Hysteresis modeling of impact dynamics using artificial neural network

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ABSTRACT

In this paper, the process of training an artificial neural network (ANN) on predicting the hysteresis of a viscoelastic ball and ash wood bat colliding system is discussed. To study how the material properties and the impact speed affect the hysteresis phenomenon, many experiments were conducted for colliding three types of viscoelastic balls known as slottars at two different speeds. The aim of the study is to innovate a neural network model to predict the hysteresis phenomenon of the collision of viscoelastic materials. The model accurately captured the input data and was able to produce data sets out of the input ranges. The results show that the ANN model predicted the impact hysteresis accurately with <1% error.

KEYWORDS: Hysteresis, viscoelastic materials, neural network, impact dynamics

1. INTRODUCTION

Research in the hysteresis phenomenon focuses mainly on studying the cases in fields such as micro-sliding friction [1–3], magnetic fields [4, 5] or smart materials [6–11]. In applications like piezoelectric actuators, the existence of the hysteresis is considered one of the drawbacks of these elements due to it causing a certain delay in time [12]. Hysteresis is nondifferentiable because it is a multivalued mapping [12]; thus, for the piezoelectric actuators, it presents a challenge in the control of these systems [12]. Hysteresis often severely limits system performance, such as giving rise to undesirable inaccuracies or oscillations, even leading to instability [13]; therefore, it is necessary to find a model describing the behavior of hysteresis [12]. This is similar to viscoelastic material behavior, where the lag occurs among the application and removal of the force [14].

For the purposes of predicting the hysteresis nature, many hysteresis models were investigated, as well as their control and applications in modeling [14]. The most famous model to predict hysteresis behavior is the Preisach model for nonlinear systems [15], which is widely used in smart materials’ hysteresis modeling [16]. The Preisach model shows a good degree of accuracy in characterizing hysteresis at no-load condition as well as narrow-band frequency [17]. The phenomenological model evaluated from the Preisach model was formalized by Krasnosel’skii, in which hysteresis was modeled by a linear combination of hysteresis operators [18]. This model related to a generalized play operator and was used to model hysteretic nonlinear behavior in smart actuators; it took into account continuous branches rather than jump discontinuities as in the Preisach operator [14]. Based on the Preisach model, Prandtl-Ishlinskii proposed a model that used stop and play operators to model the multiloop, ascending and descending hysteresis loops; this model was distinguished for smart materials to identify the nonlinear response [19–21]. Another model known as the Bouc–Wen model was used to efficiently describe smooth hysteresis behavior with respect to the time history and random vibration analyses [22, 23]. This model was formulated together with a Hammerstein linear model [24] to model the static hysteresis and the rate-dependent hysteresis in a relatively low-range frequency [24]. For both mechanical and electrical systems, the Maxwell slip model was used [25]; this model was presented to illustrate the behavior of friction in mechanical systems [26].

Because of the large number of models, a comprehensive classification of these models is considered a difficult task [27]. So, researchers went to classify them according to the type of mathematical equations [27]; it was the case for the models of Preisach, Krasnosel’skii, Prandtl-Ishlinskii and others, which mathematically characterize the variables of the outputs [28]. It is noticed that most of the models developed to explain the phenomena of hysteresis revolve around the interpretation of the behavior of the outputs depending on the nature of the inputs [28], and exploiting the differential models to explain the behavior of the hysteresis systems [23, 29–31]. Most aforementioned models consist of many parameters and are used in electrical or electromechanical applications to construct the hysteresis curve [28]. Al-Bender...
It is known that mechanical hysteresis could be a rate-independent or rate-dependent process, or it could consist of both processes at the same time [32]. It also known for having a generalized displacement that may include moment, force or stress as inputs and rotation, strain or displacement as outputs, or vice versa [32]. When studying hysteresis for rate-independent materials and mechanical systems in general, hysteresis is induced by plastic deformation and/or frictional forces [32]. Vaiana et al. [28] presented a class of uniaxial phenomenological models that can simulate hysteresis loops for mechanical systems restricted by two curves or two parallel straight lines. This could model behaviors such as materials with kinematic hardening or softening hysteretic behavior and rate-independent mechanical systems. A more advanced approach was recently proposed to describe the rate-independent hysteresis behavior [33, 34]. In [33], Vaiana et al. developed a simulation model based on uniaxial symmetric rate-dependent models. These were employed to simulate asymmetric mechanical hysteresis phenomena; in particular, the asymmetric bilinear and exponential models were used. The performance of models was evaluated in terms of accuracy and computational efficiency to produce generalized hysteresis loops; the exponential model was found to be more sophisticated to simulate a wide range of asymmetric hysteresis behaviors [33]. Also, Vaiana et al. [34] presented a new set of multi-spring models that were able to reproduce the nonlinear response typical of mechanical systems and materials comprised of biaxial kinematic rate-independent hysteretic behavior materials; this model was built by incorporating the concept of multi-shear spring model, with the class of uniaxial phenomenological models. Similarly, the multi-spring exponential model showed a better performance in terms of accuracy and computational efficiency [34].

Adly and Abd-El-Hafiz [35] proposed a neural network model considering the Preisach model as the superposition of the outputs of a set of elementary hysteresis operators and the neural network determines the weight functions of those operators. Serpico and Visone [36] proposed a feedforward hysteresis model for magnetic hysteresis modeling based on the neural network. Chuntao and Yonghong [37] also proposed a multilayer neural network model for hysteresis nonlinearity in piezoelectric actuators to describe the Preisach model to decompose the multivalued mapping of hysteresis into a one-to-one mapping between the input and output coordinates. To study the hysteresis phenomenon in colliding objects as in the hurling game in which a bat, which is called hurley, and a ball, which is called sliotar, collide. The complexity lies in the fact that the outputs of the hysteretic system depend on the inputs of the system, which in turn is affected by many factors such as ball materials, impact speed, angle of impact and more. Because of the difficulty to describe some of these factors quantitatively, it is impractical to create a mathematical model to describe the developed hysteresis. In general, mathematical models attempt to demonstrate phenomenological models, and not to explain the physical origin of the hysteresis phenomenon [38]. In the proposed model, modeling of the hysteresis phenomenon of a ball hitting bat system was achieved by conducting experiments to study the impact scenario, and then employing the measured data to build up an artificial neural network (ANN) to describe the impact system hysteresis. This kind of representation, on the opposite of the mathematical one, is easier to produce. This study will focus on the possibility of such representation in addition to its accuracy.

In this research, the neural network model was utilized using the experimental data of deflection and impact force of the ball and bat viscoelastic colliding system mentioned earlier. An ANN utilizing Levenberg–Marquardt backpropagation was implemented in MATLAB R2020a for the prediction of deflection and force during the impact status. In Section 2, the experimental setup used to capture the data is presented. Section 3 presents a brief explanation on the neural network and the used algorithm. In Section 4, the results and discussion are presented. Finally, conclusions are presented in Section 5.

2. PROPOSED NEURAL NETWORK ALGORITHM

Neural networks are an excellent method for the approximation of continuous systems or functions with one-to-one or multiple-to-one mappings. Neural networks as well as traditional techniques cannot be used directly to identify the multivalued mapping model of systems such as hysteresis [39]. In this study, the method of ANN was used. A feedforward neural network was used in this research work. The neural network was trained using Levenberg–Marquardt backpropagation implemented on MATLAB R2020a, which uses Levenberg–Marquardt optimization to update the weights and bias in the network. The network was trained to predict the deflection and force during the impact scenario.

A neural network, simply, is a function with a specified number of inputs and outputs depending on the problem in hand. This function in the case of mathematical representations such as this work connects the inputs and outputs with simple functions that predict the outputs based on trial-and-error estimates. There are no real physical relationships, just ones achieved by trial and error. A simple neural network of two inputs and one output could be represented as shown in Fig. 1 and Eq. (1).
Let the input data be represented with \( m \), and the output using \( p \). The neural network function is given by

\[
p = w_1 m_1 + w_2 m_2 + b,
\]

where \( w_1, w_2 \) and \( b \) are the weights related to inputs 1 and 2 and the bias, respectively.

The main goal when training a neural network is to be able to set the weights and biases of the network in a way that gives the most accurate relation between the inputs and the outputs. At first, the weights and biases of the network are set randomly. The training data are then used to tune these constants for the most accurate output. When having a multilayer neural network (Fig. 2), this tuning process starts by changing the weights and biases between the output layer and the layer before and continues backward, hence the name backpropagation. This is done by calculating what is called a cost function \( C(w, b) \), a function used to make small changes in the weights and biases. By calculating the partial derivative \( \frac{\partial C}{\partial w} \) for any weight or bias, an estimate of how much changing the said weight or bias will affect the cost function is obtained. The network training goal is to get \( C(w, b) \approx 0 \). A feedforward neural network is a network where the connections between the nodes do not form a cycle. The information only moves in one direction from inputs through the hidden nodes to the outputs.

The Levenberg–Marquardt algorithm [40] similar to quasi-Newton methods was designed to approach the second-order training speed without having to evaluate the Hessian matrix. The application of Levenberg–Marquardt algorithm to neural network training is described in [41, 42]. A brief explanation of the algorithm used for neural network training is given as follows.

When training feedforward networks, the performance function usually has the form of a sum of squares; in this case, the Hessian matrix is approximated as

\[
H = J^T J
\]

and the gradient is evaluated as

\[
g = J^T e,
\]

where \( J \) is the Jacobian matrix containing the first derivatives of the errors with respect to the weights and biases in the network. \( e \) is a vector of the errors in the network. Computation of the Jacobian matrix can be done through a standard backpropagation technique [41], instead of the much complex calculation of the Hessian matrix. The Levenberg–Marquardt algorithm uses this approximation as follows:

\[
x_{k+1} = x_k - \left[ J^T J + \mu I \right]^{-1} J^T e.
\]

Equation (4) is just Newton’s method when scalar \( \mu \) is zero but with the use of the approximated Hessian matrix. When \( \mu \) is large, it becomes gradient decent with a small step size. Near an error minimum Newton’s method is faster and more accurate, so it is better to as quickly as possible shift to Newton’s method. Thus, \( \mu \) is decreased after each reduction in performance function, which is a successful step, and increased only with the tentative increase of the performance function.

To identify and to extract the variation feature of the hysteresis of viscoelastic colliding objects using the neural network model, a transformation operator is proposed. Then, an expanded input space is constructed to transform the multivalued mapping of hysteresis into a one-to-one mapping. In the training process, experimental data of deflection and impact force were used as outputs, and the ball brand (material), impact speed and time as inputs. Figure 2 shows the proposed neural network, which consists of one hidden layer with 150 neurons.

3. EXPERIMENTAL SETUP

A test rig, an air cannon unit (ACU), was developed by the Department of Mechanical Engineering at Cork Institute of Technology particularly for studying the sport of hurling. It consists of a 100 L air reservoir supplied by compressed air externally, two pneumatic valves for firing purposes, two photocells to measure sliotar speed just before the impact and a metal impact wall. In parallel, a high-speed camera (Photron APX, Photron, San Diego, CA), connected to a PC, faces the sliotar path to capture 30 000 frames per second with a resolution equal to 512 × 256 pixels per frame.

In the experimental setup for the work reported in this paper, the sliotar was being struck into the bat at two different speeds,
Figure 3 The experiment setup of the sliotar–hurley impact system.

Table 1 The impact force and duration results.

| Series | Sliotar brand | Impact speed (m/s) | Impact force (N) | Impact duration (ms) |
|--------|---------------|--------------------|------------------|----------------------|
| 1      | 1             | 21.7               | 1119             | 2.60                 |
| 2      | 2             | 18.0               | 870              | 2.32                 |
| 3      | 3             | 23.0               | 1584             | 2.88                 |
| 4      | 1             | 43.0               | 2246             | 2.56                 |
| 5      | 2             | 38.4               | 1707             | 2.08                 |
| 6      | 3             | 42.1               | 2062             | 2.80                 |

Table 2 A sample of the inputs and outputs of the proposed ANN.

| Inputs | Outputs |
|--------|---------|
| Brand  | Speed (m/s) | Time (ms) | Deformation (mm) | Impact force (N) |
| 1      | 21       | 0.052     | 0.069803415      | 22.7872819      |
| 2      | 21       | 0.104     | 0.562765169      | 53.36093708     |
| 3      | 21       | 0.156     | 1.072363729      | 77.57308194     |
| 4      | 21       | 0.208     | 1.589926969      | 115.9845806     |
| 5      | 21       | 0.26      | 2.111804141      | 149.4073804     |
| 6      | 21       | 0.312     | 2.631200782      | 187.7385101     |
| 7      | 21       | 0.364     | 3.14171571       | 228.8914846     |
| 8      | 21       | 0.416     | 3.636434465      | 274.4316562     |
| 9      | 21       | 0.468     | 4.109278727      | 321.6594638     |
| 10     | 21       | 0.52      | 4.553120387      | 374.9679699     |
| 11     | 21       | 0.572     | 4.963528176      | 426.0291929     |

4. RESULTS AND DISCUSSION

In this section, the experimental and ANN results are presented. First, in Table 1, the impact speed, maximum impact force and the total impact duration are presented. For each trail, the experiment run was replicated three times to ensure the repeatability of the experiment. Then, the average impact speed, impact force and duration are considered. The results confirm the well-known relationship between the impact speed and duration [44, 45], i.e. the inverse proportionality of impact duration with the impact speeds. This result will be used later in this section to estimate the impact duration of other speeds of impact; this will allow to predict the impact hysteresis at a wide range of impact speeds.

Table 2 lists a sample of the proposed inputs and outputs of the ANN. This data set was taken from the experimental work. Two parameters were chosen to be the ANN outputs, i.e. the ball deformation and impact force.

Figure 4 presents the results for the filtered experimental data. It shows the impact force versus deformation of ball brand #1 at low and high speeds of impact. The maximum ball deformation was 6.54 and 8.91 mm at low and high impact speeds, respectively. The impact force was found to be 1.11 and 2.25 kN at low and high impact speeds, respectively. The hysteresis appears in the graph as the area between the two curves. The higher speed causes a higher maximum impact force as well as a higher deformation in the ball; therefore, a higher hysteresis results, which is represented by the larger area under the curve. Similar
Figure 4 The force–deformation during the impact system together with the ANN results.

Observations could be seen in Fig. 4b and c for ball brands #2 and #3, respectively.

Ball brand #2 showed a different behavior though. The maximum deformation at high speed was about four times higher than the deformation at lower speed, while ball brand #1 showed a 1.4 times higher deformation at higher speed in comparison to the deformation at lower speed. Moreover, ball brand #2 showed a huge hysteresis at low impact speed in comparison to ball deformation.

For ball brand #3, much hysteresis was observed at low and high impact speeds in comparison to other brands. At low impact speed, the observed hysteresis was about double the hysteresis observed for ball brand #2, and about 50% higher than the hysteresis of ball brand #1. At high impact speed, the observed hysteresis of ball brand #3 was double the observed hysteresis of ball brands #1 and #2. Table 3 lists an approximation of the hysteresis areas under the curves.

| Series | Speed = 21 m/s | Speed = 41 m/s |
|--------|---------------|---------------|
| 1      | 3584.47       | 10 578.69     |
| 2      | 2872.92       | 8486.43       |
| 3      | 5115.56       | 19 180.32     |

Table 3 Area inside the hysteresis curve in relation to collision velocity and the ball type.

The data plotted in Fig. 4 were used to train the ANN. The network was trained to predict the deformation and the impact force as listed in Table 3. The trained network predicted the impact hysteresis very well at low and high impact speeds, with correlation of >99% between the experimental and ANN results.

In spite of all balls having passed the current game standards, i.e. simple bounce test on concrete, results presented in this work demonstrate a significant difference in ball materials’ behavior at higher impact speeds. This leads to further development of the current standards of the game of hurling to include the testing of ball materials at high impact speeds. These results confirm to what has been published previously by authors in [44].

5. CONCLUSION

In this study, a neural network modeling for the hysteresis problem is presented. The problem discussed an impact problem between three sports ball brands and the bat used in the game of hurling. The proposed approach considered the impact scenario at two impact speeds, 20 and 40 m/s. Afterward, the experimental data were employed to train the ANN. A good agreement was achieved between the ANN and experimental data with <1% deviation in the ball deformation and impact force. Finally, the proposed work suggests improving the game equipment standards by including the testing of equipment at high impact speeds. Future work has been targeted to test other sports balls, e.g. baseball, to model their hysteresis.

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