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Vibration Reduction of a Magnetically Supported Rotor Using Heuristic Optimization Method

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Abstract: A heuristic optimization method is applied to reduce the vibration amplitude of a rotor system magnetically supported. The rotor system is supported by two Active Magnetic Bearings (AMB) that are operated by commonly used PID controllers. Applying the Ant Colony Optimization (ACO) method, the control parameters of both AMBs are optimized for minimizing the rotor vibrations during the run-up. The necessary steps needed to develop an ACO algorithm are described and the factors that influence the PID control parameters are discussed. Numerical simulations were performed to demonstrate the applicability and efficiency of the proposed procedure.

Key words: Active magnetic bearing, unbalance, multi-criteria optimization, PID controller, vibration reduction, heuristic optimization

INTRODUCTION

Active Magnetic Bearings (AMBs) are versatile mechanical electrical system used in many industrial applications such as compressors, turbines, pumps, motors and generators. In addition to vibration control and levitation functions, magnetic bearings can be used to fulfill other functions, such as monitoring, auto-tuning, parameter identification, fault detection and operational tolerance as presented in Schweitzer and Maslen (2009) and Dohnal and Markert (2011). The active magnetic bearings allow and contribute to the rotation of the tribological pair (bearings-shaft) without contact between their surfaces. These bearings can be used in association with fluid dynamic bearings according to theme chanical forces related to the industrial applications. In that kind of bearings, the support is promoted by electromagnetic forces to hold up the shaft. Some of the advantages of the active magnetic bearings include reduced loss load and low power consumption, characteristics which increase the lifetime due to no contact between rotor and stator. Other advantages are related to the operational conditions there is no wear of the components and reduced heat generation. The rotating speed is higher when compared to hydro dynamic or hydrostatic bearings which present loss of efficiency due to the friction generated by oil shear.

The AMBs can operate as active control system vibration in a mechanical assembly, fitting the shaft deviations in relation to bearing center. The real load capacity of a magnetic bearing is obtained in function of the gap between the rotor and the stator and considering the effects of loss of electric current. A magnetic bearing system presents the following basic components: magnetic actuators, PID controller, frequency filter, power amplifier and shaft position sensor.

The magnetic field promotes the support for the shaft inside of the journal. During the operational conditions the rotor is subject to external forces that can displace it from its initial position. In this case, a proximity sensor can be used to measure the displacement and to send a signal to the controller that it will determine the adequate electric current to the actuator in order to generate a magnetic force bringing the shaft to its initial position. In this way, on each axis of the coordinate system there must be assembled 2 actuators opposite in the diameter to guarantee the shaft position control.

PID controller considerations: A PID-controller combines proportional, integral and derivative actions generating a control output, taking advantage of the unique characteristics of each action in order to obtain a significant improvement of the transient state, as well as the improvement of the steady state behavior of the

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controlled system (Zhong, 2006). The controller output of a classical continuous PID-controller is simply the sum of these three actions resulting from the dynamics of the control error given by Eq. 1:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \tag{1}$$

The corresponding transfer function in the continuous Laplace domain is given by Eq. 2:

$$G_{PID}(s) = \frac{u(s)}{r(s)} = K_p + \frac{K_i}{s} + K_d s \tag{2}$$

This continuous controller is transferred into the discrete z-domain for experimental realization and into the following numerical studies. Each control action of a PID controller serves a specific purpose which is classified as:

The proportional action K_p applies a correction directly proportional to the control error, i.e., it is the difference between the actual and desired value. The integral action K_i provides a proportional correction to both the magnitude of the error and the duration of the error. This action compensates small errors that persist for a long time and require a more intense correction than that provided only by the proportional action. A properly designed integral action guarantees the accuracy of the system by eliminating a steady state error and avoids controller windup.

The derivative action K_d is proportional to the change rate of the control error. This action increases the response speed and enables a fast adaptation to changes in the control error. It introduces, also damping in the control loop however, a strong derivative action increases the system's sensitivity with respect to noise and inevitably destabilises the rotor-bearing-system. The configuration of a PID controller is illustrated in Fig. 1.

Multi-criteria optimization method: Heuristic algorithms: Algorithms used to solve the optimization problems can be classified as deterministic and probabilistic. The deterministic optimization includes

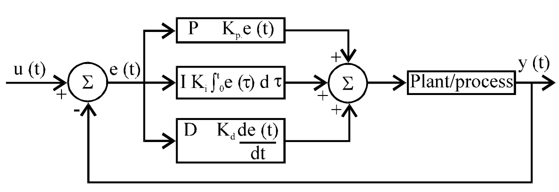

Fig. 1: Configuration of PID controller

mathematical programmed methods where it is obtained derivatives or their approximations to a studied function or functions in this last case multi-objective optimization. The stochastic optimization involves iterative procedures that consider probability elements.

According to Albuquerque, the mathematical programmed methods present some difficulties in relation to: discrete variables manipulation, identification of the optimum global solution (strongly dependent on the initial values) and to operate with non-differentiable functions. Thus, in the deterministic optimization, the objective function must be continuous and differentiable in the search space. The deterministic optimization is used in several problems in engineering. Considering problems of mechanical design, the stochastic approach using multi-criteria optimization (Paretos frontier) can provide a set of the viable solutions that satisfies to different design constraints inside of a design space.

The preliminary design and experimental validation are important steps of the mechanical design. They are used to calculate the values of the set of parameters that describe the equipment, machine or/and components. The application of optimization methods in phases of preliminary design and experimental validation leads to the improvement of the performance considering, as example, the reduction or elimination of technical contradictions, reduced weight, volume, vibration amplitudes and costs.

In recent years there has been a fast development in numerical multi-objective optimization methods based on Pareto frontier (multi-criteria optimization). This frontier provides boundaries for the optimum set of values obtained by multi-criteria optimization methods. The multi-criteria method satisfies numerically a group of objective functions that will provide optimal sets of values to minimize/maximize the objective function. There are two basic properties to be considered for developing a numerical multi-objective optimization:

- The runtime of the algorithm should be feasible
- The problem to be optimized must have an exact or at least approximate solution in all cases

A possible approach to multi-criteria optimization methods is the use of heuristics. Heuristic algorithms allow finding approximate solutions but in many cases do not ensure the choice of best solution. An approximation algorithm is heuristic, i.e., uses expert knowledge and intuition about the instance of the problem and structure to resolve it as fast as possible. Heuristic methods can be classified according to the following groups:

- Construction heuristics, such as greedy method which are those where one or more solutions are constructed element by element, following some heuristic optimization criterion, until the problem have a viable solution (Jalali *et al*., 2011)
- Neighborhood search heuristics, such as local search which necessarily start from an initial feasible solution (in some cases may be any possible solution), trying to improve this solution through exchange operations, removal or insertion until is no longer possible to improve or some other stopping criterion is satisfied (Gendreau *et al*., 2006)
- Systematic heuristics, such as limited discrepancy search (Korf, 1996) or controlled backtracking (King and Chen, 2005) where the space of feasible solutions is traversed using criteria branching and reduced bad variables
- Hybrid heuristics represent heuristics resulting from the combination of 2 or more heuristics with different strategies (Sakellariou and Zhao, 2004)
- Metaheuristcs are generic heuristics more sophisticated where a simple heuristic is managed by a procedure that aims to intelligently explore the instance of the problem and its solution space (Blum and Roli, 2003). An example of, this kind of optimization is the ant colony method, based on heuristic based on probabilities, created to solve problems involving choice of paths in graphs. It was created by Dorigo (1992), inspired by the observation of the behavior of ants when they leave their colony to find food

MATERIALS AND METHODS

In the present study, the ant colony method is applied to investigate the applicability of metaheuristics in vibration problems. According to Dorigo and Blum (2005), the use of ant colony optimization method allows the choice of the design parameters set, based on design constraints, greatly reducing the computational cost for finding an optimal solution.

The idea of ant colony algorithm is to mimic the behavior of ants through a cloud of virtual points that walk between the variables of the problem until obtaining the best solution. The ant colony can vary constantly and adapt to changes in real time. The pheromone trail (artificial) changes dynamically during the execution of the program to reflect the experience gained during the search (Karaboga, 2005; Karaboga and Akay, 2009).

Upon leaving the colony, the ants initially course without a preferred direction until they find food and return leaving a trail of pheromone. If other ants find the trail they tend to follow the trail found, reinforcing the existing pheromone on it. Over time, the pheromone of the shorter tracks tends to increase due to the increasing number of ants that pass through it while the worst tracks tend to disappear by the evaporation of pheromone. Evaporation of the pheromone, also has the advantage of avoiding the convergence to a locally optimal solution otherwise, all tracks initially chosen would be excessively attractive, limiting the search space.

Heuristic of the ant colony optimization: Initially, each ant is randomly placed in a different variable. Starting with a variable i, the ant moves choosing probabilistically the j neighboring variable (between the variables of the problem feasible). The probability that ant k is in the variable i to select the variable j, it is given by:

$$p_{ij}^{k}(t) = \left\{ \frac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}}{\sum_{i \in N_i^k}\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}} \right\} \quad (3)$$
$$\text{If } j \in N_i^k \;\; 0 \quad \text{otherwise}$$

In the pheromone τ_{ij} associated with the edge (i, j) 2 events occur. Evaporation (this prevents that the accumulated pheromone grows indefinitely and enables forgetting bad paths during past searches). Deposit of pheromone of all of the ants that went over (i, j). After all ants have built their route, the pheromone is updated according to Eq. 4:

$$\tau_{ij}(t+1) = \underbrace{(1-\rho)\tau_{ij}(t)}_{\text{evaporation}} + \underbrace{\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t)}_{\text{deposit}} \quad (4)$$

The value of the deposit of each ant, $\Delta\tau^{k}_{ij}$ is defined by condition explicated by Eq. 5:

$$\Delta\tau_{ij}^{k} = \left\{ \begin{matrix} Q / L_k \\ 0 \end{matrix} \right\} \text{if the edge}(i, j)\text{belongs} \quad (5)$$
$$\text{to the route, otherwise}$$

A flow chart of the operation of the ACO is shown in Fig. 2. The outlined optimization procedure was applied to a rotor system operated in the lab of the Institute of Structural Dynamics at the TU Darmstadt which is displayed in Fig. 3 (for more details, Dohnal and Markert, 2011). Each AMB acts radially on the rotor with two decentralized PID controllers providing 2 independent control actions in 2 perpendicular directions. In total, the system is operated by 4 PID controllers. One control loop is depicted in Fig. 4.

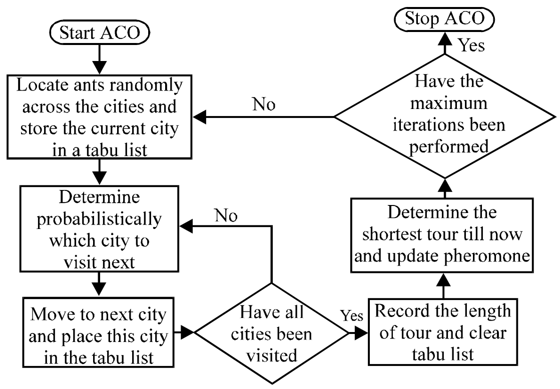

Fig. 2: Ant colony optimization flowchart

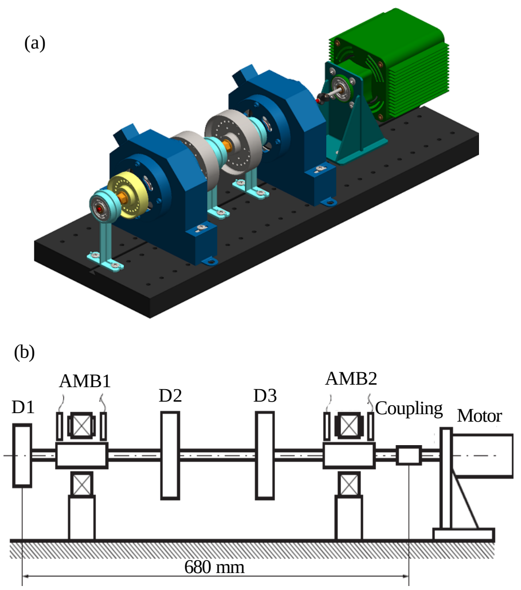

Fig. 3: Rotor system supported by two AMBs: Simplified sketch (left), detailed arrangement (right): Rigid discs D1-D3, AMB 1 and 2 with proximity sensors, rigid rotor studs within AMBs, flexible rotor shaft, coupling and motor

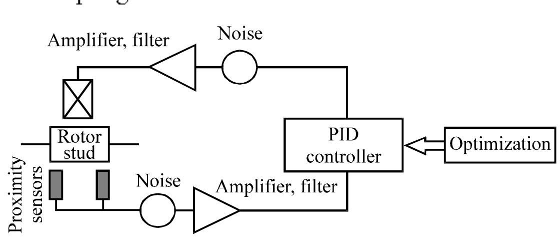

Fig. 4: Schematic of decentralized PID control in each bearing

RESULTS AND DISCUSSION

The optimization objective is minimizing the rotor vibration caused by unbalance excitation at the discs positions D1-D3 in Fig. 3. A real AMB control loop experiences always some level of noise, depending on the operation conditions, the hardware and the environmental conditions. Therefore, additive noise is introduced in the numerical model according to Fig. 4. The optimization is performed for different noise levels in order to benchmark the robustness of the optimum values found.

About 2 different optimization scenarios are considered. In the first scenario, the characteristics of both AMBs are forced to be equal and the parameters of all PID controllers are identical. In the second scenario, each AMB possesses its own characteristic allowing 2 independent sets of PID control parameters. In both cases, the performance of each AMB is kept isotropic. The initial and the optimum vibration response for a constantly accelerated run-up of the rotor system from 0-5000 rpm are shown in Fig. 5. The radial displacements of all the disks and 2 rotor studs AMB1 and AMB2 are overlaid. In the present study, the upper envelope of all vibration responses is minimized within the shown rotor speed range. Therefore, it is not important which component is producing the vibration amplitude. The initial set of optimal values was obtained experimentally by applying the ISO Standard 14839-3 (2005) which is based on the measurement of a sensitivity gain.

The heuristic ant colony optimization was applied for two competing aims: Reducing the vibration envelope as well as reducing the noise sensitivity. Table 1 lists the initial values resulting from the ISO standard and the optimal values found by the optimization process considering PID controllers with equal or independent control settings. As can be seen in Fig. 5, different values for the PID controllers are more efficient for the overall vibration reduction of the present rotor-bearing system. The criterion considered for optimization was the reduction of the area under the envelope, being this reduction considered as a reduction of the total vibration of the system. Figure 6 shows where the maximum amplitude point of the system occurs and the area colorized, presented in Table 1, under the envelope for construction.

The considered area is not the real area of the polygon shown. This area was calculated by summing the points of radial displacement at each frequency calculated by the program. The peak shown in Fig. 6 is the point where occurs the maximum amplitude of the system and this peak multiplied by the area is the function to be minimized by the optimization program. Table 1 shows the statistical values for each case considered of PID controllers. The values obtained by the optimization process for the PID controllers, considering thesystem without noise have been tested with 10, 20 and 30% of simulated noise levels, not detecting instability points of the system. This result can be seen in Fig. 7.

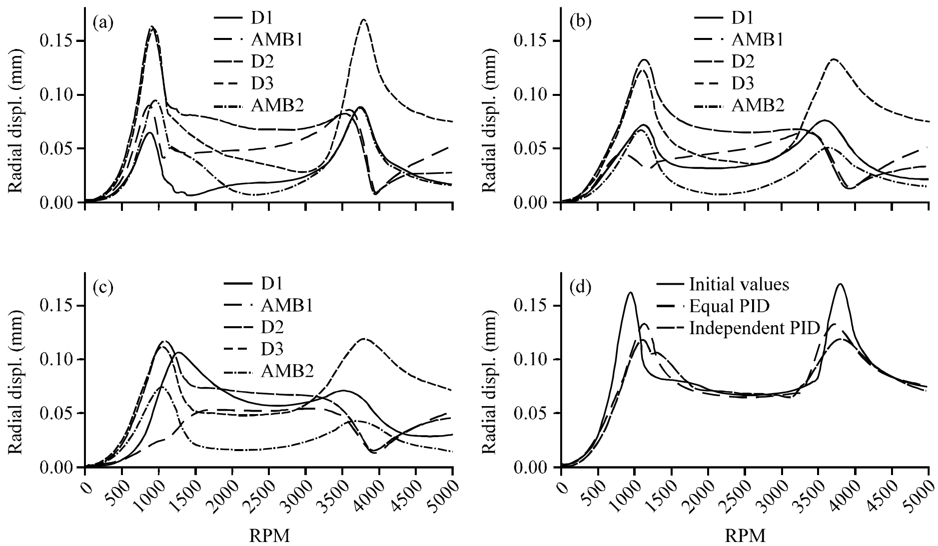

Fig. 5: Radial rotor displacements for initial and optimal PID controllers without noise: a) Initial values (ISO standard); b) Optimized for equal PID controllers; c) Optimized for independant PID controller; d) Comperison of viberation envelopes

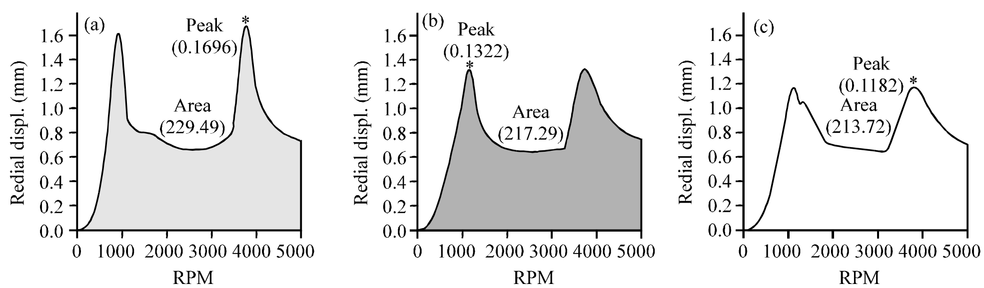

Fig. 6: Maximum amplitude and area under the curves: a) Initial values (ISO standard); b) Optimized for equal PID controllers; c) Optimized for independant PID controller; * Viberation envelope

Table 1: PID values and statistics

Stastistics	P1	I1	D1	P2	I2	D2	Vibration reduction (%)	Maximum peak reduction (%)
Initial	3000	1500	3.0	3000	1500	3.0	-	-
Equal	2874	3818	5.9	2874	3818	5.9	5	22
Different	3955	2616	8.9	2820	2899	5.0	7	30

The test of the values obtained, considering the noise of the system, is necessary to ensure that the values found in the optimization process are not close to the instability of the system. If any of the values of the PID controller is near of the stable/unstable limit, any disturbance in the system would cause serious damage to the equipment.

A heuristic optimization is an effective tool for finding lower levels of vibration amplitudes. Performing the outlined procedure, it can be obtained a reduction of up to 30% in the oscillation amplitude. This reduction minimizes the noise of the bearings and reduces failures and fatigue of the system. The main problem of the heuristic optimization methods is the convergence time which can be high. Those methods use search strategies for optimal sets of parameters based on pareto frontier.

The ant colony optimization proved to be a great method for finding the best values for the PID controllers. This method presents low time for convergence if compared the complexity of the simulated system, the expended time of each integration process and the range of the possible variables.

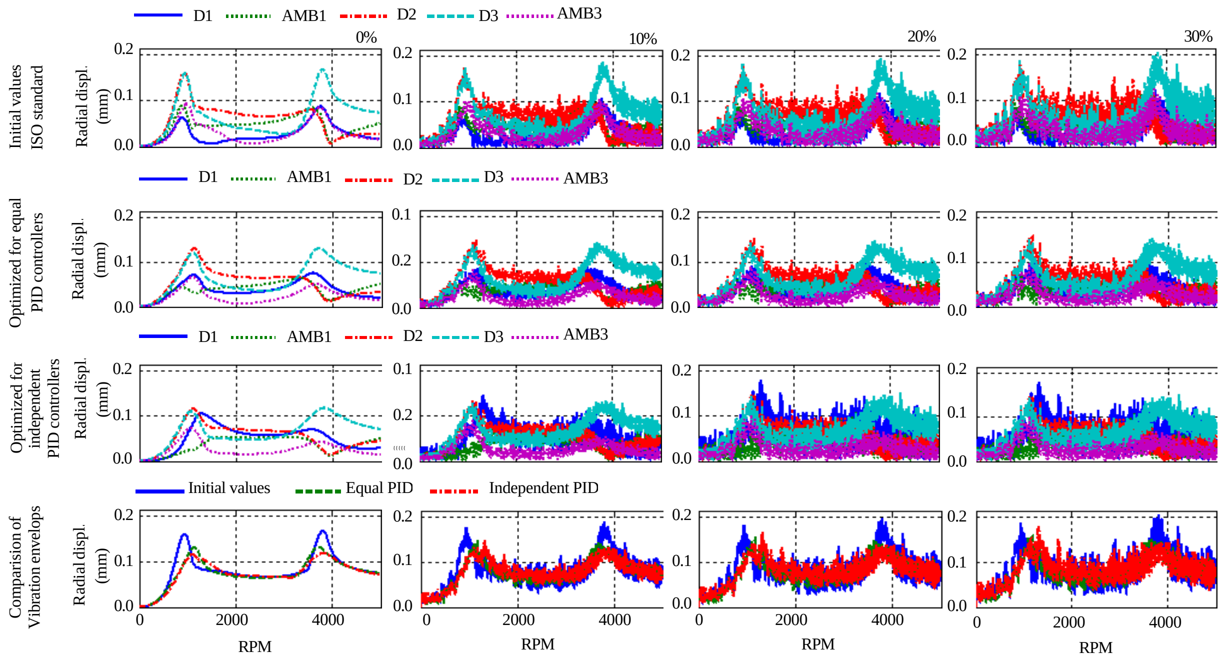

Fig. 7: System with different noise levels

CONCLUSION

In this research, it is proposed to minimize the vibration caused by unbalanced excitation by tuning the control parameters of the magnetic bearings. Different methods are used for finding the optimal values of PID controllers commonly implemented. An adjust procedure of a single PD controller based on experimental data is outlined in Buttini *et al*. (2011). In the present study, a heuristic method is applied for optimizing the values chosen for the PID controllers implemented in AMBs which provide the necessary stability to the system.

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NOMENCLATURE

K = Proportional gain (proportional action)
L_k = Path length covered by ant k after completing the course
N_i^k = Group of variables feasible and not visited by the ant k
Q = Amount of pheromone secreted by an ant at each iteration step
Td = Derivative time (derivative action)
Ti = Integration time (integral action)
α = Parameter for determining the influence of the Pheromone and heuristic information
β = Parameter for determining the influence of the Pheromone and heuristic information
$\tau_{ij}(t)$ = Amount of pheromone present in the path (i, j)
η_{ij} = Inverse of the cost function of the variables and represents the attractiveness that the ant will have to visit the variable j after visiting the variable i
ρ = Evaporation rate of pheromone
$\Delta\tau_{ij}^k$ = Amount of pheromone that the ant k deposited on the edge (i, j)

Subscripts:
i, j = City
k = Current ant

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