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TRANSMISSION SIZING OF A FORMULA-TYPE VEHICLE USING ARTIFICIAL NEURAL NETWORKS

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Abstract. *The function of a transmission is to optimize the torque of the engine to the wheels, but today there is no defined methodology that analyzes all the parameters and how they relate. For cars of performance as for the ride, the best condition for the operation of the transmission is that it can carry the greatest amount of torque optimally from the engine to the wheels, as this way the car has greater traction on the wheels and a larger acceleration, but this directly influences the fuel consumption, decreasing the final speed of the car, and modifying various other parameters of the car. When we noticed that the performance relationship is inversely proportional to ergonomics, consumption and other factors, it was noticed the need to create an Artificial Neural Network (ANN) to size a transmission from the priorities and the objectives of the user. In order to perform this work the data were collected from a SAE car since it is a competitive car of self performance, where the contour conditions need to be more critical and the parts must be designed with a lower safety factor and as a product end of the ANN were designed the half shafts, the pinion, and the crown.*

Keywords: *Transmission, Formula SAE, Artificial Neural Networks, pinion crown ratio, semi-axis.*

1. INTRODUCTION

One of the oldest challenges of the modern automobile industry is to increase the performance of cars with the consequent reduction of production costs as efficiently as possible. However, with raw materials and energy becoming more expensive, and with all concern about the emission of pollutants and waste, this challenge has become much greater. Vehicle production is divided into several subsystems, each responsible for a portion that, when united, should interact in the best possible way. For this research, the object of study was the subsystem of drivetrain whose function is to take the torque from the engine to the wheels.

As we increase the pinion crown ratio, we increase the acceleration, but we decrease the final speed, the time it takes to get to the gear shift point which consequently reduces fuel economy and affects the driver's ergonomics. It is also necessary to increase the mass of the car, because there is more torque soon the parts will be subjected to a greater effort. When analyzing this behavior it is noticeable that the relationship between some parameters of the car is inversely proportional and this phenomenon that makes the sizing of the transmission so complex, since we can not keep a focus on only one of the parameters since we would be harming others, an optimum point among all the criteria, a point that meets all the requirements without harming any other.

Due to the complexity of scaling a transmission because of the dynamic behavior of its parameters, the concept of Artificial Neural Networks will be introduced to the project. ANNs consist of a form of artificial intelligence for problem solving and approximation of functions.

The concept of artificial neural networks was created based on the functioning of the human brain, where in general we can say that ANN is a machine that works by modeling how the brain performs a particular task or function of interest. To achieve good performance ANN employs a massive interconnection of simple computational cells called "neurons" or "processing units" (Haykin, 2001).

An ANN necessarily resembles the human brain in two characteristics:

1. Knowledge is acquired by the network from its environment through a learning process;
2. Connecting forces between neurons, known as synaptic weights, are used to store acquired knowledge.

In order for an ANN to learn from the environment, a learning algorithm is needed to modify the synaptic weights of the network to reach a target.

Scaling a transmission of a high performance car is extremely expensive and time consuming and has very dynamic parameters which makes this task very difficult, so to reduce the time of scaling, cost and complexity the ANN was chosen since it has the ability to learn from the environment.

2. METHODOLOGY

To train the ANN first it was necessary to collect the theoretical data on the relationship between the crown and pinion and data of the axes.

For the axes, the literature Shigley (2005) was used, where it is taught to calculate the diameter of an axis knowing the conditions that they will be submitted. A large table with axle diameter calculated for fatigue (main reason for shaft failure) was made. This activity was simple, but it was a very simple parameter to compare the ANN result with the theoretical data

To obtain the data for the pinion crown ratio, the data were obtained experimentally in a SAE car of the KRT team UFBA Formula SAE of the Federal University of Bahia (UFBA).

After all the data were collected the two ANNs were created in a similar way, one of which calculated the pinion crown ratio and the other calculated the shaft diameter, after which the collected data were inserted into the ANN and consequently the network training was performed.

In order to choose the best network architecture, some processes have been analyzed and are described in the images below.

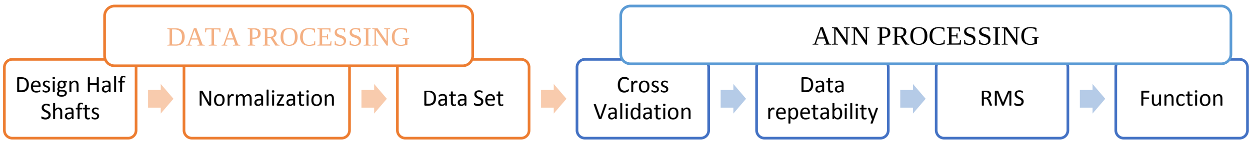

Figure 1. Flowchart of applied methodology for half shafts

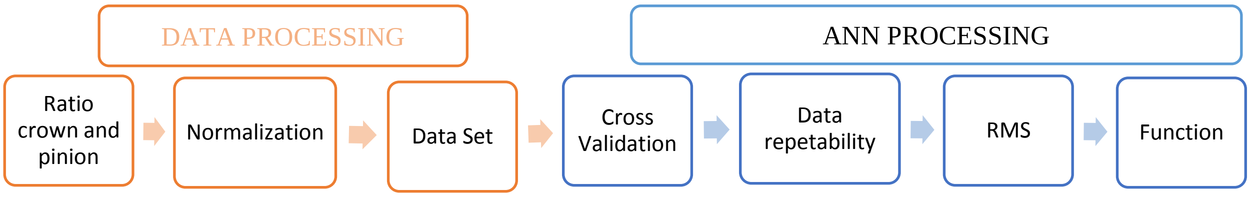

Figure 2. Flowchart of applied methodology for crown and pinion ratio

By the similarity of the processes, we noticed that both neural networks had the same architecture, which was expected, since they have almost same number of inputs and both result in a single function with only a single output.

To train the ANN first it was necessary to collect the data in literatures, with searches between the people of the area and the car used in the research.

After the data were collected, they were organized into tables and calculations for the size of the axis and for the pinion crown relationship and only from that point the ANN was created and trained with the input data obtained and with periodic updates of the their synaptic weights.

With the resulting ANN data the parts were modeled in CAD and then subjected to transient structural analyzes over time and then they were fabricated for use in the car.

2.1 Crown Pinion ration and semi-axis

The function of the transmission is to take the torque from the engine to the wheels more efficiently. In the way of torque to the wheels, depending on the ratio the torque is increased up to several times in a car of formula SAE. The last relation that makes the torque increase is the relation crown pinion and for this reason it was chosen for the beginning of the project, since to modify it is simple compared to the gear box.

Since the axes are one of the most resistant components of the entire transmission and one of the ones that has the highest safety coefficients of the automobile industry and one of the simplest to calculate the efforts, then as this ANN deals with a prototype we had two good parameters for test our ANN since the pinion crown ratio drastically modifies the performance of the car's longitudinal vehicle dynamics and the semi-axis is a way of seeing the reliability of the way the parts are being dimensioned.

Table 1. Diameters calculated for the axes for each material

FATIGUE		
Material	Diameter right half shaft (mm)	Diameter left half shaft (mm)
Steel Alloy SAE 4340 (Normalized 870 C)	24,40	27,08
Steel Alloy SAE 4140 (Normalized 870 C)	26,74	29,68
Steel Alloy SAE 4140 (Annealed 815 C)	31,09	34,50
Steel Alloy SAE 4140 (tempered in oil 315 C)	19,98	22,18
Steel Alloy SAE 4340 (Annealed 870 C)	29,83	33,11
Steel Alloy SAE 4340 (tempered in oil 315 C)	19,78	21,95
Steel Alloy SAE 1020 (cold drawn)	32,96	36,58
Steel Alloy AISI 8620 (Annealed)	31,93	35,43
Steel Alloy AISI 9255 (Normalized 900 C)	27,85	30,91
Steel Alloy AISI 9255 (Annealed 840 C)	29,46	32,70
Steel Alloy AISI 9255 (tempered in oil 885 C)	26,12	28,99
Steel Alloy AISI 9260	25,08	27,83
Steel Alloy AISI 9840 (Temperate 540 C)	22,46	24,93
Steel Alloy AISI 9840 (Temperate 595 C)	23,50	26,08
Steel Alloy SAE 5120	27,02	29,99
Steel Alloy AISI 5140 (Annealed 830 C)	34,89	38,72
Steel Alloy AISI 5140 (Normalized)	30,20	33,51
Steel Alloy AISI 5140 (tempered in oil 845 C)	23,97	26,60
Steel Alloy AISI 5140 (Normalized 870 C)	29,77	33,04
Steel Alloy AISI 5150 (Annealed)	32,65	36,23
Steel Alloy AISI 5150 (tempered in oil 830 C)	23,23	25,78
Steel Alloy AISI 5150 (Normalized)	29,36	32,58

The data that were used to calculate the diameter that entered the ANN were the size factor, surface modification factor, fatigue strength limit, left and right axis diameter and weight.

As for the pinion crown ratio, the data used for the network training that entered the calculation were final car speed, first gear torque, fuel consumption, time from 0 - 100 km/h and the gear change number, all of which they culminated in an objective function and the higher the objective function the better would be the relation crown pinion

2.2 Data Processing

In all ANN it is necessary to follow certain procedures to guarantee the reliability of the network. The first is the pre-processing of data in training. It is necessary to do this to ensure that there is no saturation in any of the neurons. To solve this problem we use the stochastic model where the neuron can only receive the value -1 and 1. Then normalization occurs, where each of the input values is divided by its respective maximum value.

After doing this initial process it is necessary to go to a second stage where the data is divided between training and tests at random.

ANN training should be performed with a large number of iterations (times) or pre-set quadratic mean error value that will act as a stopping criterion. The main importance in doing these iterations is to avoid that ANN memorize rather than to learn with the medium so if one has to know these parameters because they avoid the overlap (solution variability) and the adequacy (solutions polarization).

One way to solve the problem of data storage is the technique of cross-validation, which consists in dividing the data into two groups one for validation and another for training. The set of training and use of the weight modification and the set of validation and use to estimate the capacity of data generation during the learning process (Braga et al., 2000).

2.3 Cross Validation

The essence of retro propagation learning is to encode an input and output mapping (represented by a set of labeled examples) in the synaptic weights and thresholds of a multilayer perceptron (Haykin, 2001). From this perspective a well-trained network is expected, but this training process becomes the parameterization of the network for a data set which can generate a problem since the network will be chosen according to the data that have been parameterized what will make it difficult to learn with new data different from the previous ones.

For this reason if the cross-validation technique is so attractive. The purpose of cross-validation is to validate the network with a set of data different from those previously parameterized by the network itself. In this way it is possible to use a large number of training data to evaluate the performance of various candidate models for the network and to choose the one that fits best. However, there is a great possibility that model will fit the data to excessively the validation subset, so to ensure that this adjustment of the model is not happening, the generalization performance of the model is measured on the set of tests (Haykin, 2001).

By using cross-validation it is possible to vary the amount of neurons in the hidden layer and thus know when to stop the training.

2.4 Artificial Neural Networks

To develop the algorithm, a Multi Layer Perceptron (MLP) network architecture was used. 1000 training epochs and only one layer of hidden neurons were used, ranging from 1 to 50 neurons.

In the network training, the backpropagation error algorithm was used to determine the synaptic weights. Through the backfoward step an error signal calculated at the output is propagated from layer to layer in the reverse direction and at the end we have the weights adjusted and as a function of the error correction, leaving the network response much closer to the desired one. The weights chosen in the training were used to perform the network test (cross-validation) and with this, the data repeatability was analyzed.

The robustness (or repeatability of the results) is a way of analyzing whether ANN has the ability to generalize the result, in other words, to learn about the environment. The analysis should be done comparing the RMS of the training set with the test set and, the less dispersed the values, the more robust the network.

To calculate the RMS error, Eq. (1) is used.

$$RMS = \frac{1}{2N} \cdot \sum_{1}^{N} \sum_{k=1}^{K} \left(d_k - z_k \right)^2 \tag{1}$$

In the Eq. (1) the RMS is the mean square error, N represents the total number of data, K the number of neurons of the output layer, d_k e z_k are the desired responses and the current response of the k-th output neuron, respectively.

3. RESULTS AND DISCUSSION

The results will be divided into two topics for a better discussion: analysis of ANN robustness and analysis of the comparison between theoretically obtained data and the network.

3.1 Ann Repeatability

In order to verify the quality of the network, the cross-validation technique was used, for that the neuron number in the hidden layer was varied from 1 to 50 according to eq (1).

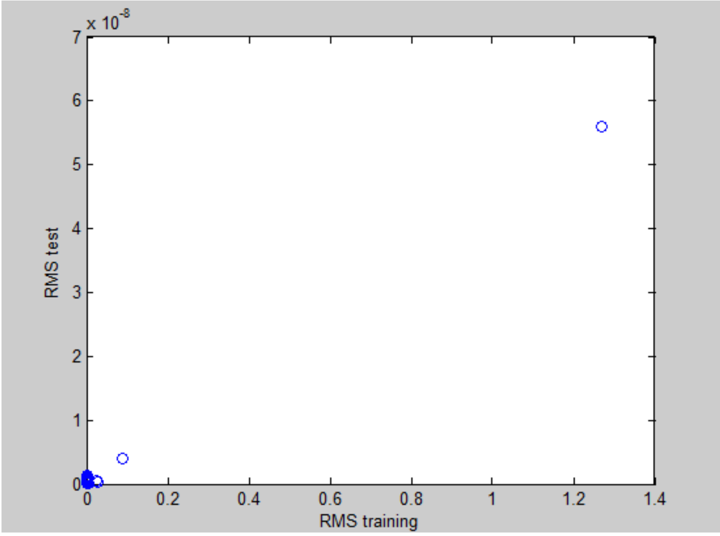

Figure 4. ANN Semi-axis repeatability

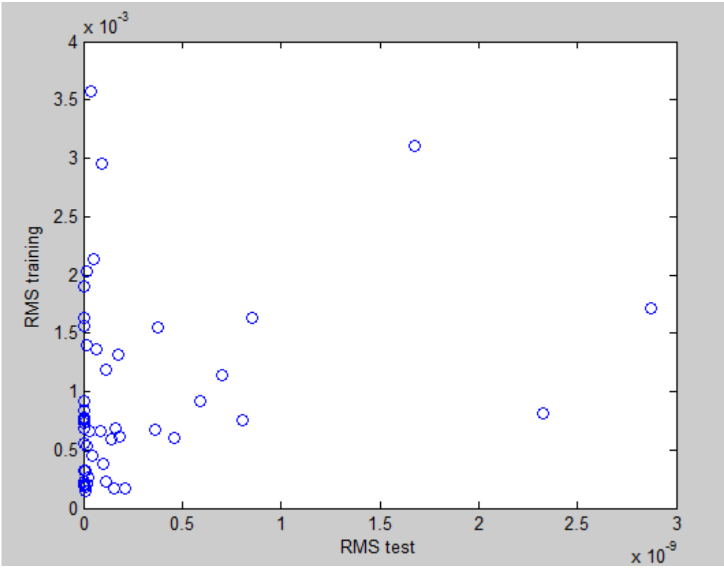

Figure 5. ANN repeatability of the Crown Pinion ratio

By analyzing the points in Fig. 4 and Fig. 5 it is possible to notice that both networks have a good robustness. In Fig. 4 we see the repeatability of ANN of the semi-axis, where only two points stand out from the others. In Fig 5 we see the repeatability of the ANN of the Crown Pinion relationship, although the graph is more dispersed than the other, all the points of the RMS training are on a scale smaller than 5×10^{-3} and for the RMS test the points are in a smaller than 3×10^{-9}, ie scales very small.

Then using the cross-validation technique and the results of the graph we can say that ANN for both cases the algorithms that make up the ANN are valid.

After finding the neuron that gave us the smallest test error (RMS test) a plot was drawn between the Mean Squared Error (RMS) for the tests and for the training (Fig. 6 and 7).

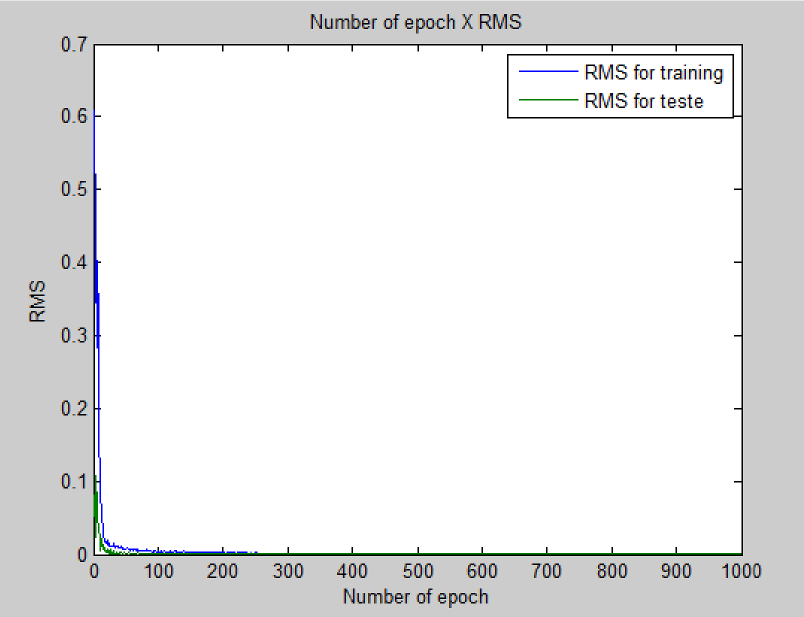

Figure 6. RMS X training epochs for ratio crown and pinion

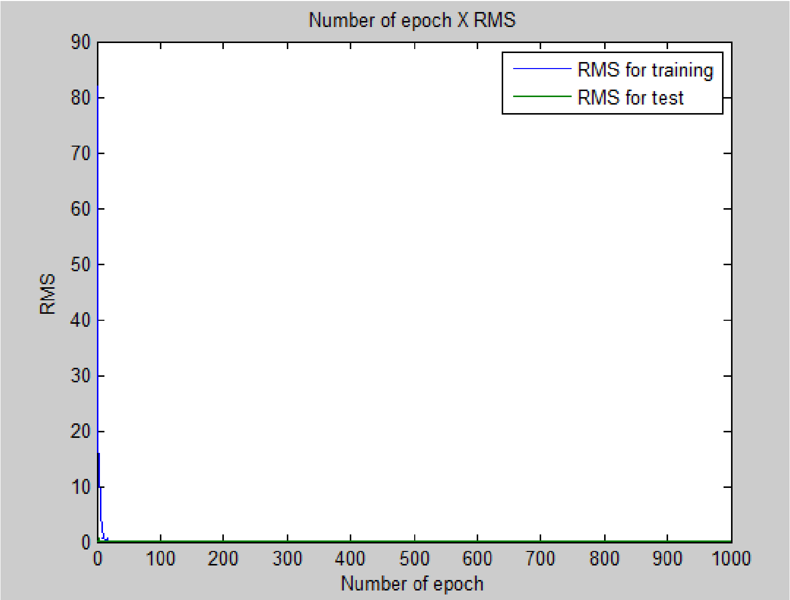

Figure 7. RMS X training epochs for half shaft

When looking at the graph, we realize that the RMS begins to stabilize before arriving in the hundredth epoch and remains stable until the last, this proves that a thousand times are enough for ANN training.

3.2 Function

Table 2. comparison between the results found theoretically and by ANN

HALF SHAFT THEORETICALLY CALCULATED	HALF SHAFT FOR ANN	RATIO THEORETICALLY CALCULATED	RATIO FOR ANN
25,05	25,06	5,33	5,36
27,46	27,46	4,92	4,94
31,92	31,94	4,80	4,77

20,52	20,53	4,77	4,75
30,62	30,64	4,62	4,60
20,30	20,33	4,50	4,50
33,83	33,86	4,46	4,46
32,78	32,80	4,31	4,32
28,59	28,60	4,15	4,17
30,24	30,25	4,00	4,00
26,82	26,84	3,86	3,87
25,74	25,77	3,71	3,71
23,06	23,05	3,69	3,70
24,13	24,14	3,57	3,57
27,74	27,75	3,43	3,42
35,82	35,82	3,38	3,37
31,00	31,01	3,25	3,25
24,61	24,62	3,13	3,14
30,56	30,57	3,00	2,99
33,52	33,55	2,88	2,87
23,84	23,85	2,75	2,75
30,14	30,15	2,69	2,69

We obtained a good result with the neural networks, as can be seen in Tab. 2, what was observed is when we compare the results obtained by the network in relation to those obtained theoretically, it is that results are very close to what was already expected after the results of the cross-validation.

4. CONCLUSIONS

After all these results we were able to verify the robustness of ANN and its success. Thanks to the repeatability analysis of the network that was made, it is concluded that it is not memorizing the data but rather learning with the input data. Another important point was the comparison data obtained with the network, for the axis the difference between the calculated by the network and theoretically was less than 1 mm and already in the relation pinion crown the difference was never above 0.1.

Based on the obtained results, it can be affirmed that it is possible to do a sizing of the transmission based on ANN. The benefits gained by this scaling method is a lower cost since it is not necessary to do so many analyzes and also the time spent for the scaling is much smaller than in the conventional way.

For future work, it is suggested to do the same work for more complex parts such as the gearbox that greatly influences the way the driver drives and the differential that affects the car not only in the part of longitudinal vehicular dynamics but also affects the side too.

5. ACKNOWLEDGEMENTS

I thank God for having empowered me to do this project and have supported me up until now, my mother who always invested in my studies, my tutor who believed in the project despite being new to the university and all teammates KRT UFBA that in the last 3 years has become a family always supporting me and making me believe that dreaming very high is almost a step to take flight

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7. RESPONSIBILITY NOTICE

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