Experimental design for Vibration Analysis on agricultural Spraying Machines

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Abstract

To investigate the effects of boom vibrations on spray liquid distribution, mathematical models of the sprayer's mechanics are constructed. This work deals with the design of the experimental testing step in order to obtain as good data records as possible for identification purpose. Different types of excitation signals i.e. swept sine, multi sine and periodic noise, have been experienced on a laboratory test set-up to design the experiment so that the experiment is maximally informative. Black box identification procedures in the time and frequency domain are compared. For the time domain, an 8-6-order output error (OE) model seemed to be sufficient. Accurate model predictions have been achieved, which is indicated by small normalised root mean square error (nrmse) values. Optimised excitation signals as multi sine and swept sine, used together with the non-linear least squares black box frequency domain identification method result as well in a nice estimation of the frequency response function.

1. Introduction

In agriculture, chemical crop protection is mainly done by means of liquids, which are up to now dispersed with spraying machines of which the boom width's reaches up to 36 meters. The efficiency of any spray application is mostly controlled by the homogeneity of the droplet deposition and the uniform spray covering on the canopy [1]. Non-uniformity of application across the swath has been shown to have a significant effect on weed and disease control [2].

In practice, uneven doses are the result of wind effects and unwanted sprayer boom vibrations. Simulations demonstrate variations in spray deposit between 0 % and 1000 % for the vertical boom vibrations and between 20 % and 600 % for the horizontal ones [3].

To investigate the effects of boom vibrations on spray liquid distribution, mathematical models of the sprayer's mechanics are constructed. Next, the models, describing the mechanical behaviour of the sprayer booms, are applied to simulate vibrating boom amplitudes in operating conditions. Combination of the sprayer boom motions with hydraulic liquid distribution models provides information about the uniformity of spray deposits.

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2. Description of test set-up

Figure1 shows an outline of the test set-up to be identified. The laboratory experiment consists of a shaking table formed by level 1 and 2 (2 degrees of freedom, translation and rotation) and 2 actuators (hydraulic cylinders), and the spray boom mounted on a horizontal suspension presented by level 3 and 4 (2 DOF). The two hydraulic cylinders simulate yawing and jolting of the tractor. A flexible beam of 12 m long with properly chosen dimensions represents a large spray boom. The rotation DOF of the boom was fixed during the experiments.

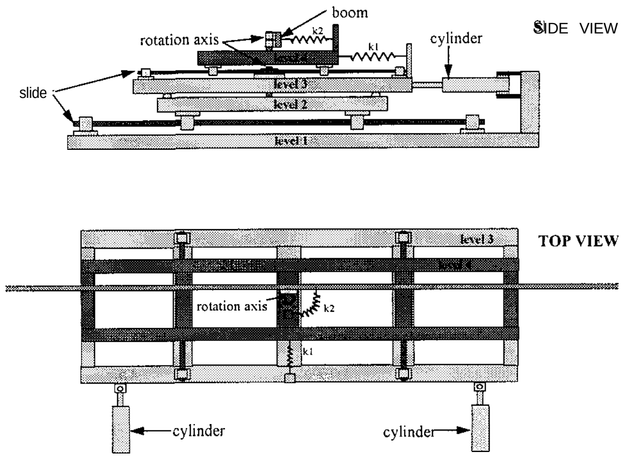

Figure1 : Schematic representation of test set-up.

The input signals are measured with LVDT type position sensors, placed on the cylinders to measure the relative displacements of the platform to the table. Even the input accelerations are recorded. Velocity responses of the sprayer boom tips are measured with a laser and the accelerations with an accelerometer mounted at the end of the boom. The same reference signal was sent to both actuators so that only translational rigid body modes were excited.

3. Excitation signals

In common linear model testing, a variety of excitation techniques are used, each of which have their typical advantages and disadvantages. For linear systems, the measured frequency response functions should be independent of the type of excitation signal used in the ideal case. However, a few general rules should be taken into account: sufficient energy should be injected into the structure to get a good signal to noise ratio and measurement errors like noise, leakage, aliasing should be avoided as much as possible.

Since the complex structure may contain some local non-linearities, especially in the different joints connecting two spray boom sections, great care must be taken during experimental testing. Attention has paid on the excitation of the structure, because the aim is to find the best possible linear estimate for the non-linear behaviour. Different types of input signals are practised, going from random noise to periodic harmonic signals (swept sine and multi sine) in order to comply the aim of the test.

Excitation signals need to be compressed to improve the S/N ratio of the measurements. The crest factor is defined as the ratio of the peak value over the effective RMS value of the signal [4]. A minimum crest factor enables to inject as much energy as possible, and the capability of creating customised amplitude spectra to get a constant S/N ratio. The measurement uncertainty will be maximum at frequencies with minimum S/N ratios. The time factor is proportional to the measurement time required for a minimal specified accuracy at all frequency points of interest [5].

The input and output signals are sampled at 100 Hz. To avoid aliasing, hardware S-order low pass Butterworth filters are used with a cut off frequency of 10 Hz.

3.1 Periodic noise

Periodic noise is defined as a noise sequence, which is periodically repeated until the transients are damped out, at which point a measurement is made. Next a new random noise sequence is generated and the procedure is repeated until sufficient measurements are collected.

The noise sequence consists of 2048 points with a frequency range between 0.1 - 5 Hz and is sent out at a frequency of 100 Hz. Ten measurement periods are taken.

3.2 Swept sine

To reduce measurement time, special compressed signals can be used such as swept sines and multi sines [5].

A swept sine (1) excitation consists of a sine sweep test, where the frequency is swept up into one measurement period, 2048 points with frequency range between 0.1 - 5 Hz and this is repeated 10 times, so that a periodic signal is created.

$$X(t) = \sin[(at + b)t] \quad 0 \leq t \leq T \qquad (1)$$

with:

- T: measurement period
- a: $\pi(f_2 - f_1)/T$
- b: $2\pi f_1$
- f_1, f2: lowest and highest frequencies respectively

3.3 Multi sine

A multi sine (2) is the sum of a number of harmonically related sinusoids with programmable amplitudes. The phases of the frequency components can be changed to reduce the crest factor of the signal. This means that at every time instant, a mixture of frequencies excites the system. The multi sine also consists of 2048 points with a frequency content between 0.1-5 Hz.

$$x(t) = \sum_{k=1}^{N} A_k \cos(2\pi f_k t + \phi_k) \qquad (2)$$

with:

$f_k = \frac{l_k}{T}$: 1_k : a positive integer; T : the measurement period

A_k : amplitude of the kth component

4. Black box identification

First an estimation of the transfer function (FRF) is performed on the different data. The errors-in-variables estimator $\hat{H}_{EV}$, one of the methods discussed in [6], is selected to calculate the FRF and is defined as follows:

$$\hat{H}_{EV}(k) = \frac{\frac{1}{M}\sum_{i=1}^{M} Y_i(k)}{\frac{1}{M}\sum_{i=1}^{M} U_i(k)} \qquad (3)$$

with:

M: number of excitation periods
k: index of the frequency line

This estimator corresponds with the maximum likelihood estimator if the input and output perturbations are complex and normal distributed. In addition, the estimator (3) is unbiased and asymptotically efficient which means that if the number of measurement periods goes to infinity, the estimate converges to the real FRF with a normal distributed probability density function and with a variance equal to the Cramer-Rao bound.

Figure 2 shows the non-parametric transfer function estimates for the 3 excitation signals. The displacements of the actuators serve as input, while the velocity responses on the boom tip were taken for output. Differences could be remarked, especially for the random excitation. Figure 3 depicts the corresponding coherence functions. In the dominant frequency range, the coherence values amount to above 0.9, which is an indication of a rather linear behaviour. However, the multi sine shows a great dip in the frequency band of 2.5-3 Hz.

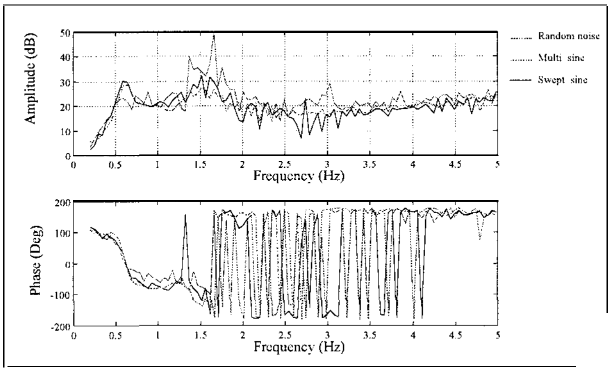

Figure 2: Transfer function between actuator displacements and boom tip velocity.

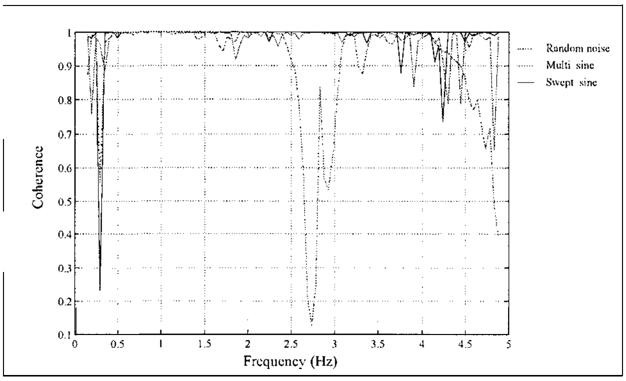

Figure 3 : Coherence function

4.1 Time domain identification

Time domain identification considers the time domain description of time-invariant finite order lumped linear dynamic systems and attempts to estimate the parameters of time domain models using finite time domain data records of the system's input and output. In practice of time domain identification, we almost exclusively deal with observations of inputs and outputs at discrete times. The general discrete model is given in (4):

$$y(t) = G(q,\theta)u(t) + H(q,\theta)e(t) \qquad (4)$$

with:

- y(t), u(t): output and input vector
- G(q,θ): transfer function of linear system
- H(q,θ): transfer function of disturbance
- e(t): sequence of independent random variables with a certain density function
- θ: parameter vector

Two types of models are described according to the different parametrizations of G(q) and H(q). First an output error (OE) model structure is proposed written as (5):

$$y(t) = \frac{B(q,\theta)}{F(q,\theta)} u(t) + e(t) \tag{5}$$

The disturbance consists of white measurement noise, and the relation between input and undisturbed output can be written as a linear difference equation. A natural development of the output model structure is to further model the properties of the output error. This yields the Box-Jenkins (BJ) model structure (6).

$$y(t) = \frac{B(q,\theta)}{F(q,\theta)} u(t) + \frac{C(q,\theta)}{D(q,\theta)} e(t) \tag{6}$$

Now, the search for the best model within the set becomes a problem of estimating θ. The parameter vector θ is estimated by minimising the prediction errors (PEM). An appropriate identification method is the Gaussian MLE method.

For these model structures, the quadratic minimisation criterion is not quadratic in the parameter vector θ. As a result, analytical methods can not be applied. The solution has to be found by non-linear least squares methods. Finding the minimum of the prediction error criterion requires itterative numerical techniques as the Gauss-Newton or Levenberg-Marquardt methods [7].

Time domain identification has been performed on the time data records. Eight measurement periods out of 10 were taken for identification and the last 2 periods served as validation set. A primitive ARX structure with varying model orders gave an indication of the best order of numerator and denumerator.

Next, an OE and BJ model structure have been identified. The best model sets are summarised in table 1. After a stabilisation check by examining the poles and zeros, a comparison is made between the amplitude and phase of the transfer function estimation and the measured FRF.

With the validation data set, simulations have been carried out. The model output has been compared with the measured response and the prediction errors or residuals have been studied on correlation. The normalised root mean square error (nrmse) (7) is calculated for each model and gives an indication of the models prediction capabilities.

$$nrmse = \sqrt{\frac{mean(E^2)}{std(y(t))}} \tag{7}$$

with: E: residuals
y(t): measured output data record

	Multi sine	Swept sine	Noise
OE	nb nf nk	nb nf nk	nb nf nk
	8 6 2	8 6 1	8 6 0
Nrmse	0.1722	0.0994	0.1944
BJ	nb nc nd nf nk	nb nc nd nf nk	nb nc nd nf nk
	8 6 6 8 0	8 6 6 8 0	8 6 6 8 0
Nrmse	0.3045	0.1345	0.0843
NLS-	D hiN loN	D hiN loN	D hiN loN
FDI	6 6 0 'd'	6 6 1 'c'	8 6 0 'c'
Nrmse	0.1747	0.1007	0.2703

Table 1: Best models for multi sine, swept sine and periodic noise excitation with corresponding normalised root mean square errors.

From table 1 can be concluded that the model orders of numerator and denumerator are the same for the different excitation signals. Only difference in delay can be found. As illustration, figures 4, 5 and table 2 represent the OE model obtained by swept sine excitation.

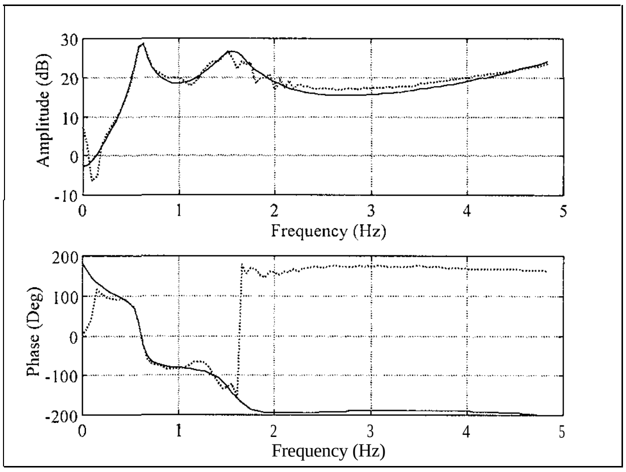

Figure 4: Comparison between amplitude and phase of the transfer function estimation (solid line) and the measured FRF (dashed line)

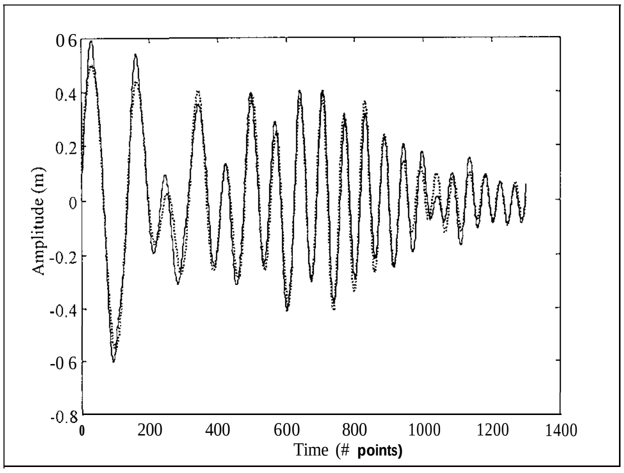

Figure 5: Simulated model output (solid line) and measured boom response (dashed line)

Poles	Zeros
-0.4578 ± 5.985 1 i	-5.383 1 +50.0000i
-0.1638 ± 1.5558i	7.1108
-0.0444 ± 0.60791	-1.2138 ± 1.59611
	0.7268
	0.1742
	- 1.4653

Table 2: Poles and zeros for OE model

4.2 Frequency domain identification

Frequency domain identification considers the transform domain description of systems and attemps to estimate the parameters of transfer functions from an estimate of the frequency response function of the system. The non-linear least squares estimator is used which tries to minimise the squared error between the measured FRF $G_m(k)$ and the estimate of the FRF represented by a parametric transfer function $G(\Omega_k, \theta)$ over N frequency lines (8).

$$V_{NLS} = \tfrac{1}{2}\sum_{k=1}^{N}\left|G_m(k) - G(\Omega_k, \theta)\right|^2 \qquad (8)$$

with:

$$G(\Omega_k, \theta) = \frac{B(\Omega_k, \theta)}{A(\Omega_k, \theta)} \qquad (9)$$

Ω_k frequency in continuous or discrete time

θ parameter vector

$A(\Omega_k, \theta)$, $B(\Omega_k, \theta)$ complex value at one particular frequency of the denominator respectively numerator for a given parameter vector

An iterative scheme based on Gauss-Newton and Levenberg-Marquardt searches the least squares solution. The linear least squares estimate serves as an initial guess for the iteration [7].

Contrary to time domain identification methods, frequency domain methods can be done in the Z-domain (discrete time) as well as in the Laplace domain (continuous time).

Table 1 summarises the non-linear least squares frequency domain identification (NLSFDI) results for the different excitation signals. The order of the denumerator (D) as the highest (hiN), respectively lowest (loN) order of the numerator are mentioned together with the normalised root mean square error of the simulations. Captions 'c' or ‘d’ refers to continuous respectively discrete time.

The nrmse- values are comparable with the time domain identification methods. Only the model orders are slightly different. The denumerator has 6th order now instead of 8th in the time domain. Figure 6 depicts the transfer function estimation, figure 7 compares model output versus measured data records and table 3 gives the poles/zeros for the swept sine data records.

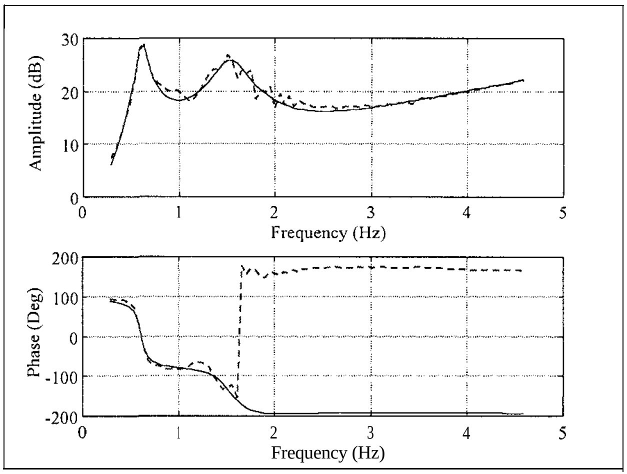

Figure 6: Comparison between the amplitudes and phases of the transfer function estimation (solid line) and the measured FRF (dashed line)

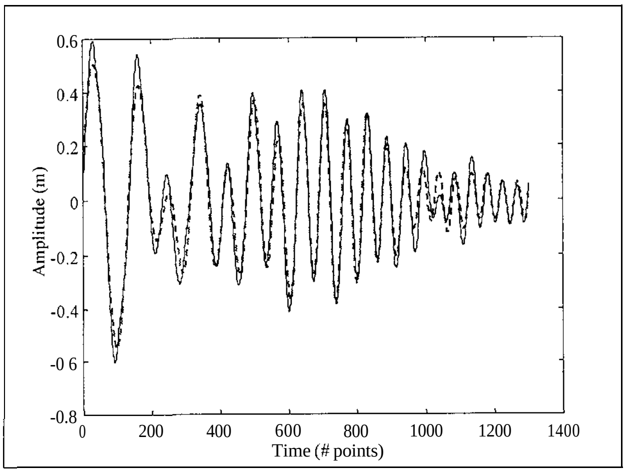

Figure 7: Simulated model output (solid line) and measured boom response (dashed line)

Poles	Zeros
-30.1245 ±71.8475i	-6.0954 ±10.2261i
-1.0477 ± 9.6613i	9.8273 ± 2.8675i
-0.2840 ± 3.8256i	-6.3058

Table 3: Poles and zeros of nlsfdi model obtained from swept sine data records.

5. Conclusions

Experience has been gained on black box identification of a small sprayer boom mounted on a sledge in a laboratory set-up. Different types of excitation signals i.e. multi sine, swept sine and periodic noise, have been compared with respect to their ability to obtain accurate frequency response function measurements in the frequency band of interest.

The errors-in-variables estimator is utilised to estimate the frequency response function of the time data records. In the frequency band of interest, the coherence values amount above 0.9, which is an indication of a rather linear behaviour of the system's dynamics.

Two model structures in the time domain (OE and BJ) and 1 frequency domain identification method are compared. For the time domain methods, an 8-6 OE model seemed to be sufficient and no significant differences could be remarked for the different excitation types. The normalised root mean square error is small. However, an 8-6-6-8 BJ model with periodic noise excitation even produces a smaller nrmse- value.

Optimised excitation signals used together with the non-linear least squares black box frequency domain identification method result as well in a nice estimation of the frequency response.

Acquired knowledge will in a next step be applied on real agricultural sprayers. Special hydraulic shakers have been designed to excite the structure under one wheel of the tractor. Black box identification will be performed in order to derive the best linear model describing the system's dynamics.

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