled drivers as well as good assessors, their vehicle handling preferences might be different compared to normal drivers. Work done by Weir & DiMarco [12] included evaluations done by an `expert' driver and sixteen ordinary drivers. The results showed that the expert driver preferred a more responsive vehicle compared to the ordinary drivers. Unfortunately data collected for the expert driver was collected

under different conditions for the other drivers, invalidating any direct comparison between the different types of driver.

2.3.4 Discussion

The review has only been able to focus on limited amount of work due to the fact that manufacturers in general do not publish the methods used to collect subjective data. It can be seen that rating scales have improved from the early use of the SAE rating scale. The reliability and sensitivity issues have been addressed in order to successfully discriminate between noticeable differences in handling. Scale linearity has been addressed by using psychologically balanced anchors and by having an uneven number of scale points. This is very important due to the use of parametric statistical methods used for averaging evaluations which would be inaccurate without using a linear scale, whilst correlating subjective and objective behaviour.

It is accepted that trained drivers represent/ reflect opinions of customers, i.e. nontrained drivers, hence automotive companies use them. Therefore, whilst researchers have used both trained and untrained drivers in their research for justifiable reasons, it seems logical to use trained drivers for further research as it is this group of people who will sign off a vehicle in the vehicle development stage.

2.4 Methodologies for Subjective-Objective Research in Vehicle Dynamics

For almost thirty years there have been papers produced on the subjective-objective handling theme using different types of test vehicles, driving manoeuvres, drivers and rating scales. Throughout most of the work simple correlations between objective measures and driver numerical ratings have been obtained. Table 2-1 shows an updated summary of work done in this field, first compiled by Chen [4].

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2.4.1 Subjective Ratings Showing Correlation To Objective Vehicle Response

Bergman [11] was the first to use open loop tests for subjective data collection and closed-loop tests to capture vehicle objective metrics for vehicle handling evaluations. Utilising the SAE rating scale and pre-selecting the better raters based on their rating ability, a subjective data set was compiled using a range of driving manoeuvres, vehicles and improved ratings. His results were based on subjective data and several objectively measured metrics including, normalised understeer angle increment,

steady state understeer rate and normalised sideslip acceleration, which through correlation were shown to have fairly high correspondence with ratings, i.e. a set of handling relevant vehicle metrics.

In studies that followed this approach, summarised in table 2-1, each further study demonstrated other physical metrics or combinations of these correlated well with ratings. The references expressed the level of correlation seen between ratings and objective data in coefficients of 0.7 to 0.9. However, each of the studies used different rating scales, samples of drivers, vehicles, manoeuvres and test conditions and selected vehicle metrics, causing difficulty in comparing the results from these

separate studies. In cases where `safe' numerical bandwidths had been specified, Weir

& DiMarco [12], the spread was so coarse that nearly all the vehicles tested fell into the 'acceptable' boundary on the rating scale. Weir $\&$ DiMarco's work however was one of the first to attempt to characterise the relationships between driver subjective ratings and objective measures, see figure 2-8. The vehicle measures used to capture handling behaviour were the yaw rate / handwheel gain, derived from steady state tests, and the yaw rate time constant, a transient measure. The Weir & DiMarco diagram clearly shows a preferable area for vehicle handling, however this was based on 1970's American automobiles, so this area of preference is questionable today. This point raises a problem with subjective assessments, namely that they are likely to

change over time and with expectation levels.

Figure 2-8: Boundaries of satisfactory vehicle response, Weir & DiMarco [12]

A method developed by Mimuro [25] known as "the four parameter evaluation method" uses four metrics extracted from lateral frequency response data by curve fitting with a two degree of freedom model to characterise vehicle performance. This is done by simply arranging the four metrics in a rhombus pattern.

The fourth parameter used is the phase delay, "Ø" at 1Hz from lateral response data. Figure 2-9 represents how the four metrics are displayed, note the unusual scales used.

Three of the evaluation metrics come from yaw velocity response data. They are;

- steady state gain, "al"
- natural frequency, "fn"
- \bullet damping ratio, " ζ "

Figure 2-9: The four parameter method proposed by Mimuro [25]

The four numerics are linked to subjective interpretations as follows:

- Steady state yaw rate gain Heading easiness
- Natural frequency Heading responsiveness
- 3. Damping ratio

Metric Subjective interpretation

4. Phase delay at 1Hz latac

Directional damping

Following controllability

The consistent theme is that outward movement away from the centre of the plot is linked to improved driver ratings - and hence, the area of the rhombus is correlated to some overall judgement of vehicle handling quality. It is a very appealing approach, based effectively on the proposition that surely there must be some simple numerics which correlate well with driver opinion - and that even if there are lots of other factors to consider, these simple numerics can at least be used as the basic starting points for good vehicle design. Unfortunately, very little further evidence has been published to confirm or question this proposition.

A technique developed by the automotive engineering consultancy company Ricardo

[26], allows six objective measurements of ride and handling to be presented on a spider graph. Each objective measure represents an aspect of either ride, handling or roll behaviour and is scored out of ten, resulting in an arc in which the biggest is judged best. Figure 2-10 shows a typical spider graph using the technique developed by Ricardo.

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Figure 2-10: Ricardo Spider Graph [26]

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Body control measures each cars primary ride quality. Pitch measurements are taken whilst the vehicle traverses over a bump, and it is assumed the greater the pitch, the less comfortable it is. Body roll was measured as body roll per g of lateral acceleration and it was generally assumed the lower the body roll, the more desirable the vehicle. The transient / steady state roll gain ratio is a measure of how well damped the vehicle is in body roll, and whether it reacts unpredictably during roll. Roll rate gives an indication of how responsive a car is to changes in direction.

However, this value can be misleading. A high roll rate could arise from either a quick responding car, or a poorly roll damped car, leading to quite different subjective opinions. The lateral acceleration ratio is related to a more general measure of vehicle responsiveness.

In the road tests used [26], the ratings derived from objective measurements shown on the spider graph were claimed to agree with the subjective ratings, but care should be taken when analysing the results due to such problems highlighted by the roll rate measurement.

Another recent contribution has come from Ford [27] who have developed an assessment procedure which attempts to position their vehicles relative to competitors. Assessing one vehicle manufacturer's product against another's is nothing new and it has been done for decades, however two features are of particular interest. Firstly, they combine subjective and objective measures in combined plots, see figure 2-11, and secondly, they claim they can characterise aspects of their own "brand". This second point infers that a brand image linked to chassis dynamics can be captured and designed in to a family of vehicles.

It can be noticed that figures 2-10 and 2-11 do not label the units for each of the axes for commercial reasons.

Despite the different methods used there does appear to be common trends in the

results. Prior to Chen [4], previous studies made little effort to conduct standardised tests which seems surprising given the apparent relationship between ratings and yaw and lateral responses. Investigators obviously want objective data that will reflect well with characteristics they expect will show good results, but standardising tests will allow comparisons with other research.

Vehicle positioning according to subjective criteria

Figure 2-11: Approach recently published by Ford [27] for comparing their vehicles with the competition based on both subjective and objective data.

Looking beyond the subjective $-\omega$ objective area of vehicle handling, progress has been made in other aspects of driver – vehicle interactions, in particular to ergonomics/ comfort of the cabin and driver safety systems. In more dynamic situations such as vehicle ride and handling the same levels of understanding have not been reached. Proposed links between subjective ratings and objective measures vary for different aspects of vehicle dynamics and four have been selected here as examples to comment

upon - ride, steerability, driveability and noise.

Research in to vehicle ride is specialist area within vehicle dynamics due to the complex manner in which humans respond to vibration. Human response to vibration can be classified in many ways, for example, motion sickness, comfort, subjective perception. However, human response to vibration can be influenced by extraneous factors such as expectation, motivation, fatigue, arousal and personal variations [28]. Despite this the best subjective-objective correlations have been shown for ride comfort, as indicated by the well-known ISO curves in figure 2-12.

More recently attention has focused on steerability issues. The term is normally used

to identify driver feel properties linked to the steering wheel position and torque feedbacks during low lateral acceleration manoeuvres, in particular high speed straight running and stability assessments, where it has become a major safety and refinement issue. Two factors that have recently influenced the growth of interest in this area are: active front steering [29] or steer-by-wire systems [30] and the fact that studies are using fixed based driving simulators. These factors present new opportunities for intelligently controlling steering gain and feel.

Figure 2-12: ISO 2631 curves for human exposure to vertical vibration.

In the quest to improve vehicle refinement and hence market appeal, manufacturers have been trying to improve subtle features that form the drivers opinion of driveability. More recently, it has been claimed [31,32] in situations such as idle

response, gearshift quality, cruising ease, engine start up, good levels of correlation can be achieved between objective measures and subjective ratings. In these studies instead of using traditional statistical methods to correlate between subjective assessments and objective measures, artificial intelligence, in particular neural networks and fuzzy logic have been used.

In the field of vehicle noise, researchers have used a number of objective metrics as an indication of subjective response to vehicle noise. Additional metrics have been developed from a combination of specific objective parameters with the aim of further improving the correlation with subjective responses, for example the Composite Rating of Preference (CRP) index. Fish [33] remarks however that the ability of any objective parameter or index to provide a good correlation will be limited by any nonlinearity present in the subjective response. Subsequently Fish discusses how neural networks can be used to model the non-linearities. Results presented in [33,34] show neural networks to successfully model vehicle noise parameters, yielding a high correlation with subject response. As of yet, no published work has attempted to use non-linear methods to identify links between subjective and objective metrics for

vehicle handling. The process of applying non-linear methods to the available data sets may reveal many links, in part due to any non-linearity present in the subjective data set.

The potential value of frequency response results which to date have not figured highly in subjective- objective correlation exists despite the fact that in the aircraft industry, frequency response results have proved very useful [35,36]. This work has shown that a correlation exists between pilot opinions and areas in a plot of natural

frequency against the damping ratio of the short period pitching mode of the aircraft. Such a plot is shown in figure 2-13. The lines on this figure are pilot opinion contours taken from reference [35].

Figure 2-13: Example of subjective - objective correlation taken from the aircraft industry. Plot shows links between pilot assessments and the natural frequency and damping ratio of one of the aircraft's characteristic roots [35].

The principal method of analysis of the frequency response results uses a control

theory approach to find the characteristic vehicle frequencies and dampings. This is done by fitting a curve of the form predicted by theoretically derived transfer functions. The transfer function of any system can be simply defined as being the ratio of the output/ input for the system.

Barter [37], in the automotive industry investigated the possibility of using the frequency response of a vehicle to a steering input as a measure of transient handling characteristics. Barter concludes that the frequency response of vehicles which display

linear response to handwheel input agree with the pattern indicated by fairly simple linear theory. This finding is in agreement with the experience of the aircraft industry that linear behaviour is desirable for satisfactory handling. Barter went on to plot values of natural frequency and damping ratio obtained for several vehicles on the diagram shown in figure 2-13. Whilst values of damping ratios fell into the good region, the frequencies were all higher than pilots would have chosen for aircraft. It cannot be assumed these aircraft results apply to cars, and as

Two experimental vehicles were used, one was kept as a reference vehicle, and one was varied in to sixteen different configurations by changing eight suspension, body and tyre characteristics between two settings, "+" and "-". The experimental vehicle

such further work must be carried out to investigate the usefulness of frequency response results.

2.4.2 Review of Linked Leeds/ MIRA Project

The following summarises the results of the work done by Chen [4], using standardised objective tests, a simple and balanced subjective rating scale and trained dri vers.

that was used is shown in figure 2-14. The eight varied vehicle metrics are shown in table 2-2.

Figure 2-14: The experimental vehicle

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The vehicles used were prototype saloons, typical of many front wheel drive cars with a manual transmission and a four cylinder engine. General vehicle specifications are given in appendix A.

Table 2-2: Vehicle metrics varied during experimental work, Chen [4]

The actual set-ups were determined using a factorial approach and are shown in table 2-3. Using this approach allows a systematic examination of the results which is helpful for quantifying the effects of each parameter on vehicle responses.

The vehicle response was captured using specific standardised tests to gather the set of objective metrics listed in table 2-4, a set designed to capture both the steady state

and transient handling behaviour of the vehicle.

Table 2-3: Arrangement of vehicle parameters for sixteen test configurations, Chen [4]

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Table 2-4: Objective test program, Chen [4]

Eight development engineers who had training and experience in the testing and

development of motor vehicles were free to conduct their evaluation conducting tests of their own choice, as done in typical practice. The questionnaire compiled for the study by Chen carefully considered how the drivers describe subjective aspects of handling, observation of track evaluation of vehicles, and an examination of a glossary defining standard terms used in the subjective evaluation of vehicle handling written by MIRA's Vehicle Dynamics Department. The questionnaire consisted of 49 questions relating to seven aspects of handling. These aspects were steady state, power change, sudden braking in a corner, transient response, straight line directional stability, obstacle avoidance and response to steering impulse.

The set of objective metrics was collected at the same site where the subjective evaluations were conducted.

Chen [4] used for the method of correlating subjective and objective response metrics, a process of variable selection in which most of the important objective response metrics were matched to a given set of ratings, followed by ordinary least squares With a suitable set of objective regressors, a model of the subjective ratings for each

regression. This resulted in equations relating the subjective evaluation to the objective response metrics of the vehicle in the form:

Subjective rating = fn (a number of objective metrics)

To simply try and evaluate every single multiple regression equation for statistically significant correlations would have been a mammoth task due to the large number of response metrics which were available to correlate with driver ratings. This was because there was forty six objective response metrics and sixteen ratings per metric due to the range of vehicle set ups used in the research. A second problem encountered was that a number of the metrics effectively represented identical or interrelated characteristics of the vehicle which meant that multicollinearity could degrade the inferential and predictive characteristics of any regression equations. To address the above problems a technique called ridge regression [38] was used which involved ridge plots to identify suitable data sets. The output using this method in general is an orthogonal data set, which is tested for correlation with the selected response.

question for each driver was calculated using the method of least squares, resulting in an equation in a linear form.

Further analysis looked into the hypothesis that the sign of the effect a metric in a regression equation has on different aspects of vehicle handling is the same regardless of driver or question and extends to show the magnitude of effect that each metric has on overall subjective handling. A table was produced [4] showing the average effect that each metric has in the formulation of ratings.

From these results, it could be clearly seen which metrics had the most effect on subjective ratings. Those were metrics that had a narrow confidence interval and did

not cross the zero effect line hence showing i) good, uniform agreement amongst the drivers as to the true value of the effect and ii) unequivocally positive or negative effects regardless of the question asked. Figure 2-15 highlights those metrics of particular interest.

Figure 2-15: Nature of the effects each metric has on rating

The results in the middle of the Venn diagram in figure 2-15 are of the most interest by being uniform and unequivocal. They are by and large derived from frequency response data with the remaining two derived from step input and steady state tests. On the left hand side, i.e. the metrics that are unequivocal but not necessarily uniform, four out the five metrics were derived from the step input test. It is interesting to see

that in these two sectors, all bar one metric relate to transient response of handling

response. This suggests that drivers identify differences in transient manoeuvring more readily than in steady state ones.

In previous studies dating back to the early 1970's different methodologies have been used to collect driver subjective ratings and vehicle objective metrics, making it difficult to compare results. No widespread use of standard tests (e.g. ISO standards) appeared to have been used. Chen collected objective experimental data based around ISO defined tests. The results of the tests confirmed that a wide range of handling characteristics had been achieved which was important in the goal of finding subjective-objective correlations.

The Chen [4] study along with other research [21] conducted shows that increasing magnitudes of yaw response implies a vehicle configuration that would be more difficult to control. Similarly an increase in phase or time response would lead to slower vehicle response to an input, something which is generally regarded to be a subjectively poor quality.

A vehicle handling model was developed to allow computer simulations of the experimental vehicle; further detail of the vehicle model is in the proceeding section. Validation of the computer model indicated that both the steady state and transient response characteristics in both the linear and non-linear handling regime can be predicted.

By using the results of this research, engineers in the early design stage should know the effect that the most influential handling characteristics have on general driver

opinions. By looking at the metrics given in figure 2-15 and noting their effects, the designers can now either increase or decrease specific levels of responses in order to

improve subjective impressions.

Overall it can be seen that some trends emerged allowing some guidelines to be set which can be used by development engineers. Despite the immense amount of data which was meticulously collected using a structured approach showing some correlation, questions still linger whether further insight could be extracted.

2.5 Computer Handling Simulations

The need to identify relationships between subjective and objective measures of

vehicle handling are necessary if computer simulation of vehicle handling is to play a part during vehicle development. Computer simulation is finding an increasing role in the research and development in the automotive design cycle. Over the years, researchers have developed vehicle models ranging from a simple single track model more commonly known as a bicycle model, to very detailed models typically using multi body code, for example ADAMS. Model complexity is an area that has received attention because there is a general perception that using increasingly sophisticated models leads to increasing accuracy. Another key issue with vehicle modelling is simulating tyre forces and moments. The main issues of vehicle modelling are discussed in the following sub sections, followed by a summary of the computer

simulations done by Chen [4] in the previous linked project.

2.5.1 Model Complexity

Studies relating to model complexity point out the need for setting the requirements for the given application and then implementing these requirements in an appropriate vehicle dynamics model. Allen [39] discusses vehicle dynamics model requirements which may or may not be required depending on its intended use. Suresh [40] discusses the issue of model complexity in the context of available input parameters, and how the improved accuracy of a more complex model should be set against the effects of errors in the additional model parameters. Whilst a more complex model may give a more realistic result, the true accuracy is also dictated by how accurate the input parameters are measured.

In terms of model formulation there are two approaches, the choice being between the lumped parameter model (LPM) approach or multi-body formulation (MBF)

approach. Using the LPM approach the analyst develops the model and derives its equations of motion (EOM). Using MBF, the analyst builds up the model by giving details of the bodies, then the computer generates the equations of motion.

For the development engineer, use of the LPM approach during the preliminary stages of design, is generally acknowledged as being of the most use. The LPM approach has the advantage of allowing the analyst to include or to ignore certain effects at the time of model development. Thus, only as many degrees of freedom (DOF) judged to be needed are used unlike in the MBF approach.

The LPM approach is further suited to preliminary design work because besides being

simple, it allows by the way the model has been defined through composite parameters to make easy comparisons between different vehicles. For example, in a LPM, the effects of roll steer on directional response could be investigated by changing this parameter independently of other input parameters [41]. In the MBF approach to account for this change, suspension pick up points and suspension link lengths need to be changed. After this has been done, checks would be necessary to ensure these changes have not affected other suspension characteristics.

2.5.2 Tyre Modelling

All forces acting on a vehicle, other than aerodynamic forces are generated at the tyreroad interface. Thus the success of any simulation depends largely on the approach

taken in simulating these tyre forces.

The most common tyre model used today uses the approach of fitting a function to the measured tyre forces and moments. Pacejka [42] proposed a model that is widely referred to as the "Magic Formula Tyre Model", which provides a set of mathematical formulae from which the forces and moments acting from road to tyre can be calculated at longitudinal, lateral, and camber slip conditions, which may occur
simultaneously. This model aims to provide an accurate description of measured steady-state behaviour. An updated version of the model presented by Pacejka [42] in 1987 is available for the current research which, for example includes extra constant terms to improve the fit of the model to real data [43].

2.5.3 Previous Linked Project Computer Modelling

Due to the considerations of simplicity mentioned in the previous sub sections the lumped parameter model approach was taken by Chen [4]. Great care and attention was taken to ensure accurate data collection for the vehicle parameters by either obtaining measurements directly from or by experimental measurements. The model included lateral, yaw and roll degrees of freedom. Wheel motions were represented as functions of handwheel angle, roll and tyre aligning moment. Tyre and damping forces were incorporated in to the simulations as non-linear functions. Model validation was carried out by comparing the simulated and experimental data. By examining how well the mathematical model represented the actual vehicle, it could be seen if the model could accurately predict vehicle behaviour.

The results achieved showed that using a LPM the predicted results agreed well with

the experimental results in steady state and transient manoeuvres both in the linear and non-linear range of handling.

2.6 Conclusions

It has been shown that whilst objective metrics are easy to obtain in order to describe vehicle handling, there are no agreed standards for assessing these metrics.

No standards exist for the collection of subjective data that describes a vehicle's handling behaviour.

Through the development of rating scales, their reliability and sensitivity issues have been addressed. Scale linearity has been improved by using psychologically balanced

anchors and by having an uneven number of scale points. It is the authors view that the scale developed by Käppler [16-18] is the best rating scale for representing overall vehicle behaviour.

The scale used by Chen was so used because only ratings relative to another vehicle were being sought, and as such was easy to use, and had a good effective length.

However, points were ordinal and not continuous which may have an effect when correlation is done with objective metrics.

The author believes the approach taken by Chen [4] to use trained drivers and standardised tests is the best way forward in order to correlate objective metrics with subjective ratings. Using a structured approach not only allows work by others to be compared, but the work shall be repeatable, much in the same way as the aircraft

industry.

From the review, the potential use of frequency response metrics has been highlighted in particular from their success in the aircraft industry.

A method using frequency response results has been identified which will allow the major vehicle handling characteristics to be realised in a glance. Moreover, these objective metrics are said to relate to subjective qualities, thus from early modelling work it should be possible to see how parameters will effect the vehicle overall. Away from the specific area of correlating subjective $-$ objective measures of vehicle handling, in other areas, in particular driveability, good correlation has been found. This has been achieved using artificial intelligence techniques to find correlations

between the two measures as opposed to traditional statistical methods.

3. Subjective Data Analysis

3.1 Introduction

Before attempting to establish links between the subjective and objective data sets, any shortcomings in the data must firstly be considered. The methods used to collect both the subjective and objective sets of data were discussed in detail in the previous chapter. Problems associated with collecting experimental subjective data were

highlighted which may affect the quality of data collected but also links between the subjective and objective data sets.

The subjective data collected for each driver has been analysed in order to make judgements on the following criteria, a) how much reliability/ consistency can be seen in each driver's judgements, and b) whether some of the original 49 questions might be redundant. The questionnaire used by Chen [4] in the initial study is shown in table 3-1. The full set of subjective ratings collected by Chen for use in this project are listed in appendix B.

By analysing the subjective data set, two aspects of the subjective data set have been investigated:

Drivers:

- What can be said about each driver?
- Do they answer groups of questions in the same way?
- Do they answer unrelated questions in the same way?

Questions:

- Are the questions too similar?
- Can the question set be reduced?

To answer the questions presented, 2 separate analyses have been conducted. Firstly,

the ratings given by each individual driver have been analysed and secondly ratings to

questions given by any of the 2 drivers have been analysed. From the analysis,

conclusions are presented for the subjective data set.

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3.2 Analysis of the Subjective Data Set

The statistical method of paired comparison was used to identify questions in each driver's subjective data set where a direct relationship existed between questions.

It would be expected to find relationships between similar questions. The subjective data set has questions which relate to seven key areas of vehicle handling, they are:

Steady state turning

2. Power change

- 3. Sudden braking in a turn
- 4. Transient cornering
- 5. Straight line directional stability
- 6. Obstacle avoidance
- 7. Response to steering impulse

Considering any two groups of questions above, it would be reasonable to expect direct relationships between some of them. For example, transient cornering and

obstacle avoidance both deal with the transient behaviour of the vehicle and so drivers might formulate their ratings for these questions in a similar manner. Conversely, it would be illogical to expect to see direct relationships between questions relating to

aspects of steady state handling and transient vehicle behaviour.

An example of the results obtained from the statistical analysis for a driver is shown in table 3-2. The table has the number of the question running along the top row and the first column of the table. For each question, a paired comparison analysis has been done with each of the other questions. Each box in the table represents the \mathbb{R}^2 value relating to the two questions associated with the respective row and column. R^2 is interpreted as the amount of variability between the two sets of data being analysed. If

r values are greater than 0.80 the variables are strongly inter-related and should not be used [44]. Where a shaded cell is shown, the R^2 value indicates multicollinearity is present. Any white cells are due to there not being enough data points necessary to do the paired comparison.

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Indicates multicollinearity is present between corresponding pair of questions \mathbb{R}^n

Table 3-2: Example results of paired comparison analysis for a drivers subjective

data

The way the table is laid out, duplicate information is presented with the data being symmetrical about the black diagonal line. In the example above, it can be seen the drivers' answers to three main groups of questions are directly related, those being:

- 4. Transient cornering
- 6. Obstacle avoidance
- 7. Response to steering input

It can also be seen that there are a significant number of questions from group 4 which directly relate with group 6 questions. Analysis of the subjective questions will indicate whether such links are understandable, and hence give an indication of the

quality of the subjective data set. The individual results of the paired comparison analysis for each driver are discussed in section 3.3.

Applying the same method to identify similar relationships in driver ratings, the method of paired comparison was used to see if drivers gave similar ratings to each other for any of the 49 questions. In the analyses, the ratings for a given question by a driver are compared to each of the other seven drivers ratings individually.

Whilst it is reasonable to expect drivers to formulate their ratings to a question on different stimuli, a lot of similarity would be expected when comparing ratings to questions given by each of the drivers.

3.3 Results of the Subjective Data Analysis

The results for the three parts of the subjective data analysis are presented and discussed.

3.3.1 Question Group Responses That Display Similarity

From the analysis using the method of paired comparison, table 3-3 indicates the group questions for each driver that display multicollinearity. Each column in the table represents one of the seven groups of handling questions, and the rows represent the drivers one to eight. A cross indicates that, for that particular driver, their subjective ratings for that set of group questions display multicollinearity. It follows that the drivers' perception of the vehicle's handling when answering these group questions is the same or similar, hence the high level of multicollinearity.

Table 3-3: Group questions whose ratings display multicollinearity

It can be clearly seen that the majority of the drivers formulate answers to the obstacle avoidance and steer impulse questions in a similar manner. This means that a lot of

¹³ the questions are essentially repeated because answers to questions in the two groups

are the same.

The fact that across the other groups of questions there is little or no linkage in the way the questions have been answered shows that the drivers are not answering these questions in a like manner. Thus, with these questions drivers are basing their rating on a different aspect of the vehicle handling behaviour. Unlike the other two groups of

questions identified earlier, there is no need to remove any questions due to drivers giving the same answers to questions.

3.3.2 Inter Group Related Questions

A method to assess the quality of the subjective data was sought. By looking to see if drivers were answering questions from different groups in a similar manner some judgement can be made with regard to the reliability of the subjective data. Some linkage between groups of questions can be expected as specific criteria are being questioned under different headings. For example, a driver answering a question about the degree of body roll when steady state cornering, might answer in the same way to a question about body roll angle under the sub heading turn in response, transient cornering.

The following section discusses questions answered by a driver where a direct relationship exists with another question or questions from other group questions.

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Driver A

Indicates multicollinearity is present between corresponding pair of questions

Table: 3-4: Results of paired comparison for driver A's subjective data

Driver A's ratings for questions 1 and 2, both steady state related show likeness to questions 15 and 17 regarding yaw response of the vehicle under power change conditions. With the latter questions relating to transient response of the vehicle, it is surprising to see the likeness shown as questions 1 and 2 which are only steady state related.

Question 3, degree of body roll is answered in a like manner to several questions asking about transient cornering and obstacle avoidance. This does seem unlikely, however some of the transient cornering questions do ask about body roll angle/ rate.

Notably question 14, steady state, over rough roads, kickback on bumps, is answered in a like manner with question 32, straight line stability, steer kickback. This match between like questions from different question groups can be checked for with each of the other drivers to check consistency between drivers.

There is a clear set of questions that are linked between the transient cornering questions and the obstacle avoidance questions. This link is feasible as the questions relate to the turn in response of the vehicle into a corner, and the single lane change manoeuvre.

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Driver B

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Indicates multicollinearity is present between corresponding pair of questions

Table: 3-5: Results of paired comparison for driver B's subjective data

There are ratings from several groups that appear to have a good likeness to question 41, Obstacle avoidance, limiting factor. Looking at the nature of the questions there seems to be no good reasoning for this. However, it can be noted that there are only seven data points for question 41, thus making it more likely to correlate with other answers to questions with fewer data points. This problem also occurs for question 46 where there are only three data points for the particular question.

Ignoring the results for these questions, the links between question groups are now

discussed. Question 12, steady state, over rough roads, ease with which a line is held is found to link with several questions, 31,34,40 and 44. The questions deal with the bump steer, ease with which the line is held over a changing surface and controllability in a single lane change. It is certainly feasible that the effects of bump steer geometry is influencing the drivers rating for these particular questions, explaining the likeness in ratings to these questions.

Question 24 sudden braking in a turn, wheel lock up and question 34 straight line stability, constant throttle, over changing surface: ease with which line is held are very different in nature making their likeness an oddity.

A likeness was found with questions 26 and 42 which both relate to vehicle turn in response for transient cornering and obstacle avoidance respectively, which can be expected.

Driver C

Examining the number of data points for each of the 49 questions, numbers 23 and 30 have only five and four points respectively, leading to several questions showing good likeness to these two questions. Therefore in the following discussion, the questions showing a good likeness to these two particular questions are ignored.

Driver C's ratings for question 2, steady state, cornering behaviour, ease with which

line is held shows a likeness to question 24, sudden braking in a turn, wheel lock up,

which are questions which show no similarity in their meaning.

Questions 3,22 and 28 relate to body roll angle and roll stability in steady state and

sudden braking in a turn conditions, which despite the different handling manoeuvres both relate to body attitude hence the likeness.

Indicates multicollinearity is present between corresponding pair of questions

Table: 3-6: Results of paired comparison for driver C's subjective data

Ratings to question 5 steady state turning, steering torque feedback, indication of available grip are found to be alike with ratings for questions 38 and 42, both obstacle avoidance, turn in response. Steering torque is one of the primary sources of feedback to the driver which can explain the likeness in ratings to the questions.

Ratings to question 17 power change, yaw response, yaw stability at high lateral acceleration show a likeness to question 43, Obstacle avoidance, single lane change, recovery. Both questions relate to vehicle behaviour in a transient state at high lateral acceleration and their likeness suggests the driver is basing his ratings for question 43 on the yaw response of the vehicle.

A likeness is also shown between questions 22 Sudden braking in a turn, roll stability

and 28, transient cornering, turn in response, body roll angle. Despite the questions being about different manoeuvres, they are both related to body roll, be it stability or roll angle, which the driver is interpreting in a similar manner.

The ratings for questions 27 and 33 show a likeness which seems unlikely as the questions ask about transient cornering, turn in response and precision on smooth surfaces and straight line directional stability, constant throttle, over changing surface camber. The two questions clearly relate to different aspects of vehicle behaviour, hence the similarity in their ratings is unexpected.

Driver D

Indicates multicollinearity is present between corresponding pair of questions

Table: 3-7: Results of paired comparison for driver D's subjective data

It can be seen that driver D has answered many questions in a like manner to questions from several other question groups.

Answers to question 2 steady state turning, over smooth roads, cornering behaviour, ease with which line is held are similar to that for question 34 straight line directional stability, constant throttle, over changing surface composition, ease with which line is held. Despite the different sub headings, the end question has been answered in the

same manner, meaning either the vehicle behaviour is directly linked between the two driving conditions or the driver is not distinguishing between the two conditions hence the similar ratings for the two questions.

Ratings for question 6 steady state turning, over smooth roads, steering torque feedback, indication of lateral acceleration are shown to be linked to questions 25, 32, 34, 39, 40 and 45. Similarly there are other steady state turning based questions which

are found to have likeness for several other transient based questions. It can be seen from previous drivers that some links between question groups can be explained but there are several questions answered in a like manner for driver D that can not be. Ratings to question 15 power change, power on, magnitude of yaw response are found to have a likeness to questions 31 and 33, both straight line directional stability

questions relating to bump steer and behaviour over changing surface camber. Although there seems no obvious link, the effects of bump steer may be what the

driver is using for the formulation of the rating to each of the questions.

There is a similar situation with question 20 power change, power off, yaw response, yaw stability of vehicle at higher lateral accelerations which has likeness with questions 32,34 and 45, which again could be explained by the driver noting the effect of bump steer in the formulation of his rating to the questions.

Ratings for question 26 Transient cornering, turn in response and precision on smooth surfaces have a likeness with questions 34 Straight line directional stability, over changing surface composition and 45 Obstacle avoidance, limiting factor. The similarity between questions 26 and 34 is strange as one clearly relates to transient

cornering whilst the other asks about straight line stability. The likeness amongst questions 26 and 45 is feasible as the driver might be picking up on steering effects. Ratings to question 30 transient cornering, steering torque feedback, steering catch-up

and question 48 Response to steering impulse, oscillation of handwheel show likeness, which can be seen in the nature of the questions.

Ratings for questions 32 to 34 associated with straight line directional stability are found to have likeness with obstacle avoidance questions mostly related to controllability and limiting factor. These are questions that don't appear to have similarity, yet the driver has clearly answered these questions in a similar manner.

Driver E

Ratings for question 46 have only been given for three vehicle configurations resulting in several questions showing a likeness with it which gives an inaccurate picture for questions which show a likeness with question 46.

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Indicates multicollinearity is present between corresponding pair of questions

Table: 3-8: Results of paired comparison for driver E's subjective data

Considering the other questions showing likeness with others, question 3 steady state turning, cornering behaviour, degree of body roll is answered in a like manner to questions 22, 28 and 29, all of which relate to body roll behaviour which follows.

The likeness in ratings given to question 6 Steady state turning, steering torque feedback, indication of magnitude of lateral acceleration to question 23 Sudden braking in a turn, wheel lift however clearly does not follow.

A likeness between questions 14 and 32 clearly follows as both questions relate to steering kickback, despite the questions being from different question groups, one and five respectively.

More likeness amongst question groups exist between questions 22 braking in a turn and 28 transient cornering which both relate to body roll. Ratings for question 22 however also show likeness with question 47 Response to steering impulse, oscillation of vehicle which at first seems unlikely. It appears the driver has formulated responses to question 47 based on roll angle as opposed to the yaw of the vehicle which seems a more natural motion to base ratings for this question upon.

The same trend is found with ratings for question 28 Transient cornering, Turn in response, body roll angle which has likeness with questions 47 and 48 Response to steering impulse, oscillation of vehicle and oscillation of handwheel respectively.

Ratings for question 39 Obstacle avoidance, single lane change, trailing throttle, recovery show likeness with ratings for all three questions related to steering impulse, something the other drivers have not done.

Finally, the ratings given for question 46 Obstacle avoidance, double lane change show good likeness to questions 47 and 49 about response to steering impulse. This seems plausible given the double lane change is a series of steering impulses, however in closed loop control with the driver reacting to the behaviour of the vehicle in the manoeuvre.

Driver F

48 0.42 0.78 0.63 0.47 0.99 0.81 0.4
49 0.61 0.91 0.56 0.85 0.90 0.98 0.3 49 0.07 0.57 0.51 0.43 0.11 0.43 0.52 0.00 0.05 0.52 0.55 0.02 0.17 0.06 0.21 0.05 0.90 0.96 0.99 0.84 0.99 0.91 0.79 0.92 0.96 0.59 0.75 0.87 0.97 0.46 0.53 1.00 0.97 0.97 0.46 0.53 1.00 0.97 0.47 0.47 0.47 0.47 0.47 0.47 49 0.61 o. 733 0.01 0.49 o a o. 025 0. o. o, oo mel o. ZOO 005 0.01 006 o. oo . oz1 0. 0.36 oa3 f

Indicates multicollinearity is present between corresponding pair of questions

Table: 3-9: Results of paired comparison for driver F's subjective data

It can be seen that a lot of multicollinearity exists amongst the questions, however this like other drivers is due to several of the questions having very few data points. Questions about response to steering impulse have four data points each, whereas

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other questions have zero or two data points meaning no analysis can be done with these questions.

Examining the rest of the subjective appraisals the following can be observed. Ratings for question 2 Steady state turning, over smooth roads, cornering behaviour, ease with which line is held are shown to be similar with questions 26 and 41. These questions relate to turn in response and limiting factor in a single lane change manoeuvre, both of which are not intrinsically linked to a steady state question.

A link between question 3 Steady state turning, over smooth roads, cornering behaviour, degree of body roll and question 28 Transient cornering, turn in response, body roll angle however can be expected.

The links between the different question groups for driver G can be seen to be mostly related to steering torque feedback and kickback/ bump steer effects.

Ratings for question 18 Power change, power on, steering torque feedback, steer torque due to power change have a likeness to ratings given for questions 35 and 36, Straight line directional stability, under acceleration, torque steer and tendency to pull to one side. In addition for question 18, there is likeness with ratings for question 37 Straight line directional stability, under braking, tendency to pull or weave. Clearly questions 18 and 35 deal with torque steer which explains their likeness, and due to

the likeness with questions 36 and 37, it can be hypothesised that the driver is basing

his ratings for these questions using steer torque.

Driver G

The first question that has ratings similar to a another question from a different question group is number 6 Steady state turning, over smooth roads, steering torque feedback, indication of magnitude of lateral acceleration with question 18 Power change, power on, steering torque feedback, torque steer due to power change. The

driver has answered the questions in a like manner and despite both questions being

related to steer torque feedback they seem to be quite different.

The ratings for question 10 Steady state turning, over smooth roads, steering torque feedback, smoothness show likeness with questions 21,26 and 42 from question groups 3,4 and 6. It is unclear why any of these questions have been answered in a similar manner and as such is more likely to be coincidence.

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Indicates multicollinearity is present between corresponding pair of questions

Table: 3-10: Results of paired comparison for driver G's subjective data

Another steady state question, 12 cornering behaviour on rough roads, ease with which line is held is shown to have likeness with questions 30, 31 and 41 from question groups 4,5 and 6. The effects of bump steer would be prominent with respect to question 12 and this clearly links in with question 31 Straight line directional stability, constant throttle, bump steer. Bump steer also effects the phase delay of the vehicles response in the frequency domain which can explain the likeness with question 30 Transient cornering, steering torque feedback, steering catch-up. The likeness with question 41 Obstacle avoidance, single lane change, trailing throttle, limiting factor can again be attributed to the effect of bump steer. This in turn leads to roll steer, which under trailing throttle conditions would be extenuated with the

additional load transfer to the front of the vehicle causing a greater steer effect in the lane change manoeuvre, hence making stability the limiting factor.

Ratings for question 14 steady state turning, over rough roads, kickback on bumps show likeness with the ratings for question 31 Straight line directional stability, constant throttle, bump steer. Kickback feedback through the steering wheel will be effected by bump steer, which explains the likeness with question 31.

The likeness of ratings for questions 16 and 26 relating to power change, progressiveness of yaw rate response and Transient cornering, turn in response and precision can be explained in the way both relate to the transient response of the vehicle, of which yaw is the primary feedback for turn in.

Ratings for question 30 Transient cornering, steering torque feedback, steering catchup are found to be like those for questions 43,44 and 46 all obstacle avoidance related, in particular recovery and controllability. Steering catch-up relates to the

response of the vehicle under transient manoeuvring which in turn can be perceived as recovery and controllability, thus explaining the likeness in ratings for these questions.

Finally, likeness is found with question 31 Straight line directional stability, constant throttle, bump steer and two obstacle avoidance questions, 43 and 44 about recovery and controllability. The likeness can be caused by the effects that bump steer have on roll steer having significant effects on the vehicles handling.

 $\overline{4}$

5

6

Driver H

 1

 $\overline{2}$

 $\overline{3}$

Indicates multicollinearity is present between corresponding pair of questions

Table: 3-11: Results of paired comparison for driver H's subjective data

1

 \mathfrak{p}

2

4

 \mathcal{L}

 \bf{U}

 $\frac{1}{2}$

Ratings for question 3 Steady state, smooth roads, cornering behaviour, degree of body roll are shown to be alike with those for question 28 Transient cornering, turn in response, body roll angle, a trend seen amongst other drivers. The questions differ due to the transient nature of question 28, where the effects of damping effect the roll rate, however as clearly seen the two questions are still answered in a like manner.

Ratings for question 6 Steady state, smooth roads, steering torque feedback, indication of magnitude of available grip show likeness with questions 35 and 36, Straight line

directional stability, under acceleration, torque steer and tendency to pull to one side. The questions all relate to steering torque feedback, however they relate to different aspects of vehicle handling.

Ratings for question 15 Power change, power on, yaw response, magnitude of response show likeness with question 36 Straight line directional stability, under acceleration, tendency to pull to one side. Examining the nature of these questions, a likeness would not be expected.

Ratings for question 16 Power change, power on, yaw response, progressiveness of yaw rate response show a likeness with question 40 obstacle avoidance, single lane change, trailing throttle, controllability. This can be explained as it follows the more predictable a vehicle is in a transient manoeuvre which demands closed loop feedback, the better the controllability in such a manoeuvre as the single lane change. Following the same logic ratings to question 17 Power change, power on, yaw response, yaw stability of vehicle at higher lateral accelerations have been answered in a similar manner to obstacle avoidance questions 39,41,43, and 45. Driver H has again answered questions relating yaw stability response with the

obstacle avoidance manoeuvre with questions 20 and 45 respectively.

Ratings to question 22 Sudden braking in a turn, roll stability are found to have been

answered in a similar manner to questions 41,44 and 45, all obstacle avoidance related questions, notably none specific to body roll. Questions 41 and 45 both relate to the vehicles limiting factor, specifically stability, grip or steering ratio, making the similarity more coincidental. Question 44 related specifically to controllability, however there would be more than just roll stability feedback involved in formulating the drivers rating to the question, in particular yaw stability and steering feedback. The link is therefore not inconceivable, but is not readily expected.

Ratings for questions 26 and 27 Transient cornering, turn in response and precision are shown to be like those given for questions associated with obstacle avoidance, 39 and 39,43,44,45,46 and 47 respectively. The obstacle avoidance questions relate to the recovery and controllability of the vehicle under the single lane change manoeuvre and so the similarity with questions about transient turn in and precision can be seen. Similar likeness is found with obstacle avoidance questions 42, 44, 45 and 46 with response to steering impulse questions, 47 and 48. The questions deal specifically

with the transient behaviour of the vehicle, and for the driver to be answering them in a like manner infers ratings based on a certain feedback related to transient manoeuvring.

3.3.3 Comparison of all the Drivers' Ratings

This section presents the results of the paired comparison analysis in which similarities in ratings for all questions between any pair of drivers was searched for. The results are presented in table 3-12. For each driver, sixteen responses for questions one through to forty nine have been compared to each of the other seven drivers' set of ratings individually. Each cell in the table represents the R^2 value obtained when doing correlation between any two drivers set of ratings for a particular question. The columns in the table represent the one to forty nine questions and each of the eight rows in each of the eight blocks represent the drivers A to H. The darkly shaded cells represent an R^2 value of 1, indicating a perfect similarity. The lightly shaded cells indicate good similarity in ratings to a question given by the two particular drivers. Each block of cells represents results comparing ratings from one driver against each of the other seven driver's ratings.

From the results, it can be seen that there is surprisingly little similarity between ratings given to questions across all the drivers. Given eight different test drivers answering the same 49 questions more similarity might be expected. It is accepted

that drivers may use different stimuli or criteria to make an assessment about vehicle

handling, but this analysis is only looking for agreement across the drivers on whether

the handling is better or worse with respect to any of the questions.

 $0.42 0.02$

 0.45

0.51

0.03 0.01 0.01 0.13

0.00 0.17 0.00 0.08 0.00 0.13 0.02 0.11 0.02 0.07 0.00 0.26 0.00 0.00 0.00 0.02

 \bullet

Indicates multicollinearity is present between corresponding pair of questions

Table 3-12: Results of the paired comparison analysis - Ratings for each

question by a driver are compared to ratings from each of the other drivers to check for similarity.

3.4 Conclusions

From the analysis of the individual subjective data sets, two conclusions can be drawn. Firstly, it is clear that the majority of the drivers answer questions relating to

obstacle avoidance and response to steering impulse in a similar manner. This infers that information is being repeated in the question set, thus the number of questions from each of these groups can be reduced

Secondly, from the individual analysis of each driver's ratings, there were very few instances of questions from different groups that displayed similarity which after examining the questions did not make any sense. On these grounds, there is no reason to eliminate any subjective data from any of the drivers.

However, it was found that with only a few data points given for questions of particular vehicle configurations, those questions displayed likeness with several questions across question groups. In particular, Driver F answered response to steering impulse questions four out of a possible sixteen times, meaning that ratings to these questions were found to have likeness with most of the other question groups. In addition, no ratings were given for four other questions, leaving large gaps in the subjective data. It is necessary to exercise caution if any correlation between subjective ratings and objective metrics relating to steering impulse questions are found for driver F.

From the comparison of all of the driver ratings it could be seen that very little similarity was found between individual pairs of drivers ratings. Although some degree of variability might be expected in any subjective assessment, it is nevertheless surprising that clear, underlying consistent trends could not be found. Analysis of the subjective data set has revealed some interesting facts. The most important being the second conclusion that provides confidence in the quality of the

subjective data set. Therefore the whole of the subjective data set has been used in all

the correlation analyses described in this thesis.

4. The Four Parameter Evaluation Method

4.1 Introduction

From the literature review, a method proposed by Mimuro [25] took four objective metrics and plotted them in such a way that the area of a particular rhombus is claimed to correlate directly to some overall measure of vehicle handling quality. The approach is very appealing because it proposes a simple link between the four

objective metrics and driver opinions.

By applying a curve fitting technique, two of the four parameters used by Mimuro can be obtained from the available lateral transient response data. This has been done by curve fitting a transfer function to the measured transient response data. The general 2 DOF handling model is written as [28]:

This chapter takes the idea that the four metrics proposed by Mimuro relate to driver opinions, and tests the proposition by trying to correlate these metrics with the subjective data set. This represents a new approach as the work presented by Mimuro showed very little correlation with any subjective data.

In the previous linked project, not all four metrics were derived for the correlation exercise, but the tests necessary to capture these metrics were carried out. The following section details how the remaining metrics were derived, followed by the correlation process.

4.2 Parameter Identification

The relationship between the input and output of such a dynamic system has been represented by a differential equation. For analysis purposes, it is useful to express the equation in the form of a transfer function. The transfer function of a linear system is defined as the ratio of the Laplace transform of the output to the Laplace transform of the input when all initial conditions are zero. The transfer function is a property of the

system and describes the dynamic response of the system. From equation (4.1) the transfer function for yaw velocity response can be obtained, equation (4.2)

$$
\frac{r}{\delta} = a \frac{\omega_n^2}{\lambda^2 + 2\zeta\omega_n\lambda + \omega_n^2} \qquad \dots (4.2)
$$

where $a = system gain$

It can be seen from equation (4.2) that the two degree of freedom vehicle model can

be simplified to a second order transfer function. A second order transfer function has therefore been fitted to the experimental data in order to extract the parameters of interest, in this case, the natural frequency, and the damping ratio as used by Mimuro. The MatLab software has a function that will allow a transfer function to be fitted to experimental data. The method used works by finding a continuous time transfer function that corresponds to the given frequency response. Thus it was possible to convert the magnitude and phase data collected from the frequency response test into

a transfer function. The output from the software is the real numerator and denominator coefficient vectors b and a of the transfer function, as shown in equation

$$
\frac{B(s)}{A(s)} = \frac{b(1)s^{nb} + b(2)s^{nb-1} + \dots + b(nb+1)}{a(1)s^{na} + a(2)s^{na-1} + \dots + a(na+1)} \qquad \dots (4.3)
$$

The function uses an equation error method to identify the parameters from the data. This provides a best fit to the experimental data. Plots of the fitted curves to the experimental data are shown in appendix C. An example is shown in figure 4-2 of the fitted curve compared to the experimental data.

Figure 4-2: An example of fitted data against experimental data for one vehicle configuration

From equation (4.2) and (4.3) it can be seen that the value of (b) is equal to the natural

frequency, ω_n value multiplied by a gain ratio for the system. Similarly (a) constitutes

values of the natural frequency and also the damping ratio, hence values of the natural frequency and damping ratio can be obtained.

From appendix C, it can be seen that poor fits were obtained for configurations (1) and (4), hence no accurate value of natural frequency or damping ratio could be found. Examining the frequency response data in closer detail for these two configurations revealed poor coherence levels in the data recorded over the frequency range of interest, hence the poor fit.

4.3 Results Plotted in the Four Parameter Method

Using a method of data fitting, the natural frequency and damping ratio of the yaw velocity response have been extracted. The final parameter derived from the yaw velocity response is the steady state gain value. This parameter can be obtained in two ways. Firstly using the steady state yaw gain value obtained from the steady state cornering tests conducted on the steering pad corresponding to the same level of lateral acceleration as used in the impulse tests. Alternatively, it is the value of yaw gain obtained at zero frequency on the impulse tests, which relates to the steady state

condition. Using both methods as a check to ensure the correct values, the steady state gain of yaw velocity was obtained.

The fourth parameter, the lateral acceleration phase at 1Hz was taken directly from the raw lateral acceleration frequency response data.

Table 4-1 shows the four parameters that have been extracted from the data set.

Parameters from yaw velocity response data

Response from
Lat Acc data

Table 4-1: Four evaluation parameters

The main feature of the Mimuro evaluation method was being able to look at the parameters simultaneously on a rhombus plot. Figure 4-3 represents the sixteen derived results in the style presented by Mimuro.

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Figure 4-3: Results of 16 different configurations for plotted in the Mimuro style

It can be seen that the 16 configurations cover a large range of rhombus shapes. Each individual configuration plot is shown in appendix D. Mimuro gives average values with standard deviation for the four parameters for twenty compact cars, thus allowing the Chen vehicle to be compared with a range of other cars. Table 4-2 summarises these findings.

Table 4-2: Comparison of 20 compact Japanese cars Vs Chen vehicle

In addition, frequency response data collected by MIRA for four European saloon and 2 MPV vehicles has been made available. Using the same fitting technique, the natural frequency and damping ratio have been derived. The steady state yaw velocity gain values have taken from the frequency response data at zero frequency. Finally

the lateral acceleration phase lag was taken directly from the frequency response phase data at 1Hz.

Figures 4-4 and 4-5 show graphically using the rhombus style graphs how the Chen vehicle handling envelope compares to the handling envelope for 20 Japanese compact cars and the six vehicles (4 European medium sized cars plus 2 MPV's).

> 2.5 Four Parameter Evaluation Method

Figure 4-4: Comparison of rhombus plots for Chen vehicle vs. 20 Japanese

compact cars

Figure 4-5: Comparison of rhombus plots for Chen vehicle vs. 4 European medium sized saloon cars plus 2 MPV's

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Comparing the Mimuro data for 20 compact Japanese cars, and the Chen vehicle listed in table 4-2, several vehicle handling traits can be seen. The Chen vehicle on average has a higher natural frequency, indicating a higher response to transient input. The damping value of yaw velocity and phase lag of lateral acceleration at 1 Hz are also significantly higher. The steady state gain of yaw velocity is lower for the Chen vehicle than the 20 compact cars. Looking at the overall figure, it can be said that the average Chen vehicle has a tall and thin rhombus shape compared to that of the

Figures 4-4 and 4-5 show the spread of rhombus patterns produced for the Chen vehicle against data for 20 compact Japanese cars and European medium sized saloons. A feature that stands out when comparing the Chen vehicle with other vehicles is that the Chen vehicle displays larger values of damping and significantly larger yaw velocity gains compared to the European saloon vehicles. This trend suggests the Chen vehicle has an oversteer tendency, something confirmed from calculating the understeer parameter from objective data collected in the steady state tests. Interestingly the smallest Chen rhombus, indicating poor overall handling performance proposed by Mimuro, is similar to that achieved with some of the 20

• Identify questions where good subjective- objective correlation exists, thus highlighting aspects of handling where drivers are able to provide reliable feedback based on objective measurements.

Japanese cars.

The next section will appraise objective metrics with respect to the subjective data set collected by Chen in order to search for further relationships between subjective and objective measurements of vehicle handling behaviour.

4.4 Correlation of Subjective and Objective Responses

The subjective and objective data can now be brought together by using the four extracted parameters and results from the subjective evaluation in order to:

• Evaluate if questions associated with the four parameters through the correlation

procedure are similar in nature to the Mimuro interpretation of the metrics.

• Identify the most important vehicle responses which formulate the drivers' subjective ratings

Whilst drivers might agree subjectively about a particular vehicle configuration which correlates to objective data, each driver's subjective formulation may consist of different objective data. For example, one drivers rating for "lane change, turn in response", might correlate with yaw gain response, whereas another drivers ratings might correlate equally well with lateral acceleration response times. Whilst this complicates what objective measures relate to a good subjective assessment, general conclusions on subjective- objective relationships can still be made.

The approach for correlating the subjective and objective relationships has been to use regression analysis, which can be defined as the analysis of relationships among variables. It provides a simple method for establishing a functional relationship among variables. The relationship between the response variable and the predictor variables takes the form of [44]:

$$
y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_k x_{ki} + \varepsilon_i
$$

 y_i is the rating from a given question corresponding to the ith configuration

 β_k are regression coefficients corresponding to the k^h objective regressor

 x_k are the objective data for the kth regressor for the ith configuration

 ε , is the random error for the ith regressor

A regression equation containing only one independent variable is called a simple regression equation. Where there is more than one independent variable, as in this case, it is referred to as a multiple regression equation. Figure 4-6 shows the correlation method by which a linear model of driver subjective ratings is obtained in terms of objective metrics.

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Figure 4-6: Correlation process

The four sets of objective response parameters, or metrics have been compared with

the sixteen ratings relating to a particular question. If any correlation existed, a linear model of the drivers' ratings for the question based on the objective metrics would be produced. Table 3-1 in chapter 3 shows the subjective questionnaire used to collect driver ratings. The ratings used in the regression analysis are tabulated in appendix B. A number of diagnostic statistics were also calculated to be used as criteria for

 \bullet *t-values* for each regression coefficient, which indicates whether the corresponding regressor is statistically significant to the equation.

If the initial R^2 value was greater than or equal to 0.7, refinements could be made by iteratively removing any of the four regressors which did not have a t-value significant to the 95% level. This ensures that only the most relevant metrics were

judging the degree of correlation and validity of the equations produced, these were:

- \bullet \mathbb{R}^2 , the square of the multiple correlation coefficient interpreted as the amount of variability in the actual data accounted for by the regression equation
- The F statistic, which quantifies the likelihood that the selected regressors are

significant

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present in the regression equation. If the value of R^2 fell below 0.7, it was assumed no correlation existed. This assumption is in line with work reviewed in chapter 2. The correlation process is shown in the flow chart in figure 4-7.

Objective Response Data: Subjective Rating for each Driver: 4 Response metrics x 16 configurations 49 ratings x 16 configurations

Figure 4-7: Flow chart of correlation process

The statistical results are presented in grid form for each of the four regression analyses. The columns respond to each of the forty nine questions used in the study. The rows are then grouped into drivers, labelled A to H. The lightly shaded cells indicate an R^2 statistic of 0.5 or higher and the dark shaded cells show R^2 values of

The following sections present the results of the correlation analysis. The ratings from forty nine questions were regressed with each of the four metrics individually in a simple regression analysis. This process was then repeated as a multiple regression for

4.4.1 Correlation of the Four Parameters and Subjective Ratings

Indicates $R^2 > 0.5$ Indicates $R^2 > 0.7$

0.7 or higher. The empty cells indicate that the regression did not have enough points to produce a reliable regression.

Figure 4-8: Good correlation between individual parameters and individual subjective ratings

4.4.2 Questions Associated With the Four Parameters

Using results from the simple regression analysis, comparisons were made between those questions that had an acceptable level of correlation with the four parameters, and the Mimuro definition of the subjective behaviour associated with each of the four parameters. Those questions identified had at least R^2 = 0.7 correlation, a good tstatistic confidence level with random residuals. Table 4-3 shows the questions

associated with the four objective parameters.

It can be observed that some similarity exists between the Mimuro interpretations and the Chen questions. However, successful correlation occurs for only a few of the eight drivers used in the study. With each of the four parameters relating to a subjective quality, it is disappointing to see only a few drivers producing a correlation.

Table 4-3: Subjective questions correlating with each of the four parameters

From the 49 questions it has been shown that eight show a significant correlation. No unusual observations in the results have been found, i.e., no questions have been highlighted where the interpretation has no bearing on that described by Mimuro.

Questions 47 and 49 relating to vehicle oscillation and damping level have a close relationship with both directional damping and following controllability.

4.4.3 Questions Associated With All Four Parameters

Figure 4-9 shows the results from the multiple regression analysis using all four evaluation parameters. The proceeding table, 4-4 contains the list of questions, summarising in each column, where each driver made a correlation using the objective metrics with a particular question. The number of questions where a correlation existed ranged from zero to thirteen for each driver.

 65_o

Figure 4-9: Good correlations between any 4 parameters and individual subjective ratings

From the results of the correlation process, questions have been identified where drivers correlate their subjective response with objective metrics. It can be assumed that these `best' questions deal with an aspect of handling that most drivers were able

to produce an objectively based rating.

Table 4-5 highlights questions for which two or more of the drivers show correlation with objective metrics.

66

Contractor

 \mathcal{L}_{max} and \mathcal{L}_{max} . The set of \mathcal{L}_{max}

Table 4-4: Questions showing correlation with objective metrics

Table 4-5: Set of questions where 2 or more drivers have strong links between

Table 4-6 Regression results for question 12, (Steady state turning, over rough roads, cornering behaviour, ease with which line is held)

their ratings and the four Mimuro objective metrics

4.4.4 Nature of the Best Correlating Questions

From table 4-5, it can be seen that drivers correlate their subjective ratings with questions dealing with control related tasks. In particular the single lane change manoeuvre which is a complex closed loop control task. Other aspects of vehicle

handling showing correlation are the response to torque steer and also response to steering impulse. Correlation where questions relate to hand wheel feedback is understandable since it is the primary control input available to the driver. These results tie closely with results obtained by Chen [4] using all 46 metrics for the correlation process.

4.4.5 Regression Results Correlating With the Best Questions

Tables 4-6 to 4-20 show the regression equations found for each driver for the best set of questions identified in the previous sub-section. The results are presented in the same style used by Chen [4], where coefficients with a positive value are highlighted in a dark grey and negative values are light grey.

Table 4-7 Regression results for question 17 (Power change, power on, yaw response, yaw stability of vehicle at high lateral acceleration)

Table 4-8 Regression results for question 22, (Sudden braking in a turn, Roll stability)

Table 4-9 Regression results for question 23, (Sudden braking in a turn, wheel lift)

Table 4-12 Regression results for question 31, (Straight line directional stability, bump steer)

Table 4-10 Regression results for question 24, (Sudden braking in a turn, wheel lock up) Ü

Table 4-11 Regression results for question 30, (transient cornering, steering torque feedback. steering catch-un)

Table 4-13 Regression results for question 39, (Lane change, trailing throttle,

Table 4-14 Regression results for 41, (Lane change, trailing throttle, limiting factor)

ver Jή	Natural Frequency	Damping Rati	Gain Steady State C	Latacc phase	R ²	ட
B	-2.84	0.62	-4.71	-1.48	0.99	320.0
		-1.7	(0.4)	-2.08	0.84	6.6
H	-0.63	1.06	-0.62	$\sqrt{7}$	0.84	7.7

Table 4-15 Regression results for 43, (Lane change, balanced throttle, recovery)

Table 4-18 regression results for 47, (Response to steering impulse, oscillation of $v₀$ h_i $l₀$ $l₁$

Driver	Frequency Natural	Damping Ratio	Gain Steady State C	\circ Latacc phase/	$\mathbf{\hat{R}}^2$	山
A		-1.21	0.61	-0.15	0.82	9.0
E	0.24	-0.56	-0.25	0.26	0.73	5.4
$\mathbf H$	-0.34		-0.19		0.77	7.5

Table 4-16 Regression results for 44, (Lane change, balanced throttle, controllability)

Table 4-17 Regression results for 46, (Obstacle avoidance, double lane change)

Table 4-19 Regression results for 48, (Response to steering impulse, oscillation of handwheel)

Table 4-20 Regression results for 49, (Response to steering impulse, level of damping)

Despite the regression equations corresponding to each driver for a particular question being made up of the same four evaluation parameters selected for analysis, the regressor coefficients vary considerably between drivers for a particular question.

4.4.6 Other Correlation Trends

A benefit of looking at the regression coefficients, is that the sign of the regression coefficient indicates whether that metric makes a positive or negative influence on the subjective formulation. It was found that drivers tended to be in general agreement over the improvement or detriment of handling perception caused by a variation in any of the four parameters. By simply looking at the sign of the regression coefficients and ignoring the diagnostic statistics that were calculated as criteria for judging the degree of correlation and validity of the equations produced, interesting patterns emerge from the data. In figure 4-10 the data has been divided into the four parameters and subdivided into the eight drivers. The columns represent the questions, 1 through to 49. The lightly shaded cells represent a positive correlation between parameter and subjective rating, thus an increase in the given parameter will

give an increase in subjective rating. The opposite applies to the darkly shaded cells.

Empty cells imply not enough data points to produce a reliable regression.

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Figure 4-10: Trend directions between subjective ratings and four objective

parameters

Examining the data in figure 4-10, the drivers' responses for the yaw velocity damping ratio are unanimously negative and for the lateral acceleration phase lag and positive. The overall sign of the regression coefficients for yaw velocity natural frequency and steady state gain of yaw velocity coefficients between positive and

negative are less uniform. However, it can be seen that an increase in yaw rate natural frequency and lateral acceleration phase lag at 1Hz causes an increase in ratings. An increase in yaw rate damping and yaw rate gain however reduces ratings.

By plotting these findings on the rhombus plots described earlier, it can be seen which direction each metric needs to move for perceived vehicle handling improvement. Figure 4-11 opposes that suggested by Mimuro, by wanting to be deflected towards the right-higher direction, indicating an understeer characteristic as opposed to `tall and wide' in shape. This clearly shows a difference in desirable vehicle handling properties between Mimuro at Mitsubishi and the drivers used by Chen. A possible explanation for this discrepancy is that the experimental vehicle was configured to oversteer in a few vehicle configurations and drivers found this subjectively poor. Thus, their preference would be for the rhombus to shift to the upper right, signifying an oversteer tendency was disliked. This can be studied by looking at table 4-4 produced earlier and comparing the average rhombus plots for 20 compact Japanese cars to the Chen vehicle.

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Natural frequency Steady state gain Lateral acceleration phase

Figure 4-11: Directions of parameter improvement based on Chen data

Data from table 4-2 shows that two of the parameters for the Chen vehicle differ significantly from the 20 compact cars.

Figure 4-12: Comparison of Chen vehicle against 20 compact Japanese cars

From the figure 4-12 it is clear that the Chen vehicle displays a much higher value of yaw rate damping. It is therefore conceivable that this value is greater than that which test drivers would prefer, hence explaining the trends that have been seen. Whilst at first they contradict Mimuro, the drivers preferences may converge to a particular area

of the rhombus, in between values stated by Mimuro and less than that obtained with the Chen vehicle.

Drivers of the Chen vehicle indicated a lower subjective rating with increased steady state gain of yaw velocity. Given that the average gain was lower than the average 20 Japanese compact cars this preference seems unlikely. However, as a cursory analysis, comparing the average value of yaw velocity gain with work by Hill [21], the Chen vehicle has an average value that would be placed at the near optimum value for this

particular metric. This might well explain why the drivers were not unanimous in the sign of the correlation coefficients shown in figure 4-10.

Although the trend results do not all agree with Mimuro, it has been seen that the Chen vehicle differs significantly in certain handling criteria from those for 20 average compact Japanese cars. This difference is the most probable reason for the increase in damping resulting in a lower subjective opinion, implying the Chen vehicle is on the other side of the satisfactory value for yaw velocity steady state gain. It has been seen that the drivers unanimously agree that each particular parameter has

a direction for desirable handling. The exception to this has been where the particular

metric of interest is suspected to lie in its satisfactory area, making drivers evaluations

more difficult, thus giving a random spread of '+'ve and '-'ve regression coefficients.

This provides strong evidence that the four chosen parameters do capture elements of

vehicle handling behaviour that drivers are able to assess subjectively.

To test the hypothesis that the Chen vehicle is on the other side of optimum vehicle handling in many of the vehicle configurations, an experiment to determine this was conducted. Examining the rhombus patterns for the Chen vehicle configurations, it can be seen the vehicle displays high values of yaw velocity damping ratio and phase delay of lateral acceleration, indicating an oversteering vehicle tendency. By removing objective data for the vehicle configurations that display oversteer

characteristics it can be seen if the same trends are repeated. Figure 4-13 shows the

results of the trend analysis but this time without the oversteering vehicle configurations being included.

Analysing the trend results, it can be seen for increases in all four of the four evaluation parameters, bar the phase delay of fateral acceleration, increase in the subjective rating.

Figure 4-13: Trend analysis results without oversteering vehicle configurations

This differs from the results obtained earlier, and is in closer agreement with work by

4.5 Conclusions

The proposition that four metrics relate to driver opinions of vehicle handling has

Mimuro. It is surprising to find the trend result for the phase delay is negative, as the is generally regarded to be a poor subjective quality. This simple trend analysis without the oversteering configurations has shown the Chen vehicle to conform more closely to previous research, with vehicle configurations which show more stable behaviour, i.e. in the understeering regime. average phase value is still higher than that of the other vehicles. A large phase delay

been investigated. Using the method of curve fitting, two of the four metrics proposed by Mimuro have been derived, the other two were taken directly from the raw data. It was seen that the experimental vehicle used in the previous linked project covered a large vehicle handling envelope, expressed by plotting the four metrics in a rhombus pattern. Interestingly, the area of handling covered by the experimental vehicle shown on the rhombus style of plot was shown to be quite different for a range of compact vehicles described by Mimuro.

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Links between subjective ratings and the four metrics were investigated using the classical simple regression technique. Very little correlation using this technique was found between the two sets of data. Further statistical analysis was conducted using the technique of multiple regression, to see if relationships could be found that linked subjective ratings as a function of up to three objective metrics. Using multiple regression compared to simple regression yielded more questions where correlation existed between ratings and metrics.

Upon inspection of the results using the regression analysis, the signs of the coefficients in the regression equations proved to be very interesting. By looking at how the sign of a metric improved or degraded subjective ratings, it was found that the results obtained here appear not to be in close accord with Mimuro's findings. However, an important observation is that the objective metrics obtained using the experimental vehicle are not particularly close with those obtained by Mimuro. Hence, they are concentrated in a different area of the rhombus plot from which Mimuro based his findings. This hypothesis was tested by removing the objective data from the vehicle configurations that showed oversteer behaviour. A repeat of the analysis showed that that the trends agreed with Mimuro's findings. The results

generated provide evidence to support the idea originally proposed by Mimuro.

5. Development of Four Parameter Evaluation Method

5.1 Introduction

It has been seen using only the four evaluation parameters, for two or more drivers that only six questions correlate well. This chapter extends the four parameter evaluation concept to include further metrics to investigate other approaches to improving the understanding of subjective vs. objective correlation in vehicle

handling. Chapter 4 identified subjective objective links with questions related to handwheel feedback, therefore it seems logical to include metrics in the regression analysis that relate to steering feedback. In addition, other parameters that relate to subjective qualities shall be included in further regression analysis. From the literature review, several objective metrics describe properties of the vehicle that may be related to subjective qualities.

- Transient: Steady state roll gain ratio, ρ . The peak roll angle taken from a transient lane change manoeuvre is compared to the roll angle achieved at the same level of lateral acceleration under steady state conditions.
- Understeer parameter, K, calculated from the steady state data collected for each of the 16 vehicle configurations.
- 9 TB characteristic. This value developed by Lincke et al [19] is defined as the product of the response time of the yaw velocity up to the first peak and the steady state side slip angle achieved from the step input test, more commonly referred to

5.2 Additional Objective Metrics

The following lists the additional metrics to be used in the correlation analysis and details of how each has been derived. There follows a complete list of the metrics to

be used in the regression analysis summarised in table 5-1.

as the J-turn test. The Chen J-turn data set for many of the sixteen different

configurations does not contain a distinct peak, hence the response time to achieve 90% of the steady state value was obtained and used as a more reliable indication of dynamic performance. However, data for the side slip angle was not recorded for the J-turn manoeuvre tests conducted by Chen. It was felt acceptable however to use side slip data recorded from the steady state steering pad tests for the calculation of the TB value.

- Effective directional time constant, Te. Te is a representative measure of the vehicle phase lag to which the driver is most sensitive [12]. Using data from the frequency response tests it is estimated by determining the frequency at which the yaw velocity to steering wheel angle response has 45 degrees of phase lag, and taking the reciprocal.
- Steering torque. Values of steering torque measured at different levels of lateral acceleration, $-/- 0.1$, 0.3, 0.5g, derived from the steady state steering test.

Table 5-1: Objective metrics used in correlation analysis

5.2.1 Chen Vehicle Data Shown On Weir/ DiMarco Diagram

A critique for satisfactory vehicle handling has been developed by Weir and DiMarco [12] whereby a vehicle's steady state yaw velocity gain is plotted against the effective time constant, Te. The latter metric is derived from frequency response data and uses the reciprocal of the frequency at which the phase lag of yaw velocity reaches 45 degrees. The reference [12] highlights an area on the plot for satisfactory vehicle handling, based on their research conducted. Figure 5-1 presents the 16 configurations achieved by the Chen experimental vehicle on the Weir and DiMarco diagram.

It can be seen that half of the vehicle configurations fall within the boundary defined by Weir and DiMarco and the others are distributed randomly around the optimum area. This indicates a good spread of handling behaviour for the different set-ups used by Chen. This also infers that drivers should be able to detect noticeable differences in the handling behaviour between different configurations.

Hill [21] proposed that there are preferable areas within the Weir and DiMarco diagram. Subjective ratings were superimposed on the corresponding objective metric results and used to generate possible contour lines, see figure 5-2.

Figure 5-1: Chen vehicle shown on Weir and DiMarco diagram

Subjective rating of 7.8

Subjective rating of 7.4

Subjective rating of 7.2

Figure 5-2: Subjective contour lines shown on Weir and DiMarco plot, Hill, [21]

Mimuro stated that the area of the rhombus used to describe vehicle handling denotes overall handling ability. This hypothesis was tested by plotting the value of the area for each experimental vehicle configuration on the Weir and DiMarco diagram. Figure 5-3 shows next to each asterisk, the area calculated for each configuration. No value of area could be calculated for vehicle configuration 1 and 4.

Weir / DiMarco plot for Chen Vehicle

0.6

Figure 5-3: Rhombus areas for Chen vehicle plotted on Weir and DiMarco diagram

It can be seen that around the optimum area suggested by Hill, several of the Chen vehicle configurations display large rhombus areas, thus showing agreement, that the size of the rhombus plot does indicate favourable handling behaviour. It can be seen that configuration 12 has a large rhombus area and lies outside of the satisfactory area denoted by Weir and DiMarco. Looking at the shape of the rhombus for this configuration, the vehicle is seen to have a large oversteer tendency, but also a large

area. Therefore although rhombus size does have a bearing on handling performance,

the shape of the rhombus is also of significant importance. However, there are several

configurations with much lower rhombus areas that lie close to the optimum area on

the diagram, which contradicts that proposed by Mimuro.

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5.3 Investigation of Additional Objective Metrics with Subjective Ratings

In this section, the additional objective metrics have been subjected to both simple and multiple correlation analyses with the subjective data set. The simple linear regression analysis has been conducted to see if the drivers were able to agree that each metric should be of a certain sign and that each metric is related to a particular subjective quality.

The statistical results are presented in grid form for the regression analyses. The columns respond to each of the forty nine questions used in the study. The rows are then grouped into drivers, labelled A to H. The lightly shaded cells indicate an R^2 statistic of 0.5 or higher and the dark shaded cells show R^2 values of 0.7 or higher.

5.3.1 Correlation of the Individual Additional Parameters With Subjective Ratings

This section presents the results of the simple linear regression correlation analysis. As before, the ratings from forty nine questions were regressed with each of the additional metrics individually in a simple regression analysis. Table 5-1 lists all the metrics used in the simple regression analysis.

The empty cells indicate that the regression did not have enough points to produce a reliable regression.

Again, it can be seen that the number of questions showing significant correlation is low.

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Figure 5-4: Simple regression analysis results with additional metrics

5.3.2 Questions Associated Individual Parameters

Using results from the simple regression analysis, comparisons were made between those questions that had an acceptable level of correlation with the parameters, and the author's definition of the subjective behaviour associated with each of the four parameters. Those questions identified had at least R^2 = 0.7 correlation, a good tstatistic confidence level with random residuals. Table 5-2 shows the questions associated with the nine objective parameters.

Table 5-2: Subjective questions correlating with each of the parameters

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Results from the simple regression analysis for each of the additional metrics has

highlighted only a few questions that show correlation with the subjective data. Surprisingly no correlation has been found with the understeer parameter and steering torque values for any of the subjective questions. This is despite the fact that in the subjective questionnaire there are several questions relating to steering torque feedback and how the vehicle maintains its course under steady state conditions. Questions where significant correlation has been shown relate to the closed control

loop tasks, in particular the response to steering impulse questions. These findings are

linked closely to those found in the previous correlation analysis using the four parameter evaluation metrics.

5.3.3 Other Correlation Trends

Using the same procedure used in chapter 4, the sign of the regression coefficient in each regression equation has been examined to see whether that metric makes a positive or negative influence on the subjective formulation. In figure 5-5 the data has been divided into the eight parameters and subdivided into the eight drivers. The columns represent the questions, 1 through to 49. The lightly shaded cells represent a positive correlation between parameter and subjective rating, thus an increase in the given parameter will give an increase in subjective rating. The opposite applies to the darkly shaded cells. Empty cells imply there was not enough data points to produce a reliable regression.

Figure 5-5: Summary of trend directions between subjective ratings and

additional parameters

Looking at the results, the data highlights several trends that would be expected, but also others not expected. Firstly the transient to steady state roll gain ratio suggests drivers prefer a vehicle to roll more in a transient manoeuvre than a steady state one for the same level of lateral acceleration. This does not follow the original thought that the car would be more predictable, hence more subjectively pleasing if the car were to roll by the same amount in both a transient and steady state manoeuvre.

Drivers prefer the vehicle to have an increased understeer parameter. This has to be

considered in relation to the levels of the understeer parameter achieved with the Chen vehicle. The average value of K, was found to be 1.0 deg/g which is close to the neutral steer condition. From the literature, values of K ranging between 2-6 deg/g are satisfactory, therefore it is not surprising to see drivers indicating a higher appraisal for increased values of K.

The driver trend results for the torque metrics are not unanimous, thus indicating no clear preference whether higher or lower values would be of any subjective improvement. The Chen vehicle steering geometry was not modified specifically to alter the steer torque, thus differentiation between steering torque may have been difficult between the 16 vehicle configurations. Reasons for the variation in the sign of the regression coefficients is discussed further below.

The trend results for the TB parameter all show increased driver ratings for a smaller value of TB. This follows as the vehicle would respond more quickly to a drivers steering input, but also drivers judge a vehicle more favourably if a small side slip angle is required under steady state conditions.

Reduced values of the effective time constant, Te, show an improvement in drivers'

subjective ratings. Again this highlights drivers' desire for a responsive vehicle.

It is important to remember that upper and lower limits can not be specified for the objective metrics being examined from the current work. Based on the handling

properties of the Chen vehicle, the trend analysis can clearly indicate in which direction a metric should move for an increase in subjective opinion. Where the trend is a mix of both $\dot{ }$ + ve and $\dot{ }$ - ve cells there are some possible explanations for this. The metrics may not relay how drivers are forming subjective opinions, or that the metric is not greatly affected by the changes made to the vehicle configuration. In

addition the vehicle may display satisfactory values for the metric under analysis, and thus driver opinions would be roughly split equally.

5.3.4 Metric Selection Process

An associated problem when using several response metrics in multiple regression analysis is that some metrics interrelate or duplicate other vehicle characteristics. This

arises from the presence of strong linear relationships among the predictive variables.

This situation can lead to the individual regression coefficients being unstable, situations known as multicollinearity and singularity, which result in misleading predictive characteristics of the regression equations. Multicollinearity is when variables are highly correlated (0.90 and above)[45], and singularity is when the variables are perfectly correlated

By identifying unsuitable metrics, these can be eliminated from the regression analysis. Statistical programs commonly screen for multicollinearity and singularity by computing the squared multiple correlation of a variable. The squared multiple correlation is computed where a variable is compared to all the rest of the included variables, if the results show a high correlation the variable is multicollinear. If the

variable is perfectly related to the other variables then singularity is present.

A second method commonly used is to examine the Variance Inflation Factor (VIF) between a variable and the rest of the variables. It is defined as:

$$
VIF(X_i) = \frac{1}{1 - R_i^2}
$$

where

 $VIF(X_i)$ is the variance inflation factor corresponding to the *ith* regressor.

 R_i^2 is the multiple regression coefficient when a least squares regression is calculated using X_i as the output and the remaining regressors as the input.

A general rule is that VIF's in excess of 10 indicates unacceptable multicollinearity.

Any regressors with a high VIF were therefore discarded for the multiple regression

analysis.

5.3.5 Regression Analysis With Additional Metrics

Taking the metrics listed in table 5-1, checks for collinear behaviour were done and any metrics displaying collinearity amongst them were systematically removed using the techniques described earlier. The set of metrics used for the regression analysis is listed in table 5-3.

Table 5-3: Objective metrics used in regression analysis

The results of the multiple correlation analysis are presented in table 5-4. The table

identifies questions for which drivers were able to provide objectively correlated

ratings. It can be assumed that these `best' questions deal with an aspect of handling

that most drivers were able to produce a reliable rating.

Table 5-4: Questions where ratings correlated with additional objective metrics

Questions where half or more of the drivers show correlation with objective metrics have been identified for further examination and are shown in table 5-5.

Table 5-5: Set of Best Questions where Drivers Formulate Subjective Rating

5.3.6 Nature of the Best Correlating Questions

From table 5-5, it can be seen that drivers correlate their subjective ratings with questions dealing with control related tasks. In particular with questions associated with lane change manoeuvres which are complex closed loop control tasks. Other aspects of vehicle handling showing correlation are the response to torque steer and also response to steering impulse. Correlation where questions relate to hand wheel feedback is understandable since it is the primary control input available to the driver. These results tie closely with results obtained by Chen using all 46 metrics for the correlation process.

5.3.7 Regression Results Correlating With the Best Questions

Tables 5-6 to 5-13 show the regression equations found for each driver for the best set

of questions identified in the previous sub-section. The results are presented in the same style used by Chen where coefficients with a positive value are highlighted in a dark grey and negative values are light grey.

Table 5-6 Regression results for question 6, (Steady state turning, over smooth roads, steering torque feedback, indication of magnitude of lateral acceleration)

Table 5-7 Regression results for question 16 (Power change, power on, yaw response, progressiveness of yaw rate response)

Table 5-9 Regression results for question 41, (Obstacle avoidance, single lane change, trailing throttle, limiting factor)

Table 5-10 Regression results for question 44, (Obstacle avoidance, single lane change, balanced throttle, Controllability)

 $T11 F \cap T$ Il stability)

Table 5-11 Regression results for question 46, (Obstacle avoidance, double lane

change)

Table 5-12 Regression results for question 48, (Response to steering impulse, oscillation of handwheel)

Table 5-13 Regression results for question 49, (Response to steering impulse, level of damping)

The results of the correlation analysis show that for a given question, drivers' ratings

are best modelled using different objective metrics. However, what is clear is that for half or more of the drivers, good levels of correlation are found only with certain questions.

Looking at the signs of the metrics in the regression equation, it can be seen for the phase delay of lateral acceleration at 1Hz and the understeer parameter, K, the trends follow that expected from earlier trend analysis. In addition, where the trend analysis seemed inconclusive, the sign of these particular metrics appears random in the driver models. It is however surprising to find a random spread of positive and negative coefficients for the TB metric which had displayed a uniform pattern in the trend analysis. With each regression equation however, the high degree of significance

associated with each metric's regression coefficient assures that each metric is statistically significant.

5.4 Inclusion of `Best' Chen Metrics

This section brings together the metrics from the last section together with a best set of metrics identified by Chen. Chen highlighted metrics which drivers had good, uniform agreement as to the true effect. In addition, the effect of the metric was identified as being unequivocally positive or negative regardless of the question asked. Table 5-14 categorises the metrics according to whether their effect is uniform and/ or unequivocal.

Table 5-14: Metric identification by Chen

Analysing the columns of metrics, general patterns can be seen. The first column of unequivocal and uniform metrics contains mostly frequency response data with the remaining being derived from the other tests. All the metrics that have an unequivocal effect but are not necessarily uniform bar one are derived from the step input test. Considering all of these metrics, it is interesting to note that they all relate to transient behaviour except for d(sslip)/0.4. The final column of metrics that display a uniform effect are derived from the step input and steady state tests.

5.4.1 Correlation Analysis With Ash and Chen Metrics

A multiple regression analysis has been conducted with metrics taken from the current work together with a set of `best' metrics identified by Chen which were shown to have a unequivocal and uniform effect on ratings given by drivers. Any variables showing collinear behaviour were systematically removed using the techniques described earlier, leaving a set of metrics displaying no collinearity amongst them. These are listed in table 5-15.

Table 5-15: Objective metrics used in regression analysis

Table 5-16 highlights the questions for which drivers were able to formulate an answer using the new objective metric data set.

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Table 5-16: Questions where ratings were modelled by objective metrics

Questions have been further identified where half or more of the drivers have been able to formulate a rating based on the objective metrics used in the regression analysis. The questions marked with an asterisk are those where five or more of the drivers have formulated a rating based on the objective ratings. This has been done to allow a comparison with the previous work by Chen to examine the number and types of question which have been identified by drivers using a much smaller set of objective metrics than that used by Chen.

Table 5-17: Questions where objective metrics are found to model majority of

drivers ratings

5.4.2 Nature of Best Correlating Questions

The number of questions where a significant correlation has been found by half or more drivers using the new set of metrics has increased. The questions can be seen to relate to all the different areas of handling, but the most common question type relates

to the lane change manoeuvre and other transient types of question, identified as being

related to closed loop handling manoeuvres.

5.4.3 Comparison With Chen Results

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This section compares results from the correlation exercise using the current approach of using the minimum number of metrics compared to the method adopted by Chen, using 46 metrics. The Venn diagram shown in figure 5-6 highlights the questions

where the majority of drivers are able to correlate their ratings for the two quite different sets of objective metrics.

Figure 5-6: Comparison of links found between subjective and objective data

using new approach and previous linked project results. Each number

represents those questions where the majority of drivers found correlation.

5.5 Addition of Unequivocal Metrics

To further try and improve the correlation links, the next step was to include the set of metrics identified by Chen as being unequivocal in effect on drivers' ratings. In order

to minimise the set of metrics used in the regression analysis some metrics were removed thus keeping the number used down to sixteen. Those metrics eliminated were selected by conducting a correlation exercise with the unequivocal and uniform metrics and the unequivocal metrics and seeing which metrics were least used in the ratings models. A search for multicollinearity was then conducted to identify and remove metrics that displayed likeness amongst each other. Table 5-18 lists the metrics used.

Table 5-18: Objective metrics used in regression analysis

Table 5-19 highlights questions where models to the drivers ratings produced using the current set of metrics.

It can be seen the number of ratings to questions that have been modelled using the current set of metrics has increased, ranging from fourteen to thirty five per driver. Table 5-20 highlights the questions where the majority of drivers ratings were ^u modelled by the set of metrics.

Table 5- 19: Questions where ratings were modelled by objective metrics

steer kickback and body roll. $\frac{1+\epsilon}{2}$

Table 5- 20: Questions where objective metrics are found to model majority of drivers ratings

5.5.1 Nature of the Best Correlating Questions

The number of questions where the majority of drivers' ratings has been modelled has increased with the new set of metrics to twenty one. The questions highlighted cover all seven question groups with the exception of the Sudden braking in a turn group. Examining the nature of the questions, the majority relate to control tasks, primarily the single lane change manoeuvre and in addition, those questions which relate to

5.5.2 Comparison With Chen Results

The Venn diagram shown in figure 5-7 shows the overlap in questions where models to drivers ratings have been found using the full Chen objective data set and the reduced data set used in the current correlation exercise.

Figure 5-7: Comparison of links found between subjective and objective data using new approach and previous linked project results. Each number represents those questions where the majority of drivers found correlation.

Besides the increase in the number of questions modelled by the ratings, there is more

The reduced set of metrics -The metrics used for the correlation exercise with drivers subjective ratings have been derived from the three main standard handling manoeuvres used to capture vehicle behaviour. Most of the metrics are derived from the frequency response test which is used to capture the transient response of the vehicle. It perhaps should come as no surprise to find that most of the questions found to have been successfully modelled as a function of objective metrics are transient

overlap with ratings being modelled by Chen's full set and the somewhat smaller set used now.

5.6 Discussion

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based. That said, in previous work by Chen, only one steady state turning question

was found to show good correlation for the majority of drivers by the full set of 46

metrics. Moreover, using the current set, three steady state turning questions have

shown good correlation with objective metrics using the reduced set.

The reduced set of questions - Whilst it is clear which questions have been successfully modelled by using objective metrics to predict subjective ratings, closer examination of these questions is necessary.

Of primary interest is the group of obstacle avoidance based questions. Good correlation was found with questions 39-41 and 43-45 which are two sets of questions which are repeated, but are answered with the vehicle firstly under trailing throttle conditions and then with a balanced throttle. The subjective data analysis showed the

majority of the drivers answered these questions in a similar manner. This can be interpreted in a number of ways. Firstly, looking at each set of three questions, the questions are interpreted by the drivers in the same way, meaning that the language used in the questions may be ambiguous or alternatively, the particular vehicle used might have displayed similar handling performance relative to the reference vehicle. Examining the likeness shown between the two sets of questions dealing with trailing and balanced throttles, it seems apparent the vehicle displayed similar handling traits for these two conditions. Consultation with MIRA's Vehicle Dynamics Department confirmed that whilst a vehicle may behave in a similar manner for these two conditions, they warned that vehicles can display a marked difference in handling under these two different situations. Therefore it would not be wise to remove one of the sets of questions. However, the obstacle avoidance manoeuvre is to ensure the controllability of the vehicle under emergency conditions. Moreover, drivers are likely to either release the throttle and or brake making little use for the questions relating to balanced throttle. Therefore the most important set of questions relate to the trailing throttle condition. Analysing the set of questions further, it can be said that recovery behaviour is a subset of the controllability of the car. If a car is difficult to control, then it follows that recovery should be difficult. To best examine this, testing with a range of vehicles would determine if there was indeed noticeable difference in

5.7 Conclusions

From further analysis of the data set containing subjective ratings and objective metrics obtained from vehicle handling experiments the following conclusions were reached:

The results were compared with those described by Mimuro [25], who used a much simpler approach involving only 4 key metrics, in contrast to the 46 metrics used here. The outcome, however, was somewhat equivocal, since in some cases these simple metrics agreed with the subjective correlations suggested by Mimuro and in some cases they did not.

This led to a proposal for a revised subset of metrics involving some completely new ones plus some of those used previously. The results of correlating this subset of 16

- " Tests I he "obstacle avoidance" and "response to steering" impulse tests
- Subjective questions The questions listed in table 5-20.
- Measured vehicle metrics The objective metrics listed in table 5-18.

metrics with the subjective ratings showed considerable improvement over previous work as evidenced by the confidence levels associated with the correlation functions/ equations of the form;

Subjective rating $=$ fn (objective metrics)

The following features of the experimental data were found to be the most important in relating to subjective ratings to objective metrics.

Overall, this correlation exercise has revealed significant areas in which driver judgements can be linked with measured vehicle behaviour.

6. Non Linear Correlation Analysis

6.1 Introduction

The methodology employed thus far to identify links between the subjective and objective data has relied upon finding linear relationships between the two sets of data. Considering the vehicle system, it is known that due to non-linearities in tyre behaviour the vehicle will not behave in a linear manner when subjected to cornering

manoeuvres under some conditions, for example at middle/ high lateral accelerations.

In addition, because the human evaluator is giving a purely subjective rating to some given stimuli, it cannot be assumed they would perceive any linear change in stimuli in a linear manner.

Due to the potential for both the vehicle system and driver subjective ratings to display non-linear properties, it follows that a non-linear approach to establishing links between the subjective and objective data should be used.

From the literature review, recently published work has claimed very good levels of correlation between driver subjective ratings and vehicle objective metrics relating to driveability issues using artificial intelligence, in particular neural networks and fuzzy

This chapter reviews the non-linear methods that have been used to establish links between two sets of data. From each review, a methodology is presented which has then been used to establish links between the subjective and objective data. The results are presented in the same style as the previous two chapters to allow direct comparison of results.

6.2 Neural Network Introduction

A neural network is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the neuronal function found in the

human nervous system. The basic biological function of a neuron is to discharge a signal to an adjoining neuron or set of neurons once a particular predefined threshold has been passed. The processing ability of the network is stored in the inter-unit connection strengths, or weights, obtained by a process of adaptation to, or learning from, a set of training patterns. This ability to learn is the desirable function of neural networks.
The basic function of all artificial neural networks is to accept a set of inputs (input vector) and produce a corresponding set of outputs (output vector), using a vector mapping technique. This general view is shown in figure 6-1.

Neural networks are made up of interconnections of neurons with each connection having an associated weighting value. Neurons fulfil two functions which are, firstly calculating the weighted sum of its inputs pw and adding a bias value, b, which is independent of the network inputs and secondly, the sum of the weighted input pw and b, n is passed to the transfer function f which produces an output, a . This is

Figure 6-1: General view of neural network

6.2.1 Neural Network Components

represented in figure 6-2.

Figure 6-2: Representation of an artificial neuron

Some of the most commonly used transfer functions are presented in figure 6-3.

Figure 6-3: Example transfer functions used in neural network designs

There are many other transfer functions that may be used in the design of a neural network. Figure 6-3 shows some of the most widely used functions.

There are two distinct types of neural network- static and dynamic. Where signals flow only from input to output, the feed-forward network, the mapping relationship between input and output vectors is *static*. Figure 6-4 shows an example of a single layer feed-forward static network with three input and output nodes. In a *dynamic*

6.2.2 Neural Network Construction

network, the output produced depends upon previous but also current inputs and or outputs. Adding feedback to the network allows dynamic mapping, shown in figure 6- 5.

Figure 6-4: A feed-forward network with three input and output nodes

The behaviour of feedback networks is dependent on the initial inputs and the system can be unstable when learning. Feed-forward networks are best suited for applications that are judged primarily on short learning times, not modelling precision. Static networks are commonly used for modelling tasks where the system outputs are not a function of previous outputs. Unlike the feedback networks, the static networks are unconditionally stable.

Figure 6-5: Feedback network with three nodes

Single layer networks are limited in their modelling ability [46]. However, to overcome these limitations, multi-layer networks, which contain hidden layers between the input and output have been developed. The configuration of a multi-layer network is shown in figure 6-6.

Figure 6-6: Multi-layer feed-forward network with three nodes in each layer

Multi layer networks may contain different transfer functions between layers. Work in this field has shown that networks with a single hidden layer [47] are capable of approximating any function, with a finite number of discontinuities. The most common used transfer functions are a sigmoid in the hidden layer, with a linear output layer.

6.2.3 Neural Network Design

In the design of a neural network, several factors must be considered depending on the application. Each network must have defined the size of the network, the number of nodes in the hidden layer, the type of transfer function used and what connections are

Determination of number of layers in a neural network

As discussed earlier, single layer networks are limited in their modelling ability.

In a multiple layer network, using non-linear transfer functions allows the network to learn non-linear and linear relationships between input and output vectors. Having a linear output transfer function allows the network to produce output values between -1 and $+1$.

Hornik [48] has shown for any continuous function with bounded input and output variables, the function can be modelled by a network comprising a single hidden layer. For a discontinuous function, Sontag [49] suggests that a neural network with two hidden layers should be used.

Hidden layer nodes

The size of the hidden layer and properties of the activation function determines the capabilities of the neural network to learn a desired function. Increasing the number of

nodes enables the network to learn more complex functions.

If the desired output from a network needs to be constrained, for example 0 or 1, then the output layer should use a sigmoid transfer function.

Network Connectivity

This section covers some of the terminology used to describe the different types of

connections used in network designs. Connections between nodes in separate layers are defined as interconnections. Connections between nodes in the same layer are termed intraconnections.

As mentioned in a previous section, neural connections can be either feed-forward or feedback, depending on the function approximation, be it static or dynamic.

6.2.4 Neural Network Learning

The neural network learns by adapting the connection weights employed within the network. There are two main types of learning algorithms; supervised and unsupervised. In supervised learning, the learning rule is provided with a corresponding target to go with each input. In unsupervised learning, there are no target outputs made available, weights and biases are therefore modified in response to network inputs only.

Before applying a neural network learning algorithm, several decisions have to be made, they are:

- Choice of learning algorithm
- Representation of the data
- Choice of learning algorithm parameters
- Training time available
- Method of initialising the network weights
- Choice of activation function

Choice of learning algorithm

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There are two main supervised learning algorithms used, known as reinforcement and

error correction. Reinforcement learning is used in systems that offer only qualitative information about the system state, typically binary failure signals.

Error learning uses only measurable outputs and is used in applications where quantitative information is available. The aim is to minimise the error norm by adjusting the network weights proportionally to the negative gradient of this norm.

The most popular method for determining the error weight gradient is the backpropagation algorithm [50]. Backpropagation learning is implemented in two

phases: feed-forward and feedback. In the feed-forward phase all the neural outputs and activations are calculated and stored. In the feedback phase the error is backpropagated through the network enabling each weight update to be calculated. Once all the weight corrections are known they are applied to the existing weights.

Representation of data

Data representation simply defines the form of the training and how the test data is presented to the network. For supervised learning, training data is provided in pairs; input value and the corresponding output value. The network then minimises the error between the desired and actual outputs for any given input.

Training data can be used in two ways, either on-line or presented as a batch. Presenting data on-line, the learning algorithm updates the network parameter values after each data pair whereas when the data is presented in a batch, the weight updates are accumulated and applied after the whole batch has been processed.

The range and number of input values used to stimulate a network is important when a network learns the properties of a function. If the number of inputs is too small then overfitting can occur [51]. Overfitting is when there is a large distance between the points on the modelled function and interpolation between these points is poor. Simulation points should be presented randomly to ensure the network does not learn the manner in which the input is presented.

training the network can start. At present there is no systematic method of selecting η and β for a particular learning task. Increasing the learning rate allows the algorithm to take larger steps in finding the minima and therefore should reduce the training time. However, if the learning rate is large, the steps taken may be too large which can result in the neural network not converging. The momentum term helps to reduce learning time by adding a proportion of the previous weight to the current weight. The added size of step increases the distance traveled towards a minima if the gradients of

The data used to test the network must be different from that used for training to in

order to evaluate the interpolation capability of the trained neural network.

Selection of the learning algorithm parameters

For each network, a learning rate η , and momentum factor β must be specified before

the error-weight curve continues in the same direction for consecutive time steps and conversely decreases the distance traveled away from a minima if the gradients change from one time step to another. The size of the momentum factor β determines the proportion of the previous weight update to apply. If the size of the momentum factor is too small then the impact of the factor will be insignificant, whereas too large a value of the momentum factor could cause instability problems.

Initial weight values

These are usually set to random values.

The user must decide depending on the function to be approximated which transfer function(s) to use, depending on the number of layers used in the network. Using different transfer functions directly effects the type of output given by the network, be it constrained (0 or 1) or any value between 0 and 1 or -1 and 1.

Choice of activation function

6.2.5 Design of Network To Be Used In the Correlation Exercise.

From the review of neural networks and considering the type data being used the following type of neural network was implemented to try and find relationships that may exist between the subjective and objective data sets.

The neural network chosen has a static network structure with a single hidden layer using a non-linear transfer function, in particular the tan-sigmoid. A linear transfer function has been used in the output layer.

To determine the number of neurons to have in the hidden layer, a series of analyses

using the two data sets was conducted and is discussed in detail in section 6.5.2.

6.3 Introduction To Fuzzy Logic

This section introduces the second non-linear approach used to find correlation between the subjective and objective data set. The fuzzy logic method lends itself to this type of data well due to the nature of subjective data, collected by humans which scientifically is not precise data. The fuzzy approach offers the benefit of being good at trading off significance and precision – something us humans are good at. Fuzzy logic is tolerant of imprecise data and can be used to model non-linear functions or arbitrary complexity. This process is made easily possible using adaptive techniques, such as Adaptive Neuro-fuzzy Inference Systems (ANFIS).

Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth - truth values between "completely true" and "completely false". It was introduced by Dr. Lotfi Zadeh [52] of UC/Berkeley in the 1960's as a means to model the uncertainty of natural language.

Zadeh [53] stated that rather than regarding fuzzy theory as a single theory, the process of "fuzzification" should be regarded as a methodology to generalise any specific theory from a crisp (discrete) to a continuous (fuzzy) form.

6.3.1 Fuzzy Subsets

Just as there is a strong relationship between Boolean logic and the concept of a subset, there is a similar strong relationship between fuzzy logic and fuzzy subset

theory. In classical set theory, a subset U of a set S can be defined as a mapping from

the elements of S to the elements of the set $\{0, 1\}$,

 $U: S \to \{0, 1\}$

This mapping may be represented as a set of ordered pairs, with exactly one ordered pair present for each element of S. The first element of the ordered pair is an element of the set S, and the second element is an element of the set $\{0, 1\}$. The value zero is used to represent non-membership, and the value one is used to represent membership. The truth or falsity of the statement x is in U is determined by finding the ordered pair whose first element is x. The statement is true if the second element of the ordered pair is 1, and the statement is false if it is 0.

Similarly, a fuzzy subset F of a set S can be defined as a set of ordered pairs, each with the first element from S, and the second element from the interval [0,1], with exactly one ordered pair present for each element of S. This defines a mapping between elements of the set S and values in the interval [0,1]. The value zero is used to represent complete non-membership, the value one is used to represent complete membership, and values in between are used to represent intermediate degrees of membership. The set S is referred to as the universe of discourse for the fuzzy subset F. Frequently, the mapping is described as a function, the membership function of F. The degree to which the statement x is in F is true is determined by finding the ordered pair whose first element is x. The degree of truth of the statement is the

second element of the ordered pair.

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In practice, the terms "membership function" and fuzzy subset get used interchangeably.

6.3.2 Membership Functions

A membership function is a curve that defines how an input is mapped to a membership value. There are many standard functions that can be used to describe the fuzzy set, figure 6-7 shows four of the most commonly used.

The point of fuzzy logic is to map an input space to an output space, and the primary method for doing this is a list of if-then statements called rules. All rules are evaluated in parallel and the order they are presented in does not matter.

Figure 6-7: Examples of fuzzy sets defined by standard functions

6.3.3 Logic Operations

La Remembering that fuzzy logical reasoning is a subset of standard boolean logic, if the

fuzzy values were kept at the extreme values, 0 (completely false) and 1(completely

true), standard logical operations will hold, see figure 6-8.

Figure 6-8: Standard truth table

A mathematical function can be applied to truth table allowing other values besides 0

and 1 to be used, which does not effect the outcome of the truth table. This gives

fuzzy logic the ability to reply to a yes-no question with a not quite yes-or-no answer.

The fuzzy sets and fuzzy operators described so far are only the subjects and verbs of fuzzy logic. To complete the sentence, conditional statements, if-then rules must be added in order to make fuzzy logic useful.

A single fuzzy if-then rule assumes the form

if x is in A, then y is B

where A and B are linguistic values defined by fuzzy sets on the universes of discourse X and Y respectively. The if-part of the rule x is in A is known as the

antecedent, and the then-part of the rule y is B is called the *consequent*.

Interpreting if-then rules is a three part process, broken down as follows:

- The antecedent part of each rule must be resolved to a degree of membership between values of 0 and 1. If there is only one part to the antecedent, this is the degree of support for the role.
- Apply fuzzy operator. If there are multiple parts to the antecedent, fuzzy operators are applied and the antecedent is resolved to a single number between 0 and 1, this being the degree of support for the role.
- \bullet Apply implication method. The degree of support from the antecedent is used to

shape the output fuzzy set. The consequent of a fuzzy rule assigns an entire fuzzy set to the output.

6.3.4 Fuzzy Inference Systems

Fuzzy inference is the actual process of mapping from a given input to an output using fuzzy logic. The process involves the three parts discussed in the previous sections; membership functions, fuzzy logic operators and if-then rules.

There are two styles of fuzzy system, the Mamdani and Sugeno system. The system referred to so far is the Mamdani type, which is the most commonly used fuzzy methodology. In this system the output from the membership functions are expected to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. It is possible in many cases however to use a single spike as the output membership function rather than a distributed membership function. This is known as a *singleton* output membership function, which can be

thought of as a pre-defuzzified fuzzy set. This method improves the efficiency of the defuzzification process because it simplifies the computational process required by the more general Mamdani process, which finds the centroid of a two dimensional function. Sugeno type systems employ the singleton output membership function to defuzzify the output.

The Sugeno style lends itself better to adaptive techniques. Table 6-1 highlights the advantages of each of the two fuzzy systems.

Table 6-1: Benefits of the two types of fuzzy systems

6.4 Neural Networks and Fuzzy Systems

Fuzzy systems and neural networks have mostly been developed separately until more recently, due to them being derived from different fields. Fuzzy systems are very good at representing linguistic and structured knowledge by fuzzy sets and performing fuzzy reason by fuzzy logic in a qualitative manner, usually relying on domain experts to provide the necessary knowledge for a specific problem. Neural networks on the

other hand are particularly good at representing non-linear relationships, and in general constructed by training procedures with sample data.

It is now possible to benefit from the strengths of both systems by integrating the two

paradigms.

Fuzzy systems can be created to match any input-output data. This is made possible by adaptive techniques like Adaptive Neuro Fuzzy Inference Systems (ANFIS). ANFIS is a technique where a Fuzzy Inference System (FIS) is tuned with a backpropagation algorithm based on a collection of input-output data.

Advantages and disadvantages using neural networks and fuzzy logic systems are listed in table 6-2.

Table 6-2: Advantages and disadvantages of neural networks and fuzzy logic systems.

A neural fuzzy system has been implemented in the MatLab mathematical software. Analyses have been run for single input using both the four Mimuro evaluation parameter metrics and the reduced set of sixteen metrics.

6.5 Correlation of Subjective Ratings and Objective Metrics Using A Neural Network Approach

This section brings together the subjective and objective data of the previous chapter, this time using a non-linear approach to identify any links. In particular, to try to:

- Test the neural network to see if it can be trained to approximate drivers' ratings.
- \bullet Identify questions where good subjective objective correlation exists.
- Identify which metrics best correlate with subjective ratings.

A feed-forward neural network with a single hidden layer has been designed using a tan sigmoid hidden layer transfer function with a linear output in order to find links between the subjective data and objective metrics.

In order to improve the generalisation of the network, the method of regularisation has been used.

6.5.1 Subjective and Objective Data Used In the Correlation Analysis

The data used in the current analysis consists of the full subjective data set listed in

appendix B and for the objective data, both Mimuro's four evaluation parameter

metrics and the final sixteen response metrics used in the previous chapter, listed in

table 6-3.

Table 6-3: Reduced set of objective metrics used in correlation analysis

6.5.2 Neural Network Training

The neural network input was the objective data consisting of four sets of sixteen

values, one for each experimental vehicle configuration and the training set was the corresponding set of subjective ratings for questions one to forty nine for the particular vehicle configuration. This was then repeated using the 16 sets of objective metrics listed in table 6-3. This is shown diagrammatically in figure 6-9.

Figure 6-9: Neural network input and training data sets

To see if the neural network can approximate the relationship between objective metrics and subjective ratings, the neural network was trained using all of the data set. Before any neural networks could be trained however, the final design of the neural network had to be chosen, with respect to the number of hidden neurons used. To determine the number of hidden neurons to be used in the network design a number of networks were compared, each with a different number of neurons in the hidden layer. By having more neurons in the hidden layer the complexity of the network fit to the

question 5 given on the y-axis for each of the 16 vehicle configurations and a corresponding objective metric, in this example phase delay of lateral acceleration at 1 Hz along the x-axis. Simulating the trained network with the initial inputs used in training reveals how complex a relationship the network has learnt.

training data increases. Having too complicated a model will ensure the network will learn the input data well, i.e. have small estimation errors. However this does not necessarily provide a robust, well generalised solution as the errors on the validation set may be large. Therefore choosing the correct model complexity is an important aspect of neural network design. By seeking the minimum error in the validation set, the model complexity was identified.

The number of hidden neurons used to determine the final neural network design desired ranged from one to three. An example of the results obtained by varying the model complexity is now given. Looking at just one driver, A in this case, each of the three networks were trained to learn the relationship between the responses to

1 hidden neuron 2 hidden neurons

3 hidden neurons

The fitted curves can be seen to vary in complexity quite markedly from using just 1 neuron in the hidden layer, up to three neurons, which yields a relatively complex curve. If too many neurons are used in the hidden layer, a situation known as `overfitting' is said to have occurred and the network generalisation is poor.

Figure 6-10: Comparison of network complexity using one, two and three hidden neurons in the network design. Training data used is phase delay of lateral acceleration at 1Hz for input data and target output data is ratings for Driver A, question 5.

If the R^2 value fell below 0.7 the network was considered not to have learnt the relationship between the input and output. It follows that for these questions the network can not approximate the function between input and output. An \mathbb{R}^2 value of 1 indicates the network has learnt the function that relates the input and target data perfectly.

To examine overfitting and network generalisation the data set has been split in to two parts, a training set and a validation set. Seventy five percent of the available data was used to train the neural network and the remaining twenty five percent was used to test the network to see how well the network generalises. This was done by simulating the neural network using unseen inputs and comparing the network output with the actual corresponding output target and the error quantified using the method of mean squared error.

To examine whether the neural network could learn the relationship between a set of objective input data and subjective training data, the network was analysed using a linear regression between the network outputs and the corresponding targets.

To examine the reliability of the relationship found by the neural network, the remaining twenty five percent of the data set unseen by the network was used. The trained neural network was then simulated with the unseen input data, objective data in this case and then the output compared to the unseen subjective ratings. To quantify the reliability of the relationship, the method of error average has been used, which averages the errors between the predicted and actual subjective data. Error averages of 0.6 on the rating scale or lower have been highlighted in the results.

Presenting the results in the form used in the previous chapter for all drivers shows clearly at a glance where the neural network has successfully approximated a function that relates the objective input to subjective output.

Examples of the results are shown in figure 6-11, taken for Driver A where a neural network has been trained to learn the relationships between subjective ratings for a given question and the corresponding objective metric. The first figure shows in tabular form the results from the training and validation of the neural network using three neurons in the hidden layer. In each of the tables each row represents one of the sixteen metrics used in the analysis. The columns represent the question numbers one through to forty nine. Each cell in the first table of each figure represents the R^2 values obtained when a linear regression was done between the simulated network response after training to the actual data. An R^2 value of 1 indicates the network has learnt the function that relates the input and target data perfectly. Each shaded cell indicates an \mathbb{R}^2 value greater than 0.7. The cells in each of the second tables in each figure represents the error average when the network is validated with unseen input and target data. Each shaded cell represents an error average of 0.6 rating points or less.

From the results presented in figure 6-11, it can clearly be seen that the neural network can learn the relationships using 3 neurons in the hidden layer

From analysing the model complexity with respect to the number of hidden neurons in the network design, a single hidden neuron has been chosen for reasons of not overfitting to the training data and having good generalisation when the network is simulated with unseen data.

Tests performed with 3 neurons

3 neuron training set

3 neuron test set

Tests performed with 1 neuron

1 neuron training set

R>"FI1Respma'o2 OA 03 10 0T 1.2 OA 0.1 02 0.1 0.1 02 09 0.7 0.1 t. 2 02 02 0.3 0.6 02 02 0,0 0.0 14 1.1 1A to 12 0.1 06 02 09 0.1 02 02 OA 07 1.3 14 09 07 OB 1.2 10 1.7 tý 19 26

1 neuron test set

Figure 6-11: Correlation between a trained neural network output and driver ratings and error average values of simulated network values against actual data against target values using both one and three hidden neurons in the neural network design.

6.5.3 Correlation Analysis Using the 4 Mimuro Evaluation Metrics

Using the four Mimuro evaluation metrics, 1536 (48 questions \times 4 metrics \times 8 drivers) neural networks were produced for the single input case. Using the criteria described above, questions where the neural network has successfully trained with subjective and objective data are highlighted in table 6-4.

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Table 6-4: Questions where the neural network has successfully trained with subjective and objective data for each driver

Questions where half or more drivers have their ratings approximated as a function by the neural network are detailed in table 6-5.

subjectively good metric value. The second column shows the "neutral" zone within which the subjective rating appears insensitive to the metric value. The first and third columns indicate a boundary of lower and higher ratings respectively. The fourth column indicates the number of the question the boundaries are associated with. Tables have been assembled for all four metrics but are not shown here, see appendix E. The results are presented in summary form after table 6-6.

Table 6-5: Questions where for half or more drivers, the neural network has

found a relationship that exists between subjective and objective data

It was seen in chapter four, using the multiple regression method to identify

correlation, that no questions where half or more drivers were found that could be correlated with the objective metrics. Using a non-linear technique, 17 questions have been identified where a metric has a relationship with subjective ratings. In addition, the graphs produced by the analysis where the model had fitted adequately to the training data have been examined to find optimum value ranges for objective metrics. These results have been summarised to obtain an overall view of the subjective/ objective links. An example of the results for a particular metric is shown in table 6-6. The table shows the general preferences for the case of the metric "natural frequency of yaw velocity". This shows where the fitted models' subjective

predictions drop off, i.e. a subjectively poor metric value, or are high, suggesting a

Table 6-6: Summary of the features of the model functions for a single metric (natural frequency of yaw velocity), created through the application of neural networks. Each column represents a single network linking the metric to the subjective ratings where several drivers agree.

6.5.4 Summary of Results

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For each of the metrics it was possible to identify preferred ranges of values, these are now summarised in the following list.

Natural frequency of yaw velocity (Hz) - The graphs indicate a natural frequency of lower than 1.7 to give poor subjective ratings. Often drivers do not change their subjective rating between values of 1.7 and 2.2. No data for a vehicle with a natural frequency higher than 2.2, therefore an upper bound can not be specified. Overall, therefore a natural frequency higher than 1.7 is beneficial.

Damping ratio optimum values - Drivers seem not to discern subjectively between values of 0.5 and 0.7. Values greater than this range always resulted in a lower subjective rating by the drivers, regardless of the question being asked.

lower if phase is > 75 degrees. No upper limit of phase delay can be made as ratings did not peak within the handling envelope of the experimental vehicle. High subjective ratings always tended to 50 degrees or lower value of phase.

Steady state gain of yaw velocity (deg/s/deg) - Low ratings were given for values of the steady state gain metric either side of the range 0.1 0.2.

Phase delay of lateral acceleration at 1 Hz (deg) - Subjective ratings were always

Using the reduced set of 16 metrics, 6144 (48 questions \times 16 metrics \times 8 drivers) neural networks were produced for the single input case. Questions where the neural network has successfully trained with subjective and objective data are highlighted in

6.5.5 Correlation Results Using the `Reduced' Set of Metrics

table 6-7. Summary tables have been produced in appendix F detailing the individual

trends found with each successful correlation.

Table 6-7: Questions where the neural network has successfully trained with subjective and objective data for each driver.

Questions where half or more of the drivers have their ratings approximated as a

function of objective metrics by the network are shown in table 6-8.

Table 6-8: Questions where for half or more drivers, the neural network has

found a relationship that exists between subjective and objective data.

6.5.6 Summary of Results

It can be seen from table 6-8 that 39 questions have been identified where half or more drivers have relationship between 1 objective metric and subjective ratings learnt by network. Comparing this result with the method of simple regression where no links were found for half or more drivers, the result is very significant. In addition, comparing with the links found with the multiple regression technique, 20 questions

overlap. There were only 21 questions where a correlation between the subjective and objective data using the multiple regression technique.

The preferred ranges for each of the sixteen metrics are now summarised.

Natural frequency of yaw velocity (Hz)- The graphs indicate a natural frequency of lower than 1.7 to give poor subjective ratings. Often drivers do not change their subjective rating between values of 1.7 and 2.2. No data for a vehicle with a natural

Steady state gain of yaw velocity (deg/s/deg) - Low ratings were given for values of the steady state gain metric either side of the range 0.1 0.2.

frequency higher than 2.2, therefore an upper bound can not be specified. Overall, therefore a natural frequency higher than 1.7 is beneficial.

Phase delay of lateral acceleration at 1 Hz (deg) - Subjective ratings were always lower if phase is > 75 degrees. No upper limit of phase delay can be made as ratings did not peak within the handling envelope of the experimental vehicle. High subjective ratings always tended to 50 degrees or lower value of phase.

Yaw Rate Gain at 0.7Hz (deg/s/deg) - Drivers seem not to discern subjectively between values of 0.20 and 0.25. Values greater than 0.25 always resulted in a lower

subjective rating by the drivers, regardless of the question being asked.

Road wheel steer gain at 1.0Hz (deg/deg) - Drivers seem not to discern subjectively between values of 0.040 and 0.045. High values of road wheel steer gain always resulted in a lower subjective rating except in only one rating. Values lower than 0.041 resulted in a higher subjective rating. It is not known from the tests conducted how small a value of road wheel steer gain is still deemed better subjectively due to the range of vehicle handling obtained during the course of the experiment. Lateral acceleration gain at 1.0Hz (g/deg X10^{-o}) - Drivers seem not to discern subjectively between values of 4.5 and 7.0. Values lower than 4.5 lead to a lower

subjective rating regardless of question. Values of lateral acceleration gain greater than 7.0 result in better subjective ratings, again regardless of question. No optimum value, or maximum value of lateral acceleration gain can be specified from the analysis of the data, as no drop off in subjective rating was recorded at the high values of lateral acceleration gain achieved by the experimental vehicle.

Road wheel steer phase at 0.4Hz (deg) - Negative values of wheel steer phase angle were disliked by the drivers. This trend was seen in most of the relationships found, regardless of the area of handling the questions dealt with. The values most preferred were those above 20 degrees.

Yaw Phase at U.4Hz (deg) - It was seen that there was a broad range of values of yaw phase for which no distinguishable change in subjective rating occurred. This was mostly between values of -20 degrees to $+20$ degrees. Outside this range, the results

TB characteristic at 0.2g - A few relationships showed that values lower than 2.10 gave improved subjective ratings. However, the stronger result was that values greater than 2.75 led to low ratings.

clearly showed that large negative values of phase delay resulted in low subjective ratings, whilst large positive values of phase resulted in high subjective ratings.

Peak Yaw rate at 0.2g (deg/s) - Values lower than 3.0 gave the best subjective ratings and conversely, values above 4.5 lead to low subjective ratings by the drivers.

Peak roll rate response time at 0.2g (s) - An optimum range for this metric was found to lie between approximately 0.3 and 0.45. Values higher than 0.5 gave low subjective ratings, and in a some instances low subjective ratings were given to values less than 0.3.

TB characteristic at 0.6g - As with the 0.2g case, values of TB characteristic at 0.6g should low to maintain positive driver response. Drivers do not discern subjectively between values of 4.20 and 6.0 but all of the relationships found indicate subjectively poor ratings if the TB characteristic value is greater than 6.0.

Understeer parameter (deg/g) - Several relationships were found relating the understeer parameter to subjective ratings. There were many relationships found where no distinguishable change in subjective ratings occurred for a large range of values, in particular between values of -1 to 1. Values regularly below 0 or -1 resulted in subjectively poor ratings. A few relationships showed subjective ratings improving

Peak steering wheel torque at 0.2g (Nm) - Lighter steering with values below 2.5 tended to give a high subjective rating, conversely, very high values of peak steering torque (>5.0) resulted in low subjective ratings. However, a few poor subjective ratings were found with low values, indicating that whilst light steering is subjectively pleasing for the majority of drivers, it is not always the case.

with an understeer parameter greater than 0. The clearest message was that understeering vehicles gave rise to subjectively better ratings than oversteering ones.

Steering torque at 0.3g (Nm) - Drivers' subjective opinions were found to be worse with values of steering torque higher than 6.5 at 0.3g. This once again shows that drivers prefer light steering.

d(sideslip)/d(lateral acceleration) at 0.4g (deg/g) - Many of the relationships found showed ratings below 4 to be worse subjectively. A few cases show high values (>10)

• Test the neural fuzzy system to see if it can be trained to approximate drivers' ratings.

- \bullet Identify questions where good subjective objective correlation exists.
- Identify which metrics best correlate with subjective ratings.

to be better subjectively. No upper bound can be specified from these results.

6.6 Correlation of Subjective Ratings and Objective Data Using the Neural Fuzzy Method

Using the second suitable non-linear method discussed, this section brings together the subjective and objective data of the previous chapter to identify any links as done

in the previous section. Once again, the following tasks were carried out:

6.6.1 Training the Neural Fuzzy System

The input data for the neural fuzzy system was the objective data consisting of four sets of sixteen values, one for each experimental vehicle configuration and the training set was the corresponding set of subjective ratings for questions one to forty nine for the particular vehicle configuration. Again, this process was repeated for the set of 16 metrics listed in table 6-3. This is shown diagrammatically in figure 6-12.

For the neural fuzzy system to approximate the relationship between objective metrics and subjective ratings, the neural fuzzy system was trained using all of the data set. Prior to training however, the final design of the neural fuzzy system had to be chosen with respect to the number of membership functions used and the type of membership

Figure 6-12: Neural fuzzy system input and training data sets

function used. To determine the number of membership functions to be used in the

system design, a number of systems were compared, each with a different number of membership functions. In the same way the number hidden neurons in a neural

network system determines the system complexity, so does the number of membership functions used in the neural fuzzy system.

The number of membership functions used to determine the final neural fuzzy system

design desired ranged from a possible minimum of two to four. An example of the results obtained by varying the model complexity is now given. Looking at just one driver, A in this case, each of the three networks were trained to learn the relationship between the responses to question 5 given on the y-axis for each of the 16 vehicle configurations and a corresponding objective metric, in this example phase delay of lateral acceleration at 1 Hz along the x -axis. Simulating the trained system with the initial inputs used in training reveals how complex a relationship the system has

learnt.

The fitted curves in figure 6-13 can be seen to vary in complexity quite markedly from using just 2 membership functions, up to four membership functions which yields a relatively complex curve.

4 membership functions

 -90 -90 -70 -70 -90 -7 Phase delay of Latac (deg)

2 membership functions

Figure 6-13: Comparison of system complexity using two, three and four membership functions in the system design. Training data used is phase delay of lateral acceleration at 1Hz for input data and target output data is ratings for Driver A, question 5.

3 membership functions

Phase delay of Latac (deg)

To determine the type of membership function used, ideally prior knowledge of the relationships that exist between the two sets of data would be known. It was seen in the previous section that many non-linear relationships were found using a sigmoidal shape transfer function. However, using a Gaussian transfer function would highlight any relationships where a peak subjective rating for a particular objective metric may

Using the four Mimuro evaluation metrics, 1536 (48 questions \times 4 metrics \times 8 drivers) neural fuzzy systems were produced for the single input case. Questions

exist. Thus a Gaussian transfer function was chosen for this analysis.

To examine whether the neural fuzzy system could learn the relationship between a set of objective input data and subjective training data, the system was analysed using a linear regression between the system outputs and the corresponding targets. If the R^2 value fell below 0.7 the system was considered not to have learnt the relationship between the input and output. It follows that for these questions the system can not approximate the function between input and output. An \mathbb{R}^2 value of 1 indicates the system has learnt the function that relates the input and target data perfectly.

The number of membership functions used in the system was determined in the same

way the number of hidden neurons was decided upon in the neural network analysis.

Two membership functions were subsequently used for the correlation analysis.

6.6.2 Correlation Analysis Using the 4 Mimuro Evaluation Metrics

where the neural fuzzy system has successfully trained with subjective and objective data are highlighted in table 6-9. A summary of the results is tabulated in appendix G.

Table 6-9: Questions where the neural fuzzy system has successfully trained with subjective and objective data for each driver.

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Questions have been further identified where half or more of the drivers have their

ratings approximated as a function of objective metrics by the network and are shown in table 6-10.

lower than 1.7 to give poor subjective ratings. Often drivers do not change their subjective rating between values of 1.7 and 2.1. Values over 2.1 however result in poor subjective ratings. Overall, therefore a natural frequency between 1.7 and 2.1 is beneficial.

Table 6-10: Questions where for half or more drivers, the neural fuzzy system

has found a relationship that exists between subjective and objective data.

6.6.3 Summary of Results

The following summarises the preferred ranges for each of the four objective metrics

Phase delay of lateral acceleration at 1 Hz (deg) - Subjective value always lower if phase is > 75 degrees. No upper limit of phase delay can be made as ratings did not peak within the handling envelope of the experimental vehicle. High subjective ratings always tended to 50 degrees or lower value of phase.

for improved subjective ratings with respect to vehicle handling.

Natural frequency of yaw velocity (Hz) - The graphs indicate a natural frequency of

Damping ratio optimum values - On the whole drivers seem not to discern subjectively between values of 0.5 and 0.7. Values greater than this range always resulted in a lower subjective rating by the drivers, regardless of the question being asked. Improved ratings occur for damping ratio values below 0.55, however no lower boundary can be specified.

Steady state gain of yaw velocity (deg/s/deg) – Drivers consistently did not discern

between values to 0.2 to 0.4 for steady state gain. Values above this range resulted in

low ratings, conversely values lower than 0.2 often gave improved subjective ratings.

6.6.4 Correlation Analysis Using the `Reduced' Set of 16 Metrics

Using the reduced set of 16 metrics, 6144 (48 questions \times 16 metrics \times 8 drivers) neural fuzzy systems were produced for the single input case. Questions where the neural network has successfully trained with subjective and objective data are highlighted in table 6-11. Appendix H contains the summary of the individual cases where good levels of correlation were found between driver ratings and each of the sixteen objective metrics.

Table 6-11: Questions where the neural fuzzy system has successfully trained with subjective and objective data for each driver.

Questions where half or more of the drivers have their ratings approximated as a function of objective metrics by the network are shown in table 6-12.

Steady state gain of yaw velocity (deg/s/deg) - Often drivers do not change their subjective rating between values of 0.1 and 0.4. Low ratings were given for values of the steady state gain metric either side of the range $0.1 - 0.4$, however most poor ratings for higher values of steady state gain.

Phase delay of lateral acceleration at 1 Hz (deg) - Subjective value always lower if phase is > 70 degrees. No upper limit of phase delay can be made as ratings did not P° peak within the handling envelope of the experimental vehicle. High subjective

Table 6-12: Questions where for half or more drivers, the neural fuzzy system has found a relationship that exists between subjective and objective data.

Yaw Rate Gain at 0.7Hz (deg/s/deg) - Drivers seem not to discern subjectively between values of 0.20 and 0.28. Values greater than 0.28 always resulted in a lower

6.6.5 Summary of Results

Road wheel steer gain at 1.0Hz (deg/deg) – No links found between subjective ratings and objective metric.

Where good levels of correlation were found, the following summarises for each metric the preferred ranges of values.

Natural frequency of yaw velocity (Hz)- The graphs indicate a natural frequency of

lower than 1.7 and higher than 2.1 to give poor subjective ratings. Often drivers do not change their subjective rating between values of 1.7 and 2.2. Overall, therefore a natural frequency between 1.7 and 2.1 is beneficial.

ratings always tended to 50 degrees or lower value of phase.

subjective rating by the drivers, regardless of the question being asked.

Lateral acceleration gain at 1.0Hz (g/deg x10⁻³) – Only one link found, driver did not discern subjectively between values of 5.0 and 8.0. Lower than 5.0 led to a lower subjective rating.

Road wheel steer phase at 0.4Hz (deg) - Negative values of wheel steer phase angle were disliked by the drivers. The values most preferred were those above 10 degrees.

Yaw Phase at 0.4Hz (deg) - It was seen that there was a broad range of values of yaw phase for which no distinguishable change in subjective rating occurred. This was mostly between values of -20 degrees to $+20$ degrees. Outside this range, the results clearly showed that large negative values of phase delay resulted in low subjective ratings, whilst large positive values of phase resulted in high subjective ratings.

TB characteristic at $0.2g$ - A few relationships showed that values lower than 2.10 gave improved subjective ratings. However, the stronger result was that values greater than 2.5 led to low ratings.

TB characteristic at $0.6g -$ Only one link was found, however as with the 0.2g case, a low value of the TB characteristic at 0.6g was preferred.

Peak Yaw rate at 0.2g (deg/s) - Values lower than 3.0 gave the best subjective ratings and conversely, values above 4.0 lead to low subjective ratings by the drivers.

Peak roll rate response time at 0.2g (s) - It was seen that there was a broad range of values of response time for which no distinguishable change in subjective rating occurred which was mostly between values 0.15 to 0.50 seconds. Values higher than 0.50 seconds resulted in poor subjective ratings.

Peak steering wheel torque at 0.2g (Nm) - Lighter steering with values below 2.5 tended to give a high subjective rating, conversely, very high values of peak steering torque (>5.0) resulted in low subjective ratings.

Understeer parameter (deg/g) - Several relationships were found relating the

understeer parameter to subjective ratings. There were many relationships found where no distinguishable change in subjective ratings occurred for a large range of values, in particular between values of 1 to 2. Values regularly below 1 resulted in subjectively poor ratings. The clearest message was that understeering vehicles gave rise to subjectively better ratings than oversteering ones.

Steering torque at 0.3g (Nm) - Drivers seem not to discern subjectively between values of 5.0 and 6.5. In a few instances drivers' ratings decreased with higher values of steer torque, once again shows that drivers prefer light steering. d(sideslip)/d(lateral acceleration) at 0.4g (deg/g) - Many of the relationships found showed no difference in ratings between values of 4.5 to 8.5. A few instances showed improved ratings for a high value of d(sslip)/d(latac), however one relationship contradicted this find.

6.7 Discussion of Results Using Non-linear Correlation Methods

Using non-linear methods to identify links between the subjective and objective data it has been possible to find relationships of different shapes. This has been made possible by the design of the neural network or fuzzy neural system used. Some examples of the relationships found are shown in figure 6-14.

Figure 6-14: Example relationships found between subjective ratings and a particular objective metric using non-linear correlation techniques.

Figure 6-15: Typical shape of the relationships found that exist between the subjective and objective data.

From the number of links found using a sigmoidal transfer function compared to a Gaussian transfer function, it can be seen that most of the relationships found are in the form shown in figure 6-15

Now, examining the objective metrics, the following has been found. Broadly, the metrics used in this analysis may be divided into three sections. Firstly the steady

state tests followed by the miscellaneous metrics (e.g. Mimuro), and finally the

responses to transient manoeuvres at 0.2 and 0.6g.

Steady-state metrics:

Gains:

On first examination it appears that the gains of lateral acceleration, steering torque and yaw rate need to be low at low lateral acceleration and higher at high lateral accelerations. However, it is seen that the lateral acceleration gain itself becomes smaller at high lateral acceleration due to non-linear handling effects. It is therefore possible that there is a constant optimal value for lateral acceleration gain (of about 0.009) across all handling regimes. Also the other gains show inconclusive results at high lateral acceleration, where perhaps drivers' opinions are likely to diverge, although at low lateral accelerations steering and yaw gains are most preferred at the lower end of the range (around 0.03 and 0.2 respectively). Strangely, this is especially true for the parts of the questionnaire concerned with obstacle avoidance and response to steering impulse.

Phases:

Generally, the measured phase angle reduces as the lateral acceleration increases, that is to say that the phase lag become larger. However, as one might expect, for all three phase lags (lateral acceleration, steer torque and yaw) a smaller lag is generally strongly preferred.

can be seen that a "high" phase angle (i.e. small phase lag), a high natural frequency and a low damping ratio are all preferred.

Miscellaneous metrics:

The only miscellaneous metrics found to show useful results were those of Mimuro. It

Transient metrics:

The response times of lateral acceleration, yaw rate and steering torque were found to provide the most convincing results. As one might expect, the test drivers generally preferred a low response time. This was found to be especially true at low lateral accelerations, even though actual response time were generally lower than for high lateral acceleration. It is likely therefore that a slightly greater value of response time is desired at high lateral acceleration to reduce the "unsettled" feeling from the

drivers' point of view.

The derivative metric "d(hw)" (d(handwheel angle)/g(lateral acceleration) was found to be preferably at the high end of the range (approaching 0.9) for both values of lateral acceleration. Finally the TB metric was preferred at the low end throughout the handling envelope, even the actual measured values of TB tended to increase. This may imply that a general increase of TB is required as the lateral acceleration increases, but beginning at a lower value that seen on this car.

The results obtained from the non-linear correlation analysis have been summarised in table 6-13. By studying the relationships where good correlation was found, typical

examples have been shown in figure 6-14, it has been possible to identify preferable values or acceptable ranges for each of the objective metrics used in the correlation exercise. By each of the objective metrics is the preferred range or value for improved driver subjective ratings. It has not been possible in all cases to determine an optimum range due to the range of vehicle handling achieved by the experimental vehicle. Further testing would be required to find upper and lower bounds for all of the objective metrics.

Table 6-13: Ranges and values of objective metrics for good subjectively perceived vehicle handling.

 $\mathbb Z$

6.8 Conclusions

• Phase delays of yaw rate and lateral acceleration and dynamic response times are preferred (within the range of the tests) to be as short as possible.

This chapter has covered two areas of work and in turn used genetic algorithms for the first time to find correlation between subjective ratings and objective measures of handling behaviour. In addition, this is the first time non-linearities of potential correlations have been identified and tackled.

Firstly, the issues of applying non-linear genetic algorithms to model subjectiveobjective links where limited numbers of data points are available were addressed. It has been seen from this that, with care, suitable neural network and fuzzy neural solutions can be used to find links within data where they are not immediately visible.

The second area of work was the collection of the neural network and neural fuzzy

results into practical design recommendations for a vehicle to handle subjectively well. Generally speaking, the ideal ranges of metric values are what the experienced vehicle test engineer might intuitively identify.

- Results from metrics concerned with steering torques suggest that light steering is preferred, again so far as the range of test vehicle is concerned. The development of modem shaped electronic power steering systems goes further towards improving the subtleties of this metric.
- The results suggest that a preferred range of values exist for steady state yaw rate gain $(0.1-0.2)$ and low values of yaw rate gain (0.25) are preferred at a frequency of 0.7Hz.
- The results confirmed that drivers subjectively rate understeering vehicle

configurations more positively than oversteering ones.

7. Interpretation and Application of Research Results

7.1 Introduction

It was found using classical regression techniques that very little correlation was found between driver subjective ratings and any single objective vehicle measurement. Significant correlation was only found when using a multiple input regression analysis. Having more than a single input clouds the relationship that a

single metric may have on subjective ratings.

Moreover, using a non-linear approach to identify links between the subjective and objective data sets, many links were found between individual objective metrics and driver subjective ratings.

Examining the results reveals insight to links between driver subjective ratings and vehicle objective metrics. This chapter discusses interpretation of the results and how the relationships found can be used by vehicle engineers and designers.

7.2 Interpretation of Correlation Analysis Results

From the analysis conducted, three hypotheses can be made on the basis of the results

of the previous 3 chapters:

- 1. Each driver formulates their ratings to questions in a unique manner to other drivers.
- 2. Drivers do not always respond to changes in vehicle handling in a linear manner.
- 3. Changes in a metric's value, be it liked or disliked, appears to be noticed across all parts of the questionnaire.

The first point is based on the observation that where good correlation was found for half or more drivers using classical regression analyses, the metrics appearing in the

regression equations were different across the drivers. The different links found

between drivers for the same question, could for example, be due to one driver basing

his ratings on yaw metrics, and another on roll metrics.

The second point is highlighted by the large number of relationships found between the subjective and objective data using non-linear techniques. Note that these methods

would also find any linear relationship that existed between the two sets of data. The majority took the form shown in figure 7-1.

(b) some functions following opposite direction to others

Figure 7-1: General form of the relationships found between subjective ratings and a particular objective metric for any question.

It can be seen from figure 7-1, in the relationships found, there tended to be large range of values for the objective metric to be acceptable in. Only when the metric reached an upper or lower threshold did subjective ratings change significantly. The results therefore mostly indicate what values of the most important metrics should be avoided.

The third point can be seen from examining where strong links between driver ratings and vehicle objective metrics exist. It is strange to see that for an increase in a metric's value whether liked or disliked, the effect appears to be noticed across all parts of the questionnaire. This seems to imply, for example, that turn-in transient response behaviour has an effect on the drivers' perception of steady-state turning. Of course, neither the drivers' perceptions nor the vehicle metrics can be considered completely mutually exclusive of one another, but this does provide some insight into the boundaries and shortcomings of the data set.

Having said that, many effects are highlighted which seem to be in keeping with what one might expect. Phase delays and response times are generally disliked, but less so at high lateral accelerations where stability may become more significant. Furthermore, opinions of steady state gains are generally consistent except at limit handling where maintenance of lateral acceleration gain would be preferred as the actual lateral acceleration drops off due to non-linear effects.

7.3 Application of Correlation Analysis Results To Vehicle Design and Development

Having established links between driver subjective ratings and vehicle objective metrics it is appropriate to consider their potential use in vehicle development. There are two main areas of vehicle development that the current work is most applicable, these being the pre-prototype stage and the prototype testing and development stage. These are discussed in the following subsections.

7.3.1 Pre-Prototype Stage

Using a lumped parameter mathematical model as described in chapter 2, it is possible

to predict with good accuracy the response of vehicle behaviour to handwheel inputs. Having identified objective metrics that have strong links to subjective ratings it is possible for the designer to experiment with parameter combinations and assess the values of these objective metrics.

An attribute of the design of experiments is that it is possible to examine the effects of changing each of the eight vehicle parameters on each objective metric. Table 7-1 shows the effect of changing each of the eight vehicle parameters on the experimental vehicle used for this project from its '-' to its '+' condition for the objective metrics under investigation. To evaluate the size of each change in objective metric, the corresponding percentage change is given in table 7-2 based on the absolute value that

the parameter changes by with respect to the average response for that metric across all 16 vehicle configurations. For clarity, an increase in a metrics response is shown with a shaded cell.

Table 7-1: Main effects of changing each vehicle parameter from its '-' level to its

`+' condition

Table 7-2: Percentage difference in objective metric with respect to changing each vehicle parameter from its '-' level to its '+' condition

For the first time vehicle designers can make use of this type of information in the early part of the development of a new vehicle. By knowing what effects changing important vehicle parameters has on objective metrics and how they effect subjective

ratings, the designers can better achieve a prototype vehicle that is subjectively pleasing from a drivers point of view.

7.3.2 Development and Testing

 $1/2$ $1/2$

Two main uses of the research present themselves to vehicle development teams. Firstly, competitors' vehicles can be tested for benchmarking purposes, or for simple comparison purposes. Secondly, whilst developing and evaluating a new vehicle from

a driver subjective point of view, those metrics that have been shown to correlate well with subjective ratings can be collected and used for analysis. This is particularly useful to track apparent improvements or worsening of subjective handling after changing a vehicle parameter. It is not always obvious to test drivers why one car may feel different from another. By recording and examining the metrics shown to relate well with subjective ratings it may help to identify the reason of the changed perception of the vehicles handling.

7.3.3 Design of Further Subjective vs. Objective Vehicle Handling Experiments

The research conducted is useful for the design of any further subjective vs. objective handling experiments. Further experiments would be conducted for the reasons outlined in the previous sub-section. In addition, over time drivers' expectations of vehicle handling can change, thus the boundaries of those objective metrics which have been shown to be linked to subjective ratings may change.

From the initial study of just the subjective data, similarity amongst ratings for particular group questions was highlighted. This infers that some of the questions are redundant as information is being repeated, and can thus be discarded from the

question set. This shall have the immediate benefit of reducing the workload and time

required by test drivers to complete subjective vehicle appraisals.

Analysis of both the subjective and objective data using both traditional statistical techniques and non-linear techniques has revealed many new links. Having identified a small economic set of metrics that appear to relate mostly to overall driver opinions, only these metrics need be recorded/ derived for analysis purposes.

8. Conclusions

For improvements to be made in the development cycle of any road vehicle, the understanding of subjective and objective vehicle behaviour must be further understood. Improved links between subjective ratings and objective measures of vehicle behaviour would substantially aid vehicle development engineers by being able to predict subjective assessments using vehicle simulations.

This project was centred around vehicle objective data collected using standardised

ISO tests to describe vehicle behaviour in both the steady state and transient handling regimes, and subjective data collected by trained test drivers using a relative rating scale.

Analysis of the subjective data set revealed two main conclusions. Firstly, it was clear that the majority of the drivers answered questions relating to two distinct areas of vehicle handling in a similar manner, obstacle avoidance and response to steer impulse. This infers that information is being repeated in the question set, thus the number of questions from each of these groups can be reduced.

Secondly, from the individual analysis of each driver's ratings, the vast majority of

ratings to questions showed no unexpected similarity to ratings of questions about other aspects of vehicle handling. On these grounds, the full subjective data set was used for all correlation analyses.

From the comparison of all of the driver ratings it could be seen that very little similarity was found between individual pairs of drivers' ratings. This result is particularly surprising considering all the questions were answered on the basis of the vehicle handling being better or worse relative to the reference vehicle. Differences would be expected, after all it is subjective opinions that are being dealt with.

The approach proposed by Mimuro that four simple metrics relate to driver opinions

of vehicle handling has been developed in two new ways.

Initially, using the classical simple regression technique, the approach was tested using the large amount of subjective data available to look for good levels of correlation with objective measures of vehicle handling. Very little correlation was found between the two sets of data. Further statistical analysis was conducted using the technique of multiple regression, to see if relationships could be found that linked subjective ratings as a function of up to three objective metrics. More questions were identified where correlation existed between ratings and metrics.

Secondly, the four evaluation parameter method was extended to include further simple metrics to further improve the links between the subjective and objective data. This led to a revised subset of metrics involving some completely new ones plus some of those used previously. The results of correlating this subset of sixteen metrics with the subjective ratings showed considerable improvement over previous work as

evidenced by the confidence levels associated with the correlation coefficients.

Non-linear correlations between driver subjective ratings and objective measures of vehicle handling have been investigated for the first time using non-linear genetic algorithms.

Great care was taken because of the limited numbers of data points that were available. It has been seen from this that, with care, suitable neural network and fuzzy neural solutions can be used to find links within data where they are not immediately visible, and allowances must be made for noise that is inherent in subjective ratings.

Overall, the non-linear methodology described has been shown to be a powerful tool

in uncovering links between measured vehicle metrics and subjective ratings, where large amounts of noise are evident and links are not clearly defined by linear functions.

Analysis of the results using non-linear methods has resulted in the collection of preferred ranges or values for a group of objective metrics that have been shown to correlate well with driver subjective ratings. Again, this has contributed to knowledge as previous attempts have been somewhat simplistic, Weir and DiMarco [12], or only covered a small range of metrics, Mimuro [25].

Finally, applications of the research results have been discussed which details how they are of use in the early stages of vehicle design or the prototype development stage in order to provide set-ups that will give good handling characteristics. In particular, the use of cause and effect tables shown in tables 7-1 and 7-2 shall aid engineers enormously in the vehicle concept stage by being able to see at a glance at how a parameter change will effect vehicle handling and hence driver subjective ratings.

8.1 Recommendations for Future Work

This research has established links between subjective driver ratings and objective measures using both classical regression techniques and non-linear correlation methods. A reduced set of metrics and questions has been identified where strong links between the subjective and objective data has been found. As a result, the following are suggestions for future work:

Where upper and lower boundaries have not been found for some of the objective

metrics shown to have strong links with driver ratings, conduct further subjective vs.

objective tests using an experimental vehicle of the same type used in the current research to establish where these boundaries lie.

Conduct further subjective vs. objective tests using different types of vehicle, for example, a compact car, sports car or MPV. Measure the objective data for the metrics that have shown strong links with subjective driver ratings and see if these correlate strongly to the questions identified as having strong links to objective data. The hypothesis that the identified set of reduced metrics link strongly with driver subjective ratings can be tested across the range of vehicles. Using this data it would

be possible to see the bounds of where drivers prefer the metrics that describe vehicle

behaviour to be for the different types of vehicle.

In addition, explore the use of driving simulators to validate the findings of the

current research or extend the scope of the work already carried out as highlighted above.

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Appendix A

Specifications for the experimental vehicle

Appendix B

Subjective ratings

Driver ratings and statistics for driver B

Driver ratings and statistics for driver C

Driver ratings and statistics for driver D

Driver ratings and statistics for driver E

 \bullet

Driver ratings and statistics for driver F

Driver ratings and statistics for driver G

Driver ratings and statistics for driver H

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Appendix C Curve fitting results

169

Configuration 10

 \mathcal{A}

172

Appendix D

Rhombus Plots For Vehicle Configurations 1-16
No plot available due to poor data.

No plot available due to poor data.

Configuration 13

Configuration 14

Appendix E

Summary – Neural network – Mimuro metrics

Ranges and trends for each metric:

Natural frequency (Hz)

Steady state gain of yaw velocity (deg/s/deg)

Damping ratio

Lateral acceleration phase delay @ 1Hz (deg)

Appendix F

Summary – Neural network – reduced set of metrics

Ranges and trends for each metric:

Natural frequency (Hz)

Steady state gain of yaw velocity (deg/s/deg)

Phase delay of lateral acceleration @ 1Hz (deg)

Yaw rate gain at 0.7Hz (deg/s/deg)

Road wheel steer gain at 1.0Hz (deg/s/deg)

Lateral acceleration gain at 1.0Hz (g/deg $(x 10^{-3})$)

Road wheel steer phase at 0.4Hz (deg)

Yaw phase at 0.4Hz (deg)

TB characteristic at $0.2g$

TB characteristic at 0.6g

Peak steering wheel torque at 0.2g (Nm)

Low rating when No distinguishable difference High rating when metric's Question

 \mathbf{u}

Peak yaw rate at 0.2g (deg/s)

 \mathbf{H}

Peak roll rate response time at 0.2g (s)

Understeer parameter (deg/g)

Low rating when	No distinguishable difference	High rating when metric's	Question
metric's value is:		value is:	number
< 5.5	5.5	> 5.5	
> 6.4	4.4:6.4		
> 6.0	4.4:6.0		
< 5.2	5.2:6.6		
< 5.2	5.2:6.6		U.
$<$ 5.2	5.2:6.5		ΙV
> 6.5	4.4:6.5		
	4.4:6.4	> 6.4	
> 6.0	4.4:6.0		
	5.5:6.7		
	4.5:5.5	> 5.5	
> 6.3	4.4:6.3		20
> 6.4	4.4:6.4		
> 6.4	4.4:6.4		22
			24
> 6.4	4.4:6.4		24
> 6.5	4.4:6.5		24
> 5.6	4.4:5.6		28
	4.4:5.7		
	4.4:6.0		

Steering torque at 0.3g (Nm)

d(sideslip)/d(lateral acceleration) at 0.4g (deg/g)

Appendix G

Summary – Neural fuzzy system – Mimuro metrics

 \mathbf{L}

Ranges and trends for each metric:

Natural frequency (Hz)

Steady state gain of yaw velocity (deg/s/deg)

Damping ratio

Lateral acceleration phase delay @ 1Hz (deg)

Appendix H

Summary – Neural fuzzy system – reduced set of metrics

Ranges and trends for each metric:

Natural frequency (Hz)

Steady state gain of yaw velocity (deg/s/deg)

Phase delay of lateral acceleration @ 1Hz (deg)

Yaw rate gain at 0.7Hz (deg/s/deg)

Road wheel steer gain at 1.0Hz (deg/s/deg)

Lateral acceleration gain at 1.0Hz (g/deg $(x 10^{-3})$)

Road wheel steer phase at 0.4Hz (deg)

100mm - Carolina Andrew March 2011

TB characteristic at $0.2g$

Yaw phase at 0.4Hz (deg)

TB characteristic at $0.6g$

 $\sim 10^{-5}$

 ~ 100 km s $^{-1}$

Peak steering wheel torque at 0.2g (Nm)

Peak yaw rate at 0.2g (deg/s)

Peak roll rate response time at 0.2g (s)

Understeer parameter (deg/g)

Steering torque at 0.3g (Nm)

d(sideslip)/d(lateral acceleration) at 0.4g (deg/g)

