Politecnico di Milano
Gaia Biasolo, Matteo Giuseppe Cigada, Federico D'Agostini

Lab 10: Handling Optimization

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Abstract

This report presents a multi-objective optimization analysis focusing on vehicle handling performance.

The core of the optimization process is implemented using a feedforward Artificial Neural Network (ANN). The ANN was trained using data obtained from Vi-CarRealTime simulations to approximate the complex non-linear relationships between two design variables (the longitudinal position of the center of gravity and the normalized stiffness of the anti-roll bar) and three specific objective functions derived from standardized handling tests.

After assessing the conflict between objectives via the Spearman correlation coefficient, the Pareto optimal set was computed. The results demonstrate the effectiveness of the ANN in generating the Pareto front, identifying the optimal trade-offs between lateral acceleration, handling diagram curvature, and yaw rate variation.

Contents

1. Introduction

In this assignment, the neural network previously explored in Lab 9 was applied to a problem related to vehicle handling.

Lateral dynamics is mostly affected by tires, suspensions system and mass distribution. The two parameters that were taken into consideration in this analysis (related to the previously mentioned factors) were the location of the center of gravity and the normalized stiffness of the anti-roll bar.

The aim of this lab is to analyze in detail the influence of these parameters on a multi-objective optimization accounting for different criteria related to vehicle handling.

1.1 Description of the problem

The optimization process is implemented by means of an artificial neural network. Specifically, the data provided is used to train the ANN that was subsequently used to implement the optimization process.

Design variables

The two design variables are the position of the center of gravity along the longitudinal axis and the normalized stiffness of the anti-roll bar. The first one determines the static vertical force distribution between front and rear axle, so the lateral forces developed by each axis. Instead, the latter governs the lateral load transfer distribution between front and rear axles during cornering.

Objective functions

The objective functions defined for the optimization process are three, and to analyze the handling behavior more thoroughly, they are chosen from different standardized tests.

They are defined as follows:

- **Maximum attainable lateral acceleration** during a steering pad maneuver. The index stands for the peak of the handling diagram, and it needs to be maximized.
- **Minimum curvature** of the handling diagram, related to a steering pad maneuver. Specifically, the maximum of the curvature of the plot $a_y \ vs \ \delta$ (second derivative) is minimized so to have a more progressive vehicle.
- **Variation of the yaw velocity** during a throttle release maneuver. The index is defined as variation of yaw velocity after the throttle release (at time t) and the one in stationary conditions:

  $$\Delta\dot{\psi} = \dot{\psi}(t) - \dot{\psi}_0$$

  This index is minimized.

The data provided to train the algorithm is obtained by running simulations of the previously described maneuvers of a compact car model on Vi-CarRealTime.

A feedforward neural network has to be built and trained to approximate the relation between the design variables and the objective functions. Then, after having assessed any possible correlation between the three objective functions using the Spearman correlation coefficient, the multi-objective optimization algorithm has to be implemented. The accuracy of the ANN had to be checked by comparing the simulated results with the training data. Finally, new combinations of design variables had to be simulated, and the Pareto optimal set had to be computed and plotted.

2. Computation of the Spearman correlation coefficient

2.1 Procedure

The **Spearman correlation coefficient** is a measure of the direction and the strength of the monotonic relationship between the objective functions considered; it provides useful information even if the relationship between the objective functions considered is strongly nonlinear.

In this case, it has been computed between the three objective functions to determine the level of conflict between them; to do this, the MATLAB function *corr* has been used on the following matrix:

$$fo = \left[\dot{\Psi}\ variation \,\middle|\, peak\ a_y \mid curvature\right]$$

The output matrix ρ is defined such that $\rho_{i,j}$ is the spearman correlation coefficient between the variables in column i and column j of the input matrix.

2.2 Results – correlation matrix

$$\rho = \begin{bmatrix} 1.0000 & -0.0933 & 0.6186 \\ -0.0933 & 1.0000 & 0.6217 \\ 0.6186 & 0.6217 & 1.0000 \end{bmatrix}$$

From this correlation matrix it is possible to see that all the three correlation coefficients are way lower than 0.85, which is the bear minimum to assess a correlation between the objective functions.

Consequently, all the three objective functions must the minimized separately, it is not possible to reduce the dimension of the problem.

3. Setup of the neural network

3.1 Procedure

Training

- Normalization of training input and output data
- *Levenberg-Marquardt* algorithm (selected after making some trials with the *Bayesian regularization algorithm* comparing the regression plots)
- Maximum number of training epochs: 2000
- Train ratio: 0.8
- Validation ratio: 0.2
- Post-regression and computation of the mean squared errors

Definition of the structure of the neural network

- Number of layers: 1
- Number of neurons per layer: 21 (selected after making some trials and comparing the regression plots)
- Definition of the activation function: *tansig* (default) = hyperbolic tangent sigmoid transfer function

3.2 Results – mean squared errors and post regression plots

The errors are computed as a difference between the reference output and the output of trained neural network.

err_psid = 6.4854e-04

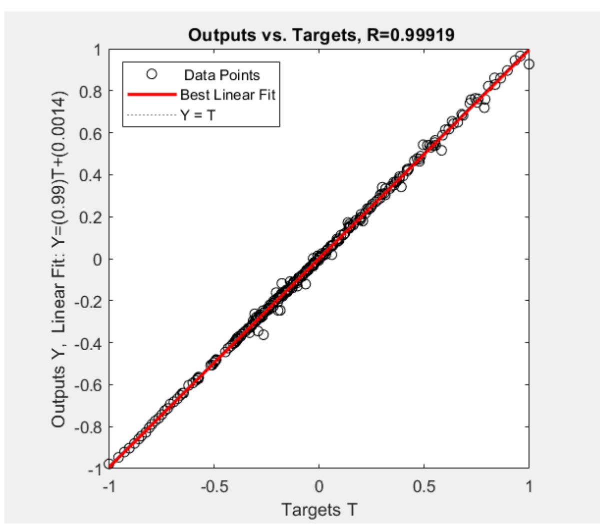

Figure 1

err_ayMax = 0.0027

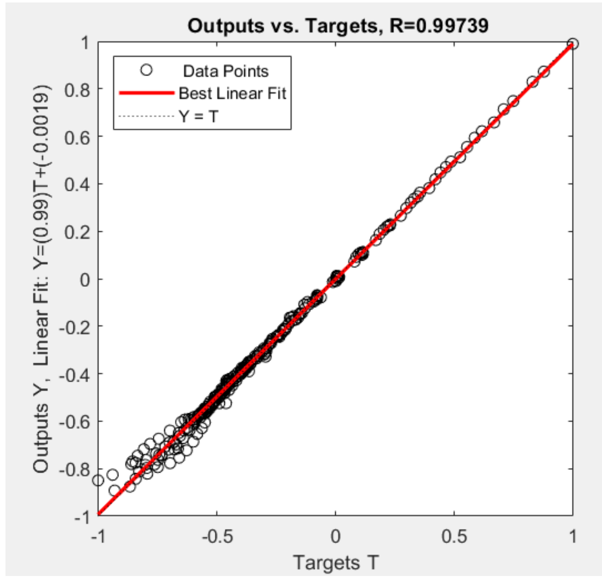

Figure 2

err_d2ayMax = 0.0916

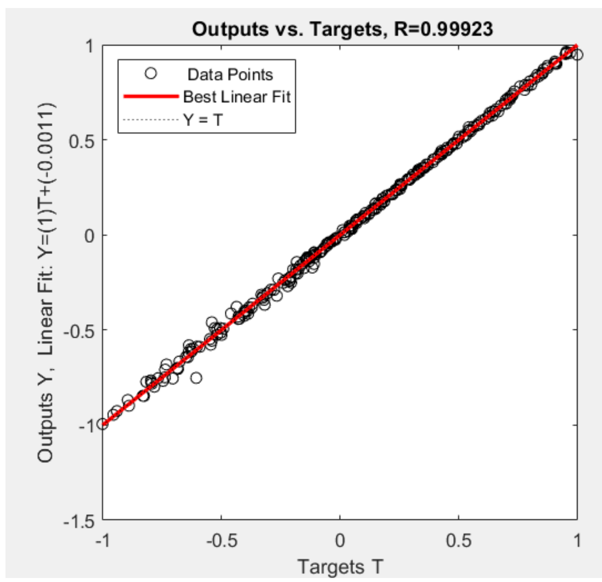

Figure 3

4. Computation of the Pareto optimal set

4.1 Procedure

The sorting algorithm is used. The MATLAB implementation is the exact same described in Lab_02_03.

4.2 Results – Pareto optimal set

Maximum lateral acceleration

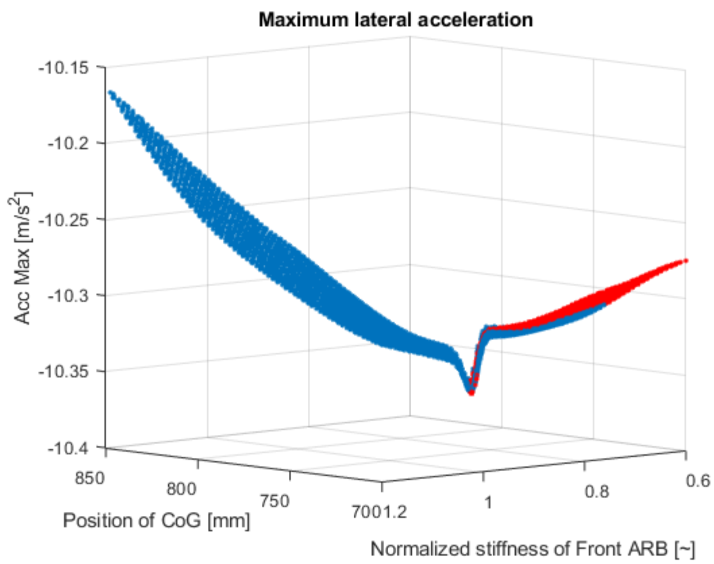

Figure 4

The maximum value of lateral acceleration is distributed along an almost straight line. Where the position of the CoG more to the rear of the car needs to be counteracted by a softer front antiroll bar. Which is coherent to the consequent difference in static load distribution.

Maximum curvature

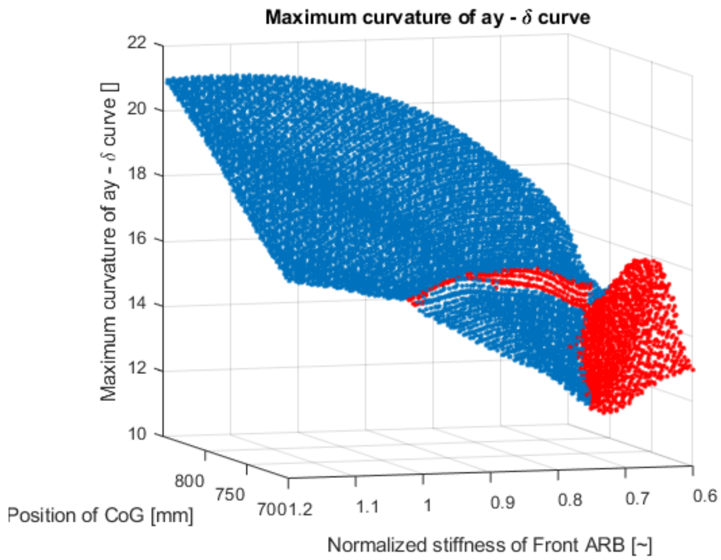

Figure 5

The best condition for the more progressive vehicle is to have the CoG more to the front as possible, with a normalized front ARB stiffness of about 0.72.

From vehicle dynamics, the most progressive behavior is for a car that has the CoG more to the front as possible, that is coherent with the fact that the car is more understeering, so the transition from linear to non linear part will be less steep in the handling diagram.

Yaw rate

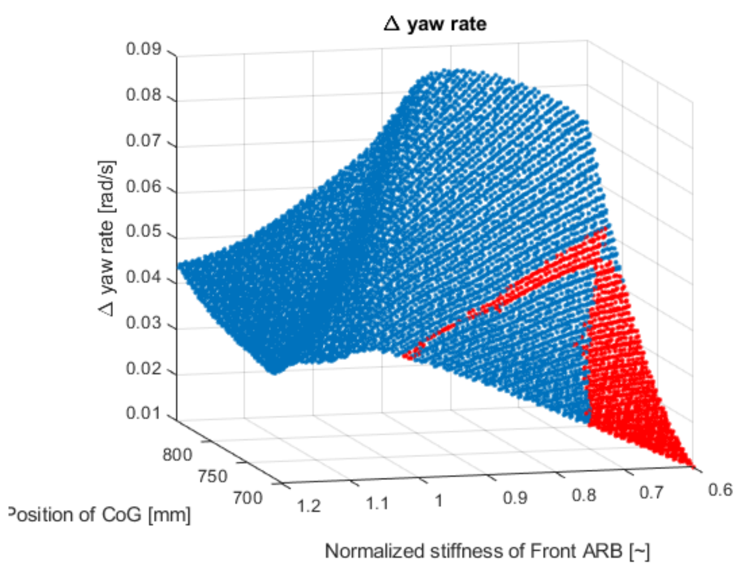

Figure 6

The best yaw rate index is for a position of the center of mass more to the front as possible and the lowest value of front stiffness as possible.

Total pareto set

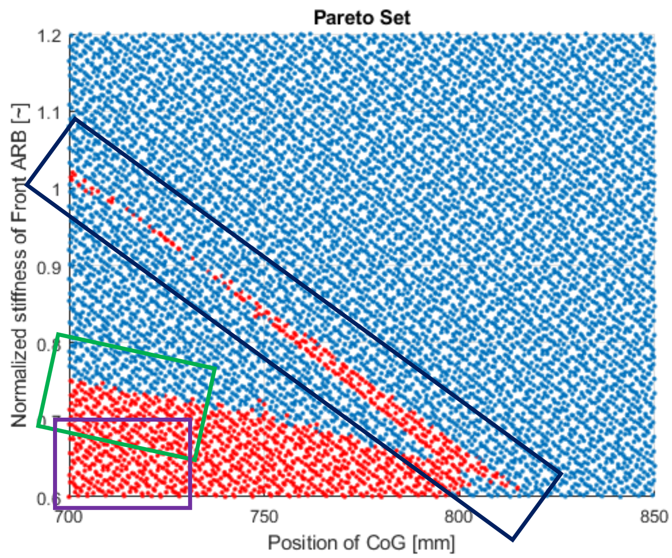

Figure 7

As show in Figure 7 the total pareto set can be also considered as a combination of the best solutions for each objective function, with some simplifications.

The following three zones can be considered, each:

- Maximum lateral acceleration
- Maximum curvature
- Yaw rate

Three dimensions pareto front

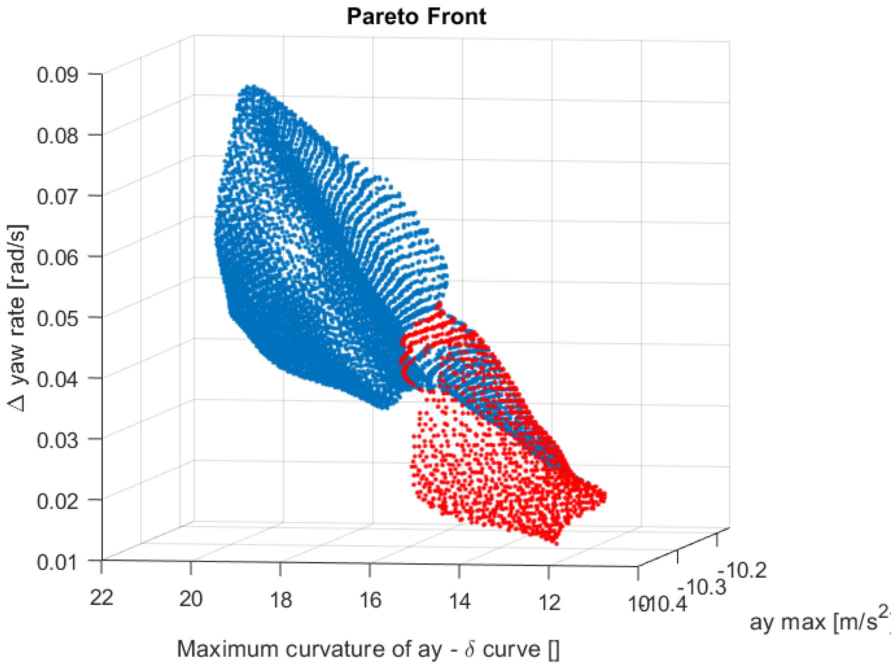

Figure 8

5. Conclusion

ANN Effectiveness

The implemented feedback on neural network, utilizing the Levenberg-Marquardt training algorithm and a specific structure of 21 neurons, proved highly accurate. The post-regression analysis showed low Mean Squared Errors and regression coefficients close to 1 for all objectives, validating the ANN as a reliable model for the vehicle simulations.

Objective Correlation

The Spearman correlation matrix indicated that there is not a strong monotonic relationship (coefficients < 0.85) between the three objective functions. This confirmed that the objectives are conflicting and must be minimized separately, preventing a reduction in the problem's dimension.

Pareto Optimization

The computed Pareto optimal set visualized the necessary design compromises. While maximizing lateral acceleration requires a Center of Gravity (CoG) shifted to the rear and a softer front anti-roll bar, optimizing the yaw rate variation requires a CoG positioned as far forward as possible. The final 3D Pareto front effectively combines these zones, providing a clear map of the optimal design solutions.