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BAYESIAN CONTROL OF A HELICOPTER MAIN GEARBOX SEMI-ACTIVE SUSPENSION SYSTEM - EXPERIMENTS ON A QUARTER-SUSPENSION PROTOTYPE

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ABSTRACT

This short paper considers the control of a helicopter gearbox semi-active suspension. As the future generation of helicopters will include variable engine RPM during flight, it is interesting to consider implementing control on their suspension systems in order to always optimally filter the main disturbance frequency. Here, a semi-active suspension based on the DAVI principle is developed, simulated and tested with its control algorithm based on Bayesian optimization. This control method based on the Bayes theorem is a trial/error algorithm allows to significantly reduce the number of evaluations of the real objective function for a given set of parameters θ . Thus the system is capable to fastly determine its own optimal set of parameters to maximize the objective function. The objective is to prove experimentally the ability of the Bayesian optimization to lead the learning behavior of a semi-active resonant suspension.

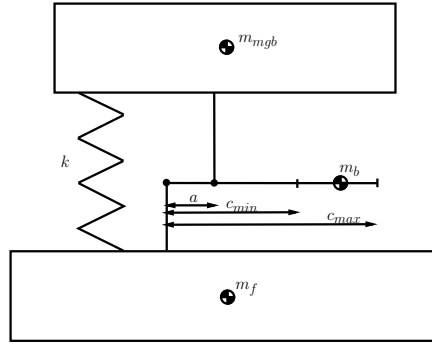


Figure 1: semi active DAVI principle adapted to helicopter, m_{mgb} : main gearbox and rotor, m_f : fuselage, m_b : flapping mass.

1 INTRODUCTION

Fuselage vibrations are a major problem in the design of helicopters. This paper will focus on the development of a new active hybrid vibration absorber which reduces the effects of the cyclic loads ($n\Omega$ harmonics) on the helicopter structure due to the main rotor.

2 THE SEMI-ACTIVE DAVI

In 1976, Flannelly [1] presents an anti-resonant vibration absorber called DAVI which uses a rigid arm carrying a flapping mass. The inertia of the bobweight mass generates an anti-resonance at the characteristic frequency ω_c depending on some parameters : dynamic amplification, overall stiffness and flapping mass. Airbus Helicopters company developed during the 1990's the SARIB[®] suspension, a DAVI suspension integrated in the helicopter between the MGB and the structure tuned to be as close as possible to the $b\Omega$ frequency (b number of blades and Ω the rotor speed).

With the arrival of variable engine RPM during flight, it is relevant to integrate some actuation in a DAVI system in order to be able "track" the $b\Omega$ frequency and adapt the steady state parameters of the suspension to the varying frequency of the disturbing input force. One can control the DAVI dynamic amplification ratio by modifying the position of the bobweight mass on its flapping arm as in figure 1 where m_f represents the helicopter structure, m_b is the flapping mass, m_{mgb} the main gearbox and rotor and k is the overall suspension stiffness. The dynamic amplification ratio λ is defined as c/a and has a direct influence on the anti-resonance frequency ω_c :

$$\omega_c^2 = \frac{k}{-\lambda(\lambda - 1)m_b} \quad (1)$$

Figure 2 shows the transmissibility H of the DAVI suspension for different values of λ . It is clearly visible that a suitable control of the variable c (position of the flapping mass) can modify in flight the anti-resonance frequency.

3 THE BAYESIAN OPTIMIZATION

The Bayesian optimization [2] [3] is used for computing the maximum of expensive cost functions. It is applicable when the estimation of the objective function for a particular case of x_i is costly and possibly noisy. The ability of the algorithm to significantly reduce the number of function evaluations before reaching the optimum value is due to the incorporation of the

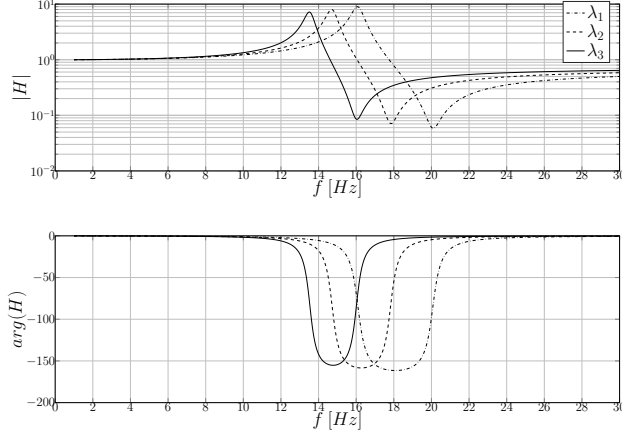


Figure 2: Transmissibility $H(f)$ of the DAVI suspension for different values of λ .

prior belief. This prior knowledge is used to determine the new input vector x_i which will be evaluated by making a trade off between exploitation (use of prior data) and exploration of the search space. At each cost function evaluation, the algorithm computes an estimation of the function $f(x)$ for the complete search space Π ($x \in \Pi$).

From the prior knowledge of the cost function is computed the posterior distribution which represents the updated beliefs about $f(x)$. Then, the Bayesian optimization uses an acquisition function to determine the next input vector x_{i+1} and measure the process response $f(x_{i+1})$.

The objective here is to adapt the dynamic amplification ratio λ i.e. the position c of the bobweight mass on the flapping arm for every solicitation frequency $\omega_0 \in [\omega_c(c_{max}); \omega_c(c_{min})]$. The input parameter x represents here the position c of the bobweight mass and the cost function $f(x)$ is mostly characterized by the acceleration level of the fuselage.

The strong assumption of the Bayesian optimization is that it is possible to consider the function $f(x)$ as a GP (Gaussian Process). For every input vector x , the GP will return the mean m and the covariance k of a normal distribution over the possible values of $f(x)$ as it follows :

$$f(x) \sim GP(m(x), k(x, x')) \quad (2)$$

In the Bayesian method, the choice of the covariance function is very important as it determines the smoothness properties of the estimation of $f(x)$. This smoothness is generally controlled by one or more hyperparameters θ . A wide variety of covariance functions has been investigated in litterature, as in [4] we propose to use the Matern 5/2 kernel. To determine the hyperparameters of this statistical model, the ARD (Automatic Relevance Determination) method has been applied. The table 1 summarizes the main steps of the Bayesian optimization with Auto Relevance Determination method described just before.

Bayesian optimization of $f(x)$	
While	<i>optimize</i> do
1	Prior knowledge available $\mathcal{D}_{1:i} = \{\mathbf{x}_{1:i}, \mathbf{f}_{1:i}\}$
2	Auto Relevance Determination of $\theta_{opt}(i)$ using gradient method
3	Computation of μ and σ^2
4	Computation of the acquisition function $EI(x)$ on the search space Π
5	Maximization of $EI(x)$ and so determination of x_{i+1}
6	Evaluation $f(x_{i+1})$
7	$i = i + 1$ and go to step 1

Table 1: Overview of the Bayesian optimization with ARD.

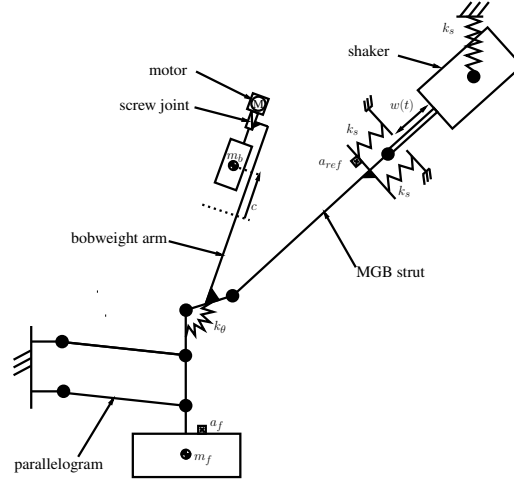


Figure 3: Test setup scheme.

4 EXPERIMENTS

As explained previously, the system we control here with the Bayesian optimization is the semi-active SARIB[®] from Airbus Helicopters. The test setup represents an isolated MGB strut linked to a semi-active DAVI bobweight arm. The figure 3 represents a diagram of the test bench (no pictures allowed due to Airbus confidentiality policy), one can notice that the flapper arm is linked by a fitting to a mass m_f representing the helicopter structure. In order to keep all movements in a plane, a mechanical parallelogram is added to the experimental set-up.

Three different learning sequences have been used to teach the program. We define a learning sequence as the order of appearance of every frequency ω within the antiresonance bandwidth of the semi-active DAVI $[\omega_c(c_{max}); \omega_c(c_{min})]$.

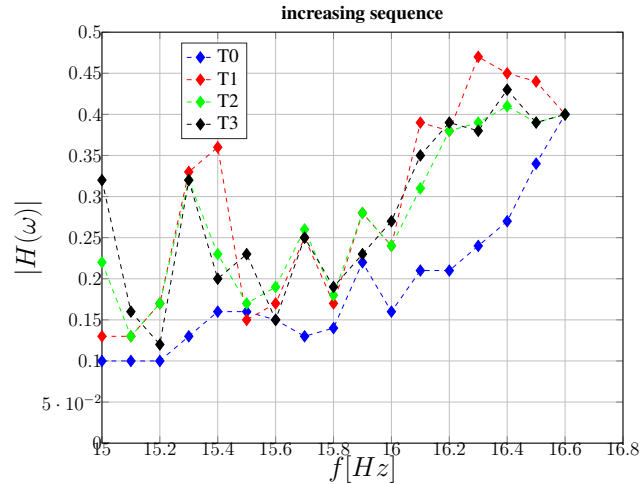


Figure 4: Increasing sequence - suspension transmissibility.

The real optimal positions $c_{ref}(\omega) \forall \omega \in \Pi$ are also computed to set a reference vector $d0$. As a result (see 4 and 5), the Bayesian optimization always finds a solution acceptable for the mass position giving a transmissibility around 0.45 for the worst results and 0.1 for the best ones. In addition to the Bayesian optimization, it has been added a learning method to keep in a database the "good" positions tested for each frequency. The objective is to reduce the number of iterations necessary to the algorithm to find the optimal position.

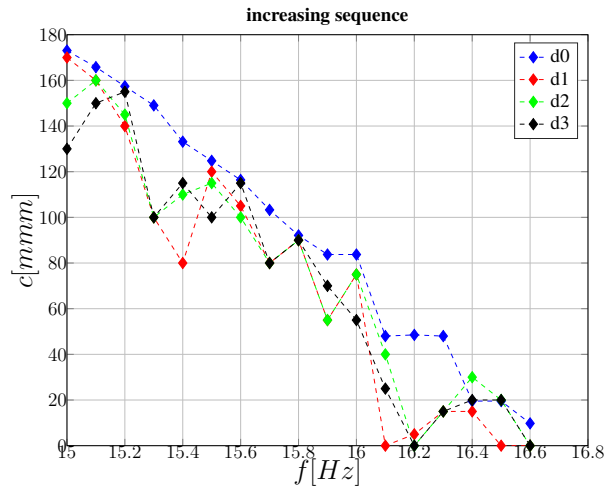


Figure 5: Increasing sequence - mass position.

5 CONCLUSION AND PROSPECTS

The main difficulties encountered during the development of the control algorithm were to deal with the resonant behavior of the DAVI. Controlling a dynamic system near its anti-resonance or resonance frequency implies fast and unstable phase changes which makes harder having a clean and fine tuning. The fact that this optimization technique is based on a stochastic, not deterministic model which is updated using prior knowledge on every measurement made, presents a strong advantage in comparison to other semi-active control methods. There is no need of a complex mathematical model of the system or prior identification.

Good results were achieved in terms of vibration isolation : a suspension transmissibility going from 0.1 to 0.41 and no absurd final mass position c were observed in spite of the system noise. The learning sequence order demonstrated to have a limited impact on the final results.

As a conclusion, control adaptivity, learning methods and auto-tuning of control parameters even without particular mathematical model of the system or prior assumptions are the current keys for the future evolutions of the dynamics control field.

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