Improving the Stiffness of Hydrostatic Bearings Using Multilayer Perceptron

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ABSTRACT

The stiffness of hydrostatic bearings is mainly affected by the flow resistance of the restrictor, however, accurate estimation of which is often unattainable because of variation of environment conditions, resistance from oil tube and incompatible assumptions in the theory of hydrostatic bearings. This paper proposed a design method to improve the stiffness of hydrostatic bearings by use of multilayer perceptron (MLP). The MLP model constructed a multi-input and multi-output (MIMO) system with supply pressure, load, and the depth of groove as the inputs and the oil-film thickness as the output. The MLP model employed gradient decent algorithm as the optimizer with an input layer, three hidden layers, and an output layer. According to this malleable nonlinear model and various functions, the MLP model could find the hidden patterns from the training data and predict the output. Simulation of bearing characteristics was performed on the basis of the hydrostatic bearing theory. An experimental setup was constructed to verify the film thickness obtained from both simulation and predictive results of the MLP model. A number of flow restrictors with distinct groove depths together with parameters such as supply pressure and load were used in experiments. Meanwhile, the pressure, flow rate, load, temperature and oil-film thickness were measured by the corresponding sensors directly. The MLP model for the stiffness of hydrostatic bearings was effectively trained with the collected data. Compared to the simulation, the proposed method demonstrates more applicable for the design of hydrostatic bearing systems.

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INTRODUCTION

Hydrostatic bearings are widely used in precision machine tools because of their superior characteristics of high stiffness, high load-carrying capacity, high damping, nearly frictionless and long life. The stiffness of hydrostatic bearings is mainly affected by the designed oil-film thickness and the characteristic of flow restrictors. With different kinds of flow restrictors, hydrostatic bearings will perform with distinct stiffness. In general, the flow restrictors can be categorized into two types: the fixed type, such as capillary, orifice and groove restrictors; and the active type, for example, a constant flow valve, a diaphragm controlled and self-compensation restrictors.

Raimondi and Boyd (1957) proposed the theoretical analysis of multi-recess hydrostatic bearing with orifice and capillary, based on the assumption of one-dimensional flow. Malanoski (1961) discovered that the constant flow valve performed higher stiffness than capillary and orifice. Moshin (1963) proved that diaphragm restrictor had higher dynamic and static stiffness than fixed-type restrictors in the same working situation. Moris (1972) compared the effect of active-type restrictors and fixed-type restrictors on oil-film stiffness. Osumi et al. also observed that under identical dynamic loading, the diaphragm restrictor or other active-type restrictors achieved higher dynamic response. Moreover, he deduced the possibility of negative stiffness and infinite stiffness. Tully (1977) proposed that in the static infinite stiffness condition, the mass of the compensation element in self-compensation restrictor reduced the vibration of hydrostatic bearing. Robert (2001) presented a new diaphragm restrictor that adjusted the preload to calibrate flow resistance error.

Hybrid flow restrictors that, for instance, combine a diaphragm restrictor with a groove restrictor have been developed recently to meet the need of high stiffness while avoid the occurrence of negative stiffness. However, to design a hybrid flow restrictor is very complicated, trials and errors are usually inevitable because of a plenty of parameters involved in the design process. To resolve this

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drawback, this paper employed MLP to optimize the stiffness of hydrostatic bearings and the properties of the groove restrictor. The training data for the MLP model were adopted from the experiment that was implemented on a single-pad hydrostatic bearing integrated individually with groove restrictors of various groove depths. In addition, the supply pressure and load were also varied and considered as design parameters. Finally, the stiffness curve of the hydrostatic bearings was predicted by this well-trained MLP model and the properties of restrictor were analyzed.

Theory

Lumped parameter modeling method

Lumped parameter modeling method is adopted herein to simplify the calculation of the hydrostatic bearing system. With the relationship of pressure and flow rate, which is derived from Navier-Stokes equation, lumped parameter modeling method assumes the hydrostatic bearing system as a circuit system. According to the hypothesis, hydraulic pressure, flow rate and flow resistance can be analogous to voltage, current and resistance in the circuit system, respectively. Thus, from the circuit formula, the relationship among flow resistance \mathbb{R} , flow rate \mathbb{Q} , and pressure difference $\Delta \mathbb{P}$ can be expressed as

$$\mathbf{R} = \frac{\Delta P}{Q} \tag{1}$$

The groove restrictor is designed to be combined with an active one to form a hybrid restrictor. The electrical circuit analogy of groove restrictor is shown in Figure. 1. P_{s} is the pressure supplied by an oil pump. P_{p} is the pressure of the pocket in hydrostatic bearing. Thus, with lumped parameter modeling method, the resistance of restrictor can be calculated directly.



Fig. 1. Lumped parameter modeling method.

Groove restrictor

The groove restrictor can be considered as a type of capillary restrictor with rectangular section. Figure 2 illustrates the configuration and symbol definition.



Fig. 2. Symbol definition of the groove restrictor.

The flow resistance of a groove restrictor can be calculated based on the equation derived in Bruus' book "Theoretical Microfluidics" (2008).

$$R_{groove} = \frac{12\mu r_{center}}{1 - 0.63 \left(\frac{W}{b}\right)} \frac{1}{w^2 b}$$
(2)

where w is the shorter side of the section, and b is the longer side of the section, as shown in Fig. 2.

Pad flow resistance

In this study, the experiment is performed on a hydrostatic bearing with single rectangular pad. The calculation of the pad flow resistance can be found in the book "Precision Machine Design" written by Slocum (1992). Figure 3 shows the rectangular pad and its symbol definition.



Fig. 3. Symbol definition of the rectangular pad.

The total resistance (R_l) of the rectangular pad can be divided into two parts as shown in Fig. 3, rounded corner region (R_a) and rectangular plate region (R_{ss}) . The formulas are

$$R_l = \frac{1}{\frac{1}{R_a} + \frac{1}{R_{SS}}} \tag{3}$$

$$R_a = \frac{6\mu \ln\left(\frac{r_p + \iota}{r_p}\right)}{\pi h^3} \tag{4}$$

$$R_{ss} = \frac{6\mu l}{\left(a+b-4\left(l+r_p\right)\right)h^2}$$
(5)

Simulation

In this study, experiments are implemented on a single-pad hydrostatic bearing matched individually with five groove restrictors, each of which has different depths, to acquire distinct stiffness performance. Figure. 4 illustrates simulation results comparing the stiffness of the five different bearings. As a result, the shallowest groove restrictor will have the highest stiffness performance. However, it may also cause lack of flow rate. Thus, how to find a compromise between them is an important issue.



Fig. 4. Simulation results of bearings with five different depths of groove restrictors.

Experiment

Experimental setup

The purpose of the experiment is to verify the accuracy of the stiffness obtained from simulation and to acquire adequate training data for the MLP model. Figure. 5 shows the experimental setup containing an oil supply system, a cooling system and a single pad hydrostatic bearing with a groove restrictor. Two manometers were installed to measure P_{a} and P_{m} . A thermometer was set to record the oil temperature in the pocket. Two eddy current sensors were used at both ends of the bearing platform to measure oil-film thickness. There were also a load cell and a flowmeter to measure load and flow rate. All of the data mentioned were read by Data Acquisition (DAQ) device. Ten groove restrictors with different dimensions were tested by giving gradually increased load under distinct supply pressure.



Fig. 5. Experimental setup

Experiment result

According to the theory, when the load increases, the pad resistance will raise. Under this circumstance, the pressure (P_p) increases while the flow rate (Q) decreases. These phenomena can be found in the experiment results shown in Figure. 6. The load increases until the pressure P_p approaches P_{g} .



Fig. 6. Relationship between pressure (Ps, Pp) and flow rate (Q).

Figure. 7 demonstrates the load capacity of same groove restrictor under three supply pressure, 10bar, 20bar, 30bar. The result indicates that higher supply pressure results in larger load capacity of the hydrostatic bearing.



Fig. 7. Comparison of the bearing stiffness under different supply pressure.

The relationship between load and oil-film thickness is shown in Figure. 8. Three groove restrictors with different depth were tested. The slope at different load points out the stiffness performance of groove restrictors in each state. Generally, the groove with thinner depth will have larger flow resistance and higher stiffness performance. However, a shallow depth will cause the lack of flow rate. Thus, the depth of groove restrictor should be select precisely.



Figure. 9 is the dimensionless chart of pressure and oil-film thickness, which displays a comparison of simulation and experiment result. The trend of the experiment result can possibly fit the simulation, but errors still exist, which may come from the experiment environment.



Fig. 9. Comparison of simulation and experiment results.

Multiple layer perceptron

With the design parameters and the measurement data from the experiment, the next task is to establish a model to find the relationship between inputs (supply pressure, load, design parameter of groove restrictors, temperature) and output (oil-film thickness). The multiple layer perceptron (MLP) is used in this study to develop the possibility of predicting the stiffness performance of hydrostatic bearing. Herein, the structure of multiple layer perceptron model is written with tensorflow.

Multiple layer perceptron (MLP) model

Artificial neural network (ANN) is a form of artificial intelligence, which imitates from the biological neural network. The multiple layer perceptron is a branch of artificial neural network. Due to the nonlinear structure of the model, artificial neural network can be used to solve many nonlinear problems. The basic unit in the artificial neural network is neuron, which is called node. Each node receives input from other node or external input and calculates its output. Every input has its own weight (w) and bias (b) and a layer containing several nodes.

Multiple layer perceptron is a kind of feedforward neural network and is often used in supervised learning. It usually refers to the neural network with three or more layers, an input layer, an output layer and several hidden layers. Except for the nodes in input layer, all of the nodes are using nonlinear active function. Furthermore, every node in one layer is connected to every node in the next layer. Because of the characteristic of several layers of neural network and nonlinear active function, MLP model has a very good perform on nonlinear classification.

Feature extraction is a method to obtain the dominant parameters from the experiment data. In this study, supply pressure, load and depth of groove restrictors have strong relevant to the oil-film thickness except temperature and width of groove restrictors. Therefore, the structure of the MLP model has three nodes in input layer. And due to the dimension, three hidden layers with 6, 9 and 3 nodes are applied. The output layer has only one node which calculated the oil-film thickness. The whole structure of MLP model is shown in Figure. 10.



Fig. 10. Structure of multiple layer perceptron.

machine learning and mathematical In optimization field, a function called loss function is to calculate the error between prediction and real value. Generally, the lower the loss function is, the more accurate the MLP model is. There are several kinds of loss function in machine learning. Usually, mean squared error (MSE) is a common choice for loss function in multiple layer perceptron. In order to minimize the loss function, gradient decent algorithm is used to compute the current gradient of the parameters and then let the parameters go a little further in the opposite direction of the gradient. Repeat this step until the loss function approaches zero. However, the structure in multiple layer perceptron is complicated. It costs a lot of time when calculating the gradient. Therefore, the model also needs to use the backpropagation algorithm to lower the cost of computation. Overall, the purpose of training is to optimize the weight and bias in the MLP model.

Cross-validation (CV) is a strategy for model or algorithm selection in order to avoid overfitting during the training process and estimate how accurately a predictive model will perform in practice. Figure. 11 is the schematic diagram of cross-validation. At the beginning, all the data will be split into two parts: training data and validation data. Later, the model will be trained by the training data. Different validation data is tested to estimate the risk for the model. At the end, after multiple rounds of cross-validation, the validation results are averaged. In this study, experiment data are divided into 9 training data parts and 1 validation part. To ensure the model operates without overfitting, 10 times of cross-validation are performed.

	Da	ita	
Train	Train	Train	Val Model Average
Train	Train	Val	Train Model
Train	Val	Train	Train Model
Val	Train	Train	Train Model of performance

Fig. 11. Cross-validation

Modeling results

Due to many inevitable sources of errors, e.g., resistance from tube, measurement error, environment vibration and so on, the simulation cannot match the experiment results accurately. However, the MLP model used in this study can properly predict the relationship of pressure and oil-film thickness through learning from training data.

The training data contained No. 1 to No. 9 groove restrictors (without No. 8) with different design parameters. Under several supplied pressure, the load was increased step by step. The loss closed to zero after the MLP model was trained for 10000 times by these experiment data. Later, test data of No. 8 groove restrictor with depth of 0.363mm and under 20 bar supplied pressure was inputted into the model. With regard to No.8 groove restrictor, a comparison between the predictive and experiment results of the relationship of load and oil-film thickness is shown in Figure. 12. Also, when the load increased, $P_{\rm m}$ would approach P_{s} . The dimensionless chart of comparison of the experiment, simulation, and prediction are shown in Figure. 13. Only a little error exists between experiment result and prediction, the MLP model can definitely predict the stiffness performance of hydrostatic bearings.



Fig. 12. Comparison of prediction and experiment result.



Fig. 13. Comparison of experiment, simulation and prediction.

Accordingly, with this MLP model, the stiffness performance of groove restrictors can be predicted by giving supply pressure, load and depth of groove restrictors. Furthermore, this method can effectively assist the design and accelerate the manufacturing process.

Conclusion

The proposed design method for improving the stiffness of hydrostatic bearings by use of multilayer perceptron (MLP) was verified in this paper. The model constructed a multi-input and MLP multi-output (MIMO) system with supply pressure, load, and depth of groove as the inputs and the oil-film thickness as the output. In addition, the MLP model employed gradient decent algorithm as the optimizer with an input layer, three hidden layers, and an output layer. According to this malleable nonlinear model and various functions, the model could find the hidden patterns from the training data and predict the output. Simulation of bearing characteristics was also performed on the basis of the hydrostatic bearing theory. An experimental setup was constructed to verify the film thickness, which can be considered as the bearing stiffness, obtained from both simulation and MLP prediction. Compared to the simulation, the proposed method by implementing the MLP model is more applicable for the design of hydrostatic bearing systems.

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NOMENCLATURE

- P_s supply pressure
- **P**_p pocket pressure
- *Q* flow rate
- *¶* flow rate through the groove restrictor
- **q** flow rate through the pad
- \mathbb{R} resistance of the entire restrictors
- R_{I} resistance of pad

Rgroove resistance of groove restrictor

- [₩] depth of groove restrictor
- *r*_{center} groove radius
- ₱ oil viscosity
- R_l land resistance
- R_{a} resistance of rounded corner region
- R_{ss} resistance of rectangular plate region
- a pocket width

- b pocket length
- r_₽ pocket radius
- *l* oil-film width

h oil-film thickness

以多層感知器改善 液靜壓軸承之剛性表現

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摘要

液靜壓軸承因其高剛性、高承載力、幾乎無摩 擦力等特性,已經被廣泛使用在精密機械加工機產 業,而使用於其中之節流器更是影響液靜壓軸承表 現的關鍵元件,因此本文致力於研究實驗室過往所 設計之溝槽式、自補償式與結合前兩者的複合式節 流器,進行物理理論之模擬與實驗驗證,完善此新 構形節流器的設計。然而,由於對於整個液靜壓軸 承系統,其數學模型過於冗長,又為非線性,在做 物理模擬時須做非常多的假設條件;再加上實驗的 過程中,來自於環境的其他干擾因素是模擬無法考 慮的,最後造成模擬結果不準確。因此,本研究利 用多層感知器模型可以接受多輸入多輸出與能處 理非線性問題等特性,以達到預測液靜壓軸承系統 搭配不同節流器時,隨著供油壓力、負載、油溫等 參數變化時其他相應參數可能的改變,並依此結果 輔助新節流器的設計。