Experimental Study on the Dynamic Modeling and Optimization of Suspension Mechanism Using Neural Network

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***Abstract*— In this paper, vehicle's suspension dynamics modeling is presented using a nonlinear one quarter car model to optimize ride & handling criteria. Experimental tests have been performed in order to achieve the characteristic damping curve (Force-Velocity) of the shock absorber. An asymmetric two-stage damper model of the shock absorber is incorporated in suspension dynamics model and is compared to that of dynamic simulation software, MD ADAMS. Results of the model, subjected to a half-sine road profile input, have been investigated and a good agreement between the two models has been shown. In the next step, an optimization process is performed on the vibration response of the suspension model in order to obtain the optimized damping characteristic curve. The target of the optimization consists in minimizing the acceleration of the vehicle body as well as the displacement of the vehicle related to the tire. The results show an improvement in the optimized shock absorber's performance in compare to the ordinary shock absorber. Finally, due to the long time of the optimization process, a neural network is employed in order to represent the optimization. This network's input is the experimental suspension system's coefficient and its output is the optimized values. This neural network shows to be a good replace for the lengthy traditional optimization. The application of this neural network can contribute to the process of design of a shock absorber in industry.**

Keywords—suspension mechanism, shock absorber, optimizing vibration modeling, neural network, machine learning

I. INTRODUCTION

Shock absorbers are one of the vehicle's parts which bear consistent static or dynamic loads. At the same time, they need to hold their performance as time passes by under various loads. They support the weight of the body of the vehicle, engine section as well as the passengers and at the same time absorb the road excitation. They are directly and crucially connected to the vehicle's stability, handling and passenger comfort. A shock absorber consists of different parts such as outer tube, piston rod, piston valve, foot valve, seal, rod guide, rod, body, cylinder, washers etc. These parts and the shock absorber's damping mechanism are designed by taking into account the required performance requested by the OE customer for vehicles ranging from passenger cars to heavy duty vehicles like buses and trucks.

Different researchers have investigated the modeling of shock absorbers. Improving comfort for passengers is a constant challenge for the automotive industry. Fernandes et al. [1] have researched the cost effective asymmetric shock absorbers in order to improve the comfort for this widely used type of shock absorbers. Chen et al. [2] have examined half and full vehicle models in order to apply different dynamic inputs to the models and verify their results. Calvo et al. [4] studied three mathematical models and concluded that in order to get accurate results the models do not need to rely be complicated shock absorber models. Bamankar et al. [3] have reviewed the researches in mathematical and vibration analysis of suspension systems. Cui et al. [5] tested a Mazda CX-7 and extracted three shock absorber model and validated them with experimental data. Sadeghi Reineh [6] has investigated the physical response of an advanced automotive racing shock absorber and modeled its shock absorber in a simulation software called AMESim. In the foregoing study, the mechanical and hydraulic library of this simulator is used in order to model the shock absorber. Sharma et al. [7] have obtained a quarter car model in order to improve the overshoot and the settling time of the response. Agostinacchio et al. [8] have presented a quarter car model for a car, bus and truck in response to stochastic surface irregularities in road pavements based on ISO standards.

Various works have researched the effects of optimization on the performance of the shock absorber. Lajqi and Pehan [9] have modeled a quarter of the car's model with MATLAB/Simulink and then optimized the model. They have reached an improved performance by increasing driving comfort and safety. In another work, Pable and Seshu [10] proposed and approach to find the best parameters to make a passive system response close to an active system. Jamali et al. [11] have investigated a half vehicle model by taking into account the conflicting performance in the design of a suspension system . In the latter study by recruiting multi-objective optimization a framework is established in order to optimize a passive vehicle shock absorber where the under study model is excited on a random road.

In recent years, artificial neural networks have experienced a boom in their applications and has stimulated the interest of many researchers . Different types of these networks such as Convolutional Neural Network(CNN), Deep Convolutional Neural Network, Recurrent Neural Network and some other types of networks like image classification [12], object recognition [13], intelligent health services, etc have played a significant role. The main idea in neural networks consists in the connection between data to predict the relevant output in relation to a specific input. If the output continuously and in an inseparable way is categorized into separated groups a regression problem could be formed. In regression, the goal is to find the connection between one or several inputs with outputs in such way later on by having this connection and feeding the network with each input an appropriate output can be presented [14].

This paper aims at modeling and optimization of shock absorber of a passenger car. A neural network is trained in the paper in order to quickly reach an output for the optimization of the shock absorber's vibration equation. This neural network can offer optimized shock absorber's coefficients in less than a minute in compare to hours of calculation for the traditional optimization approaches. To the best knowledge of the authors this type of offline optimization with the use of neural network has not been carried out.

The remainder of this paper is organized as follows. In the next section, an analytical model of a simplified shock absorber is derived. The model includes two masses, two springs for the tire and the shock absorber and a shock absorber. Then an experimental test in the laboratory is performed in order to extract the force-velocity response of a passenger car rear shock absorber. These data will be used in the vibrational model in order to model the behavior of the shock absorber. In the next step, a dynamic simulation software, MD ADAMS, is recruited in order to simulate the shock absorber's behaviors. The same experimental data are implemented in the software to define the response of the damper. In section V, the results from these two models in response to a half-sine road excitation are compared. An optimization is performed on the analytical model and an improvement on the shock absorber's response is achieved and the optimized values are presented. In the final part of this paper, a neural network is employed in order to replace the time consuming procedure of traditional optimization. Results support a good accuracy in case of objective function between the neural network predictions and those of traditional approach of optimization.

II. Analytical Modeling and Equations

There are different approaches when it comes to modeling a suspension system. The most common method is a quarter car suspension. In this method the shock absorber in addition to the tire is modeled. Fig. 1 depicts schematically a quarter car suspension which is the subject of this paper. The tire of a car can be made equivalent to a spring with a higher coefficient relative to the shock absorber which is assumed as a spring installed in parallel to a damper. By recruiting Newton laws, the following two equations are derived in order to model the above system's behavior:

Table I. Constant coefficients of dynamic equation.

Constant Coefficients of Dynamic Equations	Value
Vehicle's Mass (kg)	328
Tire's Mass (kg)	15
Shock Absorber's Spring Coefficient (N/m)	15000
Tire's Spring Coefficient(N/m)	190000

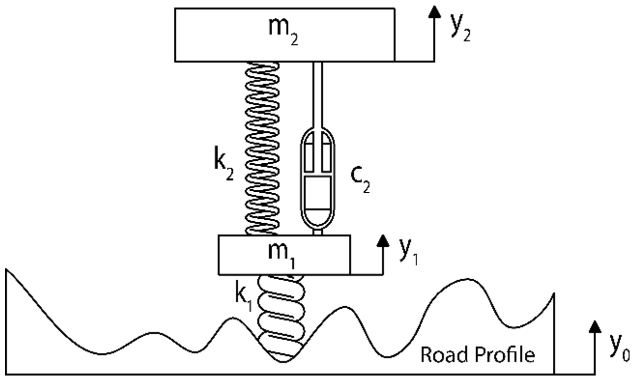

Figure 1. A schematic view of the one quarter car suspension model

$$\begin{cases} m_1 y_1'' + c_2(v)(y_1'(t) - y_2'(t)) + k_2(y_1(t) - y_2(t))\ldots \\ \ldots + k_1 y_1(t) - k_1 y_0(t) = 0 \\ m_2 y_2'' - c_2(v)\left(y_1'(t) - y_2'(t)\right) - k_2\left(y_1(t) - y_2(t)\right) = 0 \end{cases} \quad (1)$$

In the above, $c_2(v)$ is the damping ratio which is a function of velocity. This dependency can be measured with the laboratory's equipment, depicted in Fig. 2 and the Force-Velocity curve is illustrated in Fig. 3 which will be discussed in the following section. Table 1 shows the values of constant coefficients in (1). These two second-order equations can be converted into an equivalent four equations of first-order with the following assumption:

$$y^n = [y_1^{old} \quad y_2^{old} \quad y_1'^{old} \quad y_2'^{old}]^T \quad (2)$$

which leads to:

$$y^n = \begin{bmatrix} (c_2(v)y_2(t) - c_2(v)y_4(t) + k_2 y_1(t) - k_1 y_3(t) \ldots \\ \ldots - k_2 y_3(t) + k_1 y_0(t))/\mu_1 \\ -(c_2(v)y_2(t) - c_2(v)y_4(t) + k_2 y_1(t) - k_2 y_3(t))/m_2 \\ y_3(t) \\ y_4(t) \end{bmatrix} \quad (3)$$

These equations require the tire and shock absorber's coefficients in order to be dealt with. In the next section, experimental tests will be investigated in order to find damping coefficients. These equations will be solved

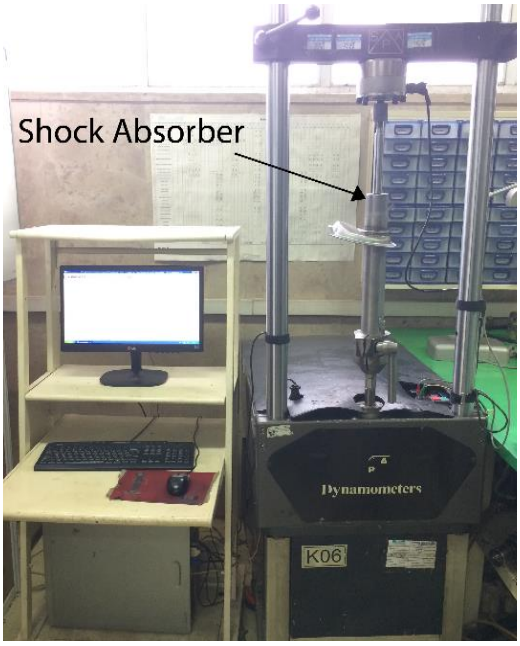

Figure 2. The experimental test equipment to measure Force-Velocity behavior

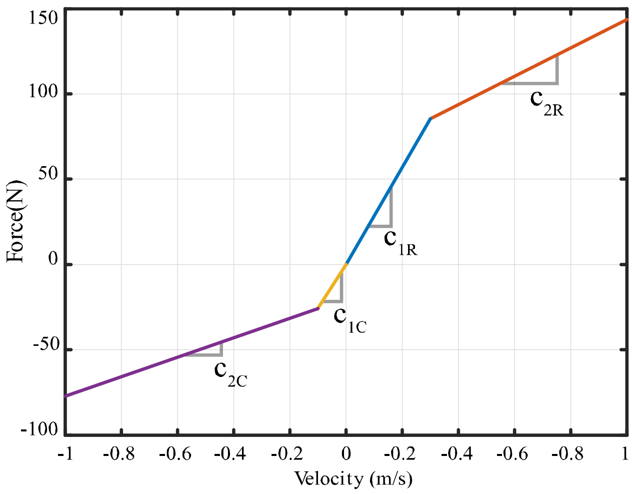

Figure 3. Shock absorber's force-velocity behavior and damping coefficients.

numerically and results will be presented and compared with simulation software in the result section.

III. Experimental Tests

The force applied by shock absorber's damper is a function of its velocity. This has been examined in the laboratory with the device illustrated in Fig. 2 and the extracted data points are used in order to obtain a curve with four different damping coefficients. The damping force characteristic curve is obtained by Dynamometer apparatus. The Sinusoidal displacement base excitation of the shock absorber is applied by a crack mechanism. The damping force is measured by a S-type loadcell connecting the piston rod to the apparatus frame. The damping ratio can be calculated form the measured force. The input displacement (x), the corresponding velocity (v) and the force (F) can be expressed as :

$$\begin{cases} x = A\sin(\omega t) \\ v = A\omega\cos(\omega t) = V_m\cos(\omega t) \\ F = AC(v)\omega\cos(\omega t) = F_m\cos(\omega t) \end{cases} \tag{3}$$

The F-V curve obtained using the above mentioned procedure is considered as damping force characteristic curve, as shown in Fig. 4. The curve plays an important role in dynamic response of shock absorber as a part vehicle suspension which should satisfy ride and handling requirements. The results are illustrated in Fig. 3. Shock absorber's responses can be categorized into two areas. The first area in which the length of the shock absorber is increasing is called rebound. In contrary, when the length of the shock absorber is decreasing it is referred to as compression

The shock absorber's damping coefficient in both rebound and compression can be divided into two areas named as low and high velocities parts. In lower velocities the damping coefficient is higher than those of higher velocities. By having this definition in mind, the area is categorized as rebound's low velocities, rebound's high velocities, compression's low velocities and compression's high velocities, respectively.

Based on obtained experimental tests, the shock absorber's behavior is extracted. These four coefficients are c_{1r}, c_{2r}, c_{1c} and c_{2c} which stand for the damping coefficients in rebound's low velocities, rebound's high velocities, compression's low velocities and compression's high velocities, respectively. The area shown by c_{1r} and c_{1c} happens when a smooth transition happens such as a lane change, while c_{2r} and c_{2c} occurs while rough surface of the road affects the shock absorber. Fig. 3 shows the shock absorber's velocity in different external stimulations.

IV. Numerical Simulation with MD-ADAMS Software

MD-Adams is a powerful simulation software widely used for kinematic and dynamic modeling of mechanical systems. The behavior of the vehicle's suspension is defined for MD-Adams as already discussed in Section II. Three translational joints limit the motion of the base and two other masses, which represent the tire and a quarter vehicle body, to a motion as the road excitation. A half-sine motion is applied as the road profile. The shock absorber's damping coefficient is defined as a curve using a point to point definition approach. The coefficients of springs are assumed to be a constant with different values for each spring. The results will be compared to analytical model in the following section.

V. Modeling's Results and Verification

In order to check the validity of analytical and MD Adams models, a bump profile input is discussed in this section. A road bump is considered as half-sine function and defined as:

$$y_0 = \begin{cases} 0.05\sin(4\pi t) & t \le 0.25 \\ 0 & t > 0.25 \end{cases} \quad (m) \tag{4}$$

The results for this input are shown in Figure . The results are

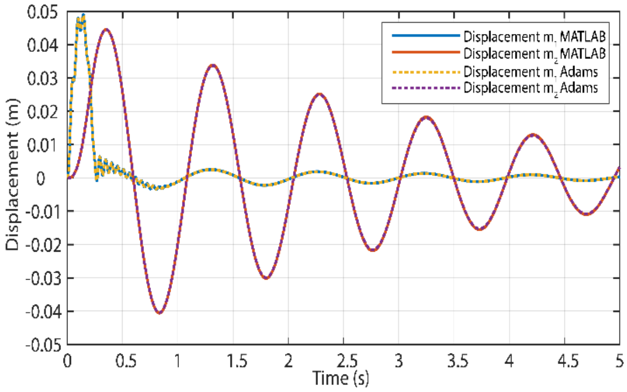

Figure 4. Displacement of tire and vehicle for a half-Sine input

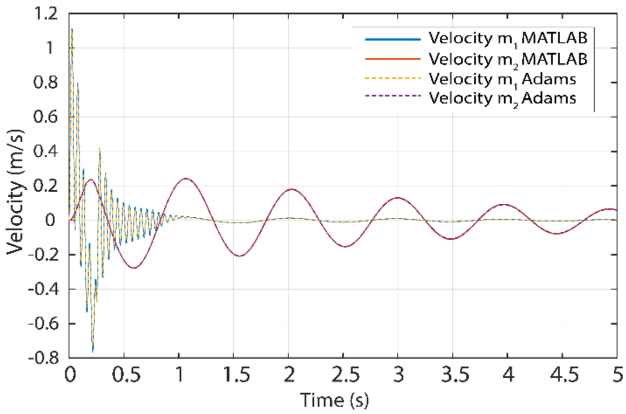

Figure 5. Velocity of tire and vehicle for a half-sine input

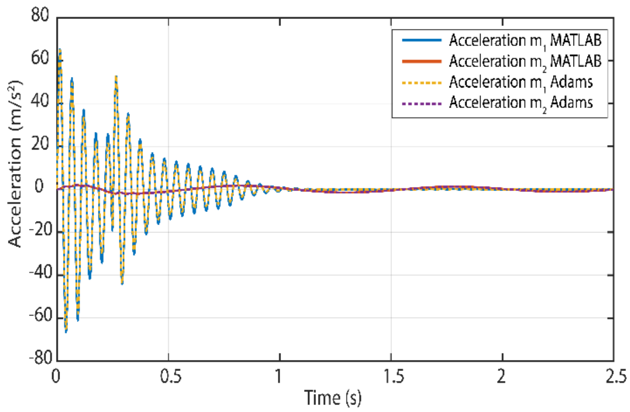

Figure 6. Acceleration of tire and vehicle for a half-sine input.

in a very good accordance which confirm the correctness of both MATLAB and MD-Adams simulation. Figure 4 shows the displacement of the tire and the vehicle body while Figs. 5 and 6 illustrate the velocity of two masses and the acceleration of them, respectively. This will make it possible to investigate the optimization problem of the model in order to find a better performance for the shock absorber which is the subject of the upcoming section.

VI. Optimization and Result Comparison

In this section, optimizing the coefficients of shock absorber regarding the ride and handling criteria of vehicle suspension's response will be addressed. In order to solve this multi-objective optimization problem, a linear combination of mentioned criteria is utilized to end of extracting optimum values of nonlinear damping model coefficients. The values which have been targeted to become minimum are the acceleration of the vehicle

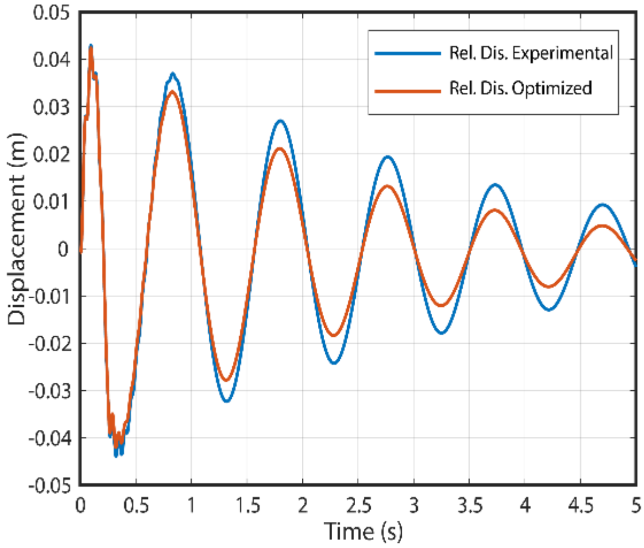

Figure 7. Relative displacement before and after optimization.

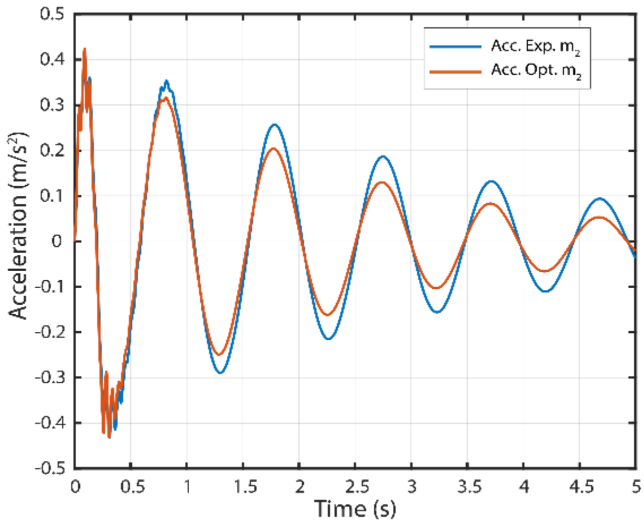

Figure 8. The acceleration of the vehicle before and after optimization.

body, a_2 , as well as the displacement of the vehicle body relative to the displacement of the tire, $(y_2 - y_1)$, with the following weighted equation:

$$f = 0.7\, a_2 + 0.3(y_2 - y_1) \quad (5)$$

The above equation describes that the importance of minimizing the acceleration is %70 and the relative displacement is improved by %30. The damping coefficients c_{1r} , c_{2r} , c_{1c} and c_{2c} of the shock absorber as well as the velocities in which slope of the shock absorber's characteristic curve changes in rebound, v_r , and in compression, v_c , are the subjects of optimization. These parameters are depicted as follow:

$$X = [V_r,\ V_c, c_{1r}, c_{2r}, c_{1c}, c_{2c}\ ] \quad (6)$$

Figure depicts the difference between the vehicle's acceleration and Figure shows relative displacement between the vehicle body and the tire before and after optimization. The improvement in performance after 5 second are about %45.

Table II. Damping coefficients and handling to ride velocities

Shock Absorber Coefficients Values	Experimental Values	Optimized Values
c_{1r} $(\frac{N.s}{m})$	285	328
c_{2r} $(\frac{N.s}{m})$	83	58
c_{1c} $(\frac{N.s}{m})$	259	334
c_{2c} $(\frac{N.s}{m})$	57	39
v_r $(\frac{m}{s})$	0.3	0.26
v_c $(\frac{m}{s})$	-0.1	-0.07
RMS Acceleration $(\frac{m}{s^2})$	0.55	0.50
RMS Relative Displacement (m)	0.27	0.25

Table II illustrates the suspension system's coefficients before and after optimization. This table shows an improvement of approximately %10 and %5 in the Root Mean Square (RMS) of the acceleration and the relative displacement, respectively. The settling time is also reduced from 12 (s) to 9 (s).

VII. Optimization of Coefficient with Neural Network

Since the above optimization procedure is relatively time-consuming and by taking the concept of regression into account, the optimization of V_r, V_c, c_{1r}, c_{2r}, c_{1c} and c_{2c} can be undergone by a neural network. By having enough sets of data form the results of the optimization problem, the connection between initial coefficients and optimized values is extracted and the trained network is employed for optimization.

In order to use a neural network for optimizing the coefficient, a group of data is required which includes the initial value for each coefficient and the optimized value.

Using a neural network instead of the traditional optimization method in MATAB reduce the processing time considerably and at the same time does not lead to a big difference in the value of objective function. The time for training the network is 20 seconds in compare to more than 2 hours for the traditional optimization method while the final error of the network stays less than %0.01.

A. *Collecting & Preprocessing of Data*

Training data are calculated by solving the dynamic model and optimization in MATLAB. The data's structure is a vector of 6 elements as the network's input. A vector with 6 elements, which are the optimized values, is introduced to the network as the appropriate output.

During the training, the weights of network, will be updated to learn the connection between input and output. In

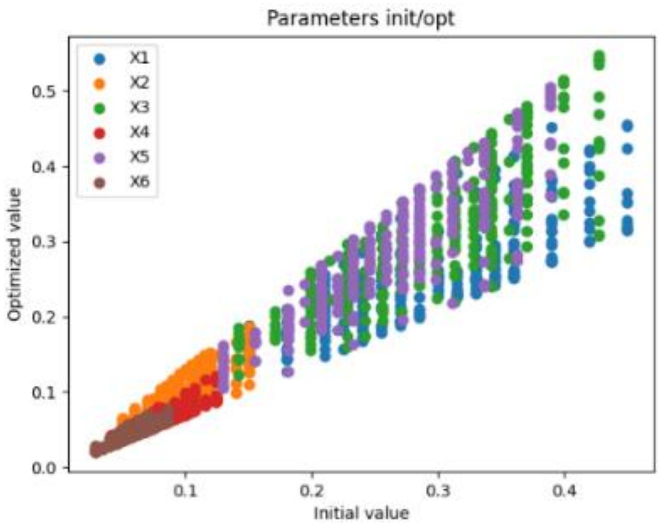

Figure 9. Distribution of the data set.

Fig. 9, the distribution of collected data is depicted. As illustrated in Fig. 9, the data is optimized in a linear form.

B. *Training the Network for Optimizing the Coefficient*

For solving the regression problem, structures such as linear regression, multivariant regression and neural network is employed. About 300 training sets are calculated using the traditional optimization method. Each of them includes 6 variables as unoptimized input and 6 variables as the optimized output. The unoptimized values are fed to the neural network in order to train and set the neurons values in the network.

C. *Results and Verifying Network's Performance*

In Fig. 10, the lost function of the network during the training is depicted. The selected lost function is a function of mean absolute error which is calculated as:

$$MAE = \frac{1}{n}\sum_{i=1}^{N}\left|y_{\text{predicted}} - y_{\text{actual}}\right| \quad (6)$$

The trend of lost function during training is continuously reducing and the trend for training data and verifying data are converging in an acceptable way. Considering Fig. 10, it can be concluded that the network is well trained and learning is completed.

The criteria for evaluating the correctness of the network's performance is the mean square error function which is employed in the network's training process and is calculated from the following equation:

$$MSE = \frac{1}{n}\sum_{i=1}^{N}\left(y_{\text{predicted}} - y_{\text{actual}}\right)^2 \quad (7)$$

The trend of (7) is illustrated for evaluating the network performance is shown in Fig. 11. The criteria's trend depict the network's learning correctness and its reduced error.

The value of objective function is also compared. By comparing the results of (5) from traditional optimization with the results of the neural network it can be inferred that they are in good coherence and in average the difference between them is less than %1. The final neural network is constructed of two layers, in which the first layer has 120 neurons and the second layer has 6 neurons. All the

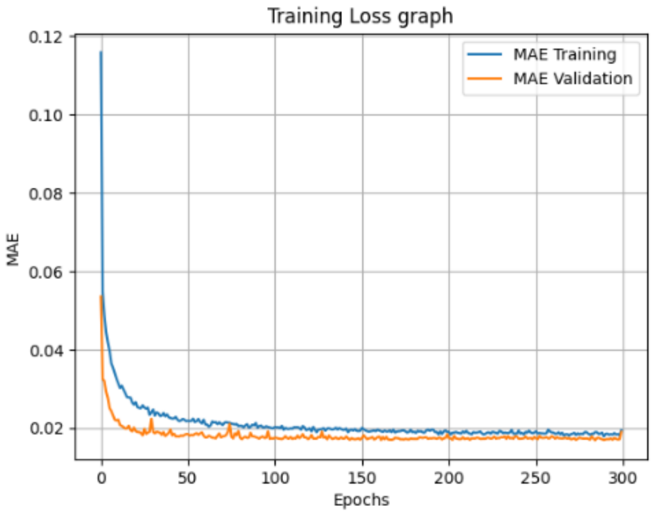

Figure 10. Lost function of the neural network.

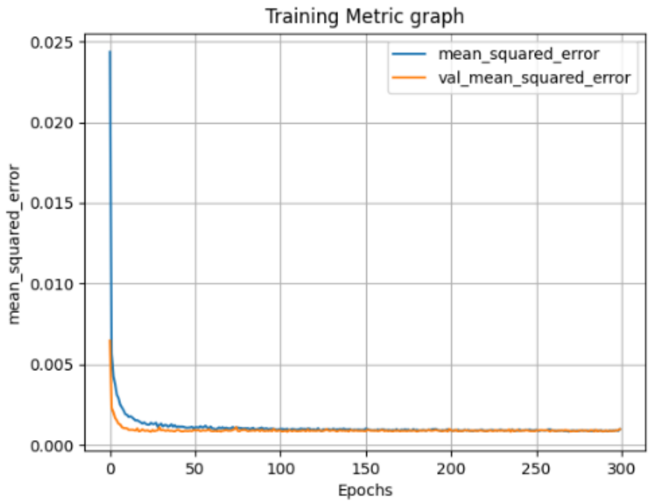

Figure 11. Evaluation function of network's performance.

parameters of this network, which needs to be updated are 1500 parameters.

VIII. Conclusions

A neural network was trained to replace the time consuming traditional optimization process of a shock absorber. This network was trained by more than 300 optimization results and its output can used to predict an optimized value for shock absorbers coefficients. The outcome of the network was proven to be very similar to that of the traditional optimization when compared about the objective function introduced in this paper. With the latter goal, a nonlinear mathematical model and a simulation in MD-ADAMS were presented in this paper using experimental measurements from tests in the laboratory. Results depicted a good accordance between two models which is certified by experimental tests. The mathematical model in the next step was then employed in order to optimize the experimental coefficients of the shock absorber and minimize the vehicle's acceleration as well as the displacement of the tire and the vehicle. The neural network is then trained using a large data set of this traditional optimization.

In future researches, the network's optimized results which has shown a better performance than the basic shock absorber in simulation can be used in further researches in order to design and select its parts (such as rod, body, rod guide, seal, washers, foot valve, etc.) with the goal of improving the performance. Moreover, the neural network's accuracy can be improved in further works by defining the the importance of the objective function for the neural network.

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