Springer

KSME

Journal of Mechanical Science and Technology 26 (5) (2012) 1419~1430
www.springerlink.com/content/1738-494x
DOI 10.1007/s12206-012-0308-8

Prediction of vibration characteristics of a planar mechanism having imperfect joints using neural network †

Selçuk Erkaya*

Erciyes University, Engineering Faculty, Department of Mechatronics Engineering, 38039 Kayseri, Turkey

(Manuscript Received April 25, 2011; Revised January 9, 2012; Accepted January 30, 2012)

Abstract

Clearance is inevitable in the joints of mechanisms due primarily to the design, manufacturing and assembly processes or a wear effect. Excessive value of joint clearance plays a crucial role and has a significant effect on the kinematic and dynamic performances of the mechanism. In this study, effects of joint clearances on bearing vibrations of mechanism are investigated. An experimental test rig is set up, and a planar slider-crank mechanism having two imperfect joints with radial clearance is used as a model mechanism. Three accelerometers are positioned at different points to measure the bearing vibrations during the mechanism motion. For the different running speeds and clearance sizes, this work provides a neural model to predict and estimate the bearing vibrations of the mechanical systems having imperfect joints. The results show that radial basis function (RBF) neural network has a superior performance for predicting and estimating the vibration characteristics of the mechanical system.

Keywords: Bearing vibration; Gaussian function; Joint clearance; Planar mechanism; RBF neural network

1. Introduction

Clearance as an actual joint characteristic plays a crucial role on the dynamic stability and the mechanism performance. In general, each joint is considered as perfect or ideal, that is, no wear or deformations, no friction and no clearance. However, the clearances always exist in the actual joints. In case of joint clearance, ideal lower pair joints have the potential of becoming higher pairs. This is due to the fact that the ideal surface between two contacting bodies really exhibits line or point contact characteristic. This kind of joint is known as a source of impact forces. These forces not only create an increase in vibration and noise levels, but also reduce system reliability, stability, precision and mechanism component's life. A lot of studies have been implemented about imperfect joints on mechanical system in the last decade.

Bauchau and Rodrigez [1] investigated the effects of clearance and lubrication for revolute and spherical joints. Formulation was developed within the framework of energy preserving and decaying time integration schemes that provide unconditional stability for nonlinear, flexible multibody systems. Jia et al. [2] presented both theoretical and experimental studies about dynamic behavior of a slider-crank mechanism with clearance. Effects of different clearance size and driving speed on dynamic behavior of the mechanism were investigated. Schwab et al. [3] presented dynamic response of mechanisms and machines having revolute joint with clearance. Assuming that a mechanism consists of rigid and elastic links, a comparison between several continuous contact force models and an impact model was implemented. A procedure was also introduced to estimate the maximum contact force during impact. Flores et al. [4] analyzed the dynamics of multibody systems with revolute joint clearances, including dry contact and lubricant effects. Flores and Ambrosio [5] presented a general methodology for dynamic characterization of mechanical systems with joint clearance. Contact detection strategy and contact force models were used in the proposed procedure and it was demonstrated through the dynamic analysis of a slider-crank mechanism having a revolute joint with clearance. Orden [6] presented a methodology for the study of typical smooth joint clearance in multibody systems. Advantage of the proposed method was proved, and some numerical applications were presented to show the stability of the proposed method especially in long-term simulations with relatively large time step size. Shiau et al. [7] studied nonlinear dynamic analysis of a 3-PRS series parallel mechanism considering the joint effects which included flexibility, clearance and friction. The obtained results show that the joint clearance significantly affects the mode shapes by which the rotational motions are dominated. The dynamic response also becomes

*Corresponding author. Tel.: +90 3524374901, Fax.: +90 3524375784
E-mail address: serkaya@erciyes.edu.tr
† Recommended by Associate Editor Hyungpil Moon.

larger as the joint clearances increase, and the contact force increases as the joint clearance and the friction coefficient increase. The effects of joint clearances on mechanism path generation and transmission quality were investigated by Erkaya and Uzmay [8-10]. Four-bar and slider-crank mechanisms having revolute joints with clearance were considered as model mechanisms, and an optimization procedure was proposed to decrease the deviations of path generation and transmission angle. Khemili and Romdhane [11] studied dynamic behavior of a planar flexible slider–crank mechanism with clearance. Simulation and experimental tests were carried out for that goal. In the presence of clearance, it is clear that the mechanism responses are greatly influenced, and the coupler flexibility has a suspension role on the mechanism. Erkaya and Uzmay [12] also investigated dynamic response of a four-bar mechanism having revolute joints with clearance. A neural network–genetic algorithm approach was proposed to model several characteristics of joint clearance and determine the appropriate values of design variables for reducing the additional vibration effects arising from joint clearance. Li et al. [13] devised a method for identifying joint parameters of modular manipulators with nine degrees of freedom (DOF) using fuzzy logic. Also, this research group [14] developed a genetic algorithm based back-propagation neural network suboptimal controller for controlling the vibration of a 9-DOF modular robot. After modeling the whole structure, simulations of the vibration control for the modular robot in several configurations were carried out. Han et al. [15] considered the nonlinear characteristics of a ball bearing to investigate the vibration response of a rotating shaft due to an unbalance force. A finite element method was used to analyze the vibration characteristics of a rotor-bearing system and a direct numerical integration was also performed to calculate the transient response of the rotor system. Bing and Ye [16] presented dynamic analysis of the reheat-stop-valve mechanism with revolute clearance joint. The effect of joint clearance variation induced by the manufacturing tolerance of components was analyzed combined with the thermal influence of the high temperature steam in working condition.

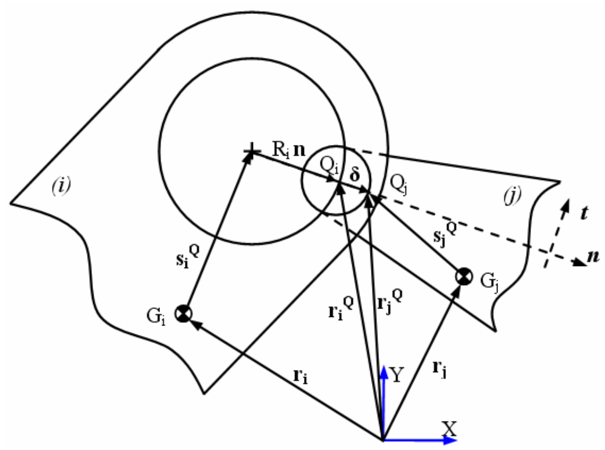
Yildirim et al. [17] analyzed the force distribution on the bearing systems of a four-bar mechanism using neural network having three layers. The hidden layer of proposed network structure was designed as a recurrent structure to keep dynamic memory for later use. The results of the proposed neural network give superior performance for analyzing the forces on the bearings. Flores [18] developed a methodology for studying and quantifying the wear phenomenon in revolute clearance joints. The numerical results show that the wear phenomenon is not uniformly distributed around the joint surface, owing to the fact that the contact between the joint elements is wider and more frequent is some specific regions. Another study of Flores et al. [19] presented a general methodology for modeling the lubricated revolute joints in constrained rigid multibody systems. The hydrodynamic forces were obtained by integrating the pressure distribution evaluated with the aid of Reynolds' equation, written for the dynamic regime. Numerical examples were presented in order to demonstrate the use of the methodologies and procedures described in this work. Erkaya and Uzmay [20] investigated how the joint clearance affects the mechanism vibration and noise characteristics? Empirical results show that the joint clearance leads to a degradation in vibration characteristics of the mechanism relative to that of mechanism without clearance. For the case of different clearance sizes and operation speeds, Flores et al. [21] implemented both numerical and experimental studies to investigate the dynamic responses of a slider-crank mechanism having revolute joint with clearance. This study emphasizes that the clearance size has an important role upon the differences between numerical and experimental results.

In this study, an experimental test rig is set up to investigate the effects of joint clearance on mechanism vibration. For the case of different clearance sizes and running speeds of mechanism, experimental measurements are performed. Two types of neural predictor are used to model the bearing vibration of the planar slider-crank mechanism having two joints with clearance. When the mechanism reaches to steady-state condition for the running speed, vibration measurements are implemented to obtain the data sets for training and testing stages of neural predictor.

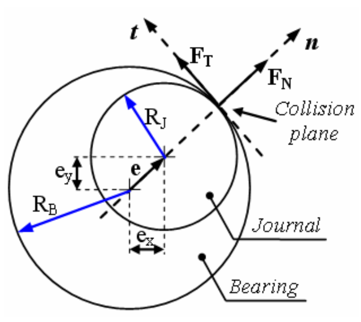
2. Theory of contact definition and force model for joint with clearance

In the classical analysis of a revolute joint, journal and bearing centers coincide, that is, the revolute joint is considered as ideal or perfect. However, the existence of clearances at the joints of mechanical systems is inevitable. An appropriate clearance for the joints between the neighbor links of mechanical systems is necessary to allow the relative motion of the connected links, as well as to permit the assembly of the mechanical systems [4]. In this study, adjacent mechanism links are connected to each other by revolute joints. Fig. 1 outlines a revolute joint with clearance, in which the radial clearance is defined as the difference between the bearing and journal radii, R_B and R_J, respectively. In the presence of clearance at a revolute joint, two kinematic constraints lost, and two degrees of freedom consisting of the horizontal (x) and vertical (y) displacements of the journal center with respect to bearing center are added to the mechanism motion. These movements may lead to uncertainties in the motion of mechanism. So, additional constraints are necessary to analyze the kinematics of system.

Three different types of motion between journal and bearing can be observed during the dynamics of the revolute joint clearance, (i) free flight mode, that is, journal and the bearing are not in contact and journal moves freely within the bearing's boundaries, (ii) impact mode, which occurs at the end of the free flight mode, (iii) continuous contact mode, in which contact is always maintained although the relative penetration



(a)



(b)

Fig. 1. (a) Representation of a revolute joint with clearance in a mechanical system; (b) Normal and tangential forces between the journal and bearing as a result of an impact.

depth between the bearing and journal. If there is no lubricant, the journal can move freely within the bearing until contact between the two bodies takes place. When the journal impacts the bearing wall, normal and tangential contact forces [22] are developed as given in Fig. 1(b).

Fig. 1(a) illustrates a revolute joint with clearance in a mechanical system. The bearing and journal are parts of i^{th} and j^{th} bodies, respectively. Relative penetration depth between the journal and the bearing is given as

$$\boldsymbol{\delta} = \mathbf{e} - c > 0 \tag{1}$$

in which **e** is the magnitude of the clearance vector between the bearing and journal centers, and c is the radial clearance. The magnitude of the clearance vector is expressed as

$$|\mathbf{e}| = \sqrt{e_x^2 + e_y^2} \tag{2}$$

where e_x and e_y represent the relative displacements of the journal inside the bearing for X and Y directions, respectively. These relative displacements can be obtained from the global position vectors of the bearing and journal centers. As given in Fig 1(a), Q_i and Q_j denote the contact points on the bearing and journal, respectively. The global position of these points is expressed by [22]

$$\mathbf{r}_k^Q = \mathbf{r}_k + \mathbf{s}_k^Q + R_k \mathbf{n} \qquad (k=i,j) \tag{3}$$

where r_i and r_j are the global position of the mass centers for i^{th} and j^{th} bodies, respectively. s_i^Q and s_j^Q denote the positions of the journal and bearing centers relative to the mass centers of i^{th} and j^{th} bodies, respectively. R_i and R_j are the bearing and journal radius, respectively. **n** is the unit vector normal to the collision plane and can be defined by

$$\mathbf{n} = \frac{\mathbf{e}}{|\mathbf{e}|}. \tag{4}$$

The velocity of the contact points Q_i and Q_j can be derived by using Eq. (3)

$$\dot{\mathbf{r}}_k^Q = \dot{\mathbf{r}}_k + \dot{\mathbf{s}}_k^Q + R_k \dot{\mathbf{n}} \qquad (k=i,j). \tag{5}$$

Also, the relative contact velocity can be defined as

$$\dot{\boldsymbol{\delta}} = \left(\dot{\mathbf{r}}_j - \dot{\mathbf{r}}_i\right) + \left(\dot{\mathbf{s}}_j^Q - \dot{\mathbf{s}}_i^Q\right) + \left(R_j - R_i\right)\dot{\mathbf{n}}. \tag{6}$$

The dynamics of a dry journal-bearing is explained by two different situations. Firstly, when the journal and bearing are not in contact with each other, there is no contact forces associated to the journal-bearing. Secondly, when the contact between the two bodies occurs the contact–impact forces are modeled according to a non-linear Hertz's force law (normal force) together with the Coulomb's friction law (tangential force). These conditions can be expressed as

$$\begin{array}{lll} \mathbf{F}=0 & \text{if} & \boldsymbol{\delta}<0 \\ \mathbf{F}=\mathbf{F}_N+\mathbf{F}_T & \text{if} & \boldsymbol{\delta}\geq 0 \end{array} \tag{7}$$

where $\mathbf{F}_N$ and $\mathbf{F}_T$ are normal and tangential force components, respectively. When the journal reaches the bearing wall, that is, the magnitude of the clearance vector is greater than radial clearance, an impact takes place and the penetration depth is given by Eq. (1). The contact force is modeled as a spring-damper element. If this element is linear, the approach is known as the Kelvin-Voigt model. When the relation is nonlinear, the model is generally based on the Hertz contact law [4, 23, 24]. In the case of unlubricated joint, Hertzian contact force model is an appropriate choice [3]. While the original Hertzian model does not include any energy dissipation, an extension by Lankarani and Nikravesh includes energy loss due to internal damping [25, 26].

$$\mathbf{F}_N = K\boldsymbol{\delta}^z + D\dot{\boldsymbol{\delta}} \tag{8}$$

where the first term represents the elastic forces and the second term explains the energy dissipation. K is the generalized stiffness parameter, $\boldsymbol{\delta}$ is the relative penetration depth, D is the hysteresis damping coefficient and $\dot{\boldsymbol{\delta}}$ is the relative impact velocity. The generalized stiffness parameter K depends on the geometry and physical properties of the contacting surfaces. The exponent z is equal to 1, 5 for metallic contact. The stiffness parameter K is given by

$$K = \frac{4}{3\left(h_i + h_j\right)}\left(\frac{R_i R_j}{R_i + R_j}\right)^{1/2} \tag{9}$$

where the material parameters h_k are expressed as

$$h_k = \frac{1-\nu_k^2}{E_k} \quad (k=i,j). \tag{10}$$

ν_k and E_k are the Poisson's coefficient and the Young's modulus associated with each body, respectively. The radius of curvature R_k is taken as positive for convex surfaces and negative for concave surfaces [3, 22]. The hysteresis damping coefficient is given as

$$D = \frac{3\left(1-\varepsilon^2\right)K\delta^z}{4v_0} \tag{11}$$

where ε is the restitution coefficient and v_0 is the initial impact velocity. Friction forces act when contacting bodies tend to slide relative to each other. These forces are tangential to the surfaces of contact and are opposite to the sliding velocity. Friction force model is expressed as

$$\mathbf{F}_T = -c_f c_d F_N \frac{\mathbf{V}_T}{\left|\mathbf{V}_T\right|} \tag{12}$$

where c_f is the friction coefficient and $\mathbf{V}_T$ is the relative tangential velocity. c_d is the dynamic correction coefficient and given by

$$c_d = \begin{cases} 0 & if \quad \left|\mathbf{V}_T\right| \le V_0 \\ \dfrac{\left|\mathbf{V}_T\right| - V_0}{V_1 - V_0} & if \quad V_0 \le \left|\mathbf{V}_T\right| \le V_1 \\ 1 & if \quad \left|\mathbf{V}_T\right| \ge V_1 \end{cases} \tag{13}$$

where V_0 and V_1 are given tolerances for the tangential velocity. The motion equation for a dynamic system with constraints is given in the following form:

$$\begin{bmatrix} \mathbf{M} & \boldsymbol{\Phi}_\mathbf{q}^\mathbf{T} \\ \boldsymbol{\Phi}_\mathbf{q} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \ddot{\mathbf{q}} \\ \boldsymbol{\lambda} \end{bmatrix} = \begin{bmatrix} \mathbf{f} \\ \gamma^{\#} - 2\alpha\dot{\boldsymbol{\Phi}} - \beta^2\boldsymbol{\Phi} \end{bmatrix} \tag{14}$$

where $\mathbf{M}$ is the mass matrix, $\boldsymbol{\Phi}_\mathbf{q}$ is the Jacobian matrix for the constraint equations. $\boldsymbol{\Phi}_\mathbf{q}^\mathbf{T}$ is the transpose of the Jacobian matrix. $\ddot{\mathbf{q}}$ includes the generalized state accelerations. $\boldsymbol{\lambda}$ denotes the Lagrange multipliers, $\gamma^{\#}$ denotes the vector of quadratic velocity terms, $\boldsymbol{\Phi}$ is the vector for kinematic constraints, $\dot{\boldsymbol{\Phi}}$ is the constraint velocity equation. α and β denote the Baumgarte coefficients. $\mathbf{f}$ is the generalized force vector. This contains all external forces such as forces developed at the imperfect joints. Theoretical investigation of bearing vibrations can be performed by using the forces at the crank-frame and piston-frame joints. Analytical model is used in the former studies and this model is also validated with the experimental investigations [11, 21, 27]. These studies indicate that there are always some differences between theoretical and experimental results due primarily to the imperfect joint characteristics such as changing of motion modes in a small time interval etc.

3. Experimental study

Slider-crank mechanism is widely used in the internal combustion engines, and converts the translational motion of piston to rotary motion of crank. In conformity with recent advances, vehicle engines work at higher speeds, and so dynamic effects such as links' inertias have a crucial role on the kinematic and dynamic characteristics of the slider-crank mechanism. Consequently, excessive loads acting at link's joints cause to wear and thereby joint clearances reach beyond desired values.

An experimental test rig is set up for analyzing the bearing vibrations of mechanism having joint clearance. Experimental system is driven by a 1.5 kW AC electric motor, and Mitsubishi S500 frequency inverter is used to control the angular velocity. An encoder is adapted to the shaft of AC motor for defining the angular position of crank arm. Also, a flywheel is used to prevent the fluctuation of the angular velocity due to the impact forces between journal and bearing at the joints with clearance. Experimental test rig is outlined in Fig. 2.

The experimental mechanism is conformity with practical purposes, that is, the kinematics of the slider-crank mechanism has a planar feature. By using the planar mechanism model, the vibration characteristics of the system are investigated. Displacements in x and y-directions of the journal center with respect to bearing center are considered in the experimental investigation. This model is widely used in former studies [3, 16, 18, 19]. As a natural result, the change in z-direction in the clearance joints is not considered. Kinematic and dynamic parameters of the model mechanism are given in Table 1.

Three accelerometers and an intelligent data acquisition (Brüel & Kjaer 3560B type IDA, 4513B type accelerometers) are used to measure the vibration on the main frame. For the vibration measurement, the first accelerometer is positioned at the y-direction of the crank-frame joint. The second one is positioned at the x-direction of the same joint. And, the third accelerometer is positioned at the y-direction of the piston-frame joint. Three different clearance configurations are used for the experimental investigation. Firstly, joints with 1 mm clearance are used at crank-connecting rod and connecting rod-piston connections. Secondly, joints with 2 mm clearance are used at the related connections. For the last measurement, 1 and 2 mm clearance joints are used at the crank-connecting rod and connecting rod-piston connections, respectively. Also, each clearance configuration is implemented for two different running speeds.

4. Neural networks

In last two decades, the application areas of neural networks have been rapidly expanded due to the advances in computer science. In system identification applications of neural networks, the main idea is usually to obtain a valid model of the system which can be used for system analysis. Most of studies about the applications of neural models in mechanical systems are particularly performed for fault diagnosis and control. In this study, two types of the neural network are implemented to model the system vibration. Descriptions of these types are outlined in the following subsections.

Table 1. Parameters of the slider-crank mechanism having joints with clearance.

Parameters	Description	Value
L_2 (mm)	Length of crank	150
L_3 (mm)	Length of connecting rod	564
m_2 (kg)	Mass of crank	0.4506
m_3 (kg)	Mass of connecting rod	1.6403
m_4 (kg)	Mass of piston	2.0205
I_{G2} (kgm^2)	Inertial moment of crank	1.8 10^{-3}
I_{G3} (kgm^2)	Inertial moment of connecting rod	9.45 10^{-2}

4.1 Radial basis function (RBF) neural network

Radial basis function (RBF) neural network is feedforward and has only one hidden layer. RBF neural network structure is good at modeling nonlinear data and can be trained in one stage rather than using an iterative process as in multi-layer perception neural network and also learn the given application quickly. RBF neural networks were introduced into the neural network literature in 1988 [28]. Due to their better approximation capabilities, simpler network structures and faster learning algorithms, RBF networks have been widely applied in many science and engineering fields. The architecture of RBF network consists of three layers that have entirely different roles. The input layer, a set of source nodes, connects the network to the environment. The second layer consists of a set basis function units that carry out a nonlinear transformation from the input space to the hidden space. The output layer supplies the response of the network, and the transfer functions of the neurons are linear units. The structure of neural model is outlined in Fig. 3.

The network model consists of one input layer with five linear neurons, one output layer with three linear neurons and also one hidden layer with ten nonlinear neurons. Input matrix of the network consists of four characteristics, that is, a series of time, running speed of the mechanism input link, material type of the mechanism and clearance sizes. The current mechanism has two joints with clearance. Therefore, two clearance sizes (c_1 and c_2) are considered in the input matrix. A lot of experimental studies are performed for the different clearance sizes, running speeds and material types of the mechanism. The main purpose of these experimental studies is to specify the effect of each characteristic on bearing vibrations. The experimental results show that these characteristics have clear effects on the kinematics and dynamics of mechanism. This information also agrees with the literature [7, 11, 21, 27]. Therefore, these characteristics of the model mechanism are evaluated as input matrix to predict the system vibra-

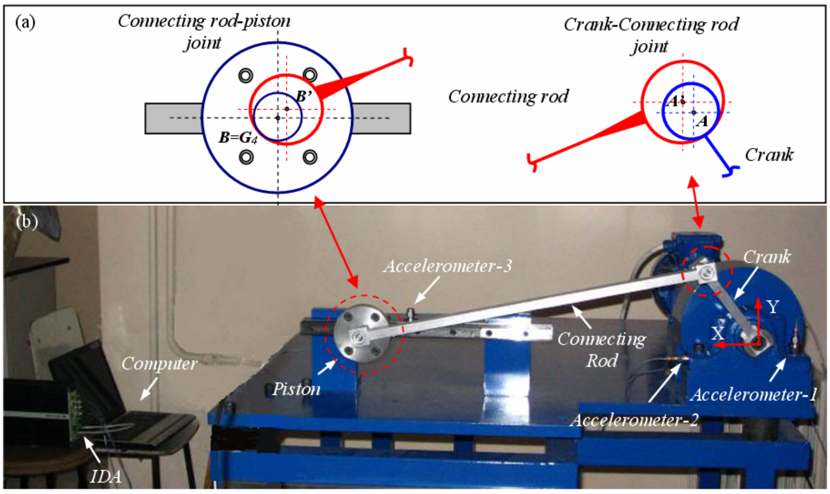


Fig. 2. (a) Exaggerate model for revolute joint with clearance; (b) Experimental test rig.

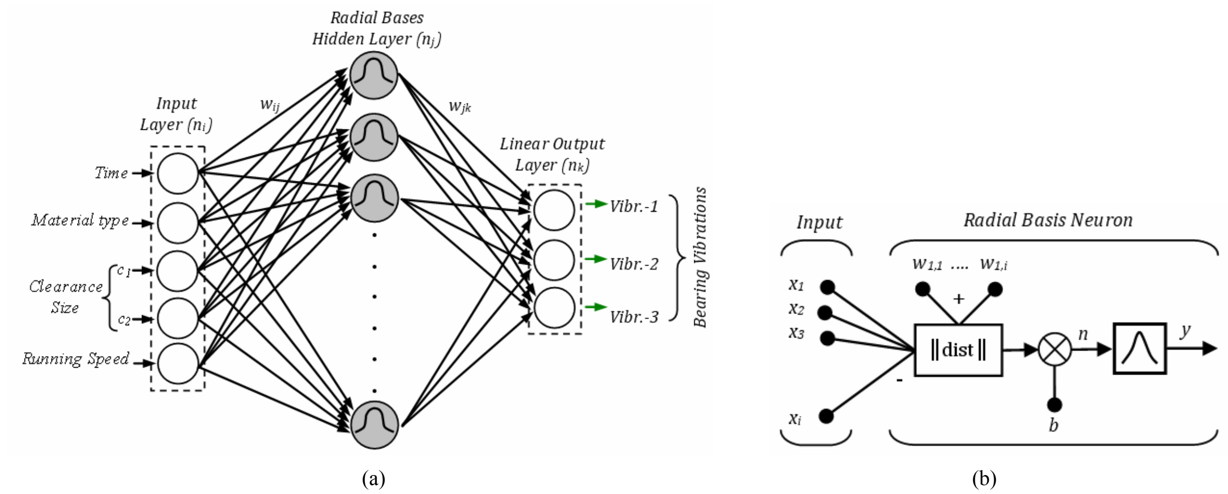


Fig. 3. (a) Structure of RBF neural network; (b) A neuron model for i inputs.

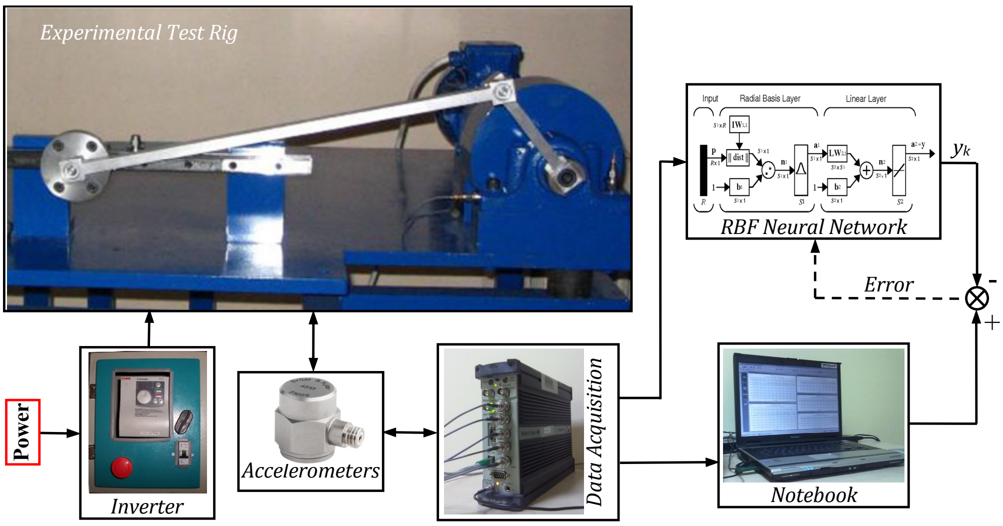


Fig. 4. Flow chart of experimental and RBF neural simulations.

tion. Fig. 4 shows the block diagram of the experimental and neural network simulation for the mechanical system with joint clearances.

The transfer function of hidden layer in RBF network is generally a non-linear Gaussian function and this equation is defined as

$$a_j = a(v_j) = \exp\left(-\frac{v_j^2}{2\sigma_j^2}\right) \tag{15}$$

where σ_j is a width of the j^{th} neuron, v_j is presented by Euclidean norm of the distance between the input vector and the neuron center calculated as follows:

$$v_j(x) = \|x - c_j\| = \sqrt{\sum_{i=1}^{r}(x - c_{j,i})^2} \tag{16}$$

where c_j is a center of the j^{th} RBF unit. The width of a RBF unit is selected as the root mean square distance to the nearest j^{th} RBF unit. For the j^{th} unit, the width σ_j is defined as

$$\sigma_j = \left(\frac{1}{\varepsilon}\sum_{h=1}^{\varepsilon}\|c_j - c_h\|^2\right)^{1/2} \tag{17}$$

where c_j is a center of the j^{th} RBF unit, c_1, c_2, . . . , c_ε are the nearest unit centers to the unit j.

Output value is defined as

$$y_k = \sum_{j=1}^{s} w_{jk} a_j \tag{18}$$

where y_k is the k^{th} subsection of the y in the output layer, w_{jk} is the weight from the j^{th} hidden layer neuron to the k^{th} output layer neuron, and a_j is the output of the j^{th} node in the hidden layer. The number of hidden RBF units is an important factor to determine the predictive properties of the network. The number of hidden units is calculated automatically until the expected error value is found [29].

4.2 Generalized regression neural network (GRNN)

GRNN does not require an iterative training procedure as in back propagation method. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. Furthermore, it is consistent; that is, as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function. The GRNN is used for estimation of continuous variables, as in standard regression techniques [30]. GRNN consists of four layers: input layer, pattern layer, summation layer and output layer. The input units are in the first layer. The second layer has the pattern units and the outputs of this layer are passed on to the summation units in the third layer. The final layer covers the output units.

GRNN is related to the radial basis function network and is based on a standard statistical technique called kernel regression. By definition, the regression of a dependent variable y on an independent x estimates the most probable value for y, given x and a training set. The regression method will produce the estimated value of y that minimizes the mean-squared error. GRNN is a method for estimating the probability density function of x and y, given only a training set. Because the probability density function is derived from the data with no preconceptions about its form, the system is perfectly general. If $f(x,y)$ represents the known continuous probability density function of a vector random variable, x, and a scalar random variable, y, the conditional mean of y given X (also called the regression of y on X) is given by

$$E\left[y|X\right]=\frac{\int_{-\infty}^{\infty} yf\left(X,y\right)dy}{\int_{-\infty}^{\infty} f\left(X,y\right)dy}. \tag{19}$$

When the density $f(x,y)$ is not known, it must usually be estimated from a sample of observations of x and y. The probability estimator $\hat{f}\left(X,Y\right)$ is based upon sample values X^i and Y^i of the random variables x and y:

$$\begin{aligned}\hat{f}\left(X,Y\right)&=\frac{1}{\left(2p\right)^{(p+1)/2}s^{(p+1)}}\frac{1}{k}\cdots\\ &\cdots\sum_{i=1}^{k}\exp\left[-\frac{\left(X-X^i\right)^T\left(X-X^i\right)}{2s^2}\right]\exp\left[-\frac{\left(Y-Y^i\right)^2}{2s^2}\right]\end{aligned} \tag{20}$$

where k is the number of sample observations and p is the dimension of the vector variable x. A physical interpretation of the probability estimate $\hat{f}\left(X,Y\right)$ is that it assigns sample probability of width σ for each sample X^i and Y^i, and the probability estimate is the sum of those sample probabilities [31]. Defining the scalar function D_i^2

$$D_i^2=\left(X-X^i\right)^T\left(X-X^i\right) \tag{21}$$

and performing the indicated integrations yields the following:

$$\hat{Y}\left(X\right)=\frac{\sum_{i=1}^{n}Y^i exp\left(-\frac{D_i^2}{2s^2}\right)}{\sum_{i=1}^{n}exp\left(-\frac{D_i^2}{2s^2}\right)}. \tag{22}$$

The resulting Eq. (22) is directly applicable to problems involving numerical data.

5. Results

In this study, bearing vibrations of a planar slider-crank mechanism having two imperfect joints with radial clearance are investigated for the case of different running speeds and clearance sizes. An experimental test rig is set up for measuring the bearing vibrations. Furthermore, two types of neural networks are used for predicting and estimating the bearing vibrations of the system. Four characteristics such as time, material type, clearance size for each imperfect joint and running speed are used to constitute the input vector of network for modeling and predicting the vibrations. Training and testing stages of the network structure are employed on neural network toolbox of MATLAB. 500 and 259 data are used in training and testing stages, respectively. After the training of network is completed, the weights are saved and used for predicting and estimating the amplitudes of the bearing vibrations. In order to specify the network stability for predicting the vibration characteristics of the system by using an input matrix, a lot of works on experimental system are carried out for the different clearance sizes, running speeds and material types of the mechanism. For the case of 150 and 200 rpm running speeds, experimental and neural simulation results for joints with 1 mm clearance are given in Figs. 5 and 6, respectively.

Vibration characteristic is mainly periodic as seen from the measuring points. This is a reflection of continuous contact mode between journal and bearing at a joint during the steady-state response of the mechanism. On the other hand, some peaks at the vibration amplitude yield different types of motion, that is, impact and free-flight modes. As seen from Fig. 5, there is a certain deviation from the experimental results. Therefore, this type of network is not suitable for modeling the bearing vibration. On the contrary to GRNN structure, RBF neural simulation gives a good convergence to the experimental results (Fig. 6). This can also be considered as an accurate prediction of bearing vibrations.

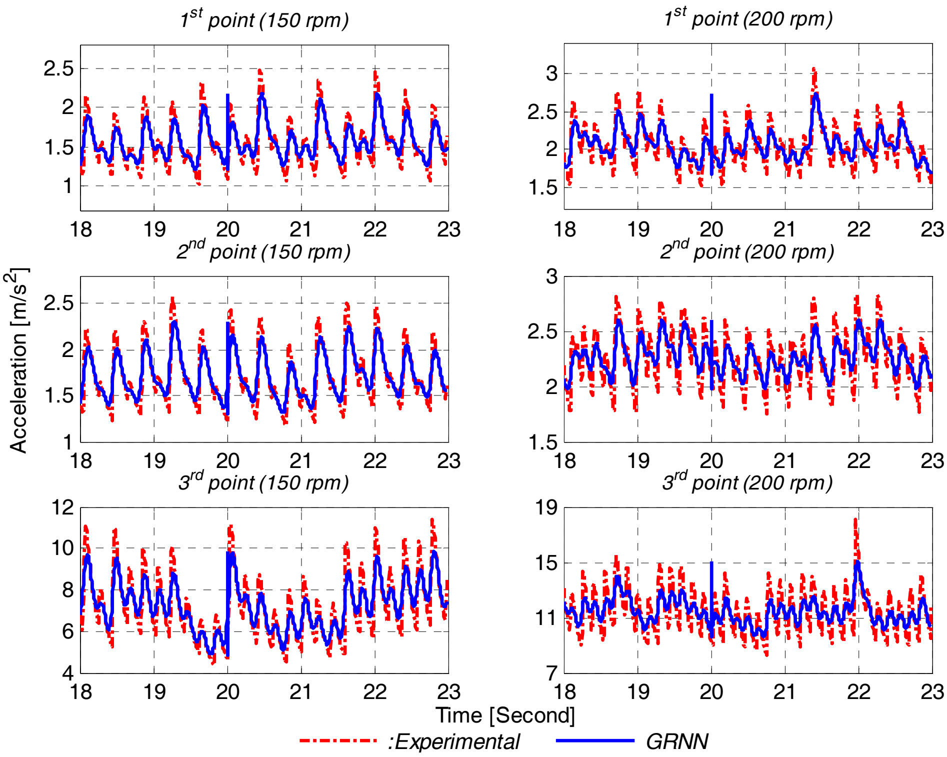


Fig. 5. Experimental and GRNN simulations for 1 mm joint clearance (c_1=c_2=1 mm).

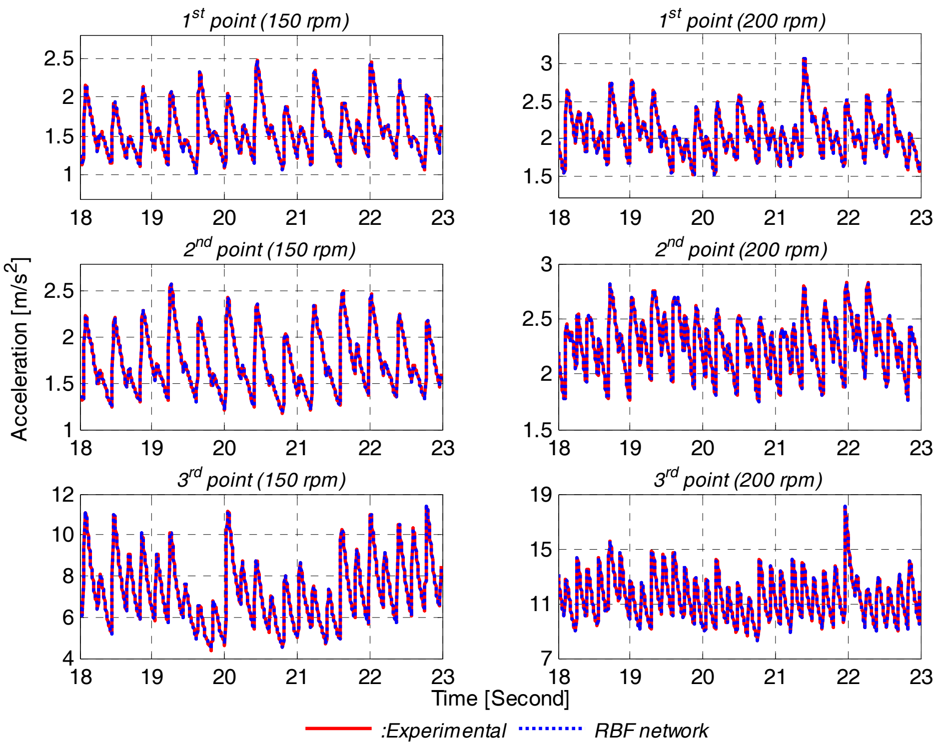


Fig. 6. Experimental and RBF neural network simulations for 1 mm joint clearance (c_1=c_2=1 mm).

Figs. 7 and 8 give the experimental and neural simulation results for joints with 1 and 2 mm clearances, that is, joint with 1 mm clearance at crank-connecting rod connection and joint with 2 mm clearance at connecting rod-piston connection.

Naturally, amplitudes of the bearing vibrations increase according to increasing running speed of the system [11, 21].

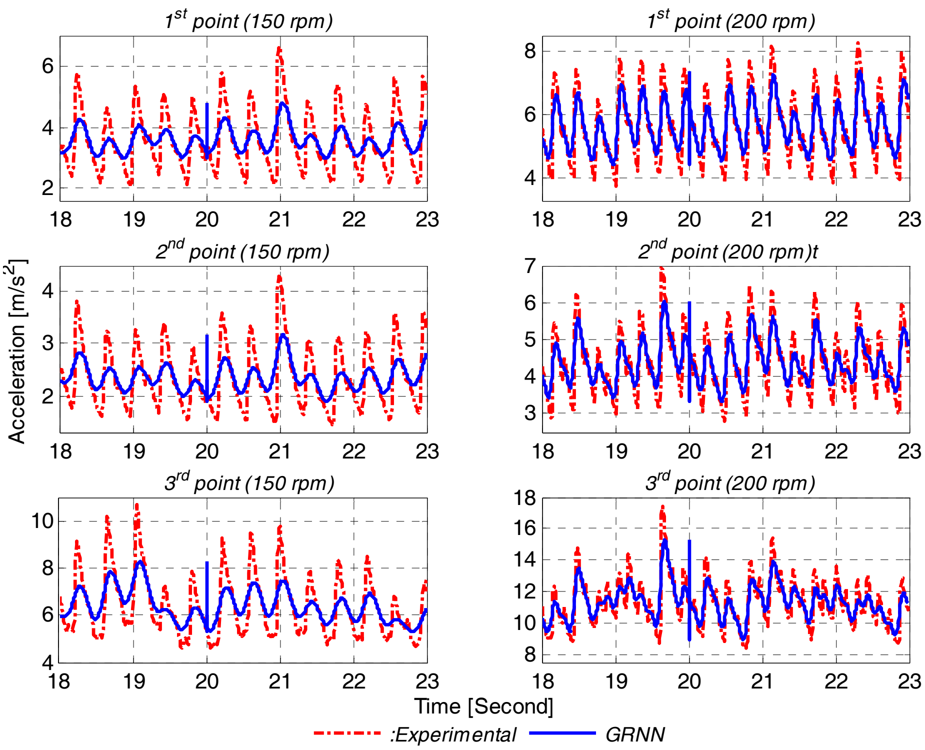


Fig. 7. Experimental and GRNN simulations for 1 and 2 mm joint clearances (c_1=1 mm c_2=2 mm).

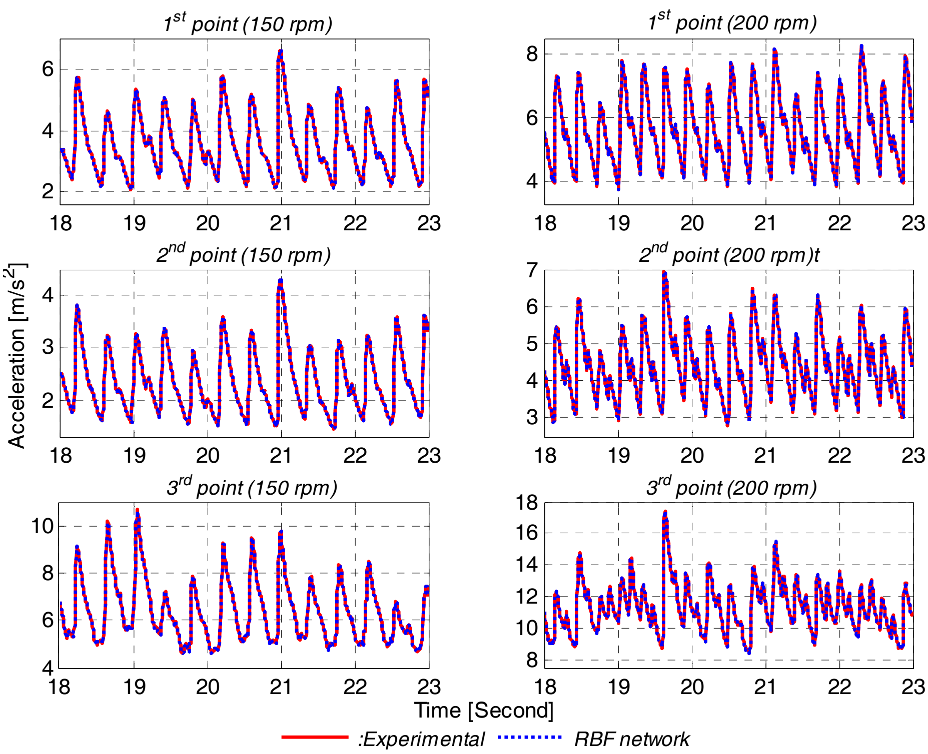


Fig. 8. Experimental and RBF neural network simulations for 1 and 2 mm joint clearances (c_1=1 mm c_2=2 mm).

Therefore, input matrix used for modeling the vibrations in network structures should comprise the mechanism's running speed. Figs. 7 and 8 denote that the running speed of the mechanism is one of the dominant effects for the definition of vibration characteristics. While the GRNN gives a poor modeling characteristic, the outputs of the RBF neural network

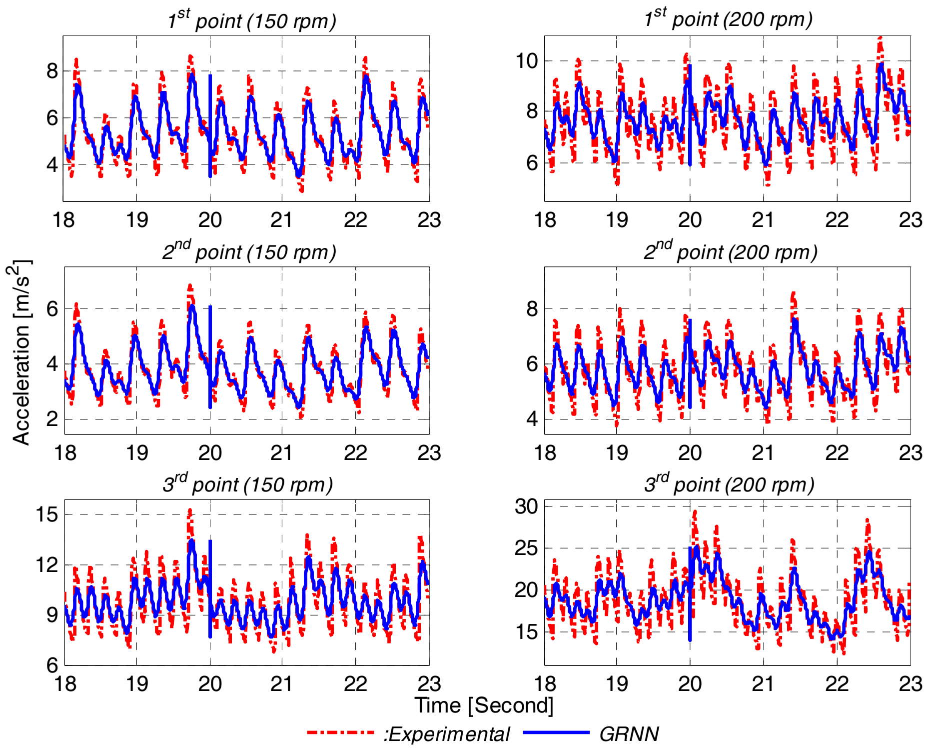


Fig. 9. Experimental and GRNN simulations for 2 mm joint clearance (c_1=c_2=2 mm).

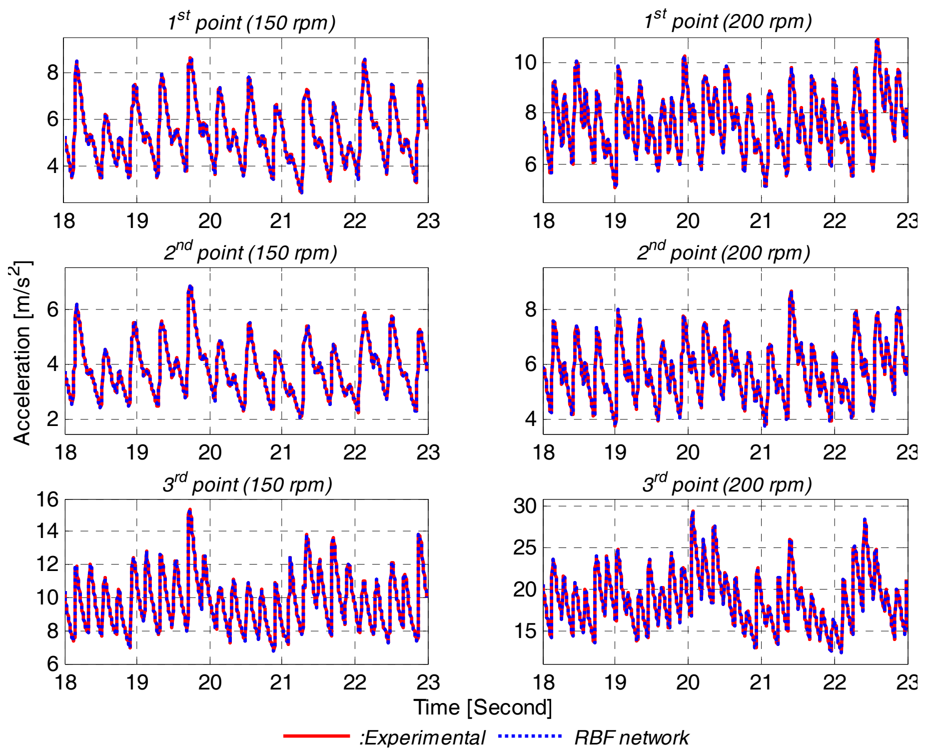


Fig. 10. Experimental and RBF neural network simulations for 2 mm joint clearance (c_1=c_2=2 mm).

fully follow the experimental values. As seen, there is an exact matching for experimental and RBF neural network results.

Experimental and neural simulation results for joints with 2 mm clearance are given in Figs. 9 and 10, respectively.

As seen from figures, clearance size at a joint has an important role on the bearing amplitude. When the clearance size

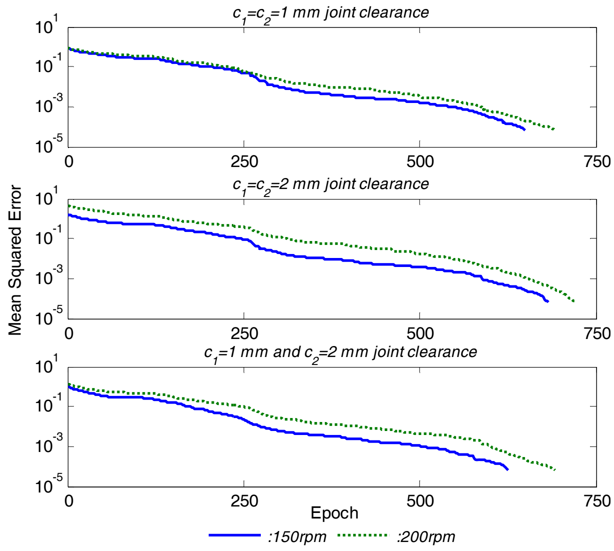


Fig. 11. Training history of RBF neural network.

increases, the bearing amplitudes also increase. This result agrees with the proposed result in the literature [7]. It is concluded that the clearance size should be considered as another dominant effect in input matrix. For the case of joints with 2 mm clearance, RBF network has better convergence ability to the experimental results than that of the GRNN. Fig. 11 gives the training history of the RBF neural network.

Training of the network weights are repeated until the desired mean squared error is obtained, which is a performance measuring criteria of the proposed network. All of the figures show that the proposed RBF neural network predictor is robust stable to analyze the bearing vibration of the mechanism. The reason for the good performance of the RBF network could be explained by the following: *(i)* The computation nodes in the hidden layer of RBF network are quite different and serve a different purpose from those in the output layer of the network. *(ii)* The argument of the activation function of each hidden unit in a RBF network computes the distance between the input vector and the center of that unit. *(iii)* RBF neural network using exponentially decaying localized nonlinearities (Gaussian function) construct local approximations to nonlinear input-output mapping.

6. Conclusion

The aim of this study is to analyze and predict the bearing vibrations of a planar mechanism having two imperfect joints with radial clearance. At the first stage of this study, experiments are performed for the case of different clearance sizes, running speeds and material types of the mechanism to evaluate the effect of each characteristic on bearing vibrations. And then, two types of neural networks are used for predicting and estimating the mechanism vibration. An input matrix, which contains a series of time, clearance sizes, running speed and material type of the mechanism, is also constituted for the neural models. At the training and testing stages, a lot of experimental studies are carried out to specify the network stability for exact modeling and predicting the vibration characteristics of the mechanism. The goal is to determine the vibration characteristics by using the proposed neural model for the case of different running speeds and clearance sizes.

In the mechanism analysis, joint with clearance has a complex nature due to the three different types of motion characteristics, which are free-flight, impact and continuous contact modes. Force variations on the mechanism can reach beyond the expected values due to the contact force acting only during a small time interval of contact. These cause to an increase in vibration amplitude. Experimental results indicate that the vibration amplitudes are affected from running speed and clearance size. In addition, material type is also important for the case of inertial phenomenon. Therefore, these characteristics and a series of time can be considered as inputs for the robust training of the network weights to predict and estimate the bearing vibrations. While the GRNN gives poor convergence ability for all simulations, the RBF neural network has a robust characteristic to model and predict the bearing vibrations for the case of different running speed conditions and mechanism characteristics. Moreover, modeling of the system vibration is possible with fast convergence and high accuracy.

Nomenclature

a_j : Output of the j^{th} node in the hidden layer
c : Radial clearance
c_1 : Clearance at crank-connecting rod joint
c_2 : Clearance at connecting rod-piston joint
c_d : Dynamic correction coefficient
c_f : Friction coefficient
D : Damping coefficient
E_k : Young's modulus
e : Magnitude of the clearance vector
$\mathbf{F}_N$: Normal force
$\mathbf{F}_T$: Tangential force
GRNN : Generalized Regression Neural Network
h_k : Material parameter
K : Generalized stiffness parameter
n : Unit vector normal to the collision plane
RBF : Radial Basis Function
R_i : Bearing radius
R_j : Journal radius
$\mathbf{r}_k$: Global position of the k^{th} link's mass center
$\mathbf{V}_T$: Relative tangential velocity
w_{jk} : Network weight from the j^{th} hidden layer neuron to the k^{th} output layer
Q_i : Contact point on the bearing
Q_j : Contact point on the journal
y : Output value of the network
z : Metallic contact exponent
δ : Relative penetration depth
ν_k : Poisson's coefficient

σ_j : Width of the j^{th} neuron
ε : Restitution coefficient

References

[1] O. A. Bauchau and J. Rodrigez, Modelling of joints with clearance in flexible multibody systems, *Int. J. Solids Struc.,* 39 (2002) 41-63.

[2] X. Jia, D. Jin, L. Ji and J. Zhang, Investigation on the dynamic performance of the tripod-ball sliding joint with clearance in a crank-slider mechanism. Part 1. Theoretical and experimental results, *J. of Sound Vib.,* 252 (5) (2002) 919-933.

[3] A. L. Schwab, J. P. Meijaard and P. Meijers, A comparison of revolute joint clearance models in the dynamic analysis of rigid and elastic mechanical systems, *Mech. Mach. Theo.,* 37 (2002) 895-913.

[4] P. Flores, J. Ambrosio and J. P. Claro, Dynamic analysis for planar multibody mechanical systems with lubricated joints, *Multib. Sys. Dyn.,* 12 (2004) 47-74.

[5] P. Flores and J. Ambrosio, Revolute joints with clearance in multibody systems, *Comp. Struc.,* 82 (2004) 1359-1369.

[6] J. C. G. Orden, Analysis of joint clearances in multibody systems, *Multib. Sys. Dyn.,* 13 (2005) 401-420.

[7] T. N. Shiau, Y. J. Tsai and M. S. Tsai, Nonlinear dynamic analysis of a parallel mechanism with consideration of joint effects, *Mech. Mach. Theo.,* 43 (4) (2008) 491-505.

[8] S. Erkaya and İ. Uzmay, Determining link parameters using genetic algorithm in mechanisms with joint clearance, *Mech. Mach. Theo.,* 44 (2009) 222-234.

[9] S. Erkaya and İ. Uzmay, A neural-genetic (NN-GA) approach for optimising mechanisms having joints with clearance, *Multib. Sys. Dyn.,* 20 (2008) 69-83.

[10] S. Erkaya and İ. Uzmay, Optimization of transmission angle for slider-crank mechanism with joint clearances, *Struc. Multidiscip. Optim.,* 37 (2009) 493-508.

[11] I. Khemili and L. Romdhane, Dynamic analysis of a flexible slider–crank mechanism with clearance, *Europ. J. of Mech. A/Solids,* 27 (5) (2008) 882-898.

[12] S. Erkaya and İ. Uzmay, Investigation on effect of joint clearance on dynamics of four-bar mechanism, *Nonlin. Dyn.,* 58 (2009) 179-198.

[13] Y. Li, Y. Liu, X. P. Liu and Z. Y. Peng, Parameter identification and vibration control in modular manipulators, *IEEE/ASME Trans. Mechat.,* 9 (4) (2004) 700-705.

[14] Y. Li, Y. Liu and X. Liu, Active vibration control of a modular robot combining a back-propagation neural network with a genetic algorithm, *J of Vib. Cont.*, 11 (1) (2005) 3-17.

[15] D. C. Han, S. H. Choi, Y. H. Lee and K. H. Kim, The nonlinear and ball pass effects of a ball bearing on rotor vibration, *KSME Int. J.*, 12 (3) (1998) 396-404.

[16] S. Bing and J. Ye, Dynamic analysis of the reheat-stop-valve mechanism with revolute clearance joint in consideration of thermal effect, *Mech. Mach. Theo.,* 43 (12) (2008) 1625-1638.

[17] S. Yildirim, I. Eski and M. Kalkat, Force analysis of bearings on a modified mechanism using proposed recurrent hybrid neural networks, *J. Mech. Sci. Tech.,* 22 (2008) 1323-1329.

[18] P. Flores, Modeling and simulation of wear in revolute clearance joints in multibody systems, *Mech. Mach. Theo.,* 44 (6) (2009) 1211-1222.

[19] P. Flores, J. Ambrósio, J. C. P. Claro, H. M. Lankarani and C. S. Koshy, Lubricated revolute joints in rigid multibody systems, *Nonlin. Dyn.,* 56 (3) (2009) 277-295.

[20] S. Erkaya and İ. Uzmay, Experimental investigation of joint clearance effects on the dynamics of a slider-crank mechanism, *Multib. Sys. Dyn.,* 24 (1) (2010) 81-102.

[21] P. Flores, C. S. Koshy, N. M. Lankarani, J. Ambrosio and J. C. P. Claro, Numerical and experimental investigation on multibody systems with revolute clearance joints, *Nonlin. Dyn.,* 65 (2011) 383-398.

[22] P. Flores, J. Ambrosio, J. C. P. Claro, H. M. Lankarani and C. S. Koshy, A study on dynamics of mechanical systems including joints with clearance and lubrication, *Mech. Mach. Theo.,* 41 (2006) 247-261.

[23] C. S. Liu, K. Zhang and R. Yang, The FEM analysis and approximate model for cylindrical joints with clearances, *Mech. Mach. Theo.,* 42 (2007) 183-197.

[24] P. Ravn, A continuous analysis method for planar multibody systems with joint clearance, *Multib. Sys. Dyn.,* 2 (1998) 1-24.

[25] H. M. Lankarani and P. E. Nikravesh, A contact force model with hysteresis damping for impact analysis of multibody systems, *J Mech. Des*., 112 (1990) 369-376.

[26] H. M. Lankarani and P. E. Nikravesh, Continuous contact force models for impact analysis in multibody systems, *Nonlin. Dyn.,* 5 (1994) 193-207.

[27] S. Erkaya, robust design approaches for mechanism with joint clearance, *Ph.D. Thesis,* Erciyes University, Graduate School of Natural and Applied Sciences (2009).

[28] D. Broomhead and D. Lowe, Multivariable functional interpolation and adaptive networks, *Comp. Sys.,* 2 (1988) 321-355.

[29] J. D. Wu, Y. H. Wang, P. H. Chiang and M. R. Bai, A study of fault diagnosis in a scooter using adaptive order tracking technique and neural network, *Expert Sys. Appl.,* 36 (2009) 49-56.

[30] H. K. Cigizoglu and M. Alp, Generalized regression neural network in modelling river sediment yield, *Advan. Eng. Soft.,* 37 (2006) 63-68.

[31] D. F. Specht, A general regression neural network, *IEEE Trans. Neural Net,* 2 (6) (1991) 568-76.

Selçuk Erkaya graduated from Mechanical Engineering Department at Erciyes University in 2001. He received M.Sc and Ph.D degrees from the same university. He currently works at Mechatronics Engineering Department at Erciyes University. His research areas are mechanism and machine theory, noise and mechanical vibrations, neural networks and optimization, robust design of mechanical systems.