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# ACTIVE HYBRID BEARING USING NEURAL NETWORK APPLIED MODEL PREDICTIVE CONTROL

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***Abstract.*** *Rotating machines are essential elements in the industry production chain. Hence, they must present high performance and availability. It is a crucial parameter to keep production and avoid financial losses. The fact that rotating machines could present instability under some operating conditions led to studies focusing on increasing the machine-damping reserve and the enlargement of stability ranges. The Hybrid Hydrodynamic-Magnetic Bearing (HHMB) is a hydrodynamic bearing with embedded electromagnetic actuator a new generation of active hybrid bearing. Although traditional control techniques are known applications for these systems, the identification of nonlinearity of the process to use them in neural network controller and attenuation of lateral shaft vibration by active hybrid bearings are still limited. In this paper describes the control of a shaft for a SISO process through a Neural Network applied Model Predictive Control (NNMPC) thus, so are attenuate the lateral vibration of a shaft through HHMB. For that, a recurrent neural network identifies the nonlinear system, this identification is done offline using the Levenberg-Marquardt learning algorithm. Thus, the controller calculate future control signals solving online at each sampling instant a quadratic optimization equations based on the error between the nonlinear prediction and the reference trajectory on a prediction horizon. Numerical results show the identification process present a high generalization ability of the nonlinear process, the error for the training data set* $MSE_{train}$ *= 3.077e-10 and for the test data set* $MSE_{test}$ *= 5.328e-10. Two cases were tested: without external disturbance (unbalance force) and with external disturbance for three different rotating speeds (20, 30 and 40Hz). In both cases, we have a good response because the displacement of the shaft was successfully follow the changes of reference trajectory. The displacement of the shaft is controlled successfully, hence increases the dynamics coefficients of hybrid bearing (equivalent stiffness and damping coefficients of oil film). Thus, the NNMPC represent a promising technique for active control the HHMB and for attenuate the lateral vibrations in rotating machines.*

***Keywords:*** *model predictive control, neural network, active hybrid bearing, lateral vibrations, control system*

## 1. INTRODUCTION

Rotating machines are essential elements in the industry production chain. Hence, they must present high performance and availability. It is a crucial parameter to keep production and avoid financial losses. The fact that rotating machines could present instability under some operating conditions led to studies focusing on increasing the machine-damping reserve and on the enlargement of stability ranges. One of the ways of achieving such objectives is designing control systems in the bearing or also design hybrid bearing systems, e.g. hydrodynamic bearing with electromagnetic actuators, named hybrid hydrodynamic-magnetic bearings (HHMB). In this case, the active control of the new hybrid hydrodynamic-magnetic bearings is necessary.

The first ideas of designing control systems in hydrodynamic bearings were presented in (Ulbrich, and Althaus, 1989), where piezoelectric actuators were mounted in the bearing casing. In this case, the modification of bearing dynamic characteristic came from the casing motion caused by the piezoelectric actuators in closed loop. Later, the use of hydraulic chambers replacing the piezoelectric actuators resulted in higher control forces but in smaller frequency ranges. The idea of controlling shaft vibration through use of hydrodynamic bearings was the active lubrication (Santos, 1994). A different design solution was presented for El-Shafei (1995) with active squeeze-film dampers. In this case, the squeeze-film chamber was connected to servo valves and the chamber internal pressure could be controlled in closed loop to increase energy dissipation. Results showed effective vibration reduction during unbalance and forced response conditions (El-Shafei, 2000). The magnetorheological fluids were used in the squeeze-film damper to change system dynamic characteristics (Kim, Lee and Koo, 2008). On the other hand, the magnetic actuators have a working principle based on the magnetic suspension of the rotor using electromagnetic forces, which are responsible for controlling the lateral vibrations. The displacement signal is measured by the sensor, whose data is sent to the controller, thus feeding back the control system (Schweitzer and Maslen, 2009).

The integration of hydrodynamic bearing with electromagnetic actuators in hybrid bearing system can be found in the patents US4827169 (Societe de Mechanique Megnetique, 1989) here, the electromagnetic actuators are mounted in the outer ring of a hydrodynamic journal bearing. In another patent US2001048257 (NTN Corporation, 2001) the actuators are mounted in an aerostatic bearing. In both cases, the load capacity of the lubricated bearings is used as the supporting mechanism of the shaft and the electromagnetic actuators are used to control shaft movements. Although, the idea of a hybrid hydrodynamic-magnetic bearing appeared in the late eighties, only recently have there been publications on the subject. Farmakopoulos, Nokilakopoulos and Papadopoulos (2013) reported a numerically analysis in terms of dynamic coefficients, for the design solution of the patent US4827169. The authors show numerically that the total stiffness and damping of the system is a combination of stiffness and damping of each mechanism (hydrodynamic and electromagnetic). Hence, the stability margins of the rotating system can be enlarged because of the variations of bearing dynamic coefficients, caused by the lubricating fluid, are compensated by the electromagnetic actuation. These results corroborate those presented earlier for El-Shafei and Dimitri (2010), where the electromagnetic actuators eliminate oil-whip and oil-whirl instabilities, observed in a Laval rotor supported by hydrodynamic bearings with control strategies appropriately chosen. In this case, however, no design solution for the system was presented, being the journal bearing and the electromagnetic actuators collocated in a linearized mathematical model.

Early experimental results of the new hybrid bearing system, showed that vibration could be reduced by using the tilting-pad bearings with embedded actuators (Moraes, Nicoletti, 2010). In this case, rms unbalance response of a vertical rotor was reduced by 54% at a rotating speed of 300 rpm. However, as the rotating speed increased, the effect of the actuators decreased, thus showing some limitations of the electromagnetic system in the frequency range. Another experimental result presented in Viveros and Nicoletti (2014), where effect of the hybrid hydrodynamic-magnetic bearing on the closed-loop dynamics of a horizontal rotor is analyzed in the frequency domain. A nonlinear mathematical model is proposed for the system, including the actuator’s dynamics, and good agreement is achieved between numerical and experimental results. Up to 18% reduction of the resonance peak amplitude is observed for a rotating speed of 1100 rpm.

In this paper, the Neural Network applied Model Predictive Control (NNMPC) is analyzed numerically with the objective of controlling the position of the shaft in single-input single-output (SISO) process. In the way, we attenuate the lateral vibrations through the hybrid hydrodynamic-magnetic bearing (HHMB). Neural networks have been applied successfully in the identification and control of dynamic systems, as the literature shows promising results in the area (Janczak, 2005; Ławryńczuk, 2014; Narendra and Parthasarathy, 1990; Suykens, Vandewalle, De Moor, 1996). The MPC has obtained an important highlight in industry since its creation in the seventies. The term MPC indicates a wide variety of control methods using the explicit model to obtain the control signal by optimization a cost function. The MPC can be applied in many processes linear, nonlinear, mono and multivariate with restrictions and delays (Camacho and Bordons, 2007; Maciejowski, 2002).

## 2. HYBRID HYDRODYNAMIC-MAGNETIC BEARING FOR SISO PROCESS

The hybrid hydrodynamic-magnetic bearing for the SISO process is composed of single degree of freedom or two tilting-pads assembled symmetrically. The system have a pair of electromagnetic forces opposite in direction as showed in Fig. 1. The tilting-pad are responsible for supporting the rotor, galleries in the bearing casing allow the oil supply by a hydraulic system. A thin oil film is formed between the sliding surfaces and the shaft (hydrodynamic lubrication), ensuring the support of the rotor (bearing mechanism).

If the shaft is centered in the bearing, the distances between shaft and the tilting-pads are $h_0$ (both upper and lower). The biases current is $i_0$, and the currents $i_1$ and $i_2$ has current control and biases. Hence, the resultant equations of motions of the system are:

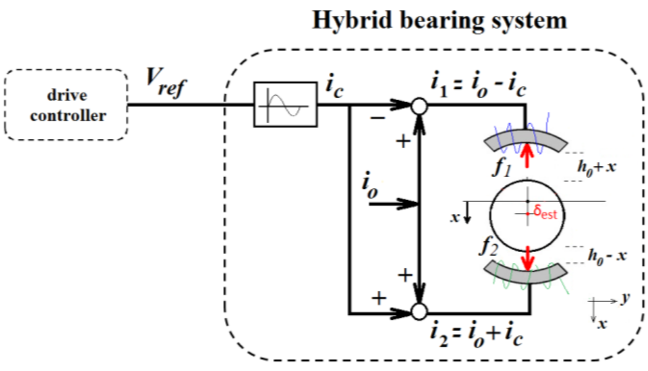


**Figure 1.** Single degree of freedom hybrid hydrodynamic-magnetic bearing

$$m\ddot{x} + d_{xx}\dot{x} + k_{xx}x = mg + f_m + f_{un} \tag{1}$$

$$f_m = \left(\frac{i_0 + i_c}{h_0 - x}\right)^2 - \left(\frac{i_0 - i_c}{h_0 + x}\right)^2 \tag{2}$$

hence:

$$m\ddot{x} + d_{xx}\dot{x} + k_{xx}x = mg + \left(\frac{i_0 + i_c}{h_0 - x}\right)^2 - \left(\frac{i_0 - i_c}{h_0 + x}\right)^2 + f_{un} \tag{3}$$

$$f_{un} = m\,e\,\Omega^2 \sin(\Omega t) \tag{4}$$

where $f_{un}$ is the external disturbing force (*e.g.* unbalance force), $f_m$ is the resultant magnetic force, $d_{xx}$ is the damping coefficient of oil film and $k_{xx}$ is the stiffness coefficients of oil film. A nonlinear mathematical model is proposed for the system (Eq. 3), including the actuator's dynamics for single-input single-output (SISO) process. However, it is necessary linearization of the force equation (Eq. 2) in a specific operation point ($x_0=\delta_{est}$; $i_c=0$) and by setting the control current equal to zero ($i_c=0$), ignoring other external forces ($f_{un}=0$). The appropriate choice of $i_c$ can be done in order to eliminate the gravity term, while the position and the current stiffness coefficients get the appropriate values, hence obtaining a linear equation:

$$m\ddot{x} + d_{xx}\dot{x} + k_{xx}x - K_x.x = K_i.i \tag{5}$$

where, the position stiffness coefficients and the current stiffness coefficient is define as,

$$K_x = \left[\frac{2i_0^{\,2}}{(h_0 - \delta_{est})^3} + \frac{2i_0^{\,2}}{(h_0 + \delta_{est})^3}\right]; \quad K_i = \left[\frac{2i_0}{(h_0 - \delta_{est})^2} + \frac{2i_0}{(h_0 + \delta_{est})^2}\right] \tag{6}$$

thus, the system equation of motion represented by the Laplace transform is:

$$(ms^2 + d_{xx}s + k_{xx} - K_x)X(s) = K_i I(s) \tag{7}$$

The SISO process has two electromagnetic actuators which introduce attraction forces on the shaft. The working principle of the electromagnets actuators is based on a two pole configuration, in such a way that they can attract the rotor along the *x*-axis (for this study, vertical orientation). The electromagnetic actuators are driven according to the controller voltage, when the control signal is ±10V, maximum force is obtained. Viveros and Nicoletti, (2014) presented a fitted model of the electromagnetic forces of the actuators. This force is a function of electric current in the winding and the gap, of the form:

$$F_a = K\left(\frac{i}{d}\right)^2 \tag{8}$$

where, $i$ is the electric current in the winding of the actuator, $d$ is the distance between the actuator and the shaft, $v_{ref}$ is the reference voltage supplied to the drive of the actuators. The experimental model of electric current is a function of the reference voltage in the drive of the actuator, then the electric current in Laplace domain is

$$I(s) = \left(\frac{\bar{a}_1 s + \bar{a}_0}{\bar{b}_1 s + \bar{b}_0}\right) V_{ref}(s) \tag{9}$$

the coefficient $\bar{b}_0$ and $\bar{b}_1$ represent the equivalent electric resistance and the equivalent inductance of the actuation system, respectively and $\bar{a}_0$ and $\bar{a}_1$ are fitting coefficients (Table 1). Finally using the Eq.7 and Eq. 9 we obtaining a transfer function in the Laplace domain (Eq. 10)

$$\frac{X(s)}{V_{ref}(s)} = \frac{K_i(\bar{a}_1 s + \bar{a}_0)}{(\bar{b}_1 s + \bar{b}_0)(ms^2 + d_{xx}s + (k_{xx} - K_x))} \tag{10}$$

Table 1. Parameters of the fitting model of the electromagnetic actuators

| Parameters | Value |
|---|---|
| $\bar{a}_0$ | 5.3310e-3 |
| $\bar{a}_1$ | 4.9047e-5 |
| $\bar{b}_0$ | 2.6 Ω |
| $\bar{b}_1$ | 0.095mH |

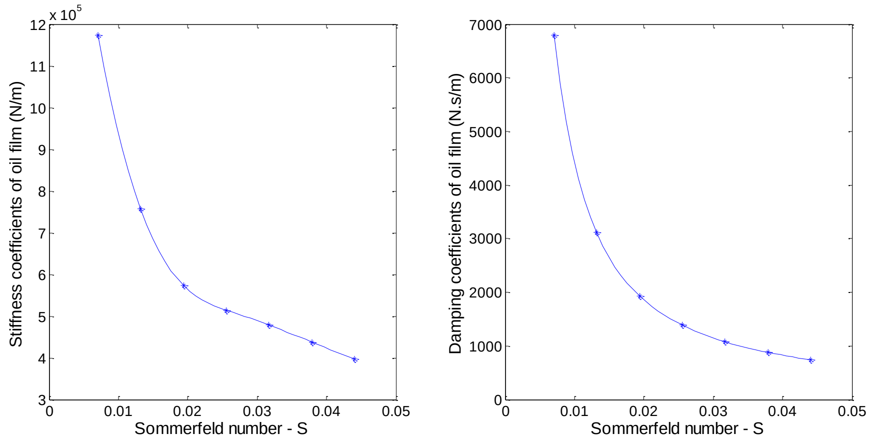


**Figure 2**. Relationship between Sommerfeld number and stiffness and damping coefficients of oil film

In recent years, methods have been developed for estimating stiffness and damping coefficients of oil film. In this work, we use a table with experimental data for the SISO process with two tilting-pad. The bearing characteristics number, or Sommerfeld number (S), is a dimensionless value very important in hydrodynamic bearing analysis because considers geometrical and operational characteristics and it is defined by the equation:

$$S = \frac{\mu \Omega R L}{W}\left(\frac{R}{c_r}\right)^2\left(\frac{L}{D}\right)^2 \qquad (11)$$

where, $\mu$ is the lubricant viscosity, $\Omega$ is the journal rotational speed, $D$ is the bearing bore, $R$ is the journal radius, $L$ is the bearing length and $c_r$ is the bearing radial clearance. The dynamic coefficients are evaluated for a particular static equilibrium position, which is a function of the Sommerfeld number. The Sommerfeld number obtains the equivalent stiffness and damping coefficient of oil film. The model of equivalent stiffness and damping is used to avoid the numerical integration of Reynolds equation the bearing oil profile. Fig. 2, presents the equivalent stiffness and damping coefficients used in this work as a function of the Sommerfeld number (Someya, 1998).

## 3. THE NEURAL NETWORK APPLIED MODEL PREDICTIVE CONTROL

The neural network applied model predictive control (NNMPC) is the algorithm that uses a predictor topology of a neural network for identification of the nonlinear plant model. Hence, it calculates future control signals solving online at each sampling instant a quadratic optimization equations based on the error between the nonlinear predictions and the reference trajectory in a horizon of prediction (Ławryńczuk, 2014; Tatjweski, 2007). There are two steps involving the implementation of NNMPC: the first is the dynamic system identification and the second is the control design.

### 3.1 Dynamic system identification

The first stage of NNMPC is the dynamical system identification of the process. The most common neural network model structure employed for identification is the Nonlinear Auto-Regressive with eXogenous inputs (NARX) architecture, used for input-output modeling of nonlinear dynamical systems. This neural architecture have one hidden layer with the hyperbolic tangent transfer function and a linear transfer function for the output layer. The NARX architecture have a relatively small number of parameters and a simple structure. The literature confirmed the universal approximation theorem is directly applicable to NARX network, and it implies that one hidden layer is sufficient (Haykin, 1999).

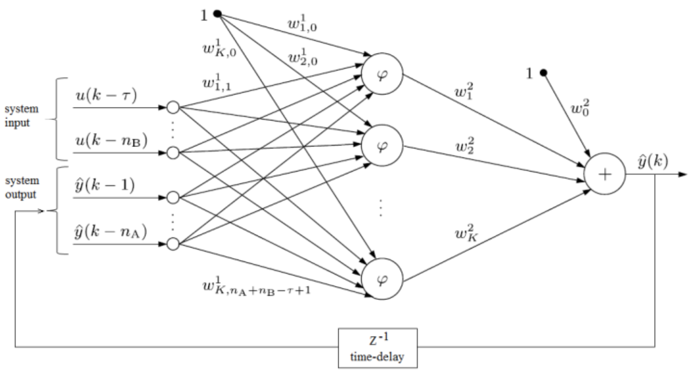


**Figure 3**. The structure of the NARX neural network

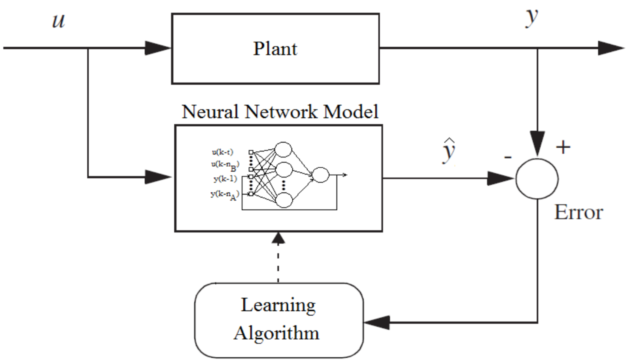


**Figure 4**. The plant identification using the recurrent parallel model

Therefore, a structure NARX network is used for this purpose (Fig. 3). Hence, the training should minimize the error between the plant output and the neural network output, based on the Mean Squared Errors (MSE).

$$MSE = \frac{1}{2P}\sum_{i=1}^{P}\left(\hat{y}_i - y_i\right)^2 \tag{12}$$

The neural network plant model was trained using the Levenberg-Marquardt: a nonlinear gradient optimization algorithm. The NARX network is a recurrent neural network for multistep ahead prediction (Ławryńczuk, 2014; Tatjweski, 2007) is training and performed offline, and the data must be in the form of input-output pairs of the plant. These pairs include also inputs and delayed model outputs. During training, two model configurations are possible: the non-recurrent serial-parallel, the output signal is a function of the process input and output signal values from previous instants. Moreover, the recurrent parallel model, the past process outputs are replaced by the model outputs calculated at previous sampling instants (Janczak, 2005; Narendra and Parthasarathy, 1990). Here, one adopts the latter model, shown in Fig. 4:

$$\hat{y}(k) = f(u(k-\tau),...,u(k-n_B),\hat{y}(k-1),...,\hat{y}(k-n_A)) \tag{13}$$

where, $u$ is the input system, $\hat{y}$ is the output of the neural model and $\tau$ is time-delay.

### 3.2 Design of Neural Network Model Predictive Control

The NNMPC shown in Fig. 5 has the control law to minimize the cost function of Eq. 14. The first part is the differences, between the predicted trajectory of the output variable and the reference trajectory over the prediction horizon N. The second part is it to reduce excessive changes of the manipulated variable $u(k)$. This variable is successively calculated online as a result of solving an optimization problem (Ławryńczuk, 2010):

$$J(k) = \sum_{p=1}^{N}\left(y_{ref}(k+p|k) - \hat{y}(k+p|k)\right)^2 + \lambda\sum_{p=0}^{N_u-1}\left(\Delta u(k+p|k)\right)^2 \tag{14}$$

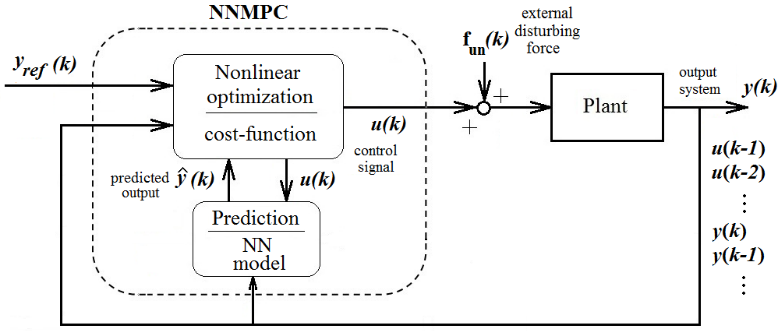


**Figure 5**. Neural Network applied MPC

where $N$ is the prediction horizon, $N_u$ is the control horizon, $\hat{y}$ is the output trajectory vector predicted at sampling $k$ over prediction horizon, $y_{ref}$ is the output reference trajectory vector at sampling instant $k$ over prediction horizon, $\lambda$ is the weighting coefficient and $\Delta$u is the input increments vector for sampling instant $k$ over control horizon. Typically, $N_u < N$ and $\lambda > 0$. Moreover, at each consecutive sampling instant $k$, a set of future control increments is calculated:

$$\Delta u(k) = \left[ \Delta u(k|k) \quad \cdots \quad \Delta u(k + N_u - 1|k) \right]^T \tag{15}$$

It is assumed that $\Delta u(k+p|k) = 0$ for $p \geq N_u$, where $N_u$ is the control horizon. The future control increments are determined from the following optimization problem (Eq. 16):

$$\min_{\Delta u(k|k) \ldots \Delta u(k+N_u-1|k)} \left\{ J(k) \right\} \tag{16}$$

subject to

$$\begin{aligned} & u^{\min} \leq u(k+p|k) \leq u^{\max}, \, p = 0, \ldots, N_u - 1, \\ & -\Delta u^{\max} \leq \Delta u(k+p|k) \leq \Delta u^{\max}, \, p = 0, \ldots, N_u - 1, \\ & y^{\min} \leq \hat{y}(k+p|k) \leq y^{\max}, \, p = 1, \ldots, N. \end{aligned} \tag{17}$$

The first element of the determined sequence is actually applied to the process (Eq. 18). At the next sampling instant, $k+1$, the prediction is shifted one step forward and the whole procedure is repeated.

$$u(k) = \Delta u(k|k) + u(k-1) \tag{18}$$

Now, using the neural network identification models for prediction future behavior of the process. We calculate predicted values of the output variable $\hat{y}(k+p|k)$, over the prediction horizon ($p = 1, \ldots, N$). Hence, the general prediction equation is:

$$\hat{y}(k+p|k) = y_{nn}(k+p|k) + d(k) \tag{19}$$

where the magnitudes $y_{nn}(k+p|k)$ are calculated from the NARX network. The unmeasured disturbance $d(k)$ is assumed to be constant over the prediction horizon (Ławryńczuk,2014, Tatjewski, 2007). It is estimated from:

$$d(k) = y_m(k) - y_{nn}(k|k-1) \tag{20}$$

where, $y_m(k)$ is measured from the linear dynamic approximation model which is defined by the difference equation (Eq. 21):

$$A(q^{-1}) y_m(k) = B(q^{-1}) u(k) \tag{21}$$

$$A_{m,m}(q^{-1}) = 1 + a_1^m q^{-1} + \ldots + a_{n_A}^m q^{-n_A}$$
$$B_{m,s}(q^{-1}) = b_1^{m,s} q^{-1} + \ldots + b_{n_B}^{m,s} q^{-n_B} \tag{22}$$

$$y_m(k) = \sum_{l=1}^{n_B} b_l^{m,s} u(k-l) - \sum_{l=1}^{n_A} a_l^m y_m(k-l) \tag{23}$$

the equation of such NARX networks $y_{nn}(k+p \mid k)$ is,

$$y_{nn}(k) = w_0^2 + \sum_{i=1}^{K} w_i^2 \varphi(w_{i,0}^1 + \sum_{j=1}^{n_u} w_{i,j}^1 u_j(k)) \tag{24}$$

the neural network has $n_u$ inputs $(u_1, \ldots, u_{nu})$, $K$ hidden neurons with the nonlinear transfer function $\varphi : \mathbf{R} \rightarrow \mathbf{R}$ and one output $y_{nn}(k)$. The first layer is the sum of the input signals connected to the $i^{th}$ hidden neurons $(i = 1, \ldots, K)$. The weights are denoted by $w_{i,j}^1$, where $i=1,\ldots,K$, $j = 0,\ldots,n_u$, the weights of the second layer are denoted by $w_i^2$, where $i = 0, \ldots, K$.

Using the prediction equation (Eq. 19) and the model outputs by NARX model (Eq. 13), output predictions over the prediction horizon are calculated from:

$$\hat{y}(k+p|k) = f(\underbrace{u(k-\tau+p|k),\ldots,u(k|k)}_{I_{uf}(p)}, \underbrace{u(k-1),\ldots,u(k-n_B+p)}_{I_u - I_{uf}(p)}, \underbrace{\hat{y}(k-1+p|k),\ldots,\hat{y}(k+1|k)}_{I_{yp}(p)}, \underbrace{y_m(k),\ldots,y_m(k-n_A+p)}_{n_A - I_{yp}(p)}) + d(k) \tag{25}$$

now, the prediction $\hat{y}(k+p|k)$ depend on $I_{uf}(p) = \max(\min(p-\tau+1, Iu), 0)$ future values of the control signal. Where $I_u = n_B - \tau + 1, I_u - I_{uf}(p)$ denotes values of the control signal applied to the plant at previous sampling instants, $I_{yp}(p) = \min(p-1, n_A)$ stands for future output predictions, and $n_A - I_{yp}(p)$ means plant output signal values measured at previous sampling instants.

## 4. SIMULATION RESULTS

It is very important to control the vibrations of shafts to avoid financial losses in the industry production chain. In this section, the results of the active control of the lateral vibrations of a shaft supported by Hybrid Hydrodynamic-Magnetic Bearing (HHMB) through Neural Network applied Model Predictive Control (NNMPC) is discussed. The objective is to control the displacement of a shaft in a SISO process. Thus, we modified the dynamics coefficients of HHMB and attenuate lateral vibrations. All simulations are carried out in Matlab.

The NNMPC discussed previously uses a neural network model of a nonlinear process to train and identify the plant. For this application, open-loop simulations are used to generate data in a system of differential equations (Eq. 3). We collect training data while applying input pulses of random period and amplitude, the voltage is allowed to range from -2 to 2 Volts. For the identification process are employed two sets of data, namely, training and test data sets shows in Fig. 6 both sets have 5000 samples.

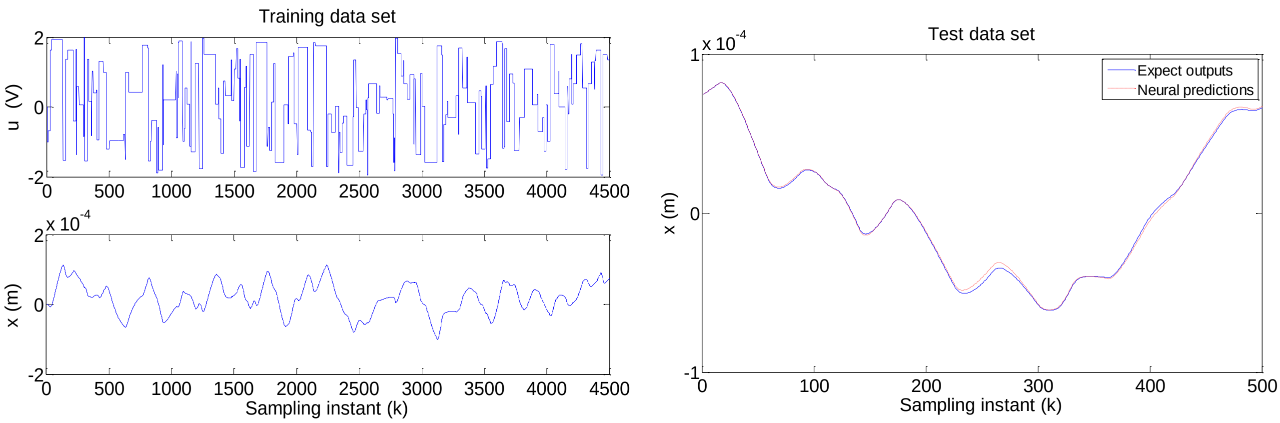


**Figure 6**. Left: The training data set used with NARX neural model; right: the process (solid line) vs. the neural model (dashed line) for the first 500 samples of the test data set.

The NARX network with one hidden layer is used for identification, the hyperbolic tangent transfer function is used in the hidden layer. The neural network plant model was trained using the Levenberg-Marquardt learning algorithm. Then, the model have the third-order dynamics

$$x_{nn}(k) = f(u(k-1), u(k-2), u(k-3), x_{nn}(k-1), x_{nn}(k-2), x_{nn}(k-3)) \tag{26}$$

where $x_{nn}(k)$ is the displacement of shaft between the static equilibrium position and the geometric center of the bearing, $\tau = 1$, $n_A = n_B = 3$. Because input and output data have different orders of magnitude, they have been normalized. After those several training process, it was determined that 10 hidden neurons are sufficient to get good generalization properties. Accuracy of the model is very high, for the training data set $MSE_{train}$ = 3.077e-10 and the test data set $MSE_{test}$ = 5.328e-10. Therefore, we obtained weights and biases (*w10, w1, w20 and w2*), that will be used to predict future outputs of the nonlinear plant. The performance of neural network predictive controllers are highly dependent on the accuracy of the identification of the nonlinear plant.

Using the transfer function of the Laplace-domain (Eq. 10) and the values of Table 1, we obtain the linear dynamic form (Eq. 27) is defined by the difference equation in a sampling interval for the controller is $\Delta t$ = 0.001(sec) with zero-order hold (zoh), as

$$x(k) = b_1 u(k-1) + b_2 u(k-2) + b_3 u(k-3) - a_1 x(k-1) - a_2 x(k-2) - a_3 x(k-3) \tag{27}$$

where Matlab function c2dm is used. The NNMPC needs to solve online at each sampling instant, a quadratic optimization problem. This Sequential Quadratic Programming (SQP) algorithm is used for nonlinear optimization necessary in the NNMPC approach. Matlab function *fmincon* is used with options *sqp* algorithm.

For this hybrid bearing in SISO model configuration, the equivalent stiffness and damping coefficients of the oil film increases with a reduction to Sommerfeld number (fig. 3). Hence, the reference trajectory is defined by shaft positions between the point of static equilibrium and the points around of the geometric center of hybrid bearing

The NNMPC controller has parameters: $N = 15$, $N_u = 3$, $\lambda = 0.09$ for $p = 1, \ldots, N$. The following constraint is imposed to the value of the control signal: $u = \pm 10$V. The simulation condition of the system is for three rotating speeds (20, 30 and 40Hz) and the parameters of the controller are fixed. The fig. 7 shows the control signals and the system response in terms of voltage and displacement respectively. The responses shows in the active condition without unbalance force and the displacement of shaft is in x-axis direction (vertical). The control algorithm NNMPC successfully follows the changes of the reference trajectory for the three rotating speeds proposed.

On the other hand, we simulated the controller with an external disturbance (unbalance force). The disturbance is initiated in sampling instant k = 162, as shown in Fig. 8. The NNMPC algorithm can successfully control changes of the reference trajectories for three rotating speeds. For speeds of 20Hz and 30Hz it is observed that the displacement of the shaft are altered but soon controlled even with the presence of the disturbance. As for rotating speed of 40Hz, the displacement of the shaft is modified at the beginning but then is controlled.

## 5. CONCLUSION

The results show that there was attenuation of the lateral vibrations of the shaft through the HHMB applying NNMPC algorithm. The identification process of the nonlinear system using neural networks has been developed successfully.

The identification of a nonlinear system by a Nonlinear Auto-Regressive with eXogenous inputs (NARX) with one hidden layer with 10 hidden neurons presented a high generalization ability of the nonlinear process. For the training data set $MSE_{train}$ = 3.077e-10 and the test data set $MSE_{test}$ = 5.328e-10, which represents a high accuracy and ensures a good performance of the predictive controller.

The NNMPC algorithm showed satisfactory results, where the manipulated variable u(k) is successively calculated by solving a quadratic optimization problem. The displacement of the shaft is controlled successfully following changes of the reference trajectory, thus increasing dynamic coefficients of the active hybrid bearing (equivalent stiffness and damping coefficients of oil film) for attenuating lateral vibrations of shaft. Two cases were tested: without external disturbance (unbalance force) and with external disturbance for three different rotating speeds (20, 30 and 40Hz). In both cases, we have a good response from the system because the displacement of the shaft successfully followed the changes of reference trajectory. In all the simulations the parameters were not modified (N, Nu and $\lambda$).

Finally, the encouraging results of this paper will be completed for a multiple-input multiple-output system and beginning of experimental applications in test rig. Thus, these results represent the beginning of a line of research which seeks to take advantage that the neural network can naturally deal with nonlinearity and apply them to predictive control, becoming a new alternative active control of lateral vibrations in shafts of rotating machines.

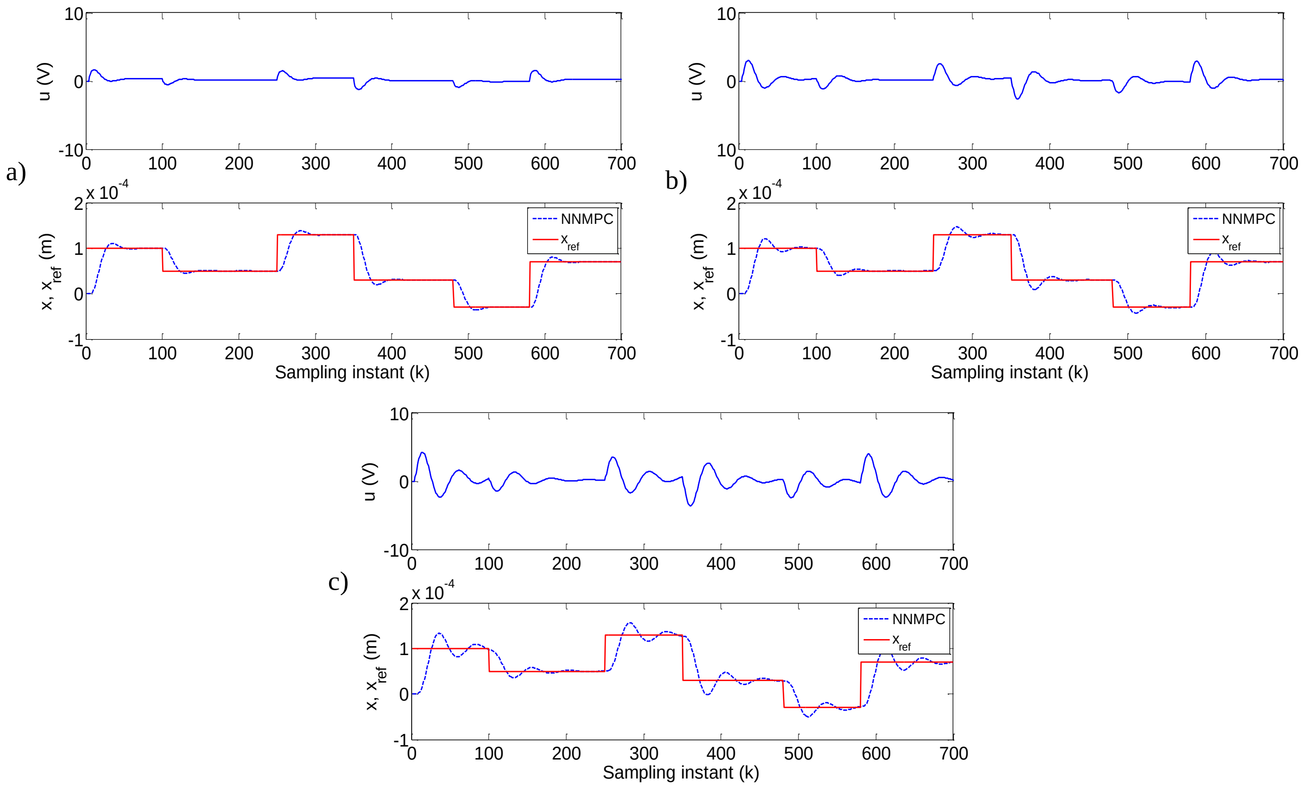


**Figure 7**. Hybrid-bearing controller response in the active condition without external disturbance, signal control (upper) and displacement signal (lower), rotating speeds: a) 20Hz; b) 30Hz and c) 40Hz.

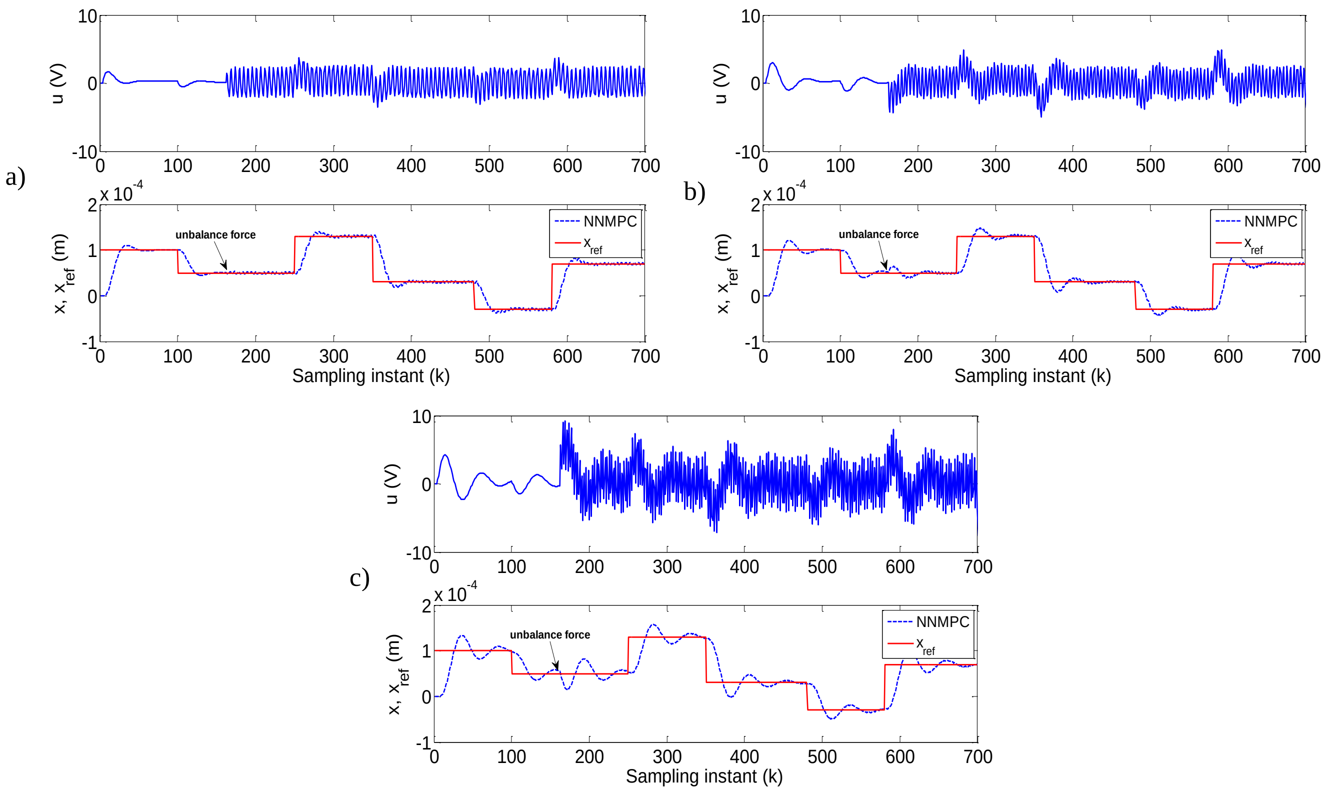


**Figure 8**. Hybrid-bearing controller response in the active condition with external disturbance, signal control (upper) and displacement signal (lower), rotating speeds: a) 20Hz; b) 30Hz and c) 40Hz.

## 6. ACKNOWLEDGEMENTS

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