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Application of a recurrent wavelet fuzzy-neural network in the positioning control of a magnetic-bearing mechanism☆

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ABSTRACT

A new recurrent wavelet fuzzy neural network (RWFNN) with adaptive learning rates is proposed to control the rotor position on the axial direction of a thrust magnetic bearing (TMB) mechanism in this study. First, the dynamic analysis of the TMB with differential driving mode (DDM) is derived. Because the dynamic characteristics and system parameters of the TMB mechanism are high nonlinear and time-varying, the RWFNN, which integrates wavelet transforms with fuzzy rules, is proposed to achieve precise positioning control of the TMB. For the designed RWFNN controller, the online learning algorithm is derived using back-propagation method. Moreover, since the improper selection of learning rates for the RWFNN will deteriorate the control performance, an improved particle swarm optimization (IPSO) is adopted to adapt the learning rates of the RWFNN on-line. Numerical simulations show the validity of TMB system using the proposed RWFNN controller with IPSO under the occurrence of uncertainties.

1. Introduction

Magnetic bearings (MBs) are a very promising technology and are now being employed for a variety of high performance applications [1-4]. Based on the noncontact and frictionless characteristics, MB offers advantages such as longer lifetime, lower frictional losses, higher rotational speed, and elimination of the lubrication [1, 3]. In most applications, the control objects should be positioned and moved precisely and functionally to deal with the different operation demands or environments. Therefore, precise positioning control is a very important issue for MBs. In [5], a nonlinear control system of a magnetic journal bearing was designed using a combination of feedback linearization and backstepping concepts for tracking control. In this design, a proportional-derivative (PD) feedback law, which was used for pseudo-input during the backstepping procedure, is unable to deal with the time-varying disturbance. In [6], a decentralized proportional-integral-derivative neural network (PIDNN) control scheme was proposed to regulate and stabilize a fully suspended five degree-of-freedom MB system. Based on the decentralized concepts, the computational burden was reduced and the controller design was simplified. A three-pole MB using a decentralized proportional integral derivative (PID) feedback law with linear quadratic Gaussian (LQG) optimization and an integral sliding mode controller was presented in [7]. Furthermore, some other control designs such as linear quadratic Gaussian control [8],

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H^{∞} control [9], backstepping control [10], feedback linearization approach [11] were reported for the positioning and tracking controls of MBs in recent years.

In the operation of MB systems, the purpose of bias current setting is to improve the linearity of the force-current relationships around the operating point and allow for a higher slew rate of force [1]. Moreover, the operating modes of the drive system which supply the currents to the electromagnets can be classified into three classes [4]. The most popular is Class-A driving mode, i.e. DDM, in which both the bias currents of the opposite MBs are set at half of the maximum allowable current. Then, the control current is added to the bias current in one electromagnetic coil and subtracted from the bias current in the opposite one. This operating mode provides maximum range of the force dynamic and good linearity of the control dynamic. For Class-B driving mode, both bias currents are set at lower values and control current is superimposed on only one side of the pair of coils. Though the energy consumption can be improved efficiently, this operating mode is only suitable for low bearing stiffness and low vibration applications due to poor slew rate and controllability of the force. If there is no bias current used, it is categorized as Class-C driving mode. Though the rotor heating is the least, high nonlinearity of the electromagnetic force dynamic degrades the control characteristic greatly.

By combining wavelet functions with neural networks (NNs), wavelet neural networks (WNNs) have been developed for a wide range of fields and applications [12]. Since the WNN introduces the wavelet decomposition property into NN, it provides quick converge and high precision with reduced network size for an alternative in nonlinear control problems. Moreover, a wavelet fuzzy neural network (WFNN) combining wavelet theory with fuzzy neural network (FNN) was further proposed [13]. In WFNN, each fuzzy rule corresponds to a sub-WNN [13]. Thus, the sub-WNNs at different resolution levels are used to capture different behaviors of the dynamic systems. Additionally, the role of the fuzzy rules of FNN is to determine the different contribution of each sub-WNN to the output of the WFNN [13]. Compared with conventional WNNs, the approximation accuracy and generalization capability of the WFNN can be improved greatly via wavelet and fuzzy sets parameters learning [13-15].

Particle swarm optimization (PSO), which is a population-based optimization method, has attracted increasing attention to achieve high efficiency solver for global optimization problems in scientific and engineering domains [16, 17]. The PSO method is based on the simulation of animal social behaviors with self-adaptive characteristic. Comparing with genetic algorithm (GA), PSO has the ability to retain a memory of good solutions by all particles, whereas previous knowledge is not considered after each evolution in GA. Meanwhile, since the unique information diffusion and interaction mechanism of PSO are comparably simple, it requires low computational burden and is suitable in various applications such as control [18, 19], system identification [20], diagnosis [21], and image process [22, 23]. These works have clearly shown that PSO is a fast and reliable tool to design the optimal strategy, and also can outperform other evolutionary algorithms. On the other hand, many variants of PSO have been proposed to further enhance the particle's learning ability and make it powerful in reasoning over the past decade [24-26]. In [24], the worst experience component is included in improved particle swarm optimization (IPSO) to give additional exploration capability.

In this study, the TMB system is first represented by a nonlinear dynamic model. Moreover, since the exact parameters of this model are unknown, the six layers RWFNN controller with IPSO is proposed to control the rotor position on the axial direction of the TMB system for tracking reference trajectory with robustness. Finally, simulation results illustrating the validity and advantages of the proposed RWFNN for the TMB control system are discussed.

2. Dynamic analysis of TMB system

2.1. System structure of MB

A typically structure of the TMB using DDM drive system is shown in Fig. 1 where a thrust disk is embedded on the rotor and used to carry out the rotor position control on the defined axial direction Z. Moreover, in the DDM drive system, both the bias currents of the left and right MBs are set as the half of maximum allowable current. The control current is added to the bias current in one electromagnetic coil and subtracted from the bias current in the opposite one. According to the dynamic adjustment of the control current, the rotor can be suspended and its position z can be moved to the reference position z_m.

As shown in Fig. 1, the deviation of the nominal air gap z_0 is denoted by variable z which is also referred as the rotor position. Moreover, a pre-designed bias voltage v_0 is used for both the magnetic bearings to produce the same basic attractive forces for both sides of the thrust disk. On the other hand, the control voltage v_z is obtained by the proposed RWFNN controller. The total current is a combination of bias current i_0 and control current i_z from the power amplifier, and circulates through coils on the stator.

2.2. Dynamic model

Using the Newton's law, the dynamic model of the TMB control system can be described as:

$$m\ddot{z} + c\dot{z} - f_{dz} = F_z \tag{1}$$

where m is the mass of the rotor; c is the friction constant; F_z is the electromagnetic force and defined as $F_z \equiv f_{z1} - f_{z2}$ in which f_{z1} and f_{z2} are the electromagnetic forces produced by the right and left electromagnets, respectively; f_{dz} is the external disturbance.