
Identification of Compliant Contact Force Parameters in Multibody Systems Based on the Neural Network Approach Related to Municipal Property Damages

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Abstract: In this paper, a new approach for identification of the compliant contact parameters model in multibody systems simulation using a neural network algorithm is presented. Based on the training and testing the network for some input and output data sets, a general framework is established for identification of these parameters. For this purpose, first, the literature devoted to the identification of contact parameters using analytical approaches and methods based on the neural network is reviewed in brief. Next, the proposed approach is outlined. Finally, considering a classical example of contact of two bodies, the proposed approach is applied for verification of the obtained results.

Keywords: Compliant Contact Force Model, Multibody Systems, Stiffness and Damping Coefficients, Neural Network

1. Introduction

The motion of bodies in multibody systems is concerned with formulating the equations of motion and calculating kinematic and kinetic quantities governing the motion. Contact and impact are among the most important and most difficult cases and play an essential role. From the modeling methodology point of view, several different methods have been introduced. As a rough classification, they may be divided into contact force based methods and methods based on geometrical constraints [1].

As an effective method in contact analysis between complex objects with multiple contacts (which belongs to the first category of the above-mentioned classification), the surface compliance method uses a penalty formulation [2]. It is assumed that each contact region is covered with some spring-damper elements scattered over the body surfaces. The normal force including the elastic and damping shares prevents penetration, i.e., no explicit kinematic constraint is considered. The magnitudes of stiffness and damping coefficients of the spring-damper elements have to be computed based on the penetration, material properties and

surface geometries of the colliding bodies.

2. Statement of the Problem

Modeling and simulation of multibody systems with compliant contact model suffers from some difficulties. Although the approaches based on such formulation are usually simple to be implemented, they face some problems in choosing suitable contact parameters (stiffness and damping coefficients, and penetration exponent in the contact force formula). They are not always applicable due to the problems arising from selection of high values of these coefficients for imposing non-penetration conditions which results in stiff systems with ill-conditioned numerical.

There exist researches cited in the literature using analytical approaches for identification of contact parameters. In these approaches, the magnitudes of contact parameters are computed based on the penetration, material properties, surface geometries of the colliding bodies, and etc., see e.g. [3, 4, 5]. However, such methodologies are basically derived for contacting objects with simple geometries. Furthermore, these approaches may not lead to

realistic results when applying to the contact modeling of general multibody systems. Therefore, it is necessary to develop new methods which rely on the numerical algorithms and can be applied to the general cases of contact modeling, and still can preserve the required accuracy.

3. Literature Review

Among analytical approaches, in [4] the required parameters for representing contact force laws are obtained based on the energy balance during contact. This formulation uses a force-displacement law that involves determination of material stiffness and damping coefficients. In [5] two continuous contact force models are presented for which unknown parameters are evaluated analytically. In the first model, internal damping of bodies represents the energy dissipation at low impact velocities. However, in the second model local plasticity of the surfaces in contact becomes the dominant source of energy dissipation. Dias and Pereira [6] described the contact law using a continuous force model based on the Hertz contact law with hysteresis damping. The effect and importance of structural damping schemes in flexible bodies were also considered. A contact model with hysteresis damping is also presented in [5]. Hunt and Grossley [7] obtained also a model for computing the stiffness coefficient from the energy balance relations. In their approach, the damping force is a linear function of the elastic penetration which is estimated from the energy dissipated during impact.

As a common approach, it is also possible to formulate the equations of motion in a compact form linear in the unknown contact parameters. Indeed, such approach defines the problem as a standard identification problem which can be solved to obtain the unknown contact parameters using different instantaneous or recursive techniques, to provide a time history of the estimated results [8].

In contrast to the analytical approaches, very limited number of publications is devoted to the context of identification of contact parameters using neural network. The work presented in [9] introduces a neural network algorithm utilized for environment identification experiments. Indeed, this paper presents the first set of evaluations on the applicability of neural networks for on-line identification and contact control of a robot in unknown environments. Based on a nonlinear visco-elastic model, the values of relevant contact parameters such as stiffness, damping, spring hardening, and shock absorbing effect coefficients are chosen arbitrary. Using these parameters, the amount of penetration, penetration rate, and contact force are evaluated, and then are used as inputs to the neural network. The outputs of the neural network are the chosen contact parameters. The inputs and outputs are used to train the network. In the next step, by performing an experiment, the inputs of the network are measured, and then are used in the trained network to determine the contact parameters.

In another study [10], identification and modeling of contact parameters between holder and machine tool for

different geometries are considered. The contact parameters depend on the clamped tool length, tool diameter, material, etc. First of all, the contact parameters for limited combinations of tool diameter and clamped tool lengths are identified experimentally using a procedure developed in an earlier study. The results are used to train a neural network which can be used to estimate the parameters for different cases. It is demonstrated that this approach can be used in the dynamic analysis of the machine tools for cutting stability predictions.

The notion of collision identification in contact applications of robotic tasks based on the neural networks is introduced in [11]. The paper introduces a framework for collision identification in robotic tasks. The proposed framework is based on Artificial Neural Networks (ANNs) and provides fast and relatively reliable identification of the collision attributes. The simulation results are used to generate training data for the set of ANNs. A modularized ANN-based architecture is also developed to reduce the training effort and to increase the accuracy of ANNs. The test results indicate the satisfactory performance of the proposed collision identification system.

4. Outline of the Proposed Approach

Using the neural network for identification of compliant contact parameters requires to carry out the following steps. It is important to mention that the neural network is merely a tool which is based on a training process for identification of unknown systems. The accuracy of the results obtained from this tool is directly connected to the training step. Therefore, it is necessary to pay enough attention to this part to ensure obtaining reliable and feasible results.

In a preliminary step, one should train the neural network. This means that, large number of input and output data sets have to be provided to the network for the problem under investigation. Generally, two approaches may be adopted: 1) performing contact simulations for some simple examples using approaches other than the compliant contact model, and 2) performing some simple experiments for measuring pre- and post-impact conditions. Both approaches can be chosen for this study.

For the first approach, one may build variety of classical examples in a Finite Element Method (FEM) package, such as ANSYS, and model contact with different available approaches. FEMs were introduced to deal with problems of structural analysis including contact events [1]. The FEM is without doubt the most powerful numerical method in the field of contact simulation. Then, feasible and meaningful contact parameters are extracted based on the pre- and post-impact conditions.

For the second approach, some simple experiments for supplement the results will be set up. Again, using the pre- and post-impact conditions measured from the experiments, the corresponding compliant contact parameters are evaluated. For doing so, one may utilize the analytical formulations of contact parameters developed for simple geometries.

In the next step, the results can then be used in a neural network algorithm for a training process. In this secondary step, the inputs and outputs of the network can be taken from any of the above-mentioned approaches.

After the network has been trained, it can be used for other more general cases of contact events. Based on this approach, after providing the corresponding inputs of the specific problem, the contact parameters are estimated. In this way, a framework is established for general identification of contact parameters.

5. Illustrative Example

Now consider here the longitudinal contact of a rigid rod and a rigid sphere. In this paper, focus is on identification of the penetration exponent in the contact force formula, and hysteresis damping coefficient. Based on the geometry of the contacting bodies, approximate value of the stiffness

coefficient directly from Eq. (1) is estimated.

As mentioned earlier, in order to achieve reliable results from the neural network, provide large number of input and output data sets to the network in the training step. For this purpose, model this example for 150 different inputs. Table 1 shows these inputs. These various cases include: five different radii for sphere, five different radii for rod with circular cross section, three different lengths for rod, and two different initial velocities for sphere, which results 150 different input cases. For example, the first simulation starts with sphere radius 0.01 (m), rod radius 0.01 (m), rod length 1 (m), and sphere velocity 0.02 (m/s). Then, in the second simulation, change sphere velocity to 0.04 (m/s) while keeping other values constant. This approach will continue till getting finally 150 different input sets. In all these 150 simulations the rod is initially at rest; its initial velocity is zero.

Table 1. Different values of inputs for simulation.

Input name	Sphere radius (m)	Rod radius (m)	Rod length (m)	Sphere velocity (m/s)
Magnitude	0.01	0.01	1	0.02
	0.03	0.03	1.5	0.04
	0.06	0.06	2	
	0.12	0.12		
	0.24	0.24		

The sphere is made from steel with Young's module $E=210$ (GPa), density $\rho = 7780 \left(\frac{kg}{m^3}\right)$ and Poisson's ratio $\nu = 0.3$. The rod is made from aluminum with Young's $E=70$ (GPa), density $\rho = 2750 \left(\frac{kg}{m^3}\right)$ and Poisson's ratio $\nu = 0.33$. Based on the results cited in [2], the maximum approaching initial velocity of the sphere is chosen below $v=0.05$ (m/s) to prevent plastic deformation during impact. This value depends on the material properties of both sphere and rod.

As the first step, model the contact between sphere and rod in ANSYS, see Figure 1. The contact modeling used in

ANSYS requires no predefined user parameters for this simulation. It is based on an approach which belongs to another category of contact modeling (the Lagrange approach) rather than the compliant contact model. In this way, establish a framework for contact simulations which gives reliable and accurate results to be used for further steps. The outputs of the contact simulations in ANSYS are actually the contact forces arising from colliding the sphere and the rod, and the post-impact velocities of both sphere and rod.

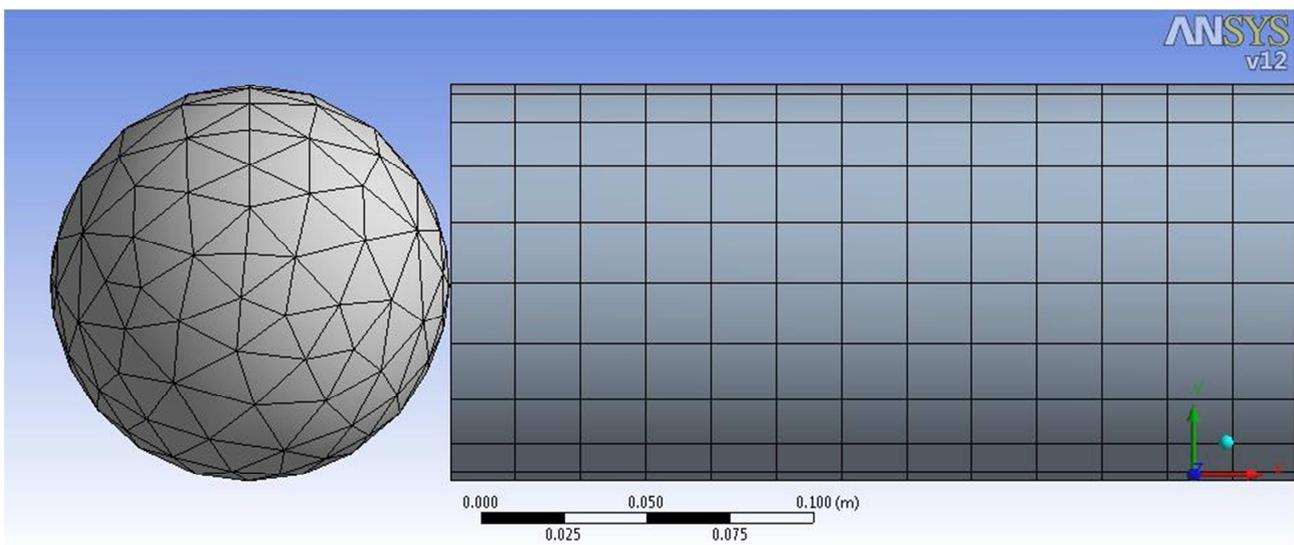


Figure 1. Longitudinal contact of a rigid sphere with a rigid rod.

In the next step, using the pre- and post-impact velocities and based on the Newton formula for coefficient of restitution e [12], the value of this coefficient is calculated. Then, the stiffness coefficient K is obtained from following equation [6]

$$K = \frac{4\sqrt{R}}{3\left(\frac{1-\nu_1^2}{E_1} + \frac{1-\nu_2^2}{E_2}\right)} \quad (1)$$

In which R denotes sphere radius, E_1 and ν_1 are Young's module and passion ratio of sphere, respectively, and E_2 and ν_2 are Young's module and passion ratio of rod, respectively. By using coefficient of restitution together with stiffness coefficient and pre-impact velocity $\delta^{(-)}$, the hysteresis damping μ is obtained from [5] as

$$\mu = \frac{3K(1-e^2)}{4\delta^{(-)}} \quad (2)$$

Now, we consider the Lankarani-Nikravesh formula [5] for contact force as

$$F_c = K\delta^n + \mu\delta^n \dot{\delta} \quad (3)$$

Which upon substituting μ from Eq. (2) yields

$$F_c = K\delta^n \left[1 + \frac{(1-e^2)\dot{\delta}}{4\delta^{(-)}} \right] \quad (4)$$

The penetration exponent n in the above equation is adjusted in a way that the maximum contact force from this equation would be equal to the maximum contact force obtained from ANSYS simulation for each separate input data set. Figure 2 illustrates values of n for inputs which are reported in Table 1 and for rod lengths 1 (m) and 2 (m). For a particular sphere radius from horizontal axis, and rod radius from right vertical axis, and based on the required rod length and sphere velocity, the associated n can be read from the left vertical axis. Based on the results shown in this figure, following remarks can be considered:

- 1- For a constant sphere radius, increasing rod radius decreases n .
- 2- For a constant rod radius, increasing sphere radius decreases n .
- 3- For the same input data, increasing contact velocity increases n .
- 4- For the same input data, increasing rod length decreases n .

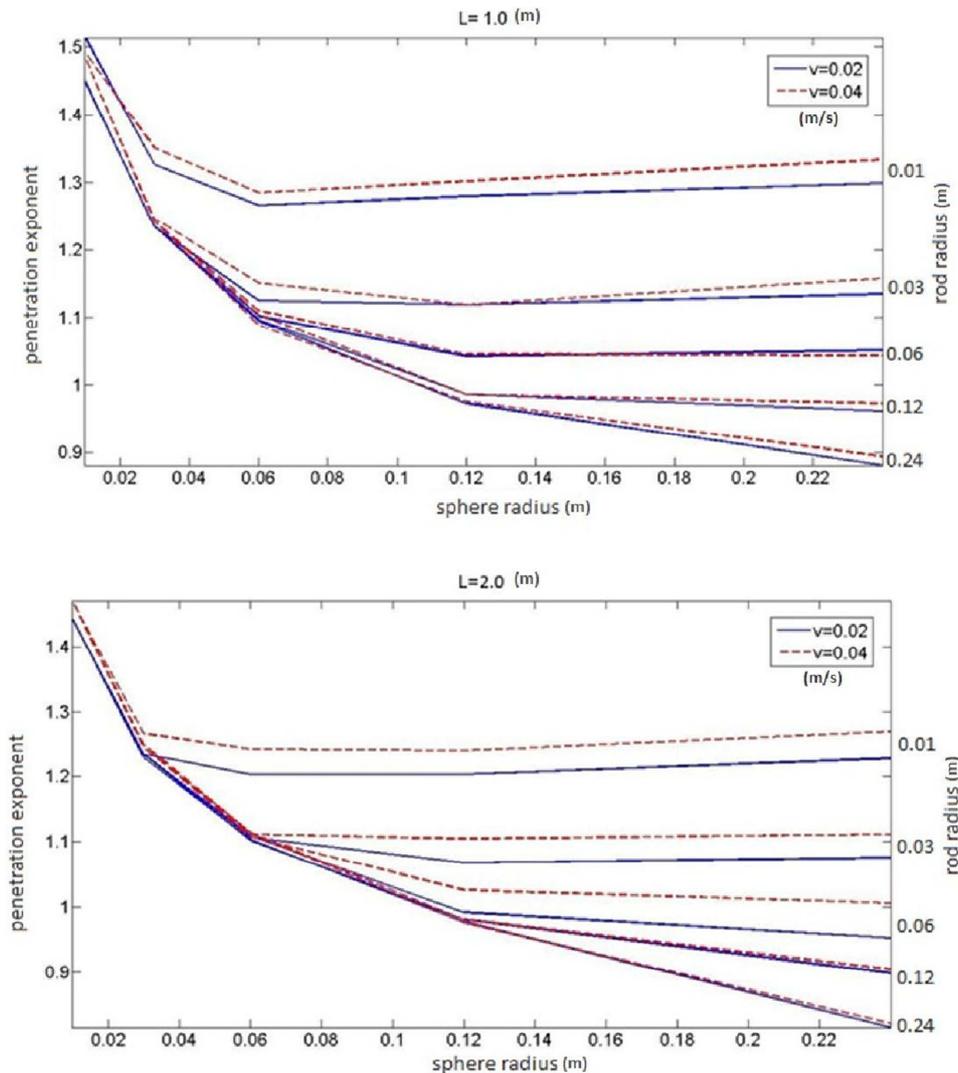


Figure 2. Values of the penetration exponent n for inputs of Table 1 and for rod lengths 1 (m) and 2 (m). dashed lines: $v=0.02$ (m/s); solid lines: $v=0.04$ (m/s).

6. Training and Testing the Neural Network

In the next step, using the results from previous step, a neural network is trained to predict the penetration exponent n in the contact force formula by providing necessary inputs.

In this network, the values for sphere radius, rod cross section radius, and sphere approaching velocity are given as inputs to the network, and the real values of n from Figure 2 are given as outputs to the network. The assumed neural network specifications in our simulation are chosen based on Table 2.

Table 2. The assumed neural network specifications.

Network type	Layers No.	Neurons No.
Feed Forward with back Propagation		1st layer 4
Normalized Mean Square Error (nmse)	3 (Logsig, Logsig, Purline)	2nd layer 20
Trainscg method for Training		3rd layer 1

The correlation of estimating error and performance of network is:

$$nmse = \frac{\sum_k(x_k - \hat{x}_k)^2}{\sum_k(x_k - \bar{x}_k)^2} \tag{5}$$

Where x_k is real value, \hat{x}_k is predicted value by ANN and \bar{x}_k is average value of x_k .

Among 150 penetration exponents n , 140 exponents are chosen randomly and used together with their corresponding input sets in the training step. After the networked has been

trained, we check it with the inputs which have already been used in the training.

Figure 3 shows the real and the predicted values of these 140 exponents which are obtained from the trained network. As can be seen clearly, the predicted values coincide well with their corresponding real values for most cases.

The percentage of error in the training step is shown in Figure 4. For about 90% of the input data sets, the error is less than 2%, which implies the efficiency of the training step is good enough to proceed to further step.

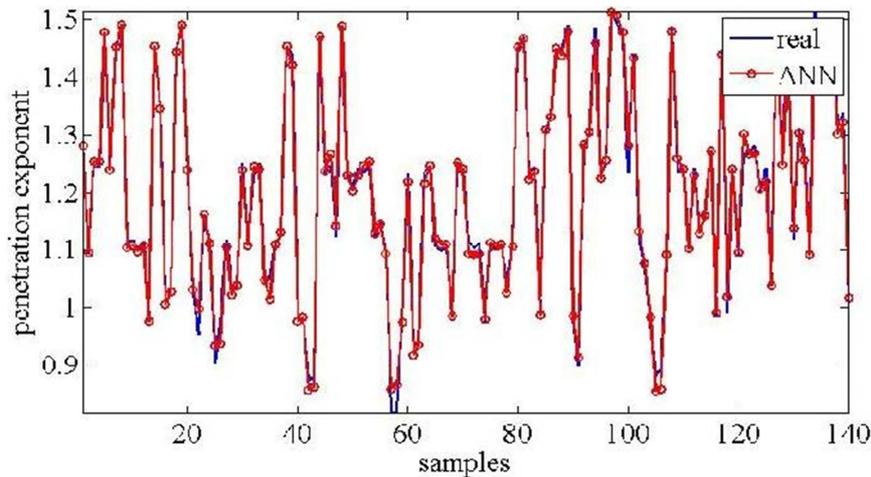


Figure 3. The real and the predicted values of 140 penetration exponents obtained from the trained network.

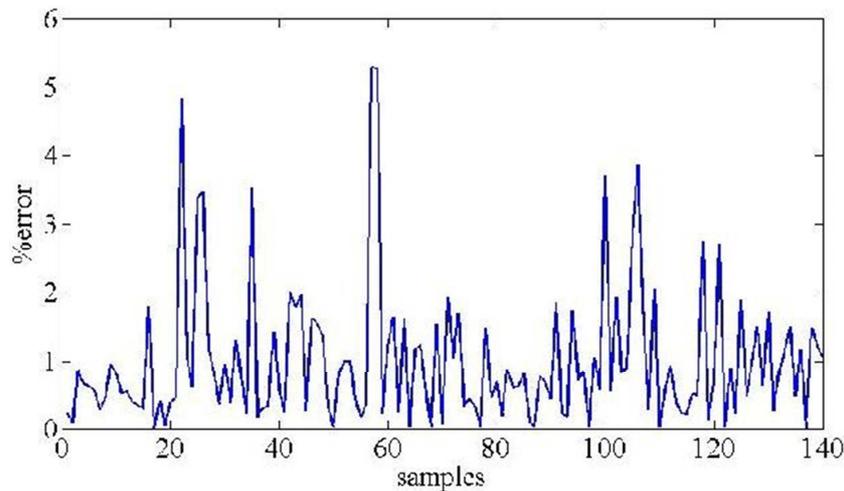


Figure 4. The error of the network for penetration exponents in the training step.

In the next step, for testing the network, 10 other input sets which are different from the 140 input sets used previously for the training step. Figure 5 compares the results for these 10 exponents obtained from ANSYS (real values) and from the network (predicted values). Based on this figure, the trained network is capable of predicting this exponent for new inputs. This approach may be utilized also for identification of stiffness and damping coefficients in the same way. Therefore, the neural network approach can be used as a reliable tool for identification of the contact parameters provided it is trained well with enough number of input sets.

The percentage of error in the testing step is shown in Figure 6. The maximum error is less than 4% in this step. As the network has not used these 10 data sets before in the training step, the amount of error shows the capability of the network in predicting the penetration exponent n for unknown situations.

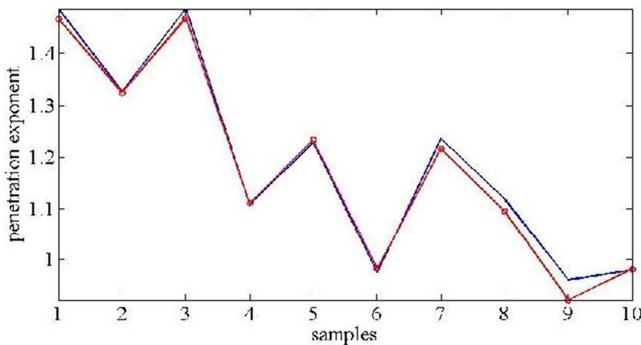


Figure 5. Testing the network for penetration exponents.

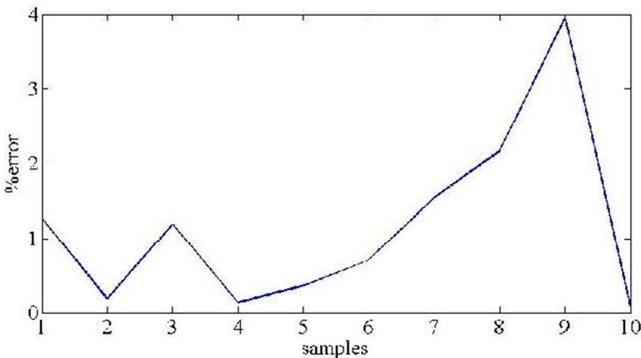


Figure 6. The error of the network for penetration exponents in the testing step.

After predicting the penetration exponent n , we may continue with predicting the hysteresis damping coefficient μ . However, since the procedure is the same as already followed for n , we therefore will not duplicate the procedure. Figures 7 and 8 show the results for hysteresis damping coefficients in the training step. Additionally, figures 9 and (10) illustrate the corresponding results in the testing step. It can be clearly seen that the network has enough accuracy in both training and testing steps in predicting the hysteresis damping coefficients.

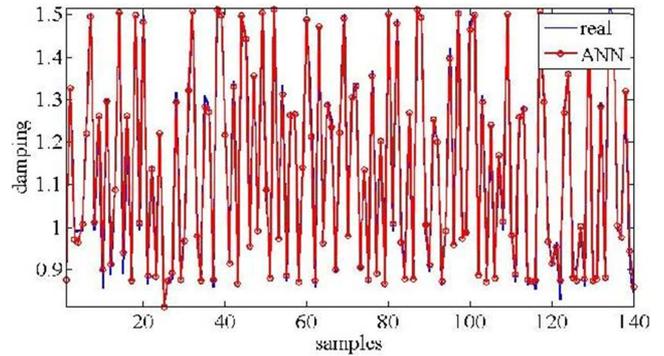


Figure 7. The real and the predicted values of 140 hysteresis damping coefficients obtained from the trained network.

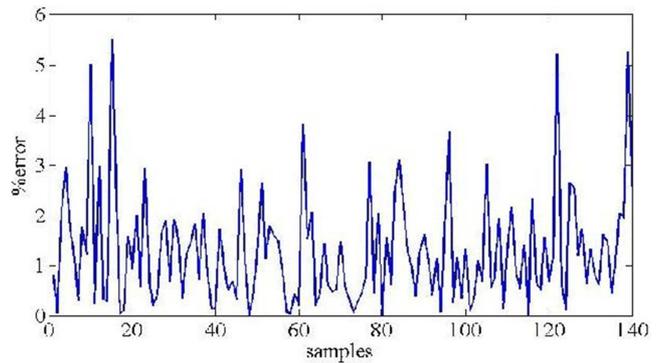


Figure 8. The error of the network for hysteresis damping coefficients in the testing step.

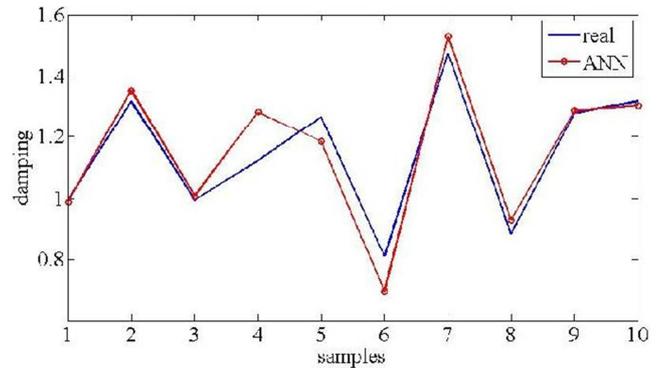


Figure 9. Testing the network for hysteresis damping coefficients.

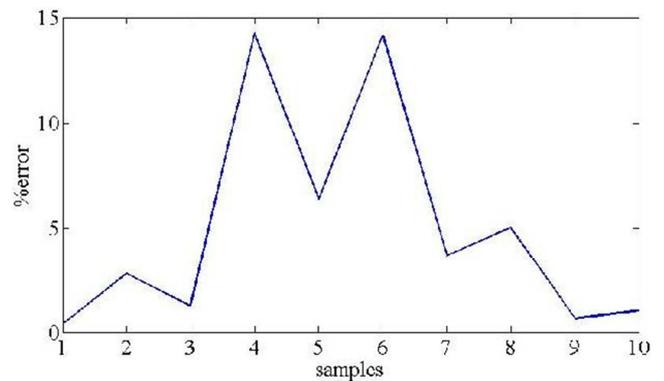


Figure 10. The error of the network for hysteresis damping coefficients in the testing step.

In order to check the efficiency and capability of the trained network in predicting contact forces based on the predicted values of the penetration exponent and hysteresis damping coefficient, we consider some new sets of input data. These input data are different from the data used before for training the network. The results are reported in Table 3 for five different cases. In each case, the network is tested for some input data, and finally, the predicted contact force is compared with the contact force obtained from ANSYS.

Table 3. Results of the trained network in predicting contact force.

Test No.	1	2	3	4	5
Sphere radius (m)	0.08	0.01	0.03	0.12	0.08
Rod radius (m)	0.12	0.2	0.03	0.19	0.12
Rod length (m)	1	2	1.7	1.3	1
Sphere velocity (m/s)	0.02	0.04	0.02	0.04	0.02
Predicted penetration exponent	1.057	1.484	1.221	0.985	1.057
Predicted hysteresis	21.72	19.31	34.15	13.60	21.72
damping coefficient (s/m)	21.72	27.30	437	48100	32.96
Predicted contact force (N)	7240	27.22	402	49479	7240
Real contact force (N)	7240.5	0.2	8.7	2.8	7240.5
% Error	0.006	27.30	437	0.12	0.006

The percentage of errors is relatively small for the new inputs. However, it is important to note that the amount of error may vary for inputs which are not close to the inputs previously used for training the network. This point implies that the error can be reduced by increasing the number and variety of the input data sets.

7. Conclusions

In this paper, we proposed an algorithm for identification of compliant contact parameters in multibody systems based on the neural network approach. Specifically, we focused here on the identification of the penetration exponent and hysteresis damping coefficient in the contact force formula. First, an FEM model of the contact model of a rigid sphere and a rigid rod was created. This example was simulated for 150 different input sets. The results obtained from these simulations were used to evaluate the real values of penetration exponent and hysteresis damping coefficients (outputs) corresponding to the input sets. Then, a neural network was trained using these inputs and outputs. In the next step, the already trained network was served to identify the value of the unknown variables for new input sets. The obtained results confirmed that the trained network can be used as a reliable tool for identification of contact parameters

provided that enough number of input data sets with suitable variety is used in the training step.

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