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Modelling of a magneto-rheological damper by evolving radial basis function networks

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Abstract

This paper presents an approach to approximate the forward and inverse dynamic behaviours of a magneto-rheological (MR) damper using evolving radial basis function (RBF) networks. Due to the highly nonlinear characteristics of MR dampers, modelling of MR dampers becomes a very important problem to their applications. In this paper, an alternative representation of the MR damper in terms of evolving RBF networks, which have a structure of four input neurons and one output neuron to emulate the forward and inverse dynamic behaviours of an MR damper, respectively, is developed by combining the genetic algorithms (GAs) to search for the network centres with other standard learning algorithms. Training and validating of the evolving RBF network models are achieved by using the data generated from the numerical simulation of the nonlinear differential equations proposed for the MR damper. It is shown by the validation tests that the evolving RBF networks can represent both forward and inverse dynamic behaviours of the MR damper satisfactorily.

Keywords: Magneto-rheological dampers; Genetic algorithms; Radial basis function networks

1. Introduction

Due to their wide dynamic range, low power requirement, large force capacity, and fast response rate to a variable control signal, magneto-rheological (MR) dampers have emerged as newly developed semi-active control devices that have been mass-produced for commercial applications. In particular, MR dampers have found considerable attraction in vibration reduction of bridges, helicopter rotors, truss structures, and buildings. Semi-active control with MR dampers for vehicle suspensions has also been studied by many researchers, and many control strategies such as skyhook, groundhook and hybrid control, H_∞ control and model-following sliding mode control have been evaluated in terms of their applicability in practice.

The practical use of MR dampers for control is, however, significantly hindered by their inherently hysteretic and highly nonlinear dynamics. This makes the modelling of MR dampers more important for their applications. In order to characterize the performance of MR dampers, several models have been proposed to describe their dynamic behaviours. These include the phenomenological model proposed by Spencer et al. (1997) based on a Bouc–Wen hysteresis model, neural network model developed by Chang and Roschke (1998) and Chang and Zhou (2002), fuzzy model (Schurter and Roschke, 2000), nonlinear blackbox model (Jin et al., 2001), NARX model (Leva and Piroddi, 2002), viscoelastic–plastic model (Wereley et al., 1998), and polynomial model (Choi et al., 2001), etc. Among these MR models, phenomenological model and viscoelastic–plastic model can accurately describe the dynamic behaviours of the MR dampers, but the corresponding models for the inverse dynamics of the MR dampers are often difficult to obtain due to their nonlinear characteristics. A multi-layer perceptron (MLP) neural

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network and an adaptive neuro-fuzzy inference system (ANFIS) models can be used to emulate the inverse dynamics of the MR dampers, but the selection of network structure and training data are essential in order to obtain accurate results. In fact, the polynomial model is a convenient and effective choice which can realize the inverse dynamic of the MR damper in an analytical form, and is easy to achieve the desirable damper force in an open-loop control system. However, polynomial model cannot characterize the behaviour of the MR damper favourably at relatively low velocity region since this model does not include variables characterizing the pre-yield property of the damper force. Since an open-loop control is easy to implement and cost-effective comparing with a closed-loop control, it is valuable to develop the accurate inverse dynamic models of MR dampers that are required in the realization of semi-active control.

The artificial neural networks (ANNs) have been effectively applied to model complex systems due to their good learning capability. It is possible to model the dynamic behaviours of the MR dampers by using ANNs. The MLP neural networks have been used to emulate the dynamic behaviours of an MR damper. However, the selection of network structures and training of samples are often complicated tasks but are essential for setting up an accurate MLP model. Moreover, the training speed is normally long due to slow convergence. Instead of using MLP neural networks to emulate the dynamic behaviours of an MR damper, this paper presents an alternative representation for modelling an MR damper in the form of radial basis function (RBF) networks.

The RBF network is a three-layer feedforward network that uses a linear transfer function for the output units and a nonlinear transfer function (normally the Gaussian function) for the hidden units. The input layer simply consists of the source nodes connected by weighted connections to the hidden layer. The net input to a hidden unit is a distance measure between the input presented at the input layer and the point represented by the hidden unit. The nonlinear transfer function (Gaussian function) is then applied to the net input to produce a radial function of the distance. The output units implement a linear weighted sum of the hidden unit outputs. In order to use an RBF network, we need to specify the hidden unit activation function, the number of nodes in the hidden layers and the training algorithm for finding the parameters of the network.

Compared with other types of ANNs, such as MLP neural networks, RBF networks have only one hidden layer, while MLP networks have one or more hidden layers depending on the application task; the hidden and output layers of MLP networks are both nonlinear, while only the hidden layer of RBF networks is nonlinear (the output layer is linear); the activation functions in the RBF nodes compute the Euclidean distance between the input examples and the centres, while the activation functions of MLP networks compute inner products from the input examples and the incoming weights, etc. These characteristics make the RBF networks having more advantages in, e.g., simple architecture and learning scheme, fast training speed (the liner output layer may not be trained), and the possibility of incorporating the qualitative aspects of human experience in the model selection and training. Hence, RBF networks are powerful computation tools and have been used extensively in the systems modelling.

In spite of a number of advantages compared with other types of ANNs, such as better approximation capabilities, simple network structures and faster learning algorithms, the development of RBF networks still have difficulties in selecting the network structure (the number of nodes in the hidden layers, i.e., the number of centres) and calculating the model parameters (e.g., centres, widths and weights). Normally, the training procedure of an RBF network is divided into two phases where the centres and widths are determined first, followed by the calculation of the weights. In order to overcome existing difficulties in developing an RBF network, an evolving RBF network that combines genetic algorithms (GAs) with other standard learning algorithms for an RBF network is presented in this paper to model the nonlinear dynamic behaviours of an MR damper. The structure of the RBF network is selected by a trial and error procedure, which only calculates several cases and compares the sum of squared errors (SSEs) between the true outputs and the network predictions to determine which structure is better. Although it is not an optimal selection for the network structure, it is time-saving because only several cases are calculated and the optimization result of SSEs can guarantee that the obtained SSE is not affected significantly by selecting different network structures, and hence a relative simple structure can be used with respect to the modelling accuracy required. The centres are searched by using GAs instead of using k-means clustering algorithm or fuzzy c-means clustering algorithm, where the SSE between the true outputs and the network predictions are minimized with respect to the given network structure and the obtained centre locations. This overcomes the drawback of standard RBF network in selecting centres using a clustering approach which is entirely separated from the actual objective of minimization of the prediction error. Finally, a uniform width, which is chosen to be the maximum distance among different centres, is used instead of using different widths for different centres. This will simplify the network structure as an uniform width is sufficient for the RBF network to achieve universal approximation (Chen et al., 1999). The weights that connect the hidden layer with the output layer are determined by calculating the pseudo-inverse matrix instead of using gradient descent optimization algorithm to save learning time. The reason that we do not apply GAs to optimize the network structure and all of the model parameters is that it is a time-consuming procedure when

the training data is large in both length and dimension, and a large search space will unavoidably increase the difficulty for GAs to find the optimal results. The application examples presented in this paper show that only using GAs to search for the network centres can obtain better results for the modelling of an MR damper. Therefore, using GAs to search for the network structure, widths and weights is not necessary here.

In this paper, the developed evolving RBF network with four input neurons, which relate displacement, velocity, force and applied voltage, respectively, and one output neuron, which corresponds to either force or voltage, is used to emulate the forward and inverse dynamic behaviours of an MR damper, respectively. Data used for the training and validating of the evolving RBF network is generated from numerical simulation of the nonlinear differential equations proposed for an MR damper by Spencer et al. (1997). By comparing the SSE results for different network structures and different approaches in selecting the network centres, we can see that the resulting evolving RBF networks are shown to satisfactorily represent complicated dynamic behaviours of the MR damper while greatly reducing SSE even when the number of centres is small. Finally, it is validated by simulation that both the forward and the inverse dynamics of the MR damper can be approximated very accurately with the evolving RBF networks.

The rest of this paper is organized as follows. Section 2 introduces the phenomenological model of the MR damper presented by Spencer et al. (1997). The basic structure of the RBF networks and the developed evolving RBF networks are introduced in Section 3. The use of the evolving RBF networks in modelling the forward and inverse dynamic behaviours of an MR damper is presented in Section 4. Conclusions are given in Section 5.

2. Phenomenological model of an MR damper

A phenomenological model has been proposed by Spencer et al. (1997) to portray the behaviour of a prototype MR damper that was developed by the Lord Corporation as shown in Fig. 1. This phenomenological model is based on a Bouc–Wen hysteresis model, which is numerically tractable and is capable of exhibiting a wide variety of hysteretic behaviours. The parameters for the model are determined from the experimental data with appropriate optimization method. This model is validated in a variety of representative experimental tests, including (1) triangular displacement/step voltage inputs; (2) random displacement/constant voltage inputs; and (3) random displacement/random voltage inputs. The validation results indicate that the phenomenological model of an MR damper is accurate over a wide range of operating conditions and adequate for control design and analysis. The phenomenological model of MR dampers are regarded as the "state-of-the-art" semi-

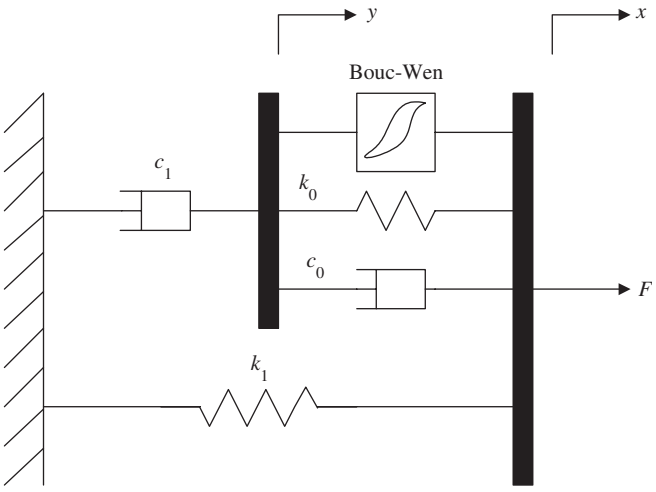

Fig. 1. Mechanical model of the MR damper.

physical model and has been extensively used in modelling MR dampers with applications in vibration control engineering, e.g., see Lai and Liao (2002) and references therein.

The phenomenological model is governed by the following seven simultaneous equations:

$$\begin{cases} F = c_1\dot{y} + k_1(x - x_0), \\ \dot{y} = \dfrac{1}{(c_0 + c_1)}[\alpha z + c_0\dot{x} + k_0(x - y)], \\ \dot{z} = -\gamma|\dot{x} - \dot{y}|z|^{n-1} - \beta(\dot{x} - \dot{y})|z|^n + A(\dot{x} - \dot{y}), \\ \alpha = \alpha_a + \alpha_b u, \\ c_1 = c_{1_a} + c_{1_b} u, \\ c_0 = c_{0_a} + c_{0_b} u, \\ \dot{u} = -\eta(u - v), \end{cases} \tag{1}$$

where F is the force generated by the MR damper; x is the displacement of the damper; y is an internal pseudo-displacement of the MR damper; u is the output of a first-order filter; v is the command voltage sent to the current driver. In this model, k_1 is the accumulator stiffness; c_0 and c_1 are the viscous damping coefficients observed at large and low velocities, respectively; k_0 is the gain to control the stiffness at large velocities, and x_0 is the initial displacement of spring k_1 associated with the nominal damper force due to the accumulator; γ, β, A are hysteresis parameters for the yield element, and α is the evolutionary coefficient. In this model, there are a total of 14 model parameters ($c_{0_a}, c_{0_b}, k_0, c_{1_a}, c_{1_b}, k_1, x_0, \alpha_a, \alpha_b, \gamma, \beta, n, \eta$ and A) to characterize the MR damper. The obtained values for the 14 parameters can be determined by fitting the model to the experimental data obtained in the experiments. As an example, a set of parameters which is obtained by Spencer et al. (1997) to characterize one MR damper using experimental data and a constrained nonlinear optimization algorithm is listed in Table 1.

Table 1
Parameters for an MR damper

Parameter	Value	Parameter	Value
c_{0_a}	21.0 N s/cm	α_a	140 N/cm
c_{0_b}	3.50 N s/cm V	α_b	695 N/cm V
k_0	46.9 N/cm	γ	363 cm^{-2}
c_{1_a}	283 N s/cm	β	363 cm^{-2}
c_{1_b}	2.95 N s/cm V	A	301
k_1	5.00 N/cm	n	2
x_0	14.3 cm	η	190 s^{-1}

3. Evolving radial basis function networks

3.1. Framework of RBF networks

A RBF network is a three-layer feedforward neural network which consists of an input layer of source nodes, a single layer of nonlinear processing units, and an output layer of linear weights, as depicted in Fig. 2 (Haykin, 1996), which includes only one input vector and one output scalar. The input–output relationship of this RBF network can be described by

$$\mathbf{y} = \sum_{k=1}^{N} w_k \varphi(\mathbf{u}, \mathbf{t}_k) + w_0, \tag{2}$$

where N is the number of hidden layer neurons; the term $\varphi(\mathbf{u}, \mathbf{t}_k)$ is the kth RBF that computes the distance between an input vector $\mathbf{u}$ and its own centre $\mathbf{t}_k$. The scaling factor w_k in (2) represents a weight that connects the kth hidden node to the output node of the network. The constant term w_0 in Eq. (2) represents a bias.

The most commonly used RBF in practice is the Gaussian form as shown in the following:

$$\varphi(\mathbf{u}, \mathbf{t}_k) = \exp\left(-\frac{1}{\sigma^2}\|\mathbf{u} - \mathbf{t}_k\|^2\right), \quad k = 1, 2, \ldots, N, \tag{3}$$

where σ is the width, and $\|\mathbf{u} - \mathbf{t}_k\|$ denotes the Euclidean distance between $\mathbf{u}$ and $\mathbf{t}_k$.

Thus, substituting (3) into (2), we may formulate input–output mapping realized by a Gaussian RBF network as follows:

$$\mathbf{y} = \sum_{k=1}^{N} w_k \exp\left(-\frac{1}{\sigma^2}\|\mathbf{u} - \mathbf{t}_k\|^2\right) + w_0. \tag{4}$$

RBF networks have proven that they are universal approximators, that is, given a network with enough hidden layer neurons, they can approximate any continuous function with arbitrary accuracy (Wasserman, 1993) and they have the properties of rapid training, generality, and simplicity. Therefore, using RBF networks to establish the input–output mapping model of an MR damper will be an applicable approach. This mapping can be established by training the RBF networks with appropriate scheme.

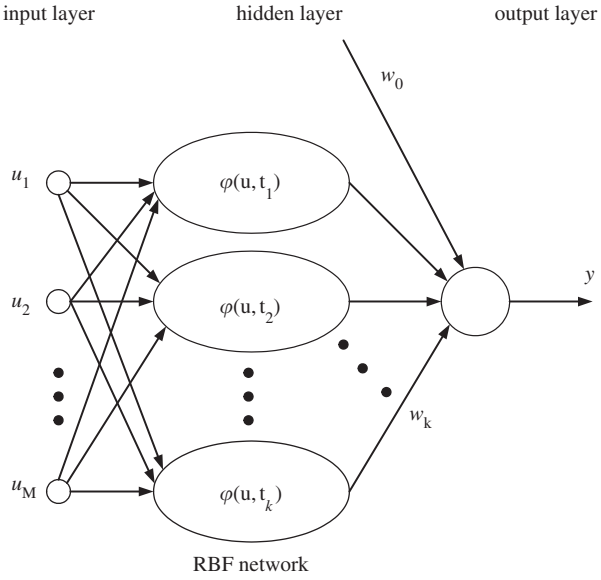

Fig. 2. The structure of a radial basis function network.

3.2. Training of RBF networks

From a design point of view, the training of RBF networks is to find the number of hidden layer neurons N and the appropriate parameter set $\{\mathbf{t}_k, \sigma, w_k\}$ to map a given input vector to a desired output scalar efficiently with good accuracy and generalization. Many different approaches have been proposed in the literature over recent years for selecting these free parameters and optimizing the complexity of RBF networks (Lee and Hou, 2002; Mao, 2002; Leonardis and Bischof, 1998). Normally, after the network structure parameter N is determined, the RBF networks are trained by using a two-phase approach, where the centres and width are computed first, and the output weights are calculated in the second phase.

In the phase of selecting the locations of centres, three main strategies have been put forward (Leonardis and Bischof, 1998). The first one is to randomly select a set of samples from training set and the positions of the centres are set according to these samples (Lowe, 1989). This approach can only produce reasonable results when the training data are distributed in a representative manner. The second approach is to perform a pre-clustering on the training set (e.g., k-means clustering, fuzzy c-means clustering), and the centres of the clusters are used as the centres of the RBF network (Darken and Moody, 1990). Since this clustering is performed without the knowledge of the weights of the output nodes, it is likely that the selection of the centres is sub-optimal with respect to the accuracy of the final result. The selection of the initial values of the centres is also a key problem. The third strategy is to use a gradient descent algorithm to determine the centres (Lowe, 1989). Convergence to a global minimum cannot be guaranteed since the problem is nonlinear with respect to the centres. Therefore, all these approaches have various shortcomings in selecting

appropriate centres. Since the practical signals are inevitably disturbed by stochastic noise, training data cannot always represent all samples even if they are acquired from a wide range of amplitude and frequency. Therefore, the pre-clustering is necessary either for the training data, or for the simplification of the network.

When the centres are selected, a uniform width can be heuristically determined from $\sigma = d_{\max}$, where $d_{\max}$ is the maximum distance between the chosen centres.

Once the centres and width are fixed, the weights can be learned very efficiently, since the computation reduces to a linear or generalized linear model. There are also some approaches for output layer weights training. One approach, which is called generalized regression neural network (GRNN) (Wasserman, 1993), assigns the target values as the output layer weights and the output of the network is divided by the sum of the output of a hidden layer neuron. GRNN is effective when a large amount of training data is used and no new training data is far from them. The other approach is to use an iterative training technique such as gradient descent algorithm. In fact, from Eq. (4), we can see that when the centres and width are determined, weights can be trained by solving the system of linear equations directly. After the final step of calculating the output layer weights is finished, all parameters of the RBF network have been determined.

3.3. Evolving RBF networks

More recently, GAs have been used to train RBF networks, which are called evolving RBF networks. In fact, GAs can be used to determine the network structure, that is, the number of hidden layer neurons (centres) and the network parameters such as centres, widths and weights in terms of different problems resolved and different calculation efficiencies required. In this paper, in order to overcome the existing drawbacks in selecting centres for an RBF network, the GAs are used for the pre-clustering of training data. The network structure, width and weights are not optimized by GAs here due to the consideration of computational efficiency. The proposed algorithm based on a binary-coded GA is described in the following steps:

Step 1: Determine network structure. The number of centres N is specified a priori.

Step 2: Initialize centres. Randomize an initial population of P individual chromosomes. Each chromosome represents a set of centres, which consists of $n \times N$ elements, where n is the dimension of the input data.

Step 3: Calculate objective functions. After the centres are generated, the objective function of each chromosome is calculated.

(1) Calculation of width. The width is calculated from $\sigma = d_{\max}$, where $d_{\max}$ is the maximum distance between the generated centres.
(2) Calculation of weights. According to Eqs. (2)–(4), given two matrices $\mathbf{H} = (\varphi(\mathbf{u}, \mathbf{t}_k))_{k=1,2,\ldots,N}$ and $\mathbf{y}$, the matrix of the output layer weights $\mathbf{W} = (w_k)_{k=1,2,\ldots,N}$ is the result of minimization of the error function: $E(\mathbf{W}) = \|\mathbf{HW} - \mathbf{y}\|^2$. The solution is given explicitly in the form of $\mathbf{W} = \mathbf{H}^+\mathbf{y}$, where $\mathbf{H}^+$ denotes the pseudo-inverse matrix of $\mathbf{H}$ and $\mathbf{H}^+$ can be defined as

$$\mathbf{H}^+ = \lim_{\alpha \to 0+} (\mathbf{H}^{\mathrm{T}}\mathbf{H} + \alpha \mathbf{I})^{-1}\mathbf{H}^{\mathrm{T}}. \tag{5}$$

The pseudo-inverse matrix becomes simply $\mathbf{H}^+ = (\mathbf{H}^{\mathrm{T}}\mathbf{H})^{-1}\mathbf{H}^{\mathrm{T}}$, provided the inverse matrix of $\mathbf{H}^{\mathrm{T}}\mathbf{H}$ is defined, therefore, $\mathbf{W} = (\mathbf{H}^{\mathrm{T}}\mathbf{H})^{-1}\mathbf{H}^{\mathrm{T}}\mathbf{y}$.
(3) Calculation of objective function. The sum of squares error (SSE) for the training data or the testing data is regarded as the objective function of each chromosome and can be calculated as

$$J_{\mathrm{SSE}} = \sum_{i=1}^{L} (y_i - \hat{y}_i)^2, \tag{6}$$

where L is data length, $\hat{y}_i$ is the predicted output and y_i is the target output. Finally, record every objective function that corresponds to every set of centres and associate every set of centres a suitable fitness value according to the rank-based fitness assignment approach.

Step 4: Based on the fitness obtained in Step 3, the offspring is chosen for the next crossover and mutation steps by using the tournament selection approach.

Step 5: Perform crossover and mutation operation on the current population to generate new individuals in the search space.

Step 6: Use the elitist reinsertion approach to guarantee that the best chromosome in the population always survives and is retained in the next generation.

Step 7: Evaluate the fitness of each individual. Steps 3–7 correspond to one generation. The evolution process will repeat for a fixed number generations or being ended when the search process converges with a given accuracy. The best chromosome will be used to determine the optimal network centres.

4. Modelling of MR damper with evolving RBF networks

This section presents the application of evolving RBF networks to emulate the forward and inverse dynamic models of an MR damper, respectively.

In this section, the development of the evolving RBF networks for modelling an MR damper is outlined as follows: (1) collect ample high-quality training and testing data as produced by the given MR damper model; (2) use the approach presented in Section 3.3 to create the evolving RBF networks that relate the displacement $x(t)$ of the MR damper at the location where the damper is attached and its velocity $\dot{x}(t)$, command voltage $v(t)$ that is sent to the MR damper and output force $F(t)$ of the MR damper; and (3) validate the new model through comparison of its output to the output of the given MR damper model.

Before the actual training of the model takes place, it is necessary to determine which variables of the MR damper should be chosen as the components of the input vector in (4). For the current study, it is assumed that the input vector for the RBF networks consist of the current inputs and past output of the MR damper. The commonly used parameters associated with the GA presented in Section 3.3 are given as follows: population size = 100, crossover probability = 0.8, mutation probability = 0.01, maximum generation = 250.

4.1. Data collection and pre-processing

In order to obtain a high-quality trained network, a high-quality training and testing data must be obtained first. In this paper, data for training and testing of the RBF networks are obtained from the phenomenological model of the MR damper proposed by Spencer et al. (1997) as done in Chang and Roschke (1998) and Chang and Zhou (2002). A set of typical parameters of the MR damper is presented in Table 1.

To make the identified model fully represent the underlying system, the training samples should cover all possible combinations and ranges of input variation in which the MR damper will operate. This is to ensure that the RBF network models trained using these samples can accurately represent the behaviours of the MR damper to be simulated. Normally, the limits of these input signals are dependent upon the characteristic and specific application of the MR damper. Advanced knowledge of the input signals enables the creation of more useful training data. Given this idea, note that the maximum operational voltage of the MR damper is 2.25 V, which is defined as the saturation voltage of the damper and is obtained experimentally, and the situation of zero voltage will also be common during operation of the MR damper. Therefore, ranges of the voltage signal and its frequency are set as 0–2.25 V and 0–1 Hz, respectively, in this study. Likewise, the displacement of the MR damper ranges from ±2 cm and its frequency ranges from approximately 0–5 Hz in this study. Signals of displacement and voltage used for training are produced using band-limited Gaussian white noise and some specified filters are used to obtain such random signals in indicated frequency ranges. Velocity signal is obtained by differentiating the displacement signal. In this paper, MATLAB is used to solve the differential equations of the system for an MR damper as presented in Section 2 for a simulation time of 8 s. A time step of 0.002 s is used to produce a total of 4000 data sets. Fig. 3 shows the histories of displacement, voltage, and damper force according to the 8 s of data. Out of these data, the first 2000 data sets are used as the training data while the remaining 2000 data sets are used as the testing data for the network. These data are scaled to zero mean and unity variance before passing into the network for training and testing. The parameters of the RBF networks have to be re-scaled proportionally once the training is completed.

4.2. Forward model

With the training and testing data established, an evolving RBF network is used to create a mapping model that emulates the "forward" dynamic behaviour of the MR

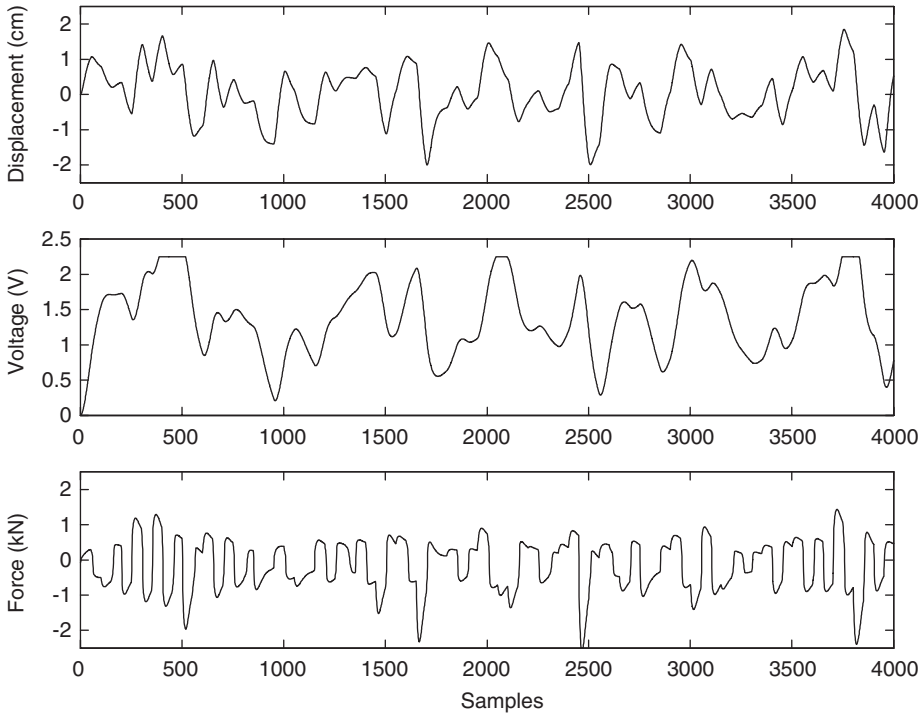

Fig. 3. Data of displacement and voltage inputs and force output for training and testing the RBF network.

damper. This model shows that the force generated by the MR damper depends on the command voltage, the displacement of the MR damper at the location where the damper is attached and its velocity.

A fully connected RBF network with one hidden layer is selected to be trained using the training data for the forward model. The model is determined to have four input neurons and one output neuron by trial and error. The four inputs to the model include current displacement $x(t)$, velocity $\dot{x}(t)$, voltage $v(t)$, and past force $F(t-1)$, where t denotes the time variable. The output is the predicted force $\hat{F}(t)$. This can be explained that to predict the force of the MR damper at time t, the inputs of the RBF network are taken to be the displacement, velocity and voltage at time t and the target force at time $t-1$.

In order to compare the effectiveness of different approaches in training the RBF network, the SSE between the true outputs and the network predictions are calculated for different approaches and listed in Table 2 where 'k-means' approach uses k-means clustering method to obtain the network centres, 'Fuzzy c-means' approach uses fuzzy c-means clustering method to obtain the network centres.

Both 'GA_1' and 'GA_2' approaches use the GA to obtain the network centres as presented in Section 3.3. The difference between 'GA_1' and 'GA_2' is that 'GA_1' selects the centres and calculates weights from the training data but calculates the objective function from the testing data. This method can avoid the over-fitting problem if only training data is used to obtain the network parameters. On the contrary, 'GA_2' only uses training data to obtain all of the network parameters. Certainly, both 'k-means' and 'fuzzy c-means' approaches use the training data to obtain all of the network parameters as well. In Table 2, 'training' means that the calculated SSE is for the training data and 'testing' means that the calculated SSE is for the testing data. Furthermore, in order to compare the effect of the number of network centres to the SSEs, different centre numbers $(20, 50, 100, 200)$ are used. The width of the network is calculated by $\sigma = d_{\max}$.

It can be seen from Table 2 that for every given centre number, both 'GA_1' and 'GA_2' can obtain small SSE values for both training and testing data compared with 'k-means' or 'fuzzy c-means' approach. For 'GA_1', we can see that the SSE values are close for both training data and testing data. However, for the 'GA_2' approach, the SSE values for the training data are smaller than the corresponding SSE values obtained by 'GA_1', but for testing data, they are larger than the corresponding SSE values obtained by 'GA_1' which may due to over-fitting of data. The increase of the number of centres, the SSE values decrease a little for every approach. Nevertheless, there is only a small decrease, hence there is a minor trade-off between the number of centres and the accuracy of the network. From the results obtained by the 'GA_1' approach, we can see that we can obtain small SSE values even with only 50 centres, and the SSE values do not decrease too much even when the number of centres is increased. Therefore, the centre number 50 may be considered as an ideal selection for the network structure although it is not optimal, however, it is time-saving for the training of the network.

When the 'GA_1' approach is used and the network centre number is selected as 50, the evolving RBF network can be obtained after the training process is finished. Fig. 4 shows the predicted force of the MR damper using the well trained evolving RBF network for the 2000 data sets of the testing data sets. Target force generated from the mathematical model are also plotted for comparison. It can be seen that predicted force matches quite well with the target force. The differences between these two forces are, in general, smaller than 0.1 kN which is about 5% of the target force. The results suggest that the evolving RBF network emulates the forward behaviour of the MR damper quite well.

4.3. Inverse model

The study on control of nonlinear systems through the use of their inverse dynamics received much of interest during the past several decades (Lane and Stengel, 1988). It is very useful to know the inverse dynamics of a system in order to control it. The main idea of inverse dynamics identification is to find the inverse mapping of a system. Following this idea, it also appears possible to use an evolving RBF network to emulate the "inverse" dynamic behaviour of the MR damper. This RBF model can provide a direct estimation of the voltage that is required to produce a target control force calculated from some optimal control algorithms. The major objective of this

Table 2
Comparison of SSEs for different approaches and different network structures

Number of centre	20		50		100		200	
Method	Training	Testing	Training	Testing	Training	Testing	Training	Testing
k-means	1.3459	1.7177	0.9354	1.4809	0.6931	1.3299	0.7073	1.3875
Fuzzy c-means	1.3373	1.7618	1.0470	1.5098	1.0091	1.3840	1.0478	1.3851
GA_1	1.0353	1.1157	0.6032	0.6006	0.5379	0.6525	0.5612	0.9249
GA_2	0.7242	1.3356	0.3339	3.4215	0.3513	2.6685	0.4079	2.7045

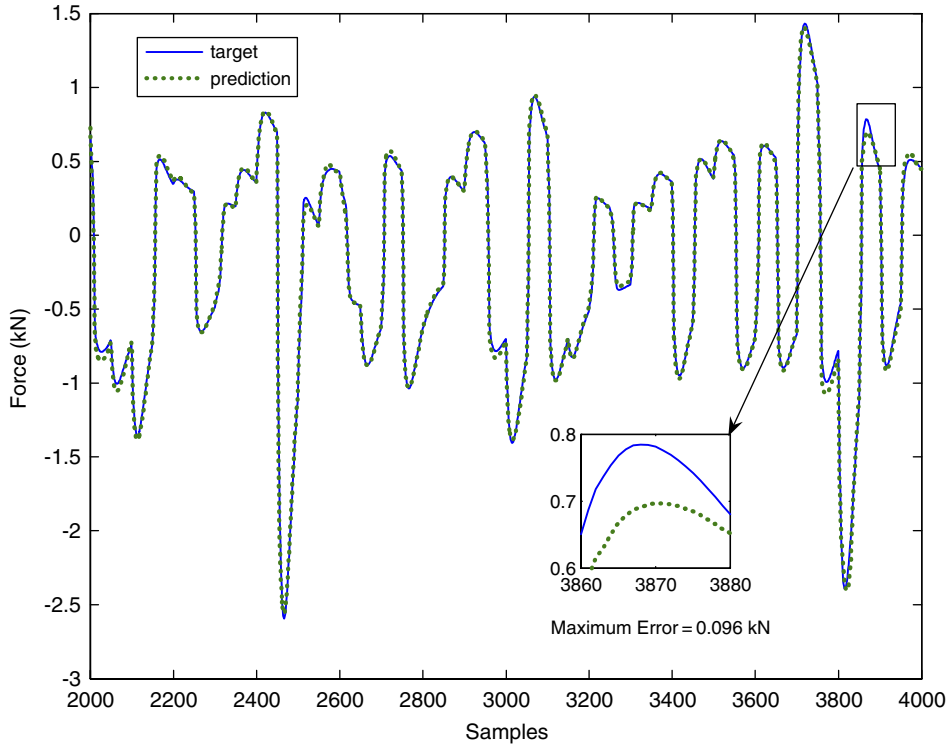

Fig. 4. Predicted force generated by the evolving RBF network.

Table 3
Comparison of SSEs for different approaches and different network structures

Number of centre	20		50		100		200	
Method	Training	Testing	Training	Testing	Training	Testing	Training	Testing
k-means	0.0449	0.0908	0.0014	0.0112	0.0013	0.0087	0.0014	0.0094
Fuzzy *c*-means	0.0826	0.1862	0.0025	0.0108	0.0022	0.0097	0.0018	0.0089
GA_1	0.0032	0.0051	0.0016	0.0037	0.0016	0.0036	0.0014	0.0041
GA_2	0.0020	0.0110	0.0009	0.0075	0.0008	0.0113	0.0009	0.0090

development is to explore whether the semi-active MR damper can be used to produce an optimal control force (Chang and Zhou, 2002).

By trial and error, the inputs to the training of this inverse model include the current displacement $x(t)$, velocity $\dot{x}(t)$, force $F(t)$ and the past command voltage $v(t-1)$. The output is the predicted voltage $\hat{v}(t)$. For practical use of this inverse model, the estimated voltage $\hat{v}(t)$ is applied to the MR damper for the generation of the force to approximate the optimal force designed by the optimal controller. The training and testing data used are the same as that used for the forward RBF model.

Similarly, the comparison of the SSE values for the training and testing data obtained by different approaches for different centre numbers are listed in Table 3. The same conclusion can also be drawn such that the 'GA_1' approach can obtain better SSE results than the other approaches for both the training data and testing data. On the other hand, a centre number of 50 is enough for the network structure without the optimization procedure and it is time-saving to finish the training of the network.

Fig. 5 shows the voltage histories predicted by the evolving RBF network using 'GA_1' approach as compared to the target voltage for the 2000 testing data sets. It is seen that the predicted voltage follow reasonably close to the target voltage. The maximum error between the predicted voltage and target voltage is less than 0.02 V. The near perfect match in the testing region indicates that the evolving RBF model is well trained. The evolving RBF model illustrates that the inverse dynamic relationship of the MR damper can be emulated by the evolving RBF network reasonably well.

4.4. Model validation

To further validate the effectiveness and the accuracy of the evolving RBF networks in modelling the forward and inverse dynamic behaviours of an MR damper, two more

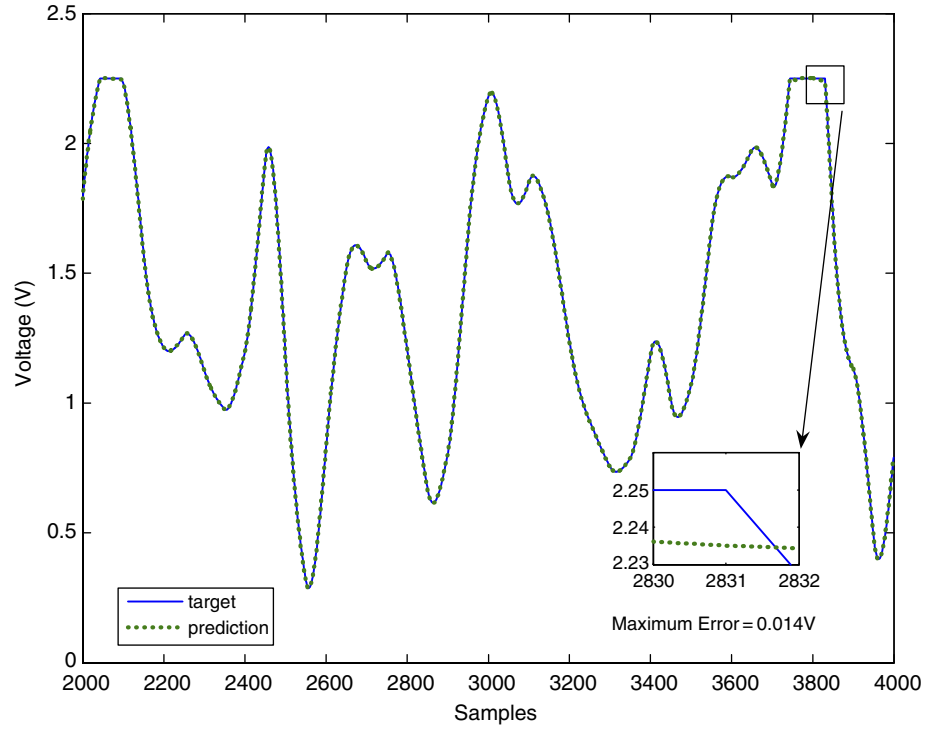

Fig. 5. Predicted voltage generated by the evolving RBF network.

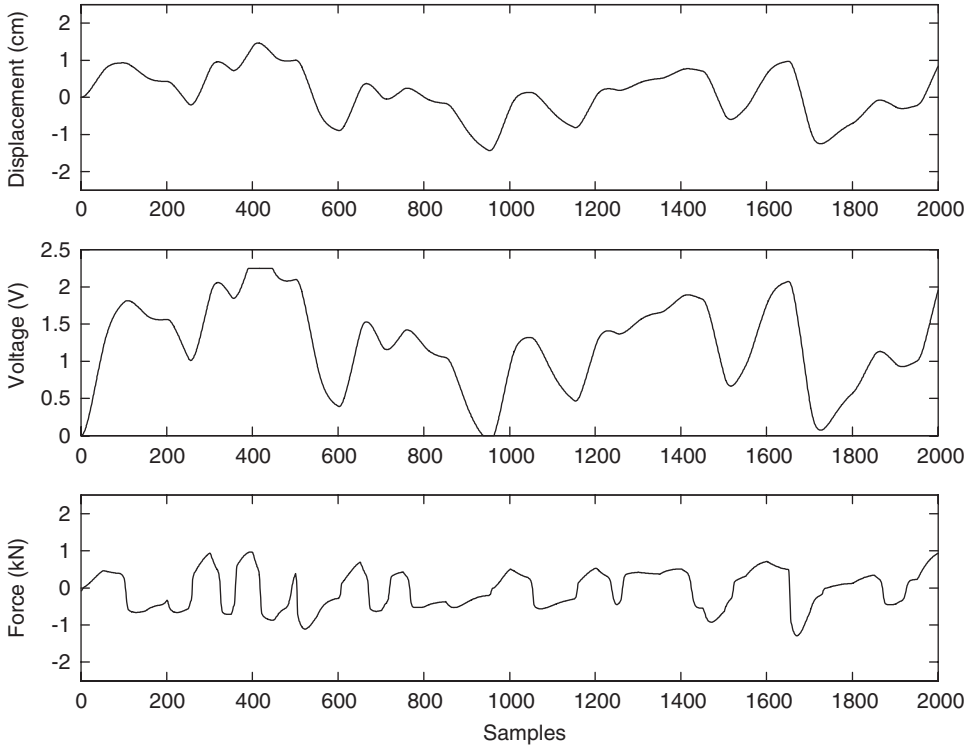

Fig. 6. Validation data I.

sets of validation data are generated from the same mathematical model of the MR damper as presented in Section 2. Validation data I is generated following the similar conditions as the training and testing data, that is, the displacement and voltage data are produced by Gaussian noise but they are all band-limited between 0–2 Hz. There are a total of 2000 data points produced with time increment 0.002 s. Fig. 6 shows the histories of validation data I for displacement, voltage and force. Fig. 7 shows the predicted force of the MR damper for the 2000

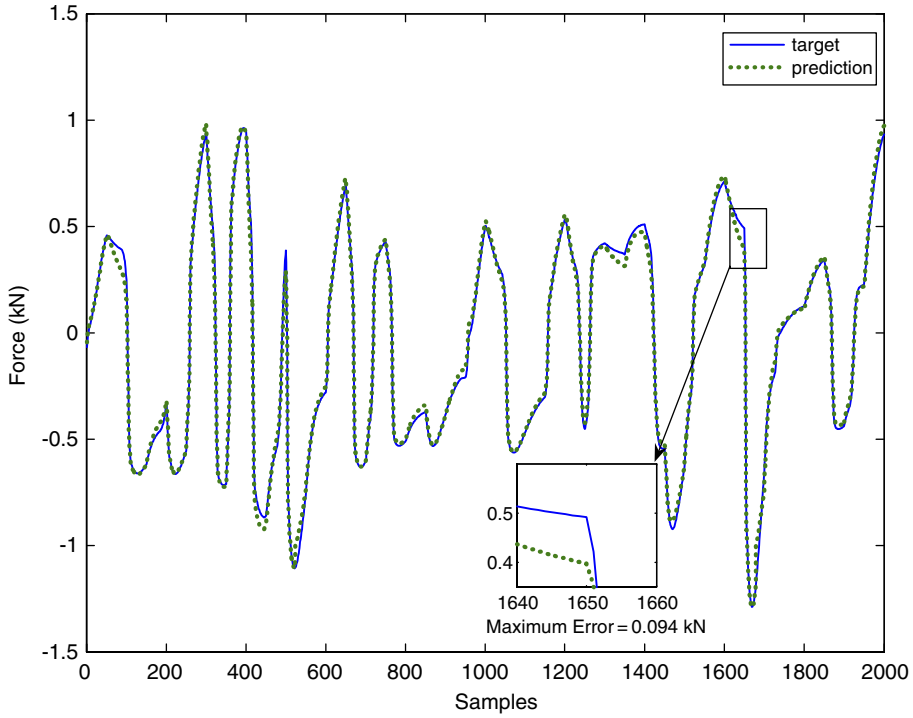

Fig. 7. Predicted force generated by the evolving RBF network.

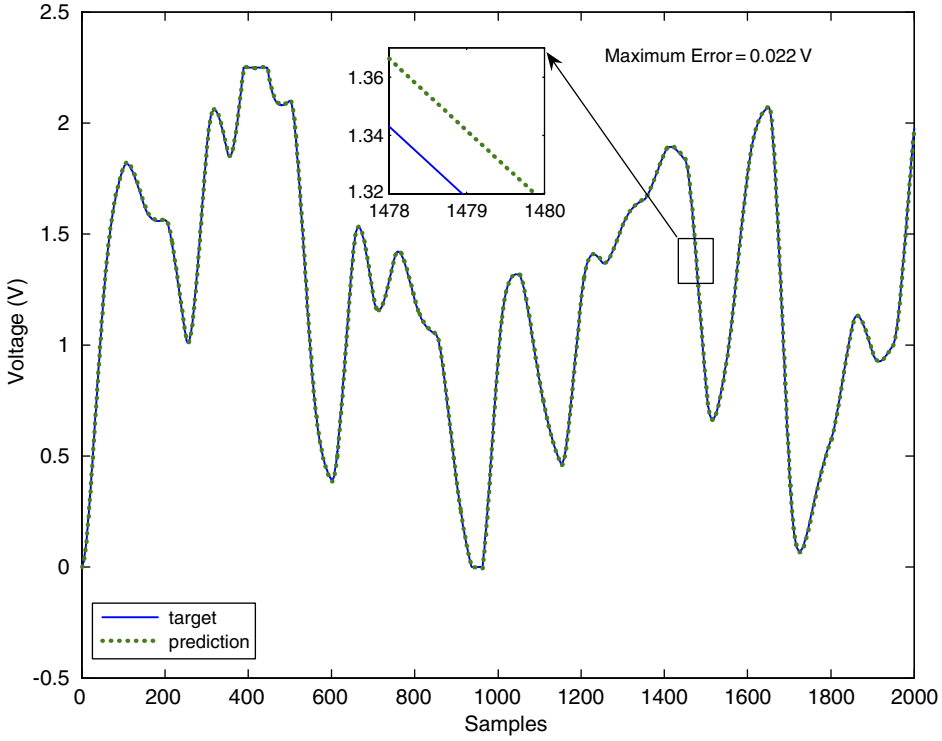

Fig. 8. Predicted voltage generated by the evolving RBF network.

data points using the well trained forward RBF network. It can also be seen that the predicted force match quite well with the target force generated by the mathematical model. Fig. 8 shows the predicted voltage of the MR damper for the 2000 samples using the trained inverse RBF network. It can be seen that the predicted voltage matches quite well with the target voltage commanded to the MR damper. Validation data II is generated using a sinusoidal displacement function with an amplitude of ±1 cm and a frequency of 3 Hz and a sinusoidal voltage function with mean value

of 1.6 V, an amplitude of 0.5 V and a frequency of 0.5 Hz. The time duration for this validation data is 4 s and the time increment is 0.002 s which amounts to a total of 2000 data points. Fig. 9 shows the histories of validation data II for displacement, voltage and force. Fig. 10 shows the predicted force of the MR damper for the 2000 data points using the trained forward RBF network. It can also be seen that the predicted force matches quite well with the target

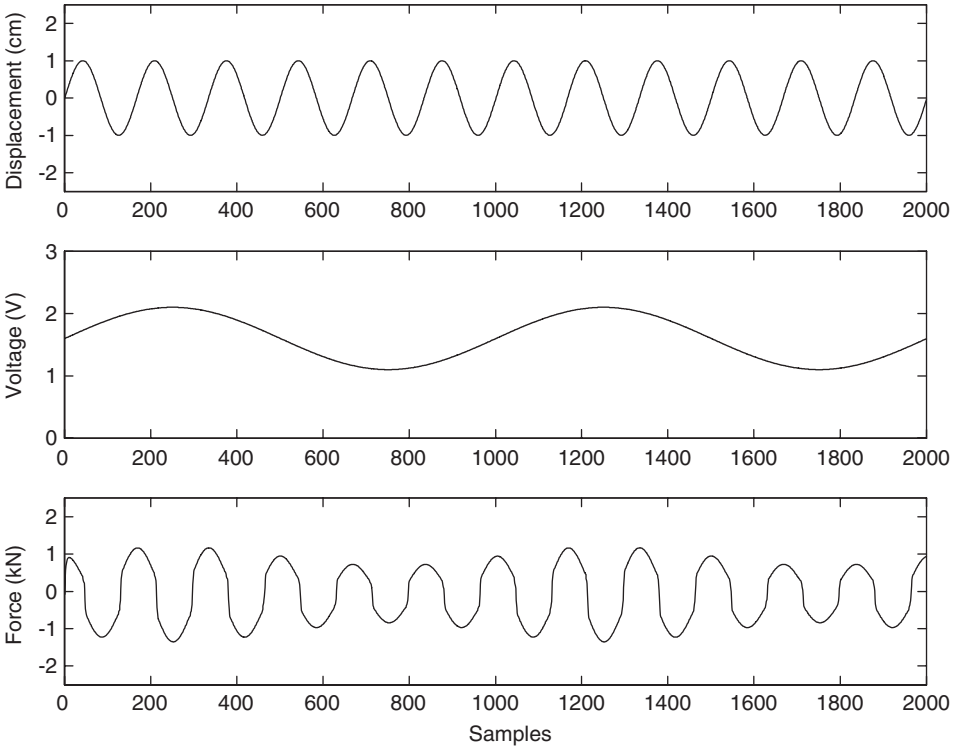

Fig. 9. Validation data II.

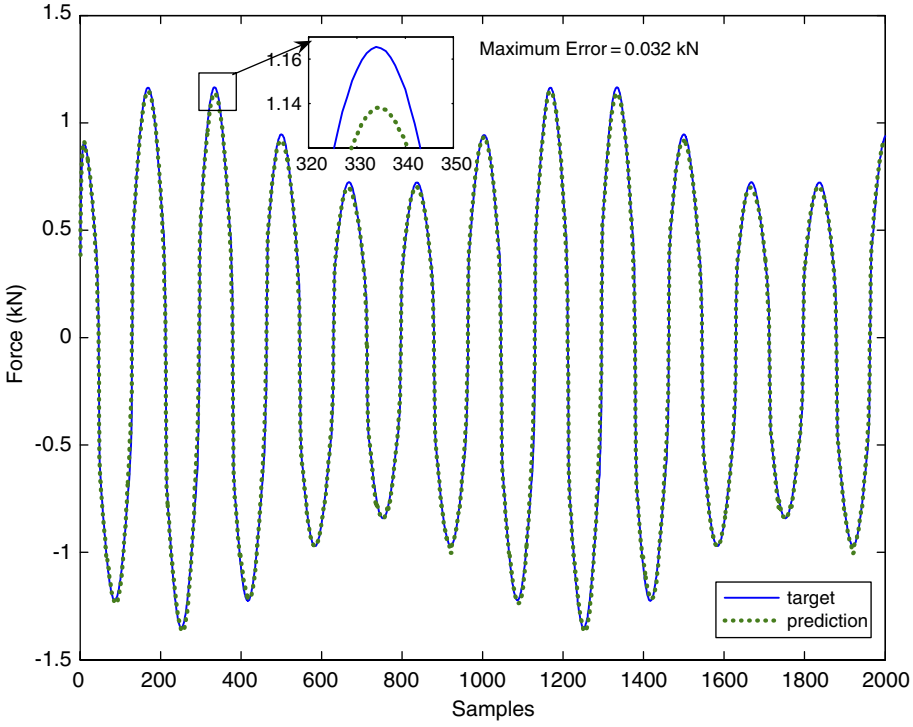

Fig. 10. Predicted force generated by the evolving RBF network.

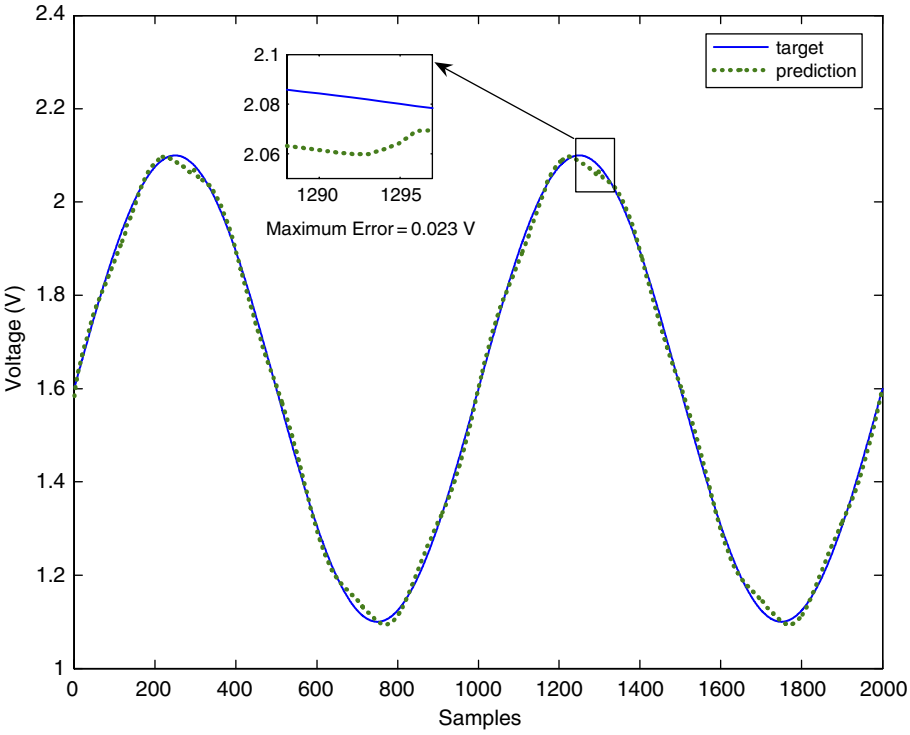

Fig. 11. Predicted voltage generated by the evolving RBF network.

force generated by the mathematical model. Fig. 11 shows the predicted voltage of the MR damper for the 2000 samples using the inverse RBF network. It can be seen that the predicted voltage match quite well with the target voltage applied to the MR damper except some small errors existing in the region where the trained data may not fully cover, however, the maximum absolute errors are still within the range of 0.03 V. It can be seen from the validation results that the trained evolving RBF networks can emulate the dynamic behaviours of an MR damper with acceptance even when the input data are different from the training data in both frequency and amplitude.

5. Conclusions

In this paper, the evolving RBF networks are developed to emulate the forward and inverse dynamic behaviours of an MR damper, respectively. It is certified by the testing and validation data that the evolving RBF network with simple structure not only can satisfactorily emulate the forward but also the inverse dynamic behaviour of the MR damper. Since RBF networks exhibit many advantages comparing with other types of ANNs in terms of the architecture, learning scheme, learning speed, etc., the RBF networks based modelling of MR dampers are more feasible to be implemented in practice. Some conclusions and further work can be given as follows: (1) selecting the network parameters based on GAs can obtain accurate modelling of the MR dampers even without the optimization procedure of the network structure; (2) the RBF networks-based approach is a spatial interpolation approach. If the selected training data can represent the full operation range of the MR damper, the obtained model will be more precise in some respects; (3) the past value of the predicted output, such as $F(t-1)$ or $v(t-1)$, is the key signal to increase the prediction accuracy for the forward and inverse model. However, more past values do not further improve the precision in this study; (4) since the dynamic range of every input signal is different, there should be some effects on the determination of the distance between the input vector and centres. A possible way to deal with this problem is to pre-process the different input signal at close range or assign the different input signal with an appropriate weighting coefficient according to its effect to the output.

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