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The experimental identification of magnetorheological dampers and evaluation of their controllers

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ABSTRACT

Magnetorheological (MR) fluid dampers are semi-active control devices that have been applied over a wide range of practical vibration control applications. This paper concerns the experimental identification of the dynamic behaviour of an MR damper and the use of the identified parameters in the control of such a damper. Feed-forward and recurrent neural networks are used to model both the direct and inverse dynamics of the damper. Training and validation of the proposed neural networks are achieved by using the data generated through dynamic tests with the damper mounted on a tensile testing machine. The validation test results clearly show that the proposed neural networks can reliably represent both the direct and inverse dynamic behaviours of an MR damper. The effect of the cylinder's surface temperature on both the direct and inverse dynamics of the damper is studied, and the neural network model is shown to be reasonably robust against significant temperature variation. The inverse recurrent neural network model is introduced as a damper controller and experimentally evaluated against alternative controllers proposed in the literature. The results reveal that the neural-based damper controller offers superior damper control. This observation and the added advantages of low-power requirement, extended service life of the damper and the minimal use of sensors, indicate that a neural-based damper controller potentially offers the most cost-effective vibration control solution among the controllers investigated.

1. Introduction

Magnetorheological (MR) fluid dampers are semi-active control devices that have received considerable interest due to their mechanical simplicity, high dynamic range, low power requirements, large force capacity and robustness. MR fluids respond to a magnetic field with a significant change in rheological behaviour. These fluids can reversibly and instantaneously change from a free-flowing liquid to a semi-solid with controllable yield strength when exposed to a magnetic field [1]. MR dampers have been applied over a wide range of vibration control applications: from automobiles [2,3] to railway vehicles [4] and civil structures such as buildings [5,6]. This paper concerns the identification techniques for modelling the dynamic behaviour of an MR damper and their use in the control of such a damper.

Identification techniques can be broadly classified into two categories: parametric and non-parametric techniques. Parametric models are based on mechanical idealization involving representation by an arrangement of springs and viscous dashpots [7–11]. The most parametric model for the identification of an MR damper is the modified Bouc–Wen model [7].

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This is a semi-empirical relationship in which 14 parameters are determined for a given damper through curve fitting of experimental results. Parametric models are useful for direct dynamic modelling of MR dampers i.e. the prediction of the damper force for given inputs (voltage signal and the time-history of the relative displacement across the damper's ends).

Unlike parametric models, non-parametric models do not make any assumptions on the underlying input/output relationship of the system being modelled. Consequently, an elevated amount of input/output data has to be used to identify the system, enabling the subsequent reliable prediction of the system's response to arbitrary inputs within the range of the training data. The principal non-parametric identification techniques proposed for MR dampers are interpolating polynomial fitting (restoring force surface (RSF) method) [12], neural networks [13–17] and neuro-fuzzy modelling [18]. Unlike the RSF method, neural-based techniques can handle hysteretic effects i.e. possible multi-valuedness of the damper force for given instantaneous values of displacement, velocity and applied voltage. Neural-based techniques have the additional advantage that they are useful not just for direct dynamic modelling of MR dampers, but also their inverse dynamic modelling. Inverse modelling involves the prediction of the voltage signal (applied to the damper's electromagnet) that will produce a desired damper force signal when the damper is subjected to a given time-history of the relative displacement across its ends.

Neural networks are able to approximate any complicated multi-input/multi-output continuous function. Neural networks used for modelling MR dampers are typically multilayer networks with either perceptron or sigmoid transfer function neurons e.g. [13–16]. Radial basis function networks have also been used to a lesser extent [17]. Due to hysteretic effects of the MR damper, the output variable of the mapping (i.e. force, in case of the direct problem, or voltage, in case of the inverse problem), suitably delayed, is included with the inputs to the neural network [13]. In the case of a "feed-forward" neural network (FNN), this extra input is the *actual* value of the output variable (i.e. the value that truly corresponds to the other input variables) and so is taken not from the network output but from some other independent source of information (e.g. a force sensor on the damper in the case of the direct problem) [13]. In the case of a "recurrent" neural network (RNN), this extra input is taken from the output of the network itself [13,15]. For the direct problem, a trained RNN has the advantage of not requiring a force sensor, although it would be slightly less precise than the FNN. For the inverse problem, the RNN is the only practical approach since the FNN would require real-time knowledge of the correct desired voltage (to include with the other inputs)—this of course would not be possible unless one has previously solved the direct form of the same problem. Direct and inverse dynamic modelling using FNN and/or RNN have been considered in [13–16]. These works used optimisation algorithms including "optimal brain surgeon strategies" to prune the weights of the network and optimise their values. It is important to note that in all such works the networks have been trained and validated through simulated data generated from the numerical solution of the modified Bouc–Wen model [7] rather than measured data.

Most of the above-mentioned works on MR damper modelling have not explored the effect of temperature on the dynamic behaviour of the MR damper. The reason for this may be attributed to the observation made by Spencer et al. [7] that MR damper performance is reasonably stable over a broad temperature range (−40 to 150 °C). However, recent research [19,20] has shown that the influence of temperature on the damper force is not insignificant. A temperature-dependent skyhook controller for an MR vehicle suspension was introduced by [19]. Using a quasi-steady damper model, simulation results were presented to show how temperature feedback can improve the suspension performance by adjusting the controller for variations in viscosity. The damper model developed in [20] took into account temperature variation and studied the effect of MR damper cylinder's surface temperature on the damping force through numerical and experimental studies [20].

A vibration control system using an MR damper requires two nested controllers: (i) an overall system controller, and (ii) an MR damper controller. The former controller computes the desired damping force required for given system conditions. This is typically done through a sliding mode control algorithm which forces the real system to emulate an idealised reference system [2]. The function of the damper controller is to command the damper to produce the desired force. The effectiveness of this controller depends on its ability to deal with the nonlinear nature of the device (i.e. the nonlinear relationship between damper force and relative velocity across it) and its semi-active nature. This latter means that it is the applied voltage, rather than the desired force, that can be commanded directly. The most basic MR damper controller algorithm is "on-off" control, also known as the Heaviside function method (HSF), where the applied voltage is either 0 or maximum [5]. An improvement on this algorithm is the Signum function method (SFM), which, under certain conditions, allows the applied damper voltage to switch between discrete voltage levels below the maximum [21]. In both these controllers, the command voltage signal is discontinuous. Allowing the voltage signal to be continuous ensures more effective control, lower power requirement and extended service life of the damper. The Continuous State control (CSC) method allows the command of a continuous voltage signal. CSC was introduced in [21] for an ER damper and was used in [2] for an MR damper, although no comparison was made in either [22] or [2] with alternative control strategies. An alternative method of commanding a continuous voltage signal is through a neural network of the inverse dynamics of the MR damper, as discussed above. This has the advantage over CSC of not requiring a force sensor. Such a strategy was introduced in [13] but it was only compared with simple "on-off" control. It should also be mentioned that the evaluation of these MR damper controllers has so far been done on simulated data obtained from the parametric modelling of the MR damper.

The novel contributions of this paper are as follows:

- The neural network identification of both direct and inverse dynamics of an MR damper through an experimental procedure.