DOI: 10.13434/j.cnki.1007-4546.2014.0106

# The Prediction of Dynamic Coefficients for Tilting-Pad Journal Bearings Based on an AGA-BP Neural Network

GAO Dang-cheng, YIN Ming-hu, CHEN Guo-ding
School of Mechanical Engineering, Northwestern Polytechnical University, Xi'an 710072, P. R. China

**Abstract:** To provide real-time dynamic coefficients of tilting-pad journal bearings (TPJBs) for the dynamic analysis of a rotor-bearing system accurately, an improved error back propagation (BP) neural network model is built in this paper. First, the samples are gained by solving the Reynolds equation with the finite differential method based on hydrodynamic lubrication theory. Secondly, the adaptive genetic algorithm (AGA) is applied to optimize the initial weights and thresholds of the BP neural network before training. Then, with a number of trial calculations, the optimum parameters for the neural network are obtained. Finally, an application case of the neural network is given as well as the results analysis. The results show that the AGA can efficiently prevent the training of the neural network from falling into a local minimum, and the AGA-BP neural network of dynamic coefficients for TPJBs built in this paper can meet the demand of engineering.

**Key words:** neural network; adaptive genetic algorithm; tilting-pad journal bearing; dynamic coefficients

## 1 Introduction

Tilting-pad journal bearings (TPJBs) are widely used in high speed rotating machinery for their stability. As the supporting parts of a rotor-bearing system, the oil-film characteristics of TPJBs, especially the dynamic characteristics, have a significant effect on its amplitude, critical speed and stability [1-4]. In a rotor-bearing system, the dynamic coefficients of a bearing are often a time variable under the interaction of internal and external excitation. Hence, it is necessary to provide real-time dynamic coefficients of the TPJB for the dynamic analysis of a rotor-bearing system. At present, the dynamic coefficients of sliding bearings are obtained mainly by solving the dynamic Reynolds equation with a numerical method [5-8], which costs a lot of time and cannot meet the real-time demand. Hence, it is necessary to propose a rapid and accurate method to calculate the dynamic coefficients of TPJBs.

Recently, many scholars have predicted the static and dynamic characteristics of journal bearings with BP neural network technology. Qin ping, et al. [9] built a BP neural network model of nonlinear oil-film force for a journal bearing. Lu. [10] built a BP neural network model of axial location for a journal bearing. Tang, et al. [11] built a BP neural network model of the static stiffness for a hydrostatic bearing. While the rotor-bearing system, the dynamic coefficients of bearings are quite sensitive to the structure parameters and operating conditions of bearings. Besides, a BP neural network has the disadvantages that the training converges slowly and easily falls into a local minimum, which seriously affects the prediction accuracy of dynamic coefficients for TPJBs.

In view of this, an adaptive genetic algorithm (AGA) is introduced to optimize the weights and thresholds of

Received 10 January 2014

the BP neural network, which can improve the convergence speed and avoid falling into a local minimum during training. And this method is applied to the prediction of dynamic coefficients for TPJBs. The results show that the neural network based on the AGA-BP algorithm has better generalizing ability and can be used to provide real-time dynamic coefficients of TPJBs for the dynamic analysis of a rotor-bearing system accurately.

## 2 AGA-BP neural network model

### 2.1 BP neural network

The BP neural network is a multilayer feed-forward neural network which consists of input layer, hidden layer(one or more) and output layer. Every node of different layers is connected to each other while the nodes of the same layer not. The typical structure of a BP neural network can be shown in Figure 1.

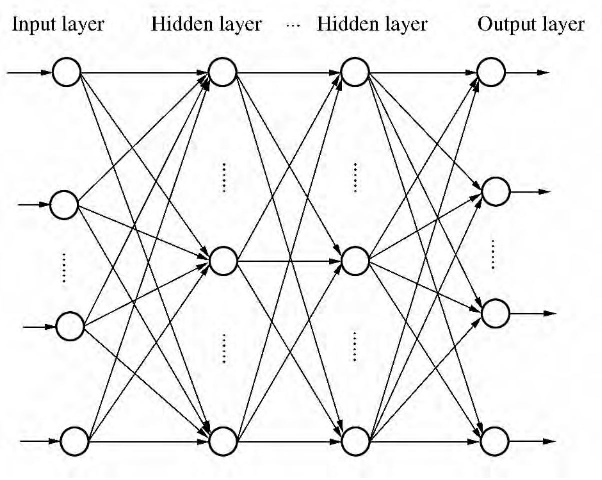


Figure 1 The structure of BP neural network

### 2.2 Adaptive genetic algorithm

A genetic algorithm (GA) is a random search method which develops from the evolution rule of biology. The basic operations of the GA are chromosome coding, initial population setting, fitness function designing and gene manipulation. Thereinto, the gene manipulation consists of selection, crossover and mutation. A GA with proportional reproduction, adaptive crossover and mutation probability is called an adaptive genetic algorithm (AGA). The crossover probability ($P_c$) and mutation probability ($P_m$) formulas are given as follows:

$$P_c = \begin{cases} \dfrac{k_1(f_{\max} - f')}{f_{\max} - f_{\mathrm{avg}}} & f' > f_{\mathrm{avg}} \\ k_3 & f' < f_{\mathrm{avg}} \end{cases} \tag{1}$$

$$P_m = \begin{cases} \dfrac{k_2(f_{\max} - f)}{f_{\max} - f_{avg}} & f > f_{avg} \\ k_4 & f < f_{avg} \end{cases} \tag{2}$$

Where $f_{\max}$ is maximum fitness, $f_{\mathrm{avg}}$ is the average fitness, $f'$ is the larger fitness of two exchanging chromosomes, and $f$ is the fitness of a mutation individual before mutating. $k_1$, $k_2$, $k_3$, $k_4$ are all constants; generally [12], $k_1 = k_3 = 1$, $k_2 = k_4 = 0.5$.

### 2.3 The algorithm flow of AGA-BP neural network

The weights and thresholds of a BP neural network, optimized with AGA, are close to their optimum values, which effectively prevent the training of the BP neural network from falling into a local minimum. At the same time, convergence speed and stability are also improved. Figure 2 shows the algorithm flow of the AGA-BP neural network.

## 3 Calculation model of dynamic coefficients for TPJBs

The training and validation samples of the neural network are obtained by calculating dynamic coefficients (stiffness coefficients and damping coefficients) of TPJBs under different structure parameters and operating conditions. In this study, based on the hydrodynamic lubrication theory, the dynamic coefficients of TPJBs are obtained by solving the dynamic Reynolds equation with the finite differential method. Figure 3 shows the basic structure of a TPJB.

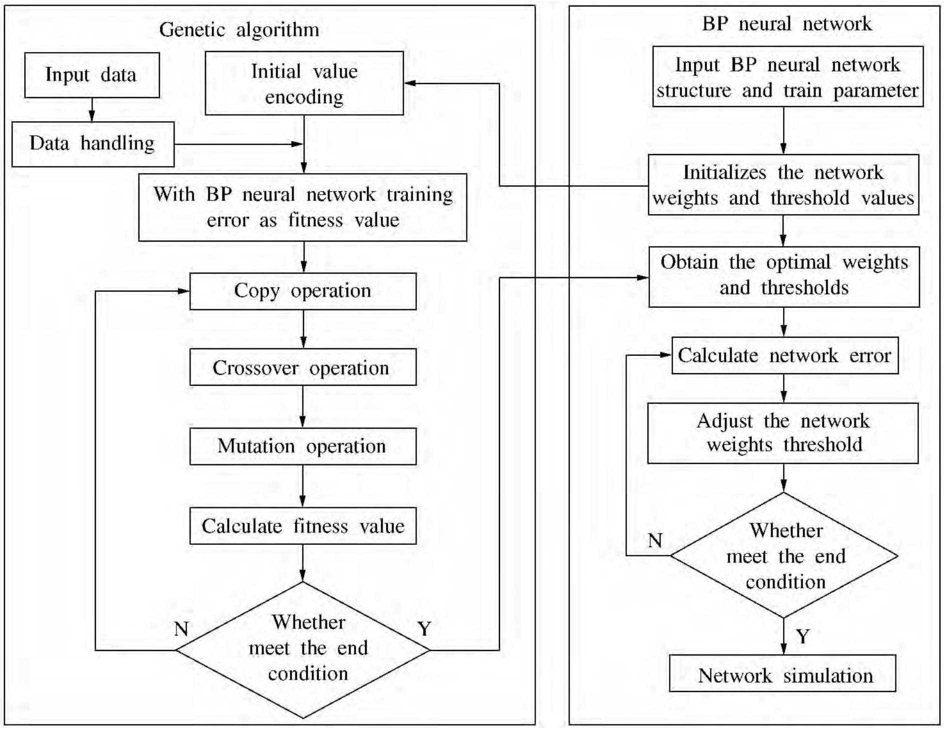


Figure 2 Algorithm flow chart of AGA-BP neural network

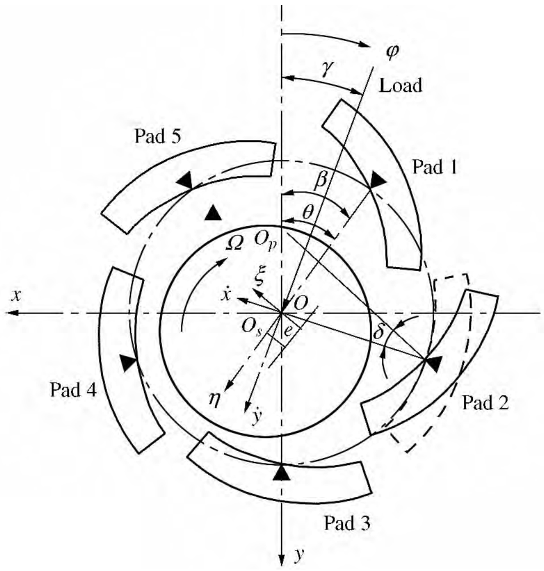


Figure 3 Structure of a TPJB

The development of the Reynolds equation requires the following assumptions.

1) The lubricant is an incompressible Newtonian fluid with constant viscosity.

2) The inertial forces of the lubricant are negligible.

3) The lubricant film pressure is constant in the radial direction.

Based on the assumptions mentioned above, the dimensionless Reynolds equation is derived.

$$\frac{\partial}{\partial\phi}\left(H^3\frac{\partial P}{\partial\phi}\right)+\left(\frac{D}{B}\right)^2\frac{\partial}{\partial\lambda}\left(H^3\frac{\partial P}{\partial\lambda}\right)=$$
$$-3\left[\varepsilon\sin(\phi-\theta)+\frac{\delta\cos(\phi-\beta)}{\psi}-m\sin(\phi-\beta)\right] \quad (3)$$

Where $D$ is the journal diameter; $B$ is the bearing width; $\psi$ is the clearance ratio; m is the preload ratio; $\varepsilon$ is the eccentricity; $\theta$ is the attitude angle; $\beta$ is the angle of pad position; $\delta$ is the tilt angle of pad.

To obtain the dynamic coefficients of a TPJB, the individual pad's ones should be obtained first. In this study, the individual pad's dynamic coefficients are calculated with perturbation method in the coordinate system associated with the pad (coordinate system $\xi o \eta$ in Figure 3). The formulas for the dynamic coefficients of individual pads are Equation (4) and Equation (5).

$$\begin{cases} K_{\xi_i\xi_i} = \dfrac{F^{\mathrm{I}}_{\xi_i} - F^{\mathrm{II}}_{\xi_i}}{2|\Delta\xi_i|} \\ K_{\eta_i\xi_i} = \dfrac{F^{\mathrm{I}}_{\eta_i} - F^{\mathrm{II}}_{\eta_i}}{2|\Delta\xi_i|} \\ K_{\eta_i\eta_i} = \dfrac{F^{\mathrm{I}}_{\eta_i} - F^{\mathrm{II}}_{\eta_i}}{2|\Delta\eta_i|} \\ K_{\xi_i\eta_i} = \dfrac{F^{\mathrm{I}}_{\xi_i} - F^{\mathrm{II}}_{\xi_i}}{2|\Delta\eta_i|} \end{cases} \tag{4}$$

$$\begin{cases} C_{\xi_i\xi_i} = \dfrac{F^{\mathrm{I}}_{\xi_i} - F^{\mathrm{II}}_{\xi_i}}{2|\Delta\dot{\xi}_i|} \\ K_{\eta_i\xi_i} = \dfrac{F^{\mathrm{I}}_{\eta_i} - F^{\mathrm{II}}_{\eta_i}}{2|\Delta\dot{\xi}_i|} \\ C_{\eta_i\eta_i} = \dfrac{F^{\mathrm{I}}_{\eta_i} - F^{\mathrm{II}}_{\eta_i}}{2|\Delta\dot{\eta}_i|} \\ K_{\xi_i\eta_i} = \dfrac{F^{\mathrm{I}}_{\xi_i} - F^{\mathrm{II}}_{\xi_i}}{2|\Delta\dot{\eta}_i|} \end{cases} \tag{5}$$

Where $\Delta\xi_i$ and $\Delta\eta_i$ are the small-amplitude wave of center displacement, $\Delta\dot{\xi}_i$ and $\Delta\dot{\eta}_i$ are the small-amplitude wave of center velocity, superscript Ⅰ and Ⅱ are the oil-film force before perturbation and after and subscript i is the number of the pad.

Then transform the dynamic coefficients of each pad from a local coordinate system into a global coordinate system, and compose them to obtain the dynamic coefficients of a TPJB.

## 4 The design of a AGA-BP neural network

Five parameters (journal diameter, width diameter ratio, clearance ratio, rotate speed and load) which have a remarkable effect on the dynamic coefficients of TPJBs, are chosen as the inputs of the network in this study. The range of every parameter is given in Table 1. The cross stiffness and damping coefficients of TPJBs are zero in theory for the development of the Reynolds equation based on the assumptions listed in Section 3. Hence, the outputs of the network are direct stiffness coefficients ($K_{xx}$, $K_{yy}$) and direct damping coefficients ($C_{xx}$, $C_{yy}$).

Table 1 The range of TPJB parameters

| Parameter | Value range |
|---|---|
| Journal diameter $D$/m | 0.01~0.1 |
| Width diameter ratio $B/D$ | 0.4~1 |
| Clearance ratio $\psi = c/D$ | 1‰~3‰ |
| Rotating speed $n$/(r · min$^{-1}$) | 5 000~30 000 |
| Load $F$/N | 100~800 0 |

To design the AGA-BP neural network for dynamic coefficients of TPJBs, the sample size, number of hidden layers, number of nodes in a hidden layer, parameters of AGA, parameters of training, etc. must be determined. Based on related theories [12-13], the optimal parameters of the AGA-BP neural network for the dynamic coefficients of TPJBs are obtained with a number of trial calculations, which are shown in Table 2 and Table 3.

Table 2 Parameters of the BP neural network

| Parameter | Training samples | Validation samples | 1st-hidden layer nodes | 2nd-hidden Layer nodes | Training algorithm | Maximum training epochs | Learning rate | Convergence error |
|---|---|---|---|---|---|---|---|---|
| Value | 8 137 | 2 509 | 18 | 15 | LM algorithm | 50 000 | 0.005 | $1\times10^{-7}$ |

Table 3 Parameters of the adaptive genetic algorithm

| Parameter | encoding mode | population size | genetic generation | Selection function | Crossover function | crossover probability | mutation function | mutation probability |
|---|---|---|---|---|---|---|---|---|
| Value | float encoding | 60 | 120 | Priority | Arithmetic | 0. 6 | Non-uniform | 0. 1 |

## 5 Training and validation of the AGA-BP neural network

### 5. 1 Training and validation

In this study, M language is used to compile the program and take advantage of the genetic algorithm toolbox and neural network toolbox of Matlab to build and train the AGA-BP neural network.

Figure 4 shows the optimization procedure of the AGA. As shown in Figure 4, the sum-squared error decreased with the increase of the generation, as well as the gap of neighboring populations. The results indicate that the weights and thresholds of the network get close to their optimum values gradually.

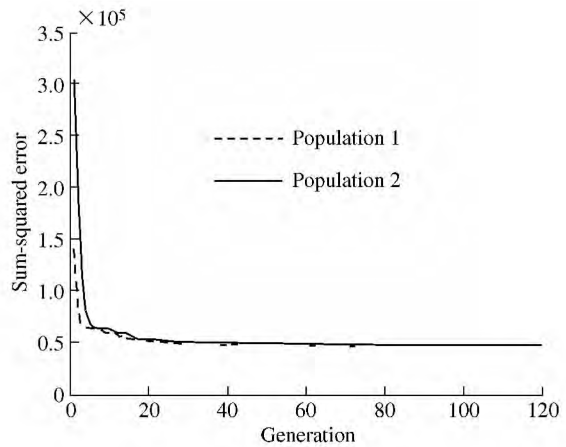


Figure 4 Variation curve of sum-squared error of neighboring populations

Figure 5 is the variation curve of the mean squared error of the network with the increase of training epoch. As shown in Figure 5, the mean squared error decreased with the increase of training epoch, which means that the gap between the theoretical values of the training samples and that calculated by the network is decreasing gradually. The training stopped at the 1579th epoch when the mean squared error reached the pre-set convergence error.

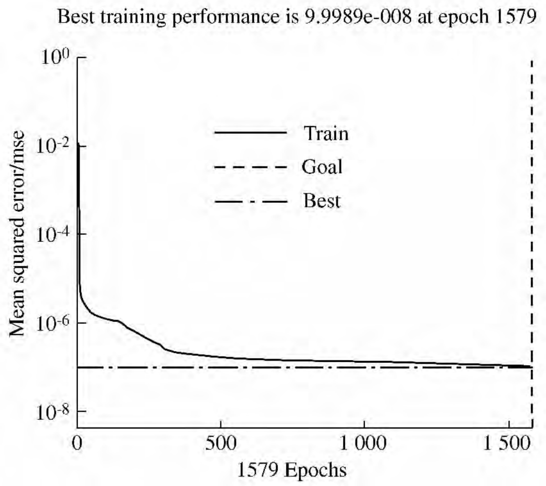


Figure 5 Variation curve of mean squared error for the network

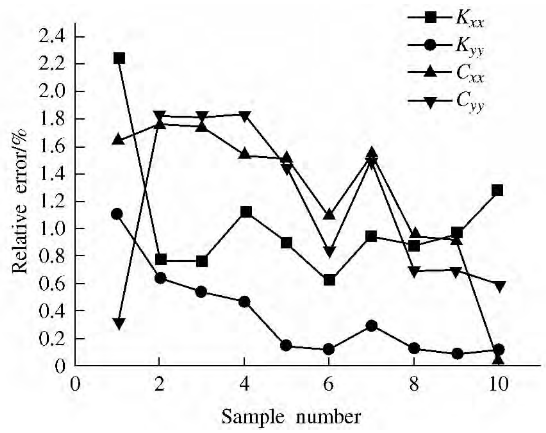


Figure 6 Error curve of neural network outputs

Figure 6 shows the relative error between the theoretical values of 10 typical validation samples and their values calculated by the network. The error distribution of all validation samples is shown in Table 4. The results show that the maximum value of the relative error is not more than 4%. That means the AGA-BP neural network of the dynamic coefficients for TPJBs shown in this study can meet the engineering demand.

Table 4 Error distribution of validation samples

| Error | $K_{xx}$ | $K_{yy}$ | $C_{xx}$ | $C_{yy}$ |
|---|---|---|---|---|
| <2% | 95.69% | 99.56% | 98.21% | 99.40% |
| 2%~3% | 3.63% | 0.42% | 1.79% | 0.60% |
| 3%~4% | 0.45% | 0 | 0 | 0 |

### 5.2 A case of prediction

A case of prediction using the proposed AGA-BP neural network is given as follows. In a rotor-TPJB system, the journal diameter is 0.05 m, width diameter ratio is 0.65, clearance ratio is 0.029, rotating speed is 28 500 r/min and load is 7 700 N. Table 5 shows the dynamic coefficients calculated with the finite differential method and the AGA-BP neural network. The results indicate that the AGA-BP neural network built in this study can predict the dynamic coefficients of TPJBs accurately.

Table 5 Results comparison between finite differential method and neural network

| Dynamic coefficients | Finite differential | Neural network | Relative error/% |
|---|---|---|---|
| $K_{xx}$ | $6.63\times10^8$ | $6.61\times10^8$ | 0.303 |
| $K_{yy}$ | $8.31\times10^8$ | $8.33\times10^8$ | 0.151 |
| $C_{xx}$ | 297 682.8 | 298 546.3 | 0.290 |
| $C_{yy}$ | 331 529.7 | 336 687.4 | 0.156 |

## 6 Conclusions

With adaptive genetic algorithm optimizing the initial weights and thresholds of a BP neural network, the training convergence speed is improved and the disadvantage of easily falling into a local minimum is overcome.

The proposed AGA-BP neural network is applied to the prediction of dynamic coefficients for a tilting-pad journal bearings. The computing time is decreased without loss of precision which meets the real time demand for dynamic analysis of rotor-bearing system.

## References

[1] Yu L, Liu H. Bearing-rotor system dynamics [M]. Xi′an: Xi′an Jiaotong University Press, 2000 (in Chinese)

[2] Li M. Non-linear dynamic behavior of rotor-bearing system trained by bevel gears [J]. Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, 2008, 222(4): 617-627

[3] Ying J Y, Jiao Y H, Chen Z B. Nonlinear dynamics analysis of tilting-pad bearing/rotor system [J]. Journal of Vibration and Shock, 2010, 29(s): 139-142 (in Chinese)

[4] Shi S H, Han Y Q, Zhang S H. Research status of the gear coupling rotor/bearing system [J]. Mechanical science and technology for aerospace engineering, 2002, 21(5):

703-706 (in Chinese)

[5] Zhang Z M, Zhang Y Y, Xie Y B. The hydrodynamic lubrication theory of sliding bearing [M]. Bejing: Higher Education Press, 1986 (in Chinese)

[6] Wang D W, Zhu J. The finite element method of calculating sliding bearing's dynamic coefficients [J]. Journal of Aerospace Power, 1995, 10(3): 272-274 (in Chinese)

[7] Dmochowski W. Dynamic properties of tilting-pad journal bearings: experimental and theoretical investigation of frequency effects due to pivot flexibility [J]. Journal of Engineering for Gas Turbines and Power ASME, 2007, 129: 865-869

[8] Wang L P, Qiao G, Zheng T S. A analysis model of the tilting-pad journal bearing' full dynamic coefficients [J]. Chinese Journal of Computational Mechanics, 2008, 25(6): 921-926 (in Chinese)

[9] Qin P, Meng Z Q, Zhu J. Neural network model of sling bearing's nonlinear oil-film force [J]. Tribology, 2002, 22(3): 226-231 (in Chinese)

[10] Lu L M. Identification of sliding bearing's axis location based on BP neural network [J]. Machine Tool and Hydraulics, 2008, 36(8): 218-220 (in Chinese)

[11] Tang J, Huang X D, Fang C G. BP neural network in prediction of the constant-current hydrostatic bearing static stiffness [J]. Advanced Materials Research, 2011, 199: 271-274

[12] Dong C H. Matlab neural networks and Applications [M]. Beijing: Defense Industry Press, 2005 (in Chinese)

[13] Zhu D Q, Shi H. Artificial neural network theory and application [M]. Science Press, 2006 (in Chinese)

## Brief Biographies

**GAO Dang-cheng** is now a master degree candidate in School of Mechanical Engineering of Northwestern Polytechnical University. His research interests include lubrication design and analysis of turbine engine. 529714481@qq.com

**YIN Ming-hu** is now a Ph.D candidate in School of Mechanical Engineering of Northwestern Polytechnical University. His research interests include lubrication design and analysis of turbine engine

**CHEN Guo-ding** is now a professor of Northwestern Polytechnical University. His research interests include tribology and mechanical design. gdchen@nwpu.edu.cn