force of MR damper may not only depend on the current dynamic state, but also influenced by its historical state. However, the parametric model only can consider the current state to predict current force.

Aim at above problems, non-parametric models based on artificial neural network (ANN) have a good development in recently years due to its good learning capability. Different from the parametric models, the nonparametric models do not consider the physical behavior, and directly builds the relationship underlying the input/output training data. The non-parametric models need amount of input/output data to identify the MR damper model without any assumptions, and then enable to predict the damper response with arbitrary inputs. The common ANN models of MR damper mainly contain feedforward neural network (FNN) model [6-8], nonlinear autoregressive with external input (NARX) neural network model [9], recurrent neural network (RNN) model [10,11] and so on. Though these non-parametric models have a good performance to modeling the MR damper response with enough information input, there are still exist some problems: the variable of input information; the coordination of computational cost and network structure; the development and applicative selection of new neural network technology etc.

Long short-term memory (LSTM) neural network has been effectively applied to model complex systems and more applicable for solving sequences problems with long-span time serious due to its good learning capability [12-14]. Noted that LSTM network is a variant of RNN, which has a similar self-loop in hidden layers as RNN. Unlike the simple way for 'memory' historical information in RNN by continuous multiplication [14], the LSTM network lead in 'gate' mechanism to eliminate the drawbacks in RNN. The LSTM network becomes more and more popular in prediction of nonlinear systems and long-term sequences problems nowadays. Actually, MR damper is a complex nonlinear system, and the modeling of the MR damper can be considered as sequences problem. Hence, LSTM network may be an appropriate way to establish the MR damper model. Noted the LSTM network have not been used to emulate the dynamic behaviors of MR damper yet.

In this work, a long short-term memory recurrent neural network (LSTM-RNN) is employed to model the response of MR damper. A forward model is established to predict the response of the MR damper directly with the necessary input, and meanwhile, an inverse model is built to generate the control current according to the desired force. The training and validation data are generated by a given MR damper under various excitations and current input. Finally, the capacity and accuracy of LSTM model are discussed.

2. Long short-term memory recurrent neural network review

In this section, a brief review of long short-term (LSTM) recurrent neural network (RNN) is introduced. It is well known that LSTM network is a special category of RNN, so RNN is firstly to review before LSTM introduced.

2.1 Recurrent neural network (RNN)

RNN have an internal self-looped cell by connecting neurons in hidden layers, which are expressed as,

$$h_t = \tanh(W_h \cdot [h_{t-1}, x_t] + b_h) \tag{1}$$

$$o_t = W_o h_t + b_o \tag{2}$$

where x_t is the input vector at time t , h_{t-1} the state of hidden layers at time t-1 and o_t is the output vector at time t. The parameters W_h, W_o are the weights matric, and b_h, b_o are the bias vector. As formulated in Eq. (1) ~(2) the current neuros output is calculated based on the current input and historical hidden state, and thereby capable of mapping the historical information to the final output (refer to 'memory' ability). So that, the RNN is a popular tool to deal with the time serious sequence problems due to its 'memory' ability. However, RNN seem unable to solve perfectly the long span sequences problems due to vanishing gradient and exploding gradient when back-propagation through time in training process [12].

2.2 Long short-term memory (LSTM) network

In terms of the drawbacks in RNN, a variant from RNN is proposed in paper [13], called long short-term memory network (LSTM), which import 'gate' theory. Like RNN, LSTM also have self-looped cell, but there lots of gates exist in each cell different to only multiplication in RNN. In LSTM cell, there exists four parts: forget gate, input gate, output gate and cell update produce. Those gates are utilized to forget, memory or transmit the historical information inside LSTM cell and current input, which are expressed as,

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{3}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{5}$$

$$C_t = f_t \otimes C_{t-1} + i_t \otimes \tilde{C}_t \tag{6}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \otimes \tanh(C_t) \tag{8}$$

where W_f, W_i, W_o are the weight matric corresponding to forget gate f_t, input gate i_t and output gate o_t, respectively. Similarly, the corresponding bias vector denoted as b_f, b_i, b_o. $\tilde{C}_t$ and C_t are the cell update state at time t. σ presents the active function. $\otimes$ is the cross-product of vectors.

As formulated above equations, it is clearly indicated the working mechanism of LSTM: the forget gate governs how much information remained in the current state, the input gate determines how much information input to current state. Meanwhile, the output gate control how much information transmit to next state. And the update state process is accomplished based on the previous and current state. Through this working mechanism, LSTM is utilized as a powerful tool to solve the problems with long-term time serious.

3. LSTM-based MR damper model

Unlike the MR damper model only considered the current information (such as damper displacement, velocity, control current and others), an MR damper model with historical information input by using LSTM network is proposed in this section.

3.1 Forward model

LSTM network is an approach to model a wide range of nonlinear systems by adjust the parameters based on given data, which adjusting parameters procedure called 'Train' or 'Learn'. To train a LSTM model off-line, an urgent question is to select the hyperparameters and structure of the LSTM model in order to obtain a desired accuracy of approximation.

Noted the structure of LSTM is often difficult tasks but also essential for establishing an accurate LSTM model. As for a complete network, input, hidden and output layers are necessary. For input layers, it is well known that the damper displacement x_t, velocity $\dot{x}_t$ and control current I_t usually as input information for both parametric and nonparametric model of MR damper, and consider the influence of historical information, the MR damper model can be expressed as follows,

$$F_t = LSTM(x_t, x_{t-1}, ..., x_{t-N}, \dot{x}_{t-1}, \dot{x}_{t-1}, ..., \dot{x}_{t-N}, I_t, I_{t-1}, ..., I_{t-N}, \tilde{F}_{t-1}, ..., \tilde{F}_{t-N}; \theta) \tag{9}$$

where $LSTM$ is the MR damper model, N denotes the time span considered for the model corresponding to input vector, and θ represent the weights and bias in LSTM network structures. The output layer only with one neuron represents the target force at current time. From this equation, it is indicated that the LSTM network acts as a nonlinear approximator of the function that describes the behavior of the MR damper. For hidden layers, there are no available methods for a priori determination of the appropriate structure of the neural network currently. And it is well known that increasing the number of hidden layers gives the neural network a better capability for good accuracy with the increasing compute time. Synthesized the modeling performance and the cost of compute, an LSTM network structure of three layers with 10 units is selected to map the input–output relationship for the MR damper.

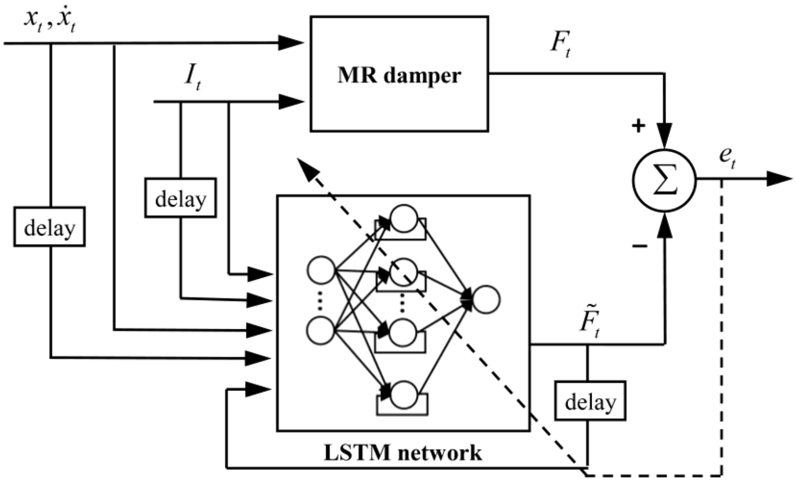


Fig. 1 – Concept of MR damper model using LSTM network

Considering the target force of MR damper have two directions, the hyperbolic tangent function is selected as the active function in this research due to its nonlinear and outputs range for [-1,1], which sign is similar as damper force. And a linear active function is selected for output layer. Meanwhile, a procedure of back-propagation through time with the Levenberg–Marquardt algorithm is utilized to update the weights and biases of RNN model in order to find the optimal parameters. The previous study [15] shown that the Levenberg–Marquardt algorithm is very efficient for training small-to medium-size networks. And the algorithm is based on minimizing the error (refer to loss function) between the network output compared to the target output. The loss function is specified by the concrete problems or features, which function defined as the sum of the root mean square errors relative to the network output and target output. The scheme of identification for the MR fluid damper using the LSTM network is given in Fig. 1. The LSTM model is considered to be well trained when the errors between simulated force and target force becomes sufficiently small.

3.2 Inverse model

As we all known, the damping force generated by the MR damper only can be controlled by the input current. Therefore, the design of the damper controller is an essential issue to play full performance of MR damper. The common controller contains PID control, fuzzy controller and inverse model control [16]. Among that, PID control is simplest but need actual force feedback, and the control current is usually not precise. Though the fuzzy controller not need accuracy model but the reasonable fuzzy rules is not easy to establish. Compared to these approaches, the inverse model control is a most straightforward and convenient method intuitively, and the control current (voltage) is calculated according to the target control force.

In this research, an LSTM network structure similar as forward model is utilized to establish the inverse model of the MR damper, which can be expressed as,

$$I_t = LSTM(x_t, x_{t-1}, ..., x_{t-M}, \dot{x}_{t-1}, \dot{x}_{t-1}, ..., \dot{x}_{t-M}, F_t, F_{t-1}, ..., F_{t-M}, \tilde{I}_{t-1}, ..., \tilde{I}_{t-M}) \tag{10}$$

where M denotes the time span considered for the model corresponding to input vector. The identification procedure of inverse model is same to forward model.

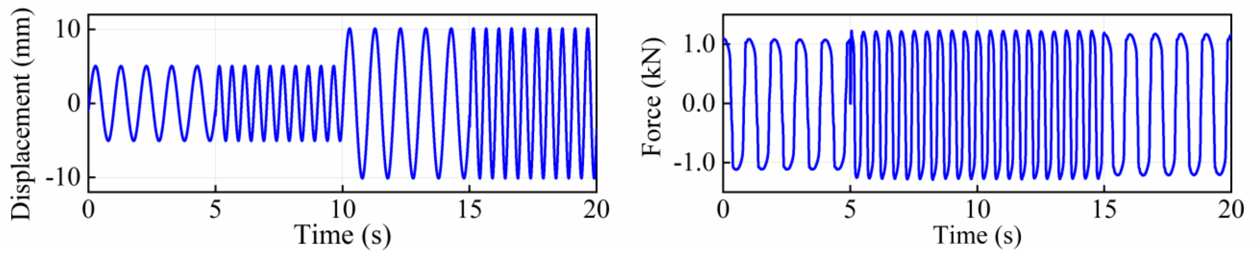
4. Model validation

4.1 Data generated

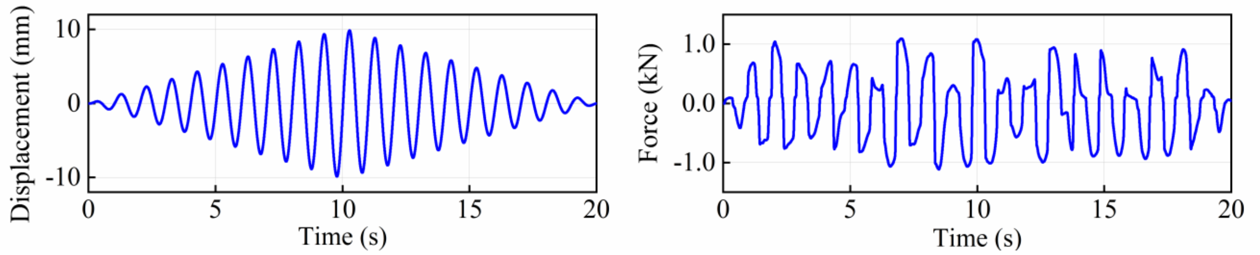
To train a LSTM model off-line, an essential task is to prepare sufficient high-quality data that describes the behavior of the given MR damper. In this research, a RD-8040-1 MR damper (LORD Corporation) is utilized, which has a stroke of ±2.5 cm and a resistance of 5 ohms. Its continuous working current is limited to 1 A and instantaneous current is limited to 2A. Considered the influence of various excitations and control current on damping force, many tests are achieved on a computer-controlled MTS machine (MTS systems corporation). All the tests conditions are listed in Table 1 and partial experimental data is plotted in Fig. 2. In those tests, a Wonder Box® device (Input 0-5V, Output 0-2A, Lord Corporation) is used to transmit voltage into current, and a dSPACE® device (dSPACE Corporation) is applied to send and collect signals.

Table 1 – Training and validation data for LSTM model

Num.	**Excitations (mm)**	**Current (A)**
1	Sinusoidal [1, 2] Hz [5, 10] mm	0, 0.2, 0.4, 0.6, 0.8, 1.0
2	Sinusoidal with various amplitude	0, 0.2, 0.4, 0.6, 0.8, 1.0
3		Random current signal
4	Sinusoidal with various frequency and various amplitude	0, 0.2, 0.4, 0.6, 0.8, 1.0
5		Random current signal
6	Random signals	0, 0.2, 0.4, 0.6, 0.8, 1.0
7		Random current signal



(a) Num. 1 in Table 1



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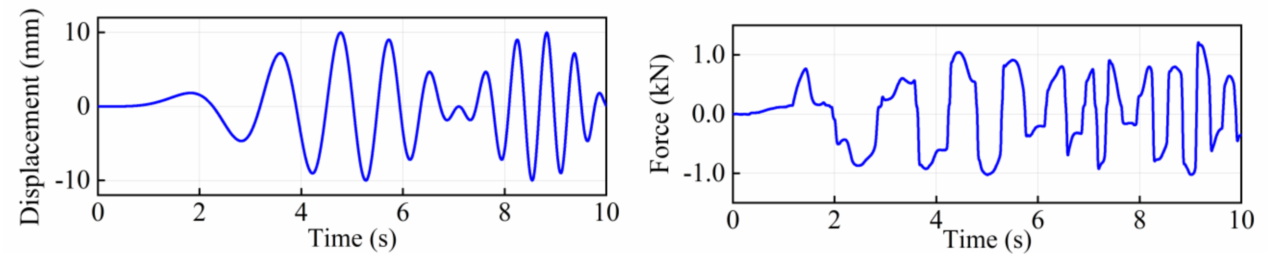

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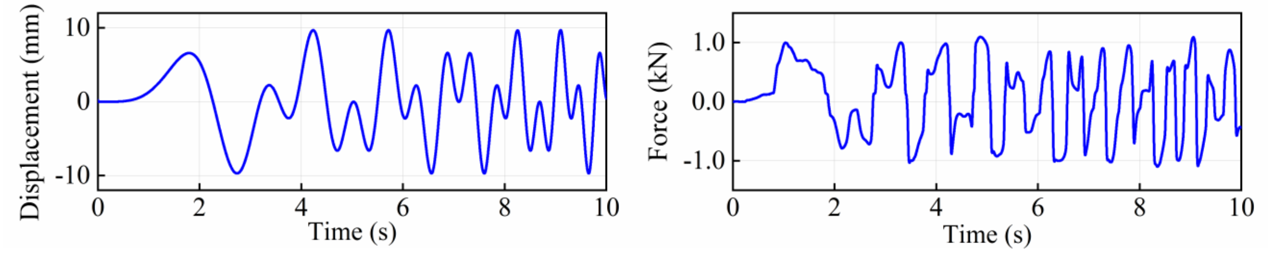


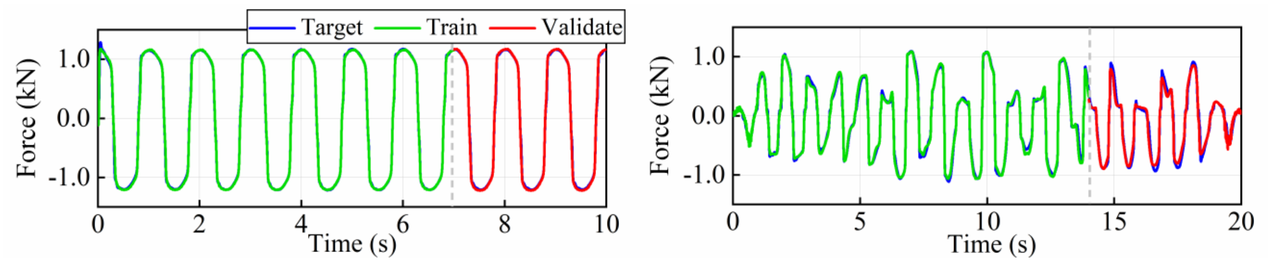
(d) Num. 7 in Table 1

Fig. 2 – Experimental data

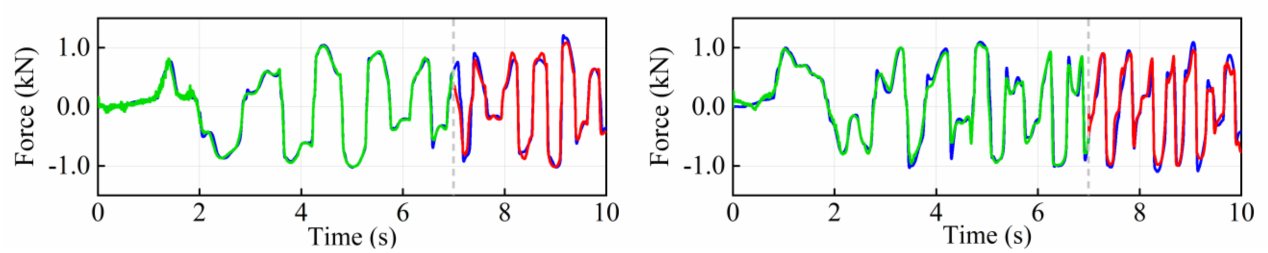
4.2 Simulation results and discussion

The validation tests are discussed in this section to evolve an LSTM model for the given MR damper. For those experimental data gathered above, 70% of the experimental data is used to trained the LSTM model and residual 30% is used to validated the model. Partial qualitative comparison results of the experimental data and simulation results are shown in Fig. 3~5.

As can be seen the validation results of forward model in Fig.3, the trained and validated force calculated from the LSTM forward model are all very close to the target force from experimental data for overall conditions, which verifies the effectiveness of the forward model. It indicates that the forward model can accurately predict the response of the given MR damper whatever the type of excitations and current input. And LSTM network can regulate weights/bias in accordance with its target to perform well, the good comparison results show its strong robustness and nonlinear processing capability. Therefore, it can be said that LSTM forward model is a reliable way to accurately describe the dynamic behavior of the given MR damper.

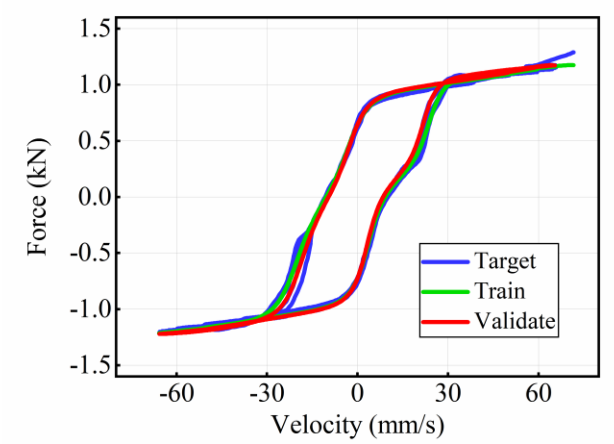


(a) Num. 1 in Table 1 (b) Num. 3 in Table 1



(c) Num. 5 in Table 1 (d) Num. 7 in Table 1

Fig. 3 – Simulation results for the forward model compared to experimental data



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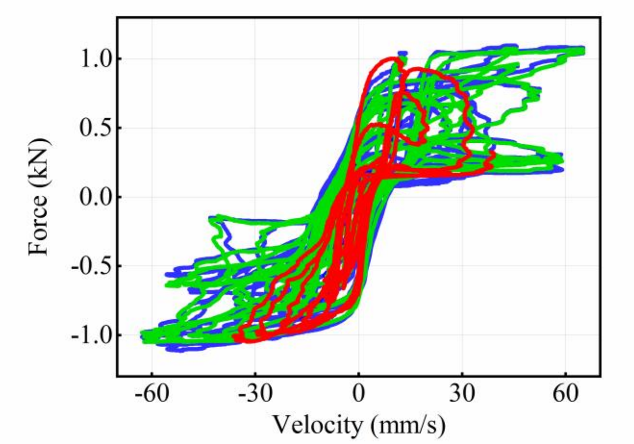

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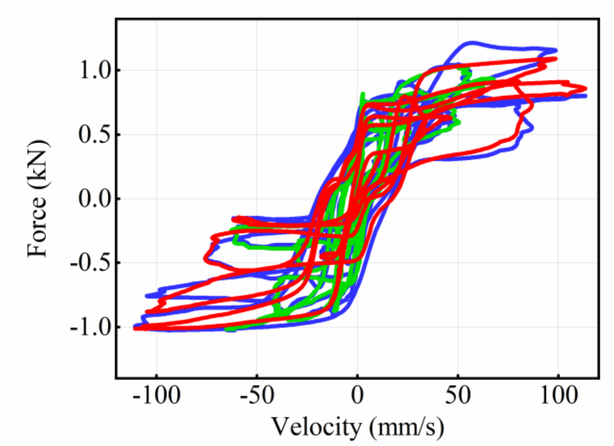

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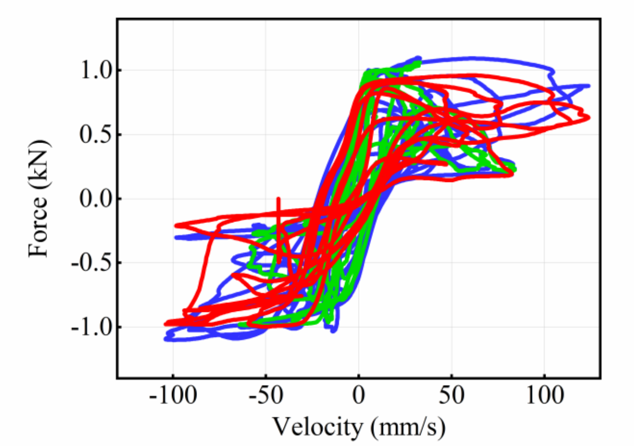
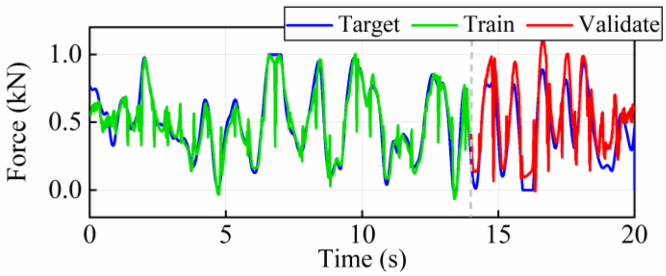


(d) Num. 7 in Table 1

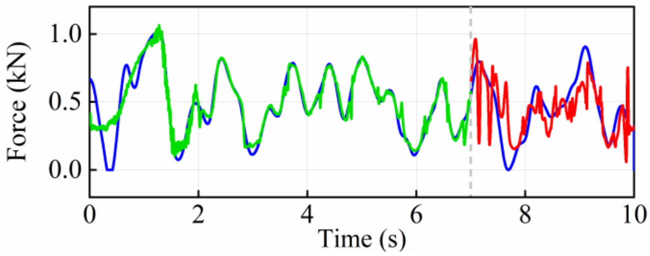
Fig. 4 – F-V diagrams of the forward model using different experimental data.

In order to further evaluate the performance of the forward model, the experimental and simulated results are compared in the characteristic force–velocity (F-V) diagram, which can legibly describe the nonlinear characteristic of the MR damper. The conditions plotted in Fig. 4 are corresponding to that in Fig.3. In Fig. 4 (a)~(c), both trained and validated results show a good agreement with experimental data. The comparison results in Fig. 4 (d) is a little bad in the region with biggest force. The reason may be that the biggest force of training data is little small than the validating data, which can be seen in Fig. 3 (d). Of course, the relative error in biggest-force region is an acceptable value. Therefore, in general, it can be seen that the proposed LSTM forward models the nonlinear behavior of the MR damper with acceptable accuracy.

The comparison results between experimental data and simulation results of inverse model is plotted in Fig.5. It can be seen that the trained and validated current can track the tendency of with the target current for different conditions, whatever the type of excitations and current input. The comparison results demonstrate the effectiveness of the inverse model in some extent. Noted that the prediction accuracy of the inverse model is inferior to the forward model. Furthermore, it can be found that the matching agree of validating data is not as good as that of training data. The reason may be that the relationship between output and input of the inverse model is not one-to-one correspondence.



(a) Num. 3 in Table 1



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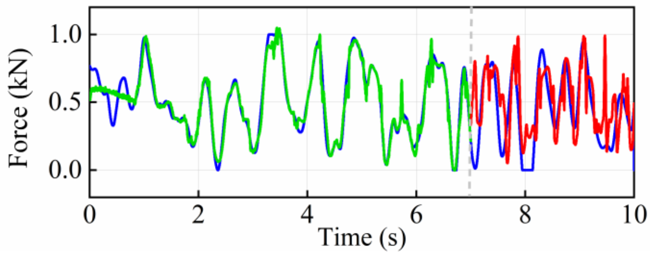

(c) Num. 7 in Table 1

Fig. 5 – Simulation results for inverse model

5. Conclusion

An alternative approach to model an MR damper using long short-term memory recurrent neural network (LSTM-RNN) has been presented and successfully applied. The nonlinear characteristics of the MR damper can be captured based on the experimental data. A forward model is used to predict the response of the MR damper with the necessary input, and the control current is calculated by an inverse model according to the target force. Further rigorous investigation is carried out to evaluate the model performance. The results reveal that the simulated force of the forward models can follow closely the target force well, and the inverse model can track the tendency of the time-varying current.

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