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SELFLEARNING CONTROLLER OF ACTIVE MAGNETIC BEARING

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Summary: *The active magnetic bearing control through self learning controller is described in this contribution. Controller's coefficient (parameter) values come from actions of Continuous Action Reinforcement Learning Automatas (CARLAs) which continuously update the controller's coefficients according to behavior of the active magnetic bearing. The goal of this on-line training is formulated as achievement of minimum mean square of control error. It is shown that CARLA method is capable of learning better parameters than standard method of optimal control design called LQ (linear quadratic) design. Described concept of control is proved by control of the active magnetic bearing.*

1. Introduction

Active magnetic bearing (AMB) inhibits contact between rotor and stator and so it eliminates limitations of classic bearing. Therefore it is possible to use AMB in specific and extreme circumstances where classic bearing is inapplicable. Electromagnets located in stator of the bearing create magnetic field. The force caused by magnetic field keeps rotor levitating in desired position in the middle of air clearance. So the control of magnetic field is necessary.

Nonlinearity of AMB's behavior causes problems when linear regulator is used for control. The linear regulator is capable of control of AMB, but its performance is poor. It is possible to recalculate desired action to corresponding input voltage of electromagnets to linearize response of AMB to action. LQ design can be used to design optimal controller of linearized AMB afterwards. Common problem of optimal control design methods is that they are not robust. Furthermore, model of AMB used to controller design is approximate only. CARLA method can be used to improve performance of designed controller.

CARLA method belongs to the group of learning automats. Its learning is based on random selection of controller parameters from predefined range during control. Update of learned value is based on real behavior of controlled system. So it is capable to learn appropriate parameter values of controller for real AMB.

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2. Active magnetic bearing

Simplified model of AMB is used for control design. Rotor is replaced by mass point, gravitation is neglected (assumed as compensated one) and the nonlinearity is considered for electromagnetic subsystem only.

$$
\begin{aligned}
m\ddot{x} + b\dot{x} + F_{m1} - F_{m2} &= F_e \\
Ri_1 + L\dot{i}_1 &= u_1 \qquad x \in \langle 0, d \rangle , \\
Ri_2 + L\dot{i}_2 &= u_2
\end{aligned}
\tag{1}
$$

where m is mass of mass point, b is damping, x is position, F_{m1} and F_{m2} are forces generated by electromagnets, F_e is disturbance affecting AMB and d is size of air clearance between coils.

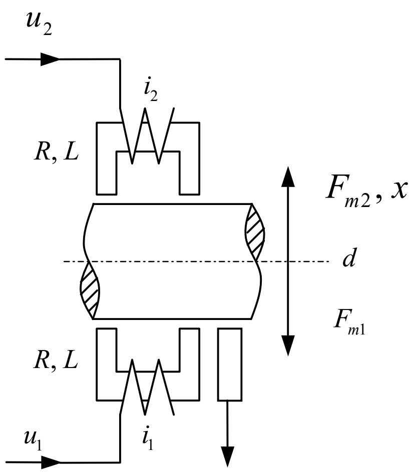

Figure 1: Model of AMB

Table 1: Parameters of AMB

Parameter	Description	Value	Unit
m	Mass of mass point	0.2	[kg]
b	Damping	20	[Ns/m]
d	Size of air clearance	0.0014	[m]
R	Resistance of electromagnets	266	[Ω]
L	Inductance of electromagnets	0.87	[H]

2.2. Magnetic force model

Behavior of magnetic force is assumed to be directly proportional to current and inversely proportional to quadratic function of distance. Coefficients of magnetic force model are obtained by measuring relation between current and distance at constant force (see fig. 2) and use of regression analysis.

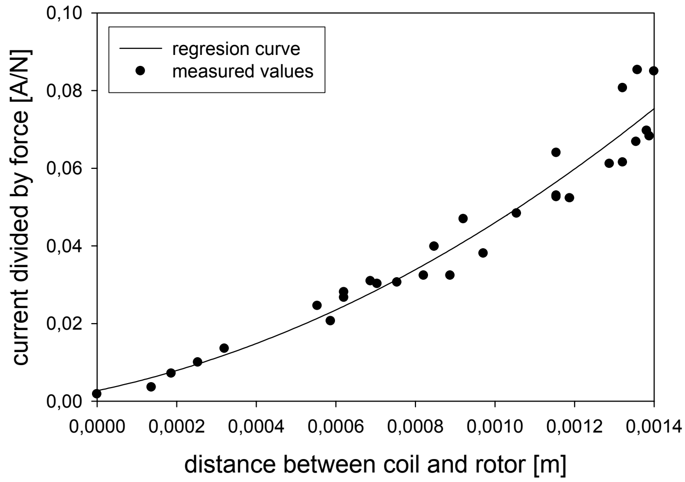

Figure 2: Relation between current and distance at constant force

Resulting model of magnetic force is

$$F_{m1} = \frac{|i_1|}{2.796 \cdot 10^{-2} - 53.37 \cdot e + 2.675 \cdot 10^4 \cdot e^2}, \quad F_{m2} = \frac{|i_2|}{2.796 \cdot 10^{-2} + 53.37 \cdot e + 2.675 \cdot 10^4 \cdot e^2} \tag{2}$$

where

$$e = \frac{d}{2} - x \,. \tag{3}$$

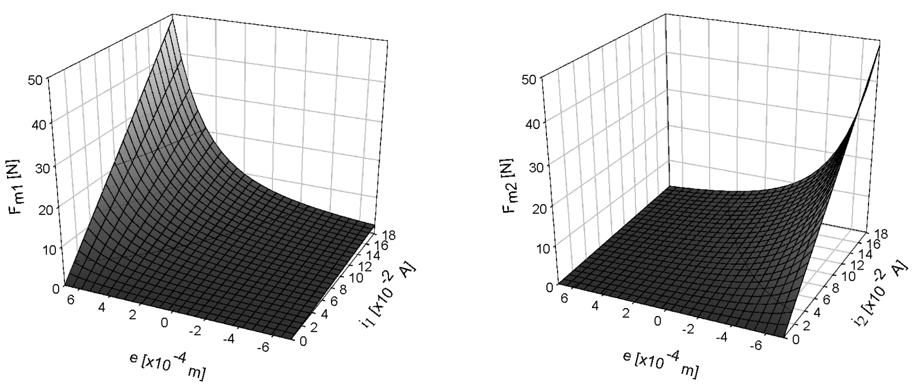

Figure 3: Magnetic force

3. Controller design

Design of controller of nonlinear system is not an easy task, but many methods exist to design controller of linear system. So it would be much easier to design controller for the AMB if it behaves like linear system.

3.1. Linearization of behavior of AMB

Only part of AMB with nonlinear behavior is electromagnetic subsystem. Its model is known, so it is easy task to derive equations for the input currents which linearize behavior of AMB by comparing desired and real behavior of AMB

$$kv = F_{m2} - F_{m1}, \tag{4}$$

where k is desired stiffness and v is input. Equation (4) is satisfied if input currents are

$$\begin{aligned} i_1 &= \begin{cases} -k \cdot v \cdot \left(2.796 \cdot 10^{-2} - 53.37 \cdot e + 2.675 \cdot 10^{4} \cdot e^2\right) & \text{if } v < 0 \\ 0 & \text{else} \end{cases}, \\ i_2 &= \begin{cases} k \cdot v \cdot \left(2.796 \cdot 10^{-2} + 53.37 \cdot e + 2.675 \cdot 10^{4} \cdot e^2\right) & \text{if } v > 0 \\ 0 & \text{else} \end{cases}. \end{aligned} \tag{5}$$

Equations (5) form so called linearizing controller. Resulting behavior of real AMB is linear approximately only. To make AMB's behavior exactly linear, it is needed to know exact model of AMB.

3.2. Controller design of linearized AMB

Any of many methods can be used to design controller of AMB once its behavior is linear. LQ design is chosen. This method designs optimal discrete PID controller. Common problem of optimal control design methods is they are not robust. It means resulting controller is not optimal for approximately linearized AMB in this case.

Table 2: Parameters of designed controller

Parameter	**Description**	**Value**	**Unit**
K_p	proportional gain	9.5919	$[-]$
K_i	integrative gain	26.512	$[s^{-1}]$
K_d	derivative gain	0.30949	$[s]$
T	sampling period	10^{-3}	$[s]$

3.3. CARLA method

CARLA method [1, 2] can be used to learn improved PID controller's parameter values. CARLA method belongs to the group of learning automats. Its learning is based on real behavior of a controlled system. It learns by random selection of action (parameter value). The selection is based on probability density function $f(x)$. The probability density function is updated according to behavior of controlled system. Learned value is value with highest probability of selection.

CARLA method is capable of minimizing defined performance criteria J without knowledge of model of controlled system. Performance criteria of AMB is defined as square value of distance of rotor from center position

$$J = e_x^2 + e_y^2, \tag{6}$$

where e_x is deviation in horizontal axis and e_y is deviation in vertical axis.

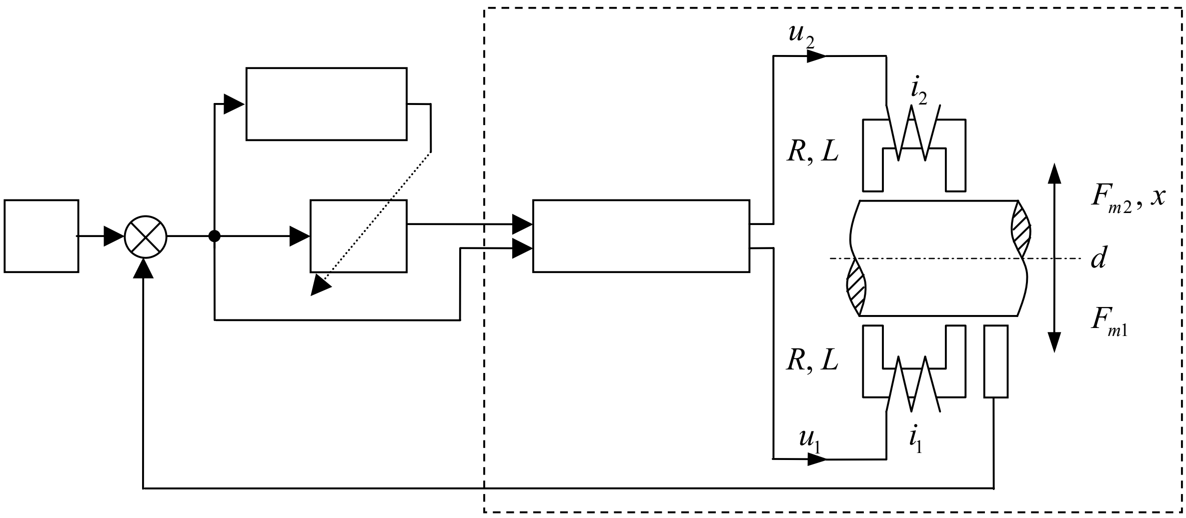

Figure 4: Controller interconnection (one axis)

3.4. Implementation notes

Building of current source is not an easy task so AMB is controlled by effective value of voltage generated by PWM (pulse width modulation) voltage source. Relation between current and voltage is defined by (1). Inductance of electromagnets can be neglected considering use of discrete controller and use of PWM. By substituting equations of linearizing controller (5) into (1) we get

$$\begin{aligned} u_1 &= \begin{cases} -R\cdot k\cdot v\cdot\left(2.796\cdot 10^{-2} - 53.37\cdot e + 2.675\cdot 10^{4}\cdot e^{2}\right) & if\ v<0 \\ 0 & else \end{cases}, \\ u_2 &= \begin{cases} R\cdot k\cdot v\cdot\left(2.796\cdot 10^{-2} + 53.37\cdot e + 2.675\cdot 10^{4}\cdot e^{2}\right) & if\ v>0 \\ 0 & else \end{cases}. \end{aligned} \tag{7}$$

Sensors with low noise are used so filtering of measured values is not needed. Selection of value of stiffness k is based on simulations. Its value is selected to achieve good performance of control. Microcontroller used to implementation of control algorithm needs indispensable time to compute action, so a nonzero time delay exist between measurement and application of action to system.

Table 3: Controller parameters

Parameter	**Description**	**Value**	**Unit**
T_D	action delay	$2.5\cdot 10^{-4}$	$[\mathrm{s}]$
k	stiffness	200	$[-]$
–	resolution of PWM	8	$[\mathrm{bit}]$
f_{PWM}	frequency of PWM	39	$[\mathrm{kHz}]$
$u_{\max}$	amplitude of voltage of PWM	48.2	$[\mathrm{V}]$

Limits of intervals of CARLA method's actions are selected as ±30% of controller parameter values designed by LQ design. Frequency of iterations of CARLA method should be higher than the used one to increase speed of learning, but it is limited by microcontroller used for implementation.

Table 4: Parameters of CARLA method

Parameter	**Description**	**Value**	**Unit**
$\left\langle K_p^{\min};K_p^{\max}\right\rangle$	range of allowed actions	$\langle 6.7;12.47\rangle$	$[-]$
$\left\langle K_i^{\min};K_i^{\max}\right\rangle$	range of allowed actions	$\langle 18.56;34.47\rangle$	$[\mathrm{s}^{-1}]$
$\left\langle K_d^{\min};K_d^{\max}\right\rangle$	range of allowed actions	$\langle 0.22;0.4\rangle$	$[\mathrm{s}]$
g_h	height of Gaussian function	0.2	$[-]$
g_w	width of Gaussian function	0.02	$[-]$
R_C	number of last costs to compute performance	50	$[-]$
N	number of samples to save probability density	50	$[-]$
T_C	delay between iterations	0.65	$[\mathrm{s}]$

4. Results

Following results are obtained by measuring behavior of real AMB. Although previous derivation was done for single axis only, real AMB is controlled in two axes – horizontal and vertical. Schema of interconnection for one axis can be seen on figure 4. Interconnection of second axis is the same. The only exception is CARLA method. It is common to both axes, i.e. it learns one set of controller parameters for both axes.

Parameters of AMB, controller and learning are given by tables 1, 2, 3 and 4. Load of rotor of AMB is constant – 0N in horizontal axis and 2N in vertical axis (weight of rotor).

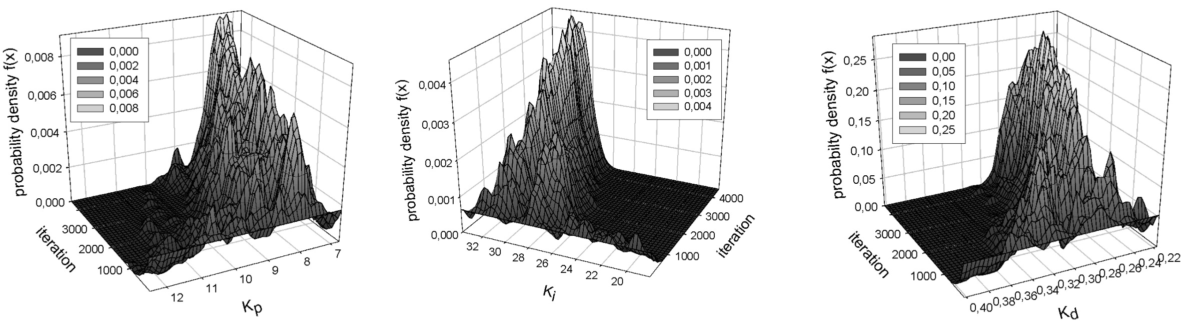

Figure 5: Learning progress

Learned proportional and derivative gains (see table 4) are smaller than ones designed by LQ design so AMB has lower stiffness if learned values are used. But it has to be considered, learning was done at constant loading force so CARLA method had no opportunity to adjust to variable loading force.

Table 5: Learned parameter values of controller

Parameter	Description	Value	Unit
K_p	proportional gain	7.6	$[-]$
K_i	integrative gain	31.7	$[s^{-1}]$
K_d	derivative gain	0.252	$[s]$

Behavior of the AMB controlled by the controller with the parameter values designed by LQ design (LQ controller) is much worse then behavior of AMB controlled by the controller with the learned ones (learned controller). The LQ controller causes oscillations with high amplitude without external reason (see fig. 6).

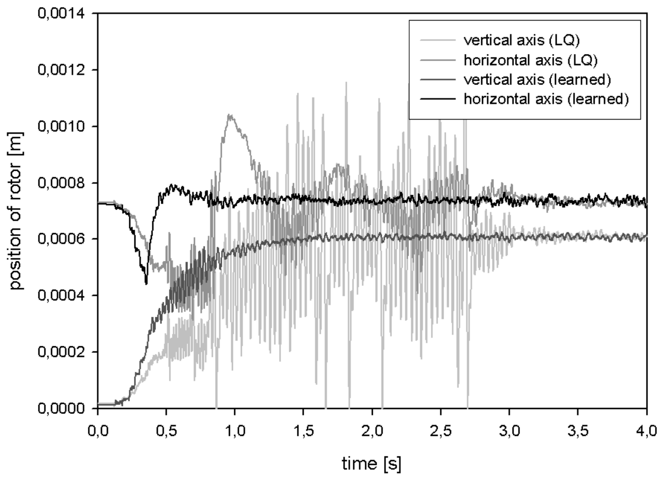

Figure 6: Behavior of AMB

Although the oscillations stop after some time, they can be invoked at any time by an application of a pulse of a loading force (see fig. 7). The learned controller stabilizes position of rotor without oscillations in short time. The amplitude of the applied impulse is 5N.

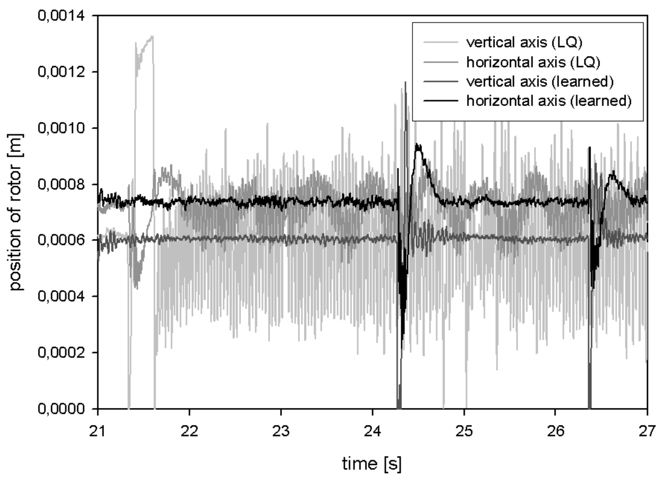

Figure 7: Behavior of AMB (response to impulse)

Disadvantage of learned controller is that it is optimized for one type of loading and concrete controlled system. If type of loading or parameters of controlled system change the performance of learned controller gets worse. On figure 8 you can se behavior of AMB if weight of rotor is changed by step. The size of change is 70%.

The learned controller cannot handle the change. But if CARLA method is still learning, it adjusts to the change (see fig. 9). Time to readjustment depends on complexity of controlled system and delay between iterations of CARLA method.

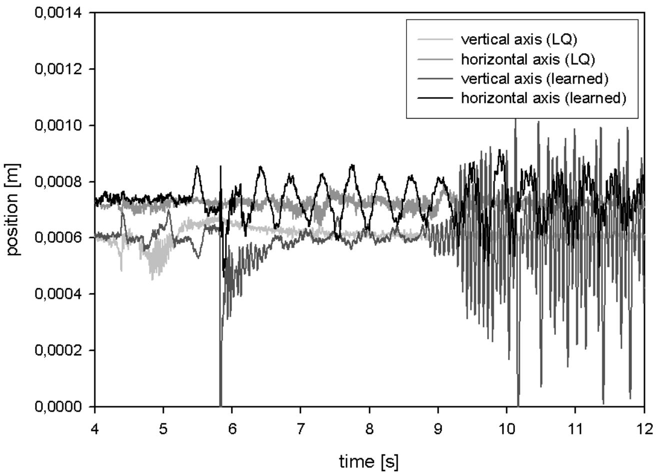

Figure 8: Behavior of AMB (changed parameters of AMB)

The readjustment takes long time in this case, because of high delay between iterations of CARLA method. The high delay is caused by low computing power of microcontroller used for implementation. If better microcontroller is used, the time to readjustment will be approximately 150s instead of actual 2000s.

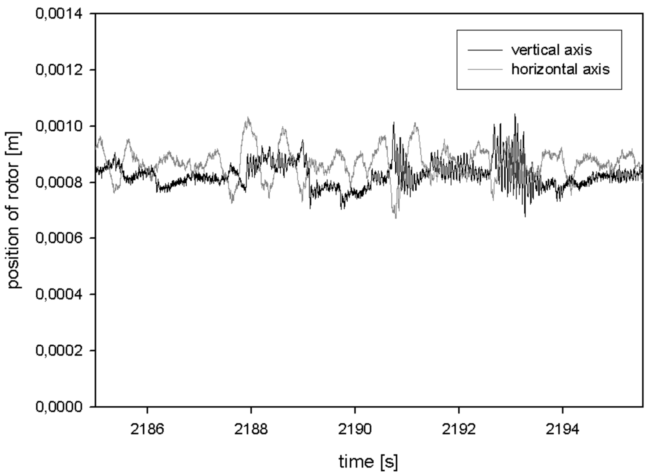

Figure 9: Behavior of AMB after adjusting to changed parameters

5. Conclusion

The analytically designed controller is capable of control of AMB, but its performance is poor. It is caused by inexact model used to control design. Improvement of model is needed to improve quality of analytically designed controller, but it cannot be done easily. Much easier is an adjustment of controller parameter values by CARLA method. It optimizes controller parameter values according to real behavior of AMB and type of loading. Advantage of this approach is CARLA method can be connected and learning whole time the controller is running. So it adjusts parameter values according to variations of type of loading.

6. Acknowledgement

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7. Literature

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[2] Howell, M. N., Frost, G. P., Gordon, T. J.,Wu, Q. H. (1997) Continuous action reinforcement learning applied to vehicle suspension control. Mechatronics, 7(3), 263 -276.