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A Motorcycle Front Fork Model Based on Neural Network and Trained Using Experimental Test Results

Modello di Forcella per Motociclo Mediante Rete Neurale Addestrata Su Dati Sperimentali

ABSTRACT: This paper discusses the use of an artificial neural network (ANN) to describe the complex behavior of a scooter front fork.

The architecture of the neural network is explained. The network was trained using a on-road experimental measurements. A different set of experimental data was used for the validation of the neural network, finding a good agreement between simulations and tests.

The comparison with the traditional parametric models, such as force-velocity model, shows that the ANN model is more accurate.

SOMMARIO: Questo lavoro illustra l'utilizzo di una rete neurale artificiale (ANN) per descrivere il comportamento complesso di una forcella per scooter.

Viene spiegata l'architettura della rete neurale utilizzata. Questa rete è stata addestrata usando dati sperimentali su strada. Per la validazione della rete neurale sono stati impiegati differenti set di misure sperimentali ottenendo un buon accordo tra simulazioni e test.

Il confronto con modelli parametrici tradizionali, come il modello forza-velocità, evidenzia una maggiore accuratezza del modello con ANN.

INTRODUCTION

As evident in the automotive and other motor sports industries computer simulation tools offer great benefits in the design of suspension systems for optimum ride, comfort, and handling. One of the most difficult suspension elements to model is the shock absorber. The reaction force generated by the damper presents highly nonlinear characteristics depending on many variables such as: its velocity, frequency, and amplitude of displacement, and significant dependence on temperature. As a result this combination of factors warrants the use of particularly complex mathematical modeling techniques.

Traditionally there are two approaches to model the damper: the *whitebox* model and the blackbox model. The first of these tries to describe the behavior of each individual component of the entire assembly, including fluid dynamics. This method allows the designer to examine the influence of various parameters (such as valve settings) on the design. *Blackbox* models, by contrast, are strictly empirical, attempting to correlate inputs and outputs using a mathematical model based on experimental data. As for the the damper the control input is typically a displacement profile, while the output is the force produced by the damping element.

Among the *blackbox* models artificial neural networks (ANN) have been applied to a variety of nonlinear problems. ANN have been used in damper design modelling, identification, control, and condition monitoring. Giacomin [1] first applied this approach to shock absorber behavior. He used a 4-input feed-forward multilayer perceptron network to model damper force as a function of input displacement and velocity. In a subsequent work [2] damper characterization was performed under constant amplitude sinusoidal testing. Results showed improvement over traditional velocity dependent models.

Barber's [3] work provides a comprehensive overview of modeling with ANN. He applied its advantages to both an automotive shock absorber and a biaxial rubber bushing, interfacing these models to ADAMS virtual prototyping environment.

In Patel and Dunne [4] a NARX neural network model was developed using measured damper data to model isothermal damper characteristics. This was compared with the physical model described in Duym [5], with the ANN showing higher accuracy and significantly improved prediction speed.

The current work starts from the definition of forces regarding the motorcycle front fork functioning under service loading conditions. Several constituents of the suspension force are identified and isolated. Multiple traditional *blackbox* approaches are then utilized to model the shock absorber behavior. Among these the neural network approach is developed in full. The architecture and function of the ANN model are detailed followed by a discussion of its capabilities. The model shows great potential with numerous benefits over the other methods described herein.

As previous studies about ANN damper modeling are focused on sinusoidal or random loading conditions on test benches, this investigation endeavors to train and test the damper model using real-world damper measurements collected from a motorcycle front fork under service loading conditions.

FORK PROPERTIES

The principal components of the hydraulic front fork are: inner and outer tubes, spring, piston and valve assembly (Fig. 1). The properties of a vehicle suspension are identified with two characteristics: stiffness and damping. The stiffness represents the force exhibited per unit of displacement, while damping is velocity dependent.

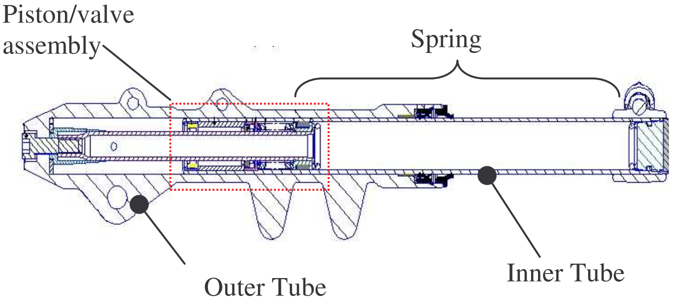

Fig. 1 - Cross section of a motorcycle front fork

The forces associated with one leg of the fork assembly can be expressed as follows:

$$F = F_S + F_G + F_O + F_f$$

where F_S represents the force generated by the spring; F_G the force due to the compressed air inside the tube; F_O is the force derived from oil passing through the valve; F_f is the (coulomb) friction force between suspension components. In some suspension configurations there is also a bumper (bump stop) force and a force generated by the negative spring. They are not included in this investigation.

Spring force: the force exerted by the spring is elastic and depends on the fork displacement. Within the assembled shock absorber the spring is always compressed and exhibits a certain preload. Additional compression occurs as the suspension is displaced. Figure 2 represents the stiffness data supplied by the manufacturer for the suspension subassembly used in the current study.

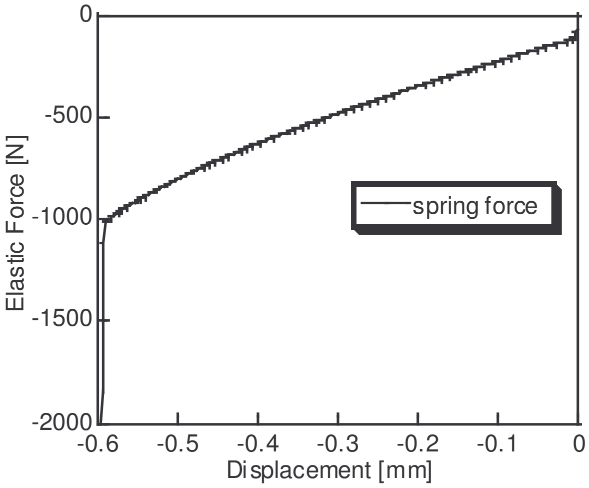

Fig. 2 - Elastic characteristics of the spring

Gas force: this is due to the presence of gas (air) in a volume that is compressed or expanded during fork travel. The gas force tends to oppose the compression of the fork and exhibits non-linear behavior. Gas force and friction force are obtained experimentally by means of a gas test (e.g. MTS System). Figure 3 shows the results for the suspension considered in this study

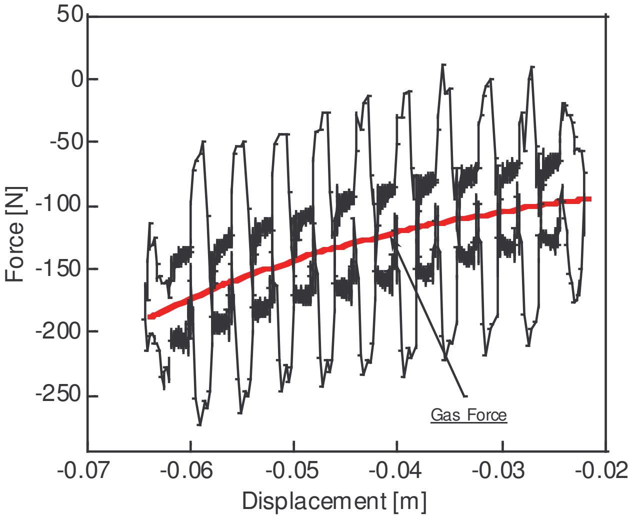

Fig. 3 – Results of the Gas Test. Isolated gas force

Damper force: force generated as oil passes through a series of valves or orifices. The flow rate of the oil, and hence the reaction force, depends the velocity of the suspension movement. Damping can be either linear or non-linear. In this investigation non-linear damping is considered.

Friction force: this term represents the coulomb damping and depends on the surface roughness and contact conditions between suspension components. The architecture of the motorcycle fork tends to increase this friction since the presence of the caster angle (around 25°); produces a bending moment in each fork leg. This bending moment exaggerates the sliding friction between the inner and outer tubes.

It should be noted that modern shock dynamometer techniques can be used to isolate each of the aforementioned force components. The convention adopted in this work is that displacement and velocity are assumed positive if spring-damper is extended. The maximum fork extension is the origin of the deformation.

CONVENTIONAL DAMPER MODELING

Blackbox model definition

As mentioned previously *blackbox* models (fig. 3) seek to relate inputs and outputs of a system through the use of mathematical models derived from experimental data. Normally these empirical mathematical expressions are developed using various curve fitting techniques or regression. Examples for damper force vs. velocity typically include polynomial or spline curve fits.

Blackbox methods are often enticing because they seek to represent the internal operation of the physical system in a cumulative sense. This is an obvious advantage, when the physical principles are not completely understood or the system model would otherwise require an enormous number of variables.

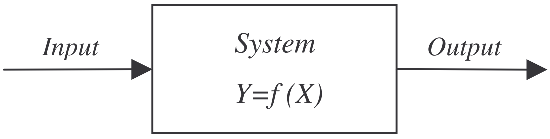

Fig. 3 – General *blackbox* schematic

Blackbox friction-damping model

The friction and damping force are grouped into a single *blackbox* element. Experimental measurements are carried out on a fork assembly with the spring removed. After accounting for the gas force, an analytical model for the friction and damping forces can be expressed as follows:

$$F_{friction} = F_{\max} \cdot \frac{2}{\pi} \tan^{-1}\left(\frac{V}{V_{ref}}\right)$$

where F_{max} represents the maximum value of the force generated during the test, V is the velocity during the test, V_{ref} is a reference velocity having a very small value. Over this velocity range friction is considered constant. The model obtained is reported in fig 4.

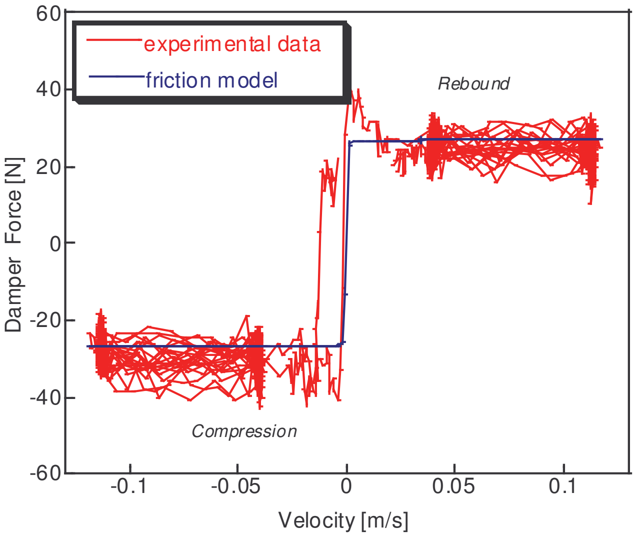

Fig. 4 - Friction model correlation

Blackbox force-velocity model

This model is the traditional model used for dampers. As is well known this type of model is typically limited to a particular range of frequencies. However results within the targeted frequency band are often satisfactory for limited cases. Tests were carried out on the bench with the fork inclined and subjected to sinusoidal displacements. The model is obtained with a 4th order polynomial fit passing through the origin. Results are reported in the figure 5. The blue line represents the model while the red shows experimental measurements. It can be noted that this model does not closely follow the actual behavior of the damper especially at maximum velocities. This is the previously mentioned limit of this type of model. Its validity is confined to a regular profile of the damper response for low velocities and frequencies.

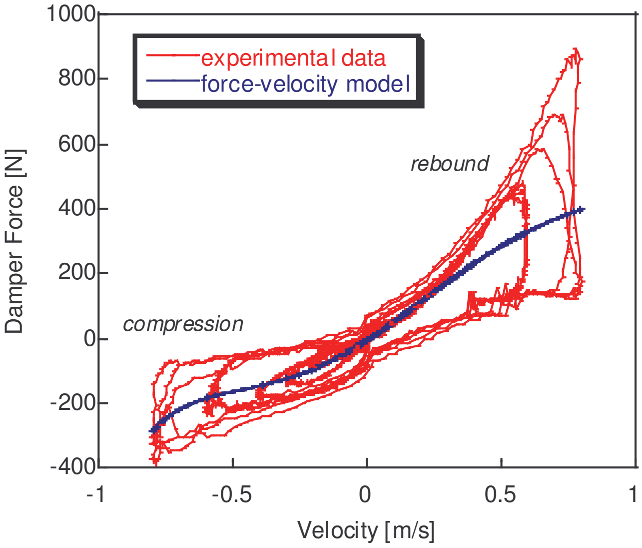

Fig. 5 – Force-velocity model correlation

Blackbox FRF model

In contrast to the force-velocity model this frequency dependent model is based on frequency response functions (FRFs) methods. Such models are applied to systems where the frequency of the input is a particularly critical aspect. As with any FRFs the relation between input and output signals is characterized in terms of magnitude and phase vs. frequency. Results of the FRF model of the damper as obtained from road testing (after averaging) is reported in Figure 6. The magnitude gives the ratio of force over velocity amplitude (FRF phase is omitted). It can be observed that the model fails to reproduce the non linear behavior of original data; this is not surprising since FRFs are applicable only for linear systems, while the damper response is strongly dependent on amplitude input.

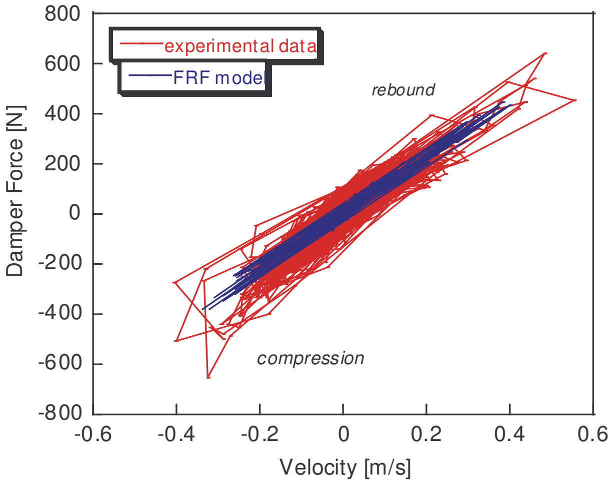

Fig. 6 FRF model correlation.

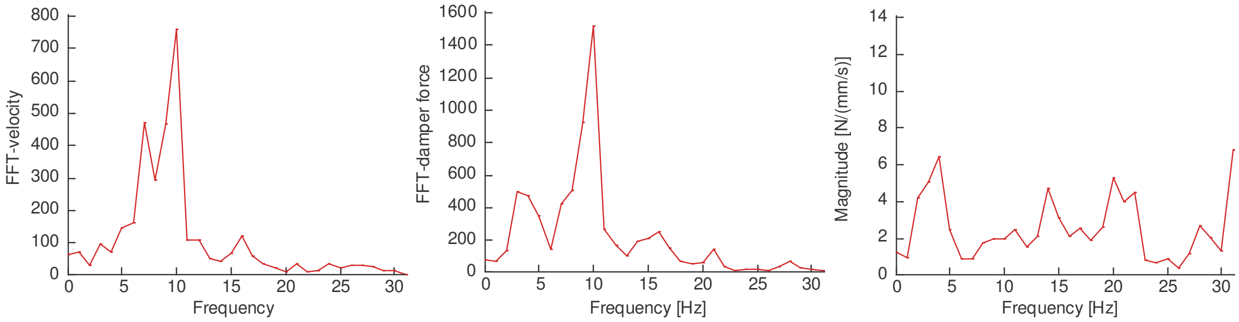

Fig. 6b – FFT of damper velocity and damper force and resulting FRF of the damper.

As can be discerned from the above analysis conventional *blackbox* models for complex nonlinear components like dampers are often inadequate to represent behavior over wide range of frequencies, and at large amplitudes. The obvious choice to accommodate such variable response is with an adaptive modeling technique such as a neural network with learning.

NEURAL NETWORK MODELLING

Artificial Neural Network (ANN) models provide a nonlinear, dynamic, *blackbox* approach to damper modeling. With the correct architecture and appropriate training, the approximation capabilities of the ANN afford the ability to model most any damper. An ANN is a computational paradigm that tries to emulate the physiological function of the human brain and its low-level information processing capabilities.

An ANN is constructed from fundamental units called neurons. As explained in [3] a neuron takes a series of varying inputs u_k and multiplies them by weights w_k (which vary during training but constant during subsequent model use) sums the products, along with a constant bias term, to yield a nonlinear ‘activation’ function from which the output value y is derived. The activation function is usually a sigmoid function. A schematic of this process is shown in Figure 7. A layered network is constructed by connecting multiple neurons to the same inputs to make a ‘layer’, and then the outputs of one layer are cascaded as inputs to the next. This structure is known as a *multilayer perceptron* (MLP, Figure 8).

Since the output for a dynamic system at any time depends on values of present and past inputs plus past outputs, a functional relationship of the following form is used:

$$y_k = f\left(u_k, u_{k-1}, \ldots\ldots u_{k-M}, y_{k-1}, \ldots\ldots y_{k-N}\right)$$

where k is a time index;
u’s are inputs,
y’s are outputs;

f is a nonlinear function to be determined as the primary goal of regression problem.

M is a parameter equal to the number of past inputs to include in the model. Ideally, M is infinite to represent the fact that all past inputs affect the current output;

N is a parameter denoting the number of past outputs to use.

The function *f* maps a space of M+N dimensions to a space of one dimension.

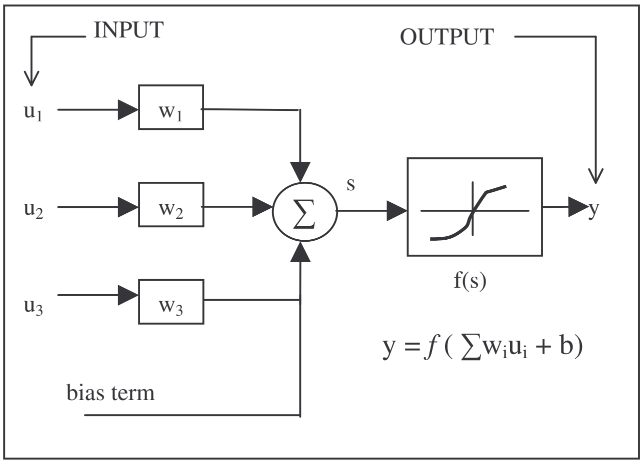

Fig 7- Conceptual schematic of ANN

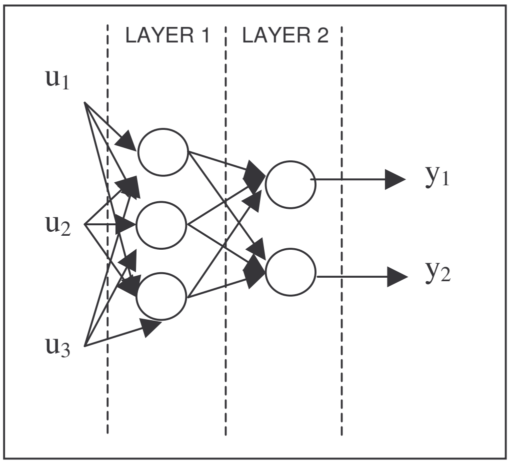

Fig. 8 – Basic architectural of the MLP

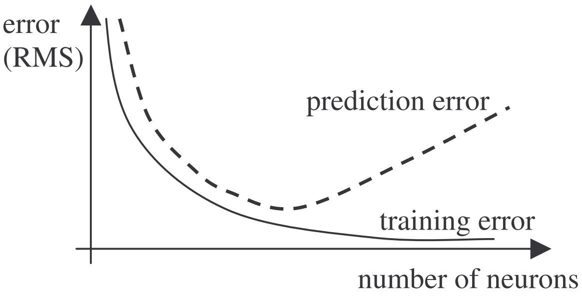

Fig. 9 Training vs. Prediction Error

As the network model size, increases it can be demonstrated that the training error, i.e. the error between network results and training data reaches a minimum while the prediction for novel input data tends to reach a minimum and then increases at a non-linear rate. Hence, a perfect fit is not desired (it would accommodate not only the signal but also the noise) but a compromise in prediction error, training error, and network size should be reached.

EXPERIMENTAL MEASUREMENTS

This study has been executed on a scooter front fork produced by Paioli Meccanica that is adopted on a 150cc scooter. It has a diameter of 36 mm and a travel of 93 mm. For this investigation, force and displacement data from proving ground measurements were used in developing the neural network model. The scooter was instrumented for data acquisition purposes. The experimental equipment is described in [6]. Specifically designed load cells were mounted on the fork, at the wheel spindle, modifying the original manufacturer design only to a small extent. These tri-axial load cells permits the measurement of forces in all three directions. Actually in this study only the forces parallel to the damper were of interest. The displacement exhibited by the fork was measured using a traditional linear potentiometer (LVDT). Data was collected at 800 points per second and then filtered at 100 Hz. The proving ground tests were carried out near Peugeot Motocycles headquarters in France, on both urban and highway roads, with good surface conditions.

Since the subject of the current modeling deals strictly with the damper the damper force was isolated within the measured data by subtracting out the spring force and the gas force, known from laboratory tests.

ANN DEVELOPMENT

In this section the procedure to obtain the neural network is illustrated. It started from the experimental measurements obtained on road; the effectiveness of the network is verified and its behavior and validity is studied.

The software used to obtain the neural network was MATLAB [7]. This does not preclude the use of other software since training and testing of ANN can be carried out with various other programs (such as FORTRAN). MATLAB has the advantage that it presents a toolbox specifically dedicated to ANN handling and manipulation, so training and testing algorithms are already coded; then the user has only to organize his own routines according to his needs.

Every data set has been divided in sections (of around 10-20 sec) in which no braking occurs. These sections can be used both for training and testing the effectiveness of network. In this paper results are reported of a neural network obtained starting from a selected section with roughly 20 seconds of the track being considered (training set). The ANN is trained on this section and subsequently tested with others datasets (generalization or prediction dataset). It has to be reminded that this choice is completely arbitrary, different sections would yield equally adequate results.

The definition of the architecture of the ANN is the crux of the design challenge; finding the optimal scheme is a design process, involving iteration, subjective evaluations, long trial and error sessions. Despite increasing use of ANN models there is not an established ANN damper architecture.

In this case the architecture has been defined through a procedure that requires a certain number of trials varying different parameters: type of network, input type, number of layers, number of neurons, training time, algorithm.

In nonlinear modeling, there are two types of (feedforward) network: the Multi-Layer Perceptron (MLP), and the Radial Basis Function (RBF) network. In this study MLP was selected because it is more efficient than RBF (whose implementation is more elaborate). MLP, uses stochastic approximation within a feedforward structure. Feedforward networks can be trained routinely using the standard backpropagation (BP) algorithm. Such algorithms are widely known and the power of fast gradient descent methods such as the Levenberg-Marquardt algorithm can be captured with the Matlab function *trainlm* in the neural network toolbox.

The following step is to select the number of hidden layers, establish the number and type of input variables, and then to find the optimum number of neurons in each hidden layer. Physical damper models vary in complexity from single input (velocity) models to more complex models using two or more inputs (such as displacement, velocity and acceleration). A larger number of input variables does not necessarily lead to good network design. An important objective therefore is to keep the network structure as simple and efficient as possible.

The network referred to in this study is composed of two layers, 15 neurons in the lower layer and 1, neuron representing the force output in the upper layer. The input variable selected was the displacement of the fork. The number of delayed inputs equals 9, in this way information about velocity and acceleration of the shock absorber is incorporated. The number of epochs of iterations was limited to 200. Above this limit it has been observed that accuracy does not justify the required time. The activation functions have been the sigmoid tangent for the first layer and the simple linear function for the output layer. As evident in the feed forward structure of this network (figure 10) no explicit feedback loop is included.

The sample rate is 100 Hz, high enough to encompass all of the phenomena of interest. It should be noted that a rather important parameter to fully understand the damper behavior, the temperature, is not fed to the network but incorporated within the *blackbox*. This approach is intended to alleviate the need to record oil temperature during experimental test, a difficult task under the service conditions of the motorcycle front fork.

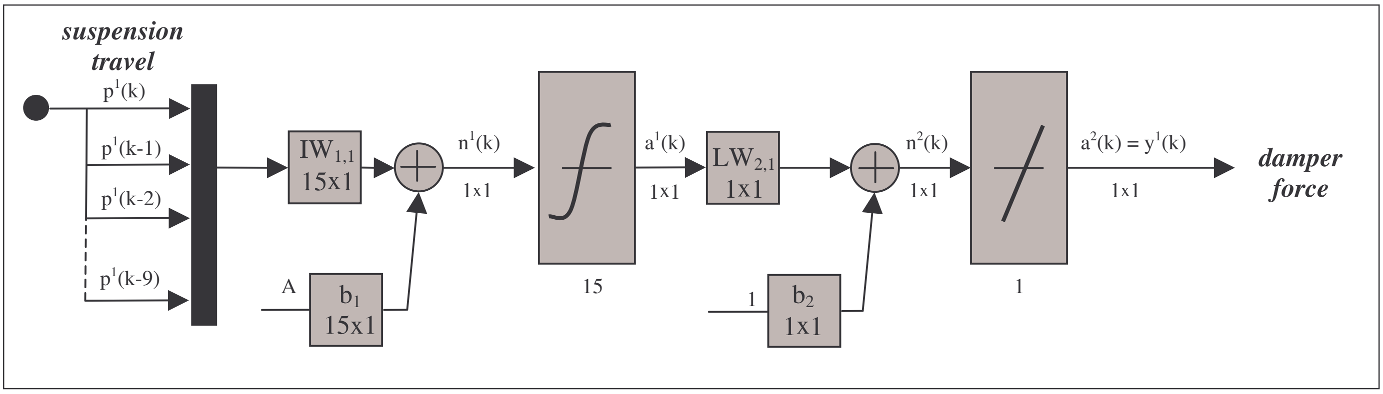

Fig. 10 - Architecture of the current network

TRAINING

Once the constituents of ANN architecture have been defined (number of neurons, layers etc.) the next step is the training. Training is performed by submitting a set of input data to the delay inputs, and adjusting the neural network weights for each layer, until the neural net output approximates the corresponding recorded signal from the dynamic system with minimum mean square.

$$mse = \frac{1}{q} \sum (y_i - t_i)^2$$

where $(y_i - t_i)$ is the difference between data calculated with ANN and the target data, q is the number of input data (equal to the interval being examined, Δt, times the sample rate).

This adjustment process is called back propagation, because the calculations are performed beginning with the neural net output and proceeding backward through the network.

For the current model training has been carried out using a particular set of track data. The result of the training is shown for a short interval in Figure 11. As can be seen the agreement to experimental data is quite good. It is not perfect, however as mentioned correlation to training data is only one of the factors in obtaining a sufficient generalized network.

TESTING

The ability of the ANN to generalize can only be assessed by testing it on data that was not used for model generation; this data is the prediction set. The parameter for evaluating the discrepancy is the root mean square (See Table 1).

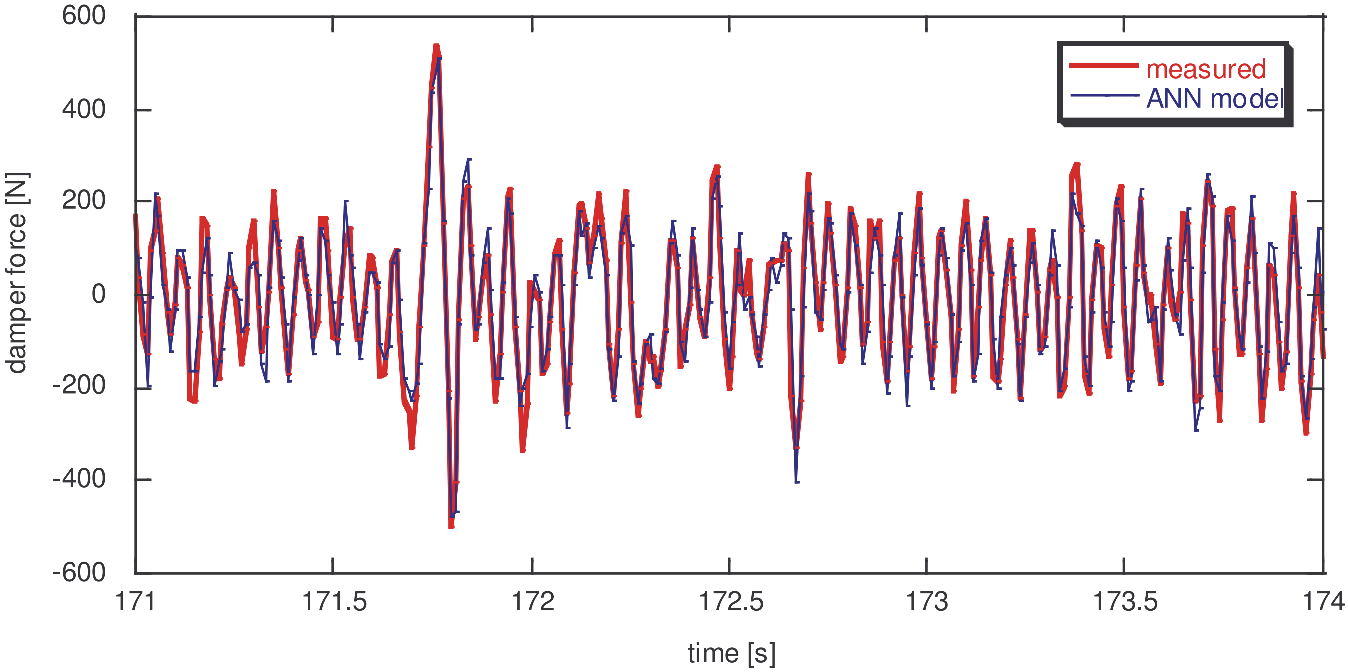

Fig 11 - Training data. Comparison ANN – experimental data

Table 1. Assessment of ANN performance.

	Interval Δt [s]	number of points $\Delta t \cdot$ sample rate	$rms = \sqrt{mse}$ [N]
dataset 1 (training data)	17	1700	35
dataset 2 (generalization data)	8	800	20
dataset 3 (generalization data)	9	900	15

Figure 12 shows the ANN response for a different section of the same experimental dataset (2).

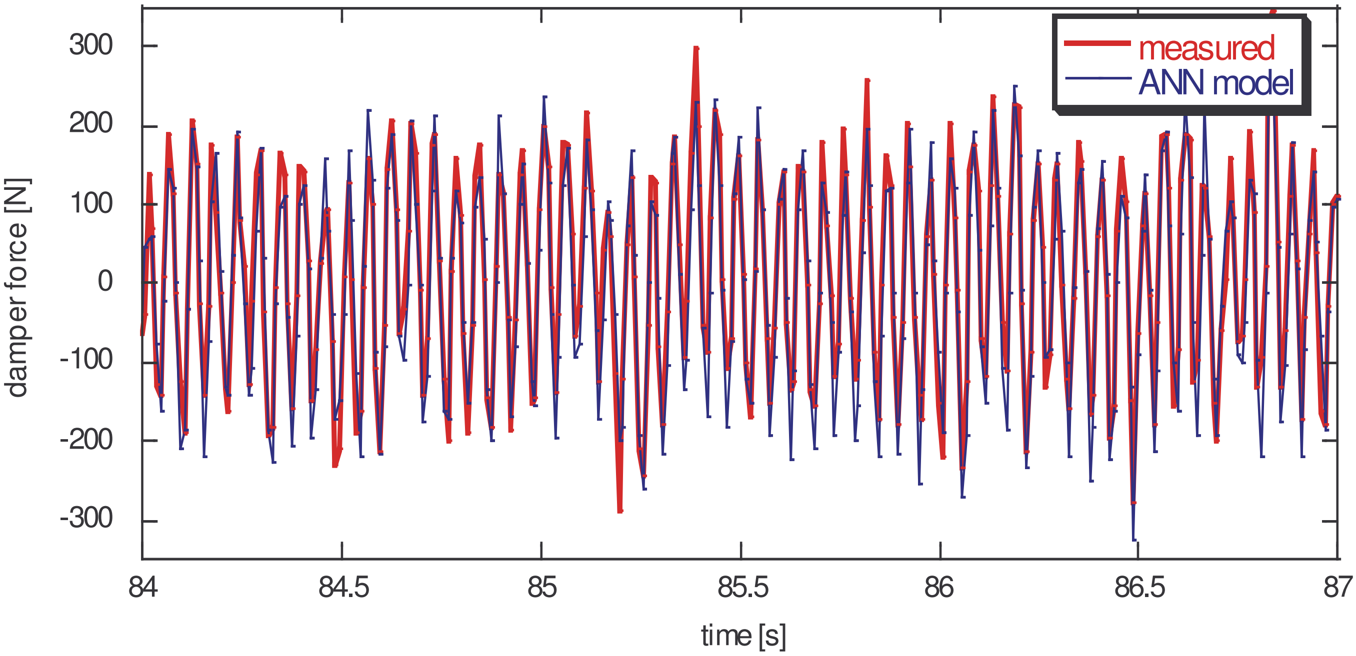

Fig 12 - Test data. Comparison of ANN with experimental data for a different section

In Fig. 13 the behavior of the net is examined for yet another section of the experimental data (dataset 3), which includes the addition of a passenger. As can be seen in this case agreement between test data and simulated results is quite good.

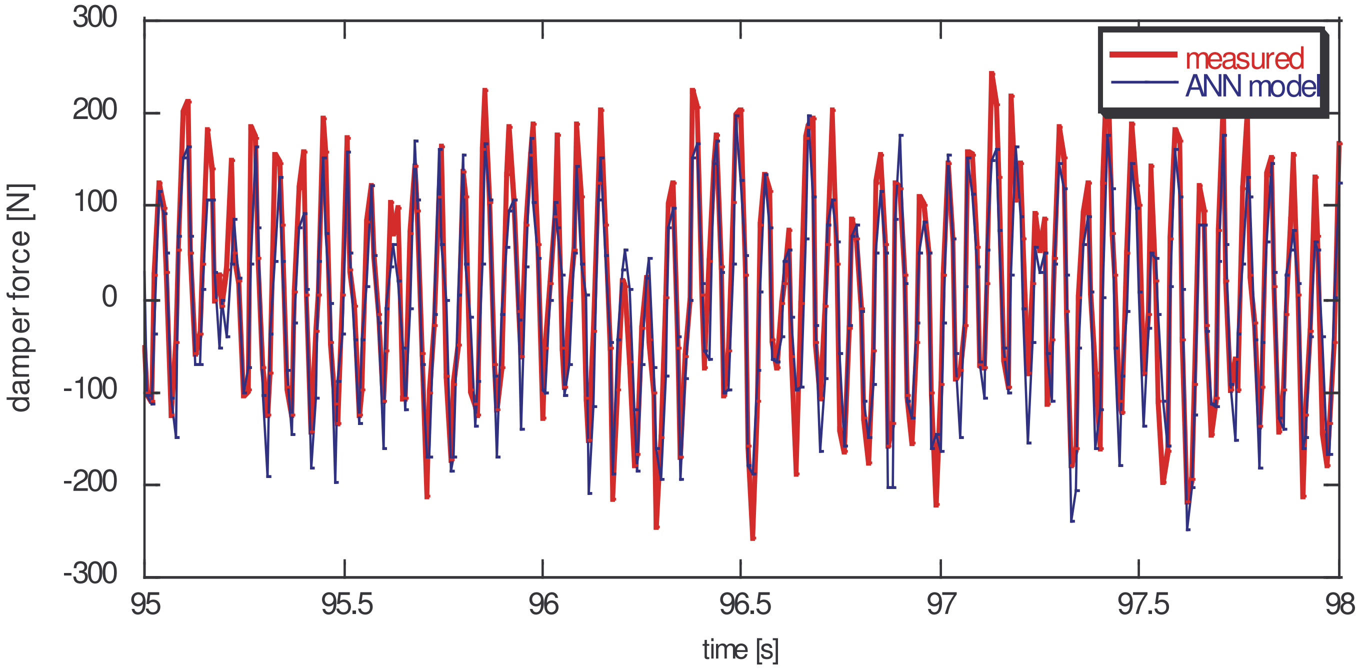

Fig 13 - Test data. Comparison of ANN with experimental data. Motorscooter with a passenger

DISCUSSION

In the current study an ANN model has been developed capable of predicting damper behavior over a wide range of frequencies, displacements, and velocities. This model presents a number of benefits over many conventional models in terms of solve time, applicability over a wide range of conditions, and usability. After the model architecture has been established further implementation of the model is quite straightforward. The end user of the model does not require a deep conceptual understanding of artificial neural networks to use the model effectively. In essence, after its development, the model is self tuning requiring only a limited set of input data. The versatility of the model also permits the same model architecture to replicate many different shock absorbers simply by training the model on the appropriate data. It should also be noted that the training time for the model is considerably shorter than the time needed to correlate an analytical model. The time benefit over other *blackbox* models varies depending on the model content. Arguably the greatest feature of the model is however its ability to capture not only trends in damper response across a range of frequencies (as does the FRF model) but also to provide a full description of the damper behavior at discrete points in time.

Looking toward the future interfacing the ANN model with a multi-body solver some problems occur. First of all the solver usually uses a time step that varies during the integration, whereas ANN model uses a fixed sample rate. The ANN model also requires inputs and outputs of the past simulations while the solver has no use for that information. Furthermore the multibody integrator of uses a trial values for the time increment eventually converging on the correct step size. Although all values, including the trials, are often stored in the solver buffer and must be excluded before input of the data to ANN [3]. A solution about all of these problem should be matter of a future development.

ACKNOWLEDGMENT

The authors would like to thank Paioli Meccanica for funding the continuing Ph. D. research at the University of Padova and for supplying the experimental data in this study.

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