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# Comparative Analysis of Different Neural Networks for Tyre Model Parameters Identification of Longitudinal Brake Formula

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***Abstract*— This paper presents a comparative study between Self-Organising Maps (SOMs) Neural Network and Multilayer Perceptron Neural Network to obtain Pacejka-96 Formula parameters of the braking of a vehicle on a bank of roller testers at the Ministry of Transport (MOT) and on flat ground. There are different methods to fit the values of Pacejka-96 Formula parameters, but this is the first time that through Self Organizing Maps interactively, we can obtain the optimum Pacejka-96 tyre model parameters. SOM methodology has been compared with Multilayer Perceptrons neural network (MLP).The feasibility of methodology of neural networks has been demonstrated for a good generation of Pacejka-96 formula parameters of the brake-slide relationship when presented with data not used in network training. This tool will easily find the brake-slide equations of each brake measurement and will attempt to compare the brake on two different experimental tests.***

*Index Terms*— **Self Organizing Maps, Tyre Model, Pacejka-96 Parameters Identification.**

## I. INTRODUCTION

A brake test is made on a roller bed to check the brake circuit when a vehicle is taken to the Ministry of Transport (MOT) testing facilities. We study the efficiency of MOT testing facilities in order to know if braking on a roller tester faithfully reproduces braking on flat ground. An effective contribution to these programmes requires detailed knowledge of each brake through definition of "The Pacejka96 formula" [2] of experimental data. The main objective of this paper is:

- The evaluation of Self-Organising Maps (SOMs) to get "The Pacejka-96 formula" of each brake measurement.
- To compare the Pacejka-96 formulas of measurements taken on flat ground and on the MOT brake tester, and use these results to assess the reliability of the machine in testing brake systems.

## II. BACKGROUND

Tyre models are used to calculate the tyre forces and torque as responses to the wheel motion that may be given in terms of various slippage quantities. We can distinguish theoretical models based on the physics of the tyre construction, and empirical or semi-empirical models which are solely based on experimental results [3-4], these are the types of tyre model used by Pacejka-96 and Bakker in 1993 [1]. Also, combinations of both approaches are used in the development of tyre models. To achieve proper performance of the efforts in the contact patch, some of the most popular tyre models used by Pacejka and Bakker 1993, the so-called Pacejka-96 Formula or "Magic Formula", need to tune their parameters. To obtain these tyre model parameters, an intense research effort by the automotive community is required so there are methods to fit the values of these parameters [5-7]. Different methodologies are available to find Pacejka-96 tyre model parameters, in this paper we evaluate which technique could be the best to find these parameters. Classification methodologies are grouped in different categories according to the main task they are usually focused on: artificial intelligence techniques (neural networks and fuzzy logic), statistical techniques (linear regression and discriminant analysis), and visualization techniques (histograms, dendograms, and scatter plots). Fig. 1 shows a compendium of the techniques mentioned above and tested for this paper.

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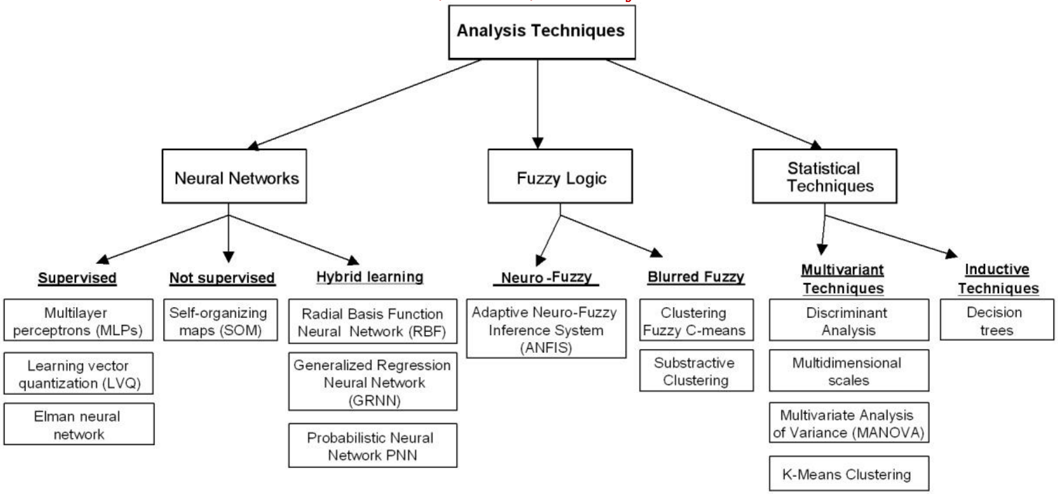


**Fig.1 Compendium of the Classification Techniques**

***A) Statistical Techniques:*** Two main groups of techniques can be distinguished: multivariate statistics and intuitive techniques.

***B) Fuzzy Logic Techniques:*** Another possibility, for clustering purposes, is the use of fuzzy methods: ANFIS, fuzzy C-means, originally introduced by Bezdek in 1981 [8].

Both techniques perform the operations slower than Artificial Neural Networks.

***C) Artificial Neural Network Techniques:*** Artificial Neural Networks (ANNs) [9] try to reproduce the way the human brain acts: a highly complex, nonlinear, and parallel information processor able to perform certain computations many times faster than the most powerful digital computer available today.

Actually, ANNs find applications in such diverse fields as modelling, time-series analysis pattern recognition, and others by virtue of their ability to learn from input data with or without a teacher. Three different techniques are presented for hybrid learning: radial basis networks, Generalized Regression Neural Networks (GRNN) [10], and Probabilistic Neural Networks (PNN) [11]. The GRNN and PNN have a disadvantage: they perform the operations slower than SOM and Multilayer Perceptron (MLP) networks [12], [13].MLP is a feed-forward neural network with more than one perceptron that can be used to solve more difficult problems. Self-organizing maps (SOMs) [12] are unsupervised networks able to learn both the distribution (as competitive layers do) and the topology of the input vectors on which they are trained, consequently, excellent clustering results are obtained. In addition, an easy evaluation of the result is possible through the graphical representation on maps whose different labels (vectors identifiers) can be grouped by visual inspection.An extended method to obtain the Magic Formula is used. This method based on a Starting Values Optimization technique (SVO) is the MLP supervised technique [13]. The algorithm needs very close starting parameter values to obtain good results and too much time is required to calculate the suitable parameters. After comparing the learning techniques error of each neural network we can see that it is only obtained a cero percentage in Self organizing Map and in Multilayer Perceptron techniques. So we continue the research comparing the Pacejaka parameters obtained with both techniques with experimental data in order to observe which Pacejka brake formula is closer to the experimental curve.

**Table 1. Neural Network learning error compared**

| | | |
|---|---|---|
| NEURAL NETWORK TECHNIQUES | | |
| MLPs | Levenberg-Marquardt algorithm | 4 |
| | Resilient backpropagation | 0 |
| | Gradient descent backpropagation | 123 |
| Learning Vector quantization (LVQ) | | 5 |
| ELMAN Neural Network | | 2 |
| Self-Organizing Maps | | 0 |
| Radial Basis Function Neural Network (RBF) | | 2 |
| Generalized Regression Neural Network (GRNN) | | 1 |
| Probabilistic Neural Network | | 1 |
| FUZZY LOGIC TECHNIQUES | | |
| ANFIS | | 1 |
| Subtractive Clustering | | 2 |
| STATISTICAL TECHNIQUES | | |
| Discriminant Analysis | | 5 |
| Decision Trees | | 2 |

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This paper examines the performance of both techniques by comparing Mean Absolute Percentage Error (MAPE) because this is the first time that a Self-Organizing Maps (SOM) application has been used for tyre model coefficient identification. n addition, this is the first time that a comparative analysis of longitudinal braking on flat ground and on roller testers has been done comparing parameters of “Pacejka-96 tyre model” in both tests.

## III. FORMULATION OF THE PROBLEM

We use the Pacejka-96 tyre model parameters in the research to compare the longitudinal braking on flat ground and on MOT roller testers and quantify the differences between both brake experiments. An extended method to obtain the Magic Formula is used in the MF-Toll software. This method is based on a Starting Values Optimization technique (SVO), MLP supervised technique. The algorithm needs very close starting parameter values to obtain good results and too much time is required to calculate the suitable parameters. The objective of this paper is to compare the advantages and disadvantages of using Self Organizing Maps with Multilayer Perceptron for parameter identification of the Pacejka tyre models. The authors study the approach of using an unsupervised neural network like Self Organizing Maps instead of Multilayer Perceptrons neural network (MLP). It has been alkalized which technique obtain better results. This paper examines the performance of both techniques, MLP and SOM, by comparing Mean Absolute Percentage Error (MAPE) because this is the first time that a Self-Organizing Maps application has been used for tyre model coefficient identification. In addition, this is the first time that a comparative analysis of longitudinal braking on flat ground and on roller testers has been done comparing parameters of “Pacejka-96 tyre model” in both tests.

### *3.1. Testing methods*

The vehicle used in the test was a previously owned Renault 21, 7-seater diesel, “Nevada” model, see fig.3. The front brakes are of the disc type with sliding clamps and the rear wheels have drum brakes. Measurements of slippage were obtained from two SICK STEGMANN DKS type encoders fitted to the brake roller tester and the front right wheel of the vehicle Measurement of braking was obtained with a pressure sensor fitted to the vehicle’s brake circuit. This sensor was used to measure the pressure in the hydraulic circuit after pressing the brake pedal Brake data has been related to the data of the slippage of the right front wheel. The two tests carried out are described below:

#### *A. Test 1*

Measurement of braking on the brake roller tester at the MOT centre is carried out by placing the vehicle on rollers rotating at 5 km/h which the vehicle wheel tries to stop by braking. A hydraulic sensor in the hydraulic pipe placed on the front right wheel is used to measure the braking force. The percentage of slippage value was measured using known data on the angular velocity of the rollers and vehicle wheels.

$$\%\ \text{Slippage} = 1 - \frac{\text{speed of vehicle wheel}}{\text{speed of roller}} \qquad (1)$$

Slippage is measured from 0 to 100% [14-16].

**Fig.2: Test 1 measuring brake force on the brake roller tester at the MOT station.**

#### Test 2

In this test, the vehicle runs on flat ground until it obtains 40 km/h of velocity and then it stops until the car slides totally. This velocity is enough to obtain 100% of slippage. In this test, the vehicle runs on flat ground with the same signals recorded as those that had been taken on the brake roller tester in the first test. Encoders were fitted, one on “the fifth wheel” of the vehicle to which a spring was attached to ensure good contact, see figure 3, with a second on the front, right-hand wheel of the vehicle, as in the test 1.

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**Fig.3. Encoder on Fifth wheel, Test 2**

The pressure in the hydraulic brake circuit for the right front wheel, of the vehicle was also measured with a hydraulic sensor in the hydraulic pipe of the right wheel to obtain the brake data on the wheel.

## IV. THE PACEJKA-96 FORMULA

After an important study the Pacejka-96 formula is chosen because its curve most closely replicates the experimental data [2]. The official Pacejka-96 longitudinal formula goes thus [2]:

$$F(x) = D \sin[ C \arctan \{ B(1- E)x + E^* \arctan(Bx)\}] \qquad (2)$$

The B, C, D and E are variables that have to be obtained by the neural network.

We need to know x, longitudinal slip, to obtain the curve of $F_x$= longitudinal brake.To find the variables in the MLP and SOM techniques, the steps to follow are these: First, we introduce in a data base many variations in value of each parameter, then an array of force data is calculated for each change of values and labelled with a number, finally those curves of equation are plotted. So we have used “The Pacejka-96 formula” databases with many possible variables to obtain that which is most similar to the experimental one. Next, an experimental curve of brake and slide on an MOT tester and flat ground were obtained. Next, we introduce the experimental array in the SOM and MLP toolbox to obtain the value of each parameter of the Pacejka-96 Formula and it has been analyzed which is the best technique.Lastly,it has been compared brake on MOT and on flat ground curves to quantify how different the Pacejka-96 variables are.

## V. SELF-ORGANIZING MAPS (SOM) VS. MULTILAYER PERCEPTRON

SOM and MLP algorithms were developed using Matlab toolbox libraries [17]; in order to evaluate the classification ability of both techniques they were used to find the Pacejka-96 formula of experimental brake data and then compared, with the objective to select one of them. The computer used was a Pentium IV CPU at 2.5 GHz and 512 Mb of RAM. Several tests with the data profiles were made to check the clustering results for each methodology.Both MLP and SOM techniques are useful for clustering, but at this stage of the research work the authors compare advantages and disadvantages of each technique.MLP is a supervised technique, and the basic MLP learning algorithm is outlined below. This is what you should attempt to implement.

- Initialize the network, with all weights set to random numbers between -1 and +1.
- Present the first training pattern, and obtain the output.
- Compare the network output with the target output.
- Propagate the error backwards

SOM methodology was introduced by Kohonen two decades ago [11]. These networks are a kind of unsupervised Artificial Neural Network (ANN) that performs a transformation from the original input space, (n dimensional data vector), to a reduced output space, (bidimensional).The number of neurons can vary from a few dozen up to several thousands, each neuron is represented by a d-dimensional weight vector, (prototype vector, codebook vector).The neurons are connected to adjacent neurons by a neighborhood relation which dictates the topology or structure of the map. This topology is defined by two factors; local lattice structure and global map shape. A hexagonal lattice structure and a sheet map shape were used (see Fig. 5), in this figure discreet neighborhoods, (sizes 0, 1, and 2), of the centermost unit are defined. The innermost polygon corresponds to the 0-neighbourhood, the second to the 1-neighbourhood, and the biggest to the 2-neighbourhood.

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The SOM training algorithm resembles vector quantization algorithms. The important distinction is, that in addition to the best-matching weight vector, its topological neighbours on the map are also updated and the region around the best-matching vector is stretched toward the presented training sample. The final result is that the neurons on the grid become ordered and then neighbouring neurons have similar weight vectors. Since the weight vectors of the SOM have well-defined low dimensional coordinates on the map grid, the SOM is also a vector projection algorithm. Together, the prototype vectors and their projections define a low dimensional map of the data manifold.In addition, an index named "learning error" was defined to evaluate the relative quality of the learning and segmentation capacities in order to select the best configurations previously commented. The learning error in both techniques was 0% so we cannot use this parameter to select any neural network for classification. Both methodologies show good performances for the research interest; quick processing capacity, high quality results, (even when the problem reaches high levels of complexity), and the ability to learn from a database to produce classifications and identification of the winning neuron, even when the input space growths. We then study the repeatability of the system and how many clusters of different behaviors will be able to be grouped together for the same type of braking. Once the curves are grouped by the SOM and MLP map in different clusters, this same map will allow the identification and association of a new braking curve in one of these segments or patterns of behavior, both automatically and reliably.To understand the maps quality is necessary to measure some analytic indexes. Typically, two evaluation criteria are used; resolution and topological preservation. If the dimension of the data set is higher than the dimension of the map grid, these usually become contradictory goals. This quality is analysed in terms of mean quantization error (Qe), which measures the resolution of the map, and the topographic error (Te) which measures the distortion of the map. We also calculate the average quantization error, which is simply the average distance from each data vector to its Best Matching Unit (BMU) and it has been seen that it similar in both cases. We have realized successive simulations using the SOM and MLP networks. Diverse parameters of training have been changed to obtain the best results with the spectrum of data introduced to the network, see figure 5. Every curve has a concrete form due to the different values of the variables of the Pacejka-96 formula; table 1 shows the best parameters of the SOM network:

**CHARACTERISTICS OF SOM**

**Table2. Characteristic of SOM method used**

| PARAMETER DESCRIPTION | Value or Type |
|---|---|
| Algorithm for initialization of the input data | Randi nit |
| Algorithm for training the input data | Saquen |
| Map grid size | 10 x 10 neurons |
| Epochs of training | 1000 for rough training and 2000 for fine tuning training |
| Algorithm for initialization of the input data | Randi nit |

We have used the Pacejka-96 formula databases with all possible formula of brake and slide and we found the data for each variable D,C,B and E of the curve calculated with the formula.Once trained, the SOM and MLP memorizes the topographic configuration and it is then possible to test a new curve that has not been used in the training. The aim is to analyse the capacity of the network to identify, and associate, a new experimental curve with the theoretical curves trained in the network. MLP cannot give visual output graphic as SOM technique. A hexagonal network formed by a total of 100 neurons (10 x 10) was used for SOM. This size was chosen to allow a better visualization of the output data of the training map. A network with a greater number of cells would have hindered the visualization of the labels in each neuron. In the same way, a smaller map than the one used by the authors would cause many labels to be overlapped.Finally, random initialization of the map and a batch training algorithm with 1000 and 500 steps for the rough and the fine tuning training, respectively, was used. The figures 4 show the curves used for training. It has been used numerical label that we have assigned to every curve placed in every winning neuron.

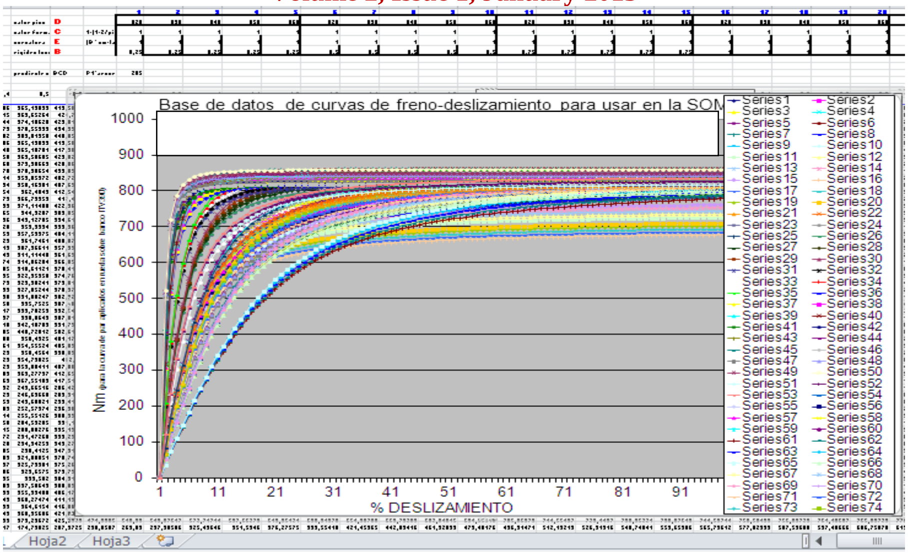


**Fig 4. Data base of brake formula obtained with different Pacejka parameters**

Labels are grouped in every cluster, so we can determine the set of curves and the associated parameters that define them. Each cluster has different ranges of values of the parameters of the Pacejka-96 formula that define the behaviour of the curves classified under every cluster. The Best Matching Unit will contain the theoretical curve(s) that are most like the real one. In the case of the Best Matching Unit, this contains several curves, it has been verified that the average of all of these provides us a curve very close to the experimental one obtained by measuring by any test. Therefore, we have to identify the parameters associated with the theoretical curves of the winning neuron, (The Best Matching Unit), so the average of these, see table 3, will be the most similar curve to the experimental one, see figure 5.

**Table 3. Pacejka Parameters of the Wining Neuron**

LABELS OF CURVES OF THE WINNING NEURON

| | **100** | **101** | **102** | **103** | **104** | **105** | **Average** |
|---|---|---|---|---|---|---|---|
| | 250 | 220 | 240 | 222 | 225 | 250 | |
| **D** | 0 | 0 | 0 | 5 | 0 | 0 | **2339** |
| **C** | 1 | 1 | 1 | 1 | 1 | 1 | **1** |
| **E** | 50 | 50 | 50 | 50 | 50 | 50 | **50** |
| **B** | 0,25 | 0,5 | 0,5 | 0,5 | 0,5 | 0,5 | **0,46** |

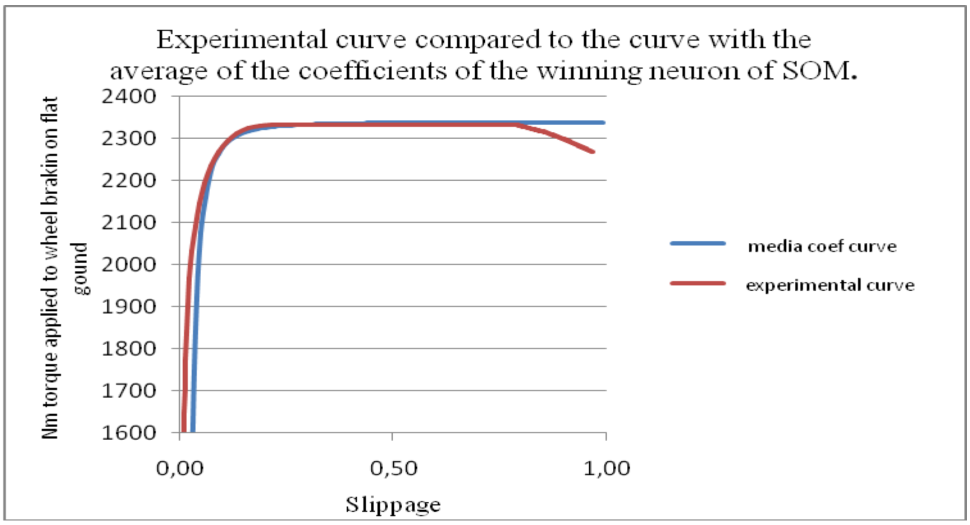


**Fig. 5: Curve obtained with SOM vs experimental curve**

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Here is an example of a Pacejka-96 formula using the average of the coefficients of the winning neuron:
F(x) for1 bar of pressure tyre inflated on MOT tester:

$Mf(x) = D \sin[ C \arctan \{ B(1- E)x + E^* \arctan(Bx)\}]$ (3)

$Mf(x)_{media\ ceof} = 2339 \sin[ 1^* \arctan \{ 50^* \arctan(0{,}46x) - 23 x \}]$ (4)

We obtain the values of variables of the Pacejka-96 formula using an SOM neural network and an MLP neural network where we observe in the following table III that coefficients obtained are different and in graph in fig. 8 that the resultant SOM curve, (represented with outlines), is practically like the experimental one, (when we brake on an MOT brake tester with 1 bar of tyre pressure), (in continuous black) and the MLP curve is not as similar as the experimental one, see fig.6.

PACEJKA-96 PARAMETERS WITH SOM AND MLP

| | SOM | MLP |
|---|---|---|
| **D** | **2339** | **2352** |
| **C** | **1** | **0,93** |
| **E** | **50** | **45** |
| **B** | **0,46** | **0,53** |

**Table 4. Comparing Pacejka parameters obtained with SOM and MLP method.**

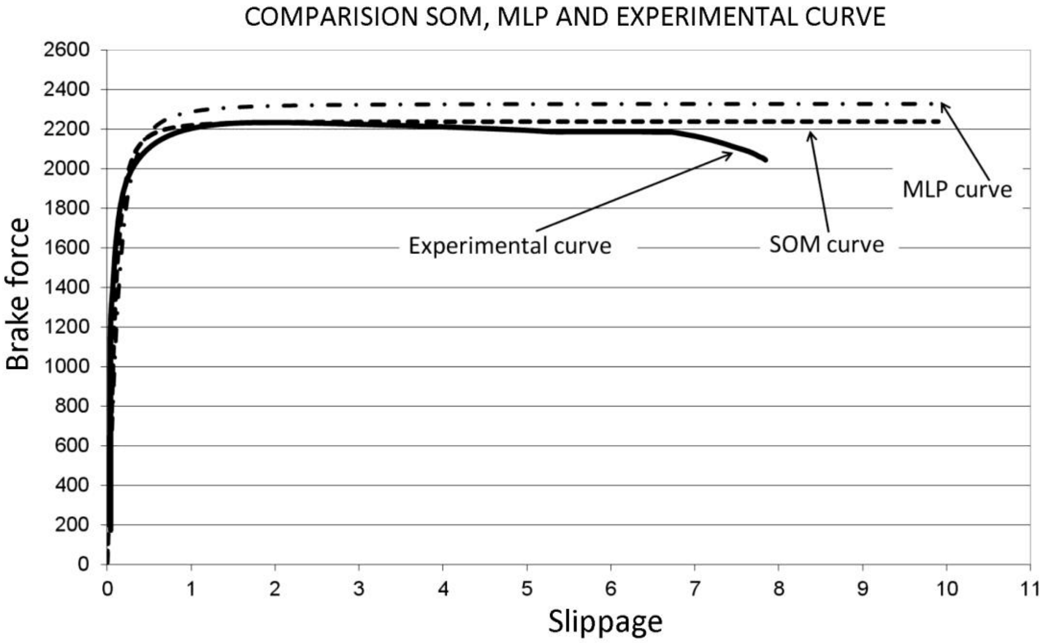


**Fig 6: Comparison Nm brake force-slippage curves from experimental data, SOM and MLP.**

As we can see in figure 8 Pacejka formula parameters obtained with Self Organizing Maps Neural Network give us a curve closer to the experimental data that the one obtained with MLP technique.

## VI. RESULTS

In order to express the accuracy of the SOM and MLP models, a measurement index isdefined. This index is the Mean Absolute Percentage Error (MAPE), which measures and compares the experimental curve and the curve obtained with the SOM and MLP models.

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left[ \frac{|L_{Ri} - L_{Pi}|}{L_{Ri}} \right] x100\% \quad (5)$$

Where: N is the number of slippages (in this case X axis), $L_{Ri}$ is the real and experimental value of the i slippage number and $L_{Pi}$ is the obtained value for SOM (or the MLP) model of the *i* slippage number. With the SOM model the best average value of the MAPE index was 1.5%, which is a good index. However, with the MLP model the best average value was only 3.2%.

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Obviously, the proposed SOM method is validated due to the low average value of the MAPE index by comparison with the experimental data.

## VII. CONCLUSION

Through the proposed integration of tools such as SOM and MLP methodologies, with the options selected by the SOM, we can determine the parameter value of the Pacejka-96 formula of any experimental brake curve. We can obtain an experimental curve of brake and slide on an MOT tester or flat ground. We introduce the experimental array in the SOM toolbox to produce the value of each parameter of the Pacejka-96 Formula so we compare both curves to quantify how different they are. We have to obtain the average of the values of the variables of the Pacejka-96 formula, when the winning neuron has more than one curve as a result and we observe that the theoretical resultant curve obtained with SOM neural network is more like the experimental curve rather than the one obtained with MLP Neural network.Once the Pacejka-96 formula for experimental brake-slide had been identified, the researchers tried to test if the SOM could be used as a quick detection tool to see how different the curve of brake is on both an MOT bank and flat ground. Now we can quantify how different are the curves of experimental data of brake-slip on flat ground and on the MOT tester, and how different are the parameters of the Pacejka-96 formula for both experiments, (both tests at the same tyre pressure), to see the difference in braking measurements between the roller tester and on flat ground, see table 4 and figure 7:

**TABLE VI.ACEJKA-96 FORMULA PARAMETERS**

| PARAMETER | MOT TESTER | FLAT GROUND |
|---|---|---|
| D | 848 | 2339 |
| C | 1 | 1 |
| E | 50 | 32 |
| B | 0,57 | 0,46 |

Table 4. Pacejka-96 Formula Parameters of brake-slide data on an MOT tester and flat ground

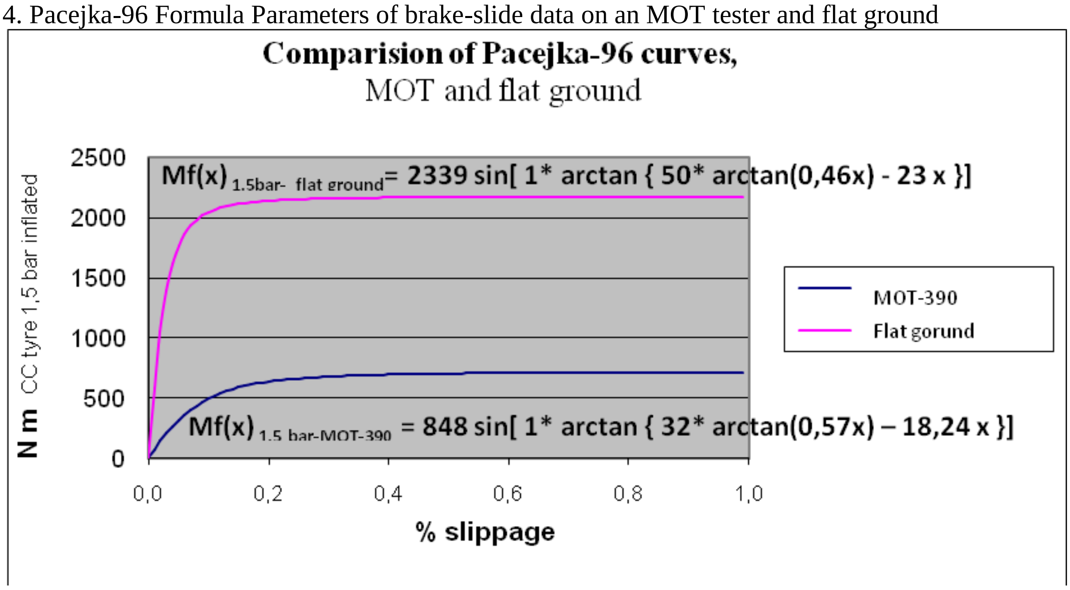


**Fig 7: Comparison of curves of Pacejka-96 formula of brake-slide on Flat ground and on an MOT tester, when the tyre is inflated with 1bar of pressure.**

Among the advantages of SOM are: low computation time, low tyre test data numbers are needed to evolve every generation of tyre model parameters and a high level of efficiency.The advantage of SOM is that the relationship between the original vectors is, to some extent, preserved in the output space, providing a visual format where a human operator can “easily” discover clusters, relations, and structures in the usually complex input space database. The map consists of a regular grid of processing units, neurons. A model of some multidimensional observation, eventually a vector consisting of features, is associated with each unit.

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SOM has been considered a good application for Pacejka-96 coefficient identification of longitudinal brake formula because the Mean Absolute Percentage Error (MAPE) is lower than 1.5 %. With SOM neural Networks we can ascertain standards of behaviour of braking on an MOT brake tester and compare them with braking on flat ground.

## VIII. ACKNOWLEDGEMENT

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**Sergio Valero** received in 1998 the Industrial Engineer degree from the Polytechnic University of Valencia (Spain). PhD degree on Industrial Engineering.
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He has authored numerous publications and contribution to congresses, at the moment he has taken part in the publication of two books on Electric Machines and electric technology.