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New Approaches for High Speed and Accurate Weight Measurements

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Abstract

Accurate and fast weighing is an important requirement throughout the modern world. The application of an object to a weighing platform results in a transient output waveform, which can take a considerable time to settle sufficiently before the object can be accurately measured or predicted. In this study, an improved method is investigated based on the Gauss-Newton method of the Non-Linear Regression (NLR) in which a time-domain model is fitted to displacement data from a weighing platform. The applied mass is accurately predicted in the early part of the transient response for different cases. Simulations confirm that the various modeling, identification and prediction approaches are successful over a wide range of applied masses and noise amplitudes. Comparisons with previously known dynamic weighing methods show signal that significant speed and accuracy advantages can be obtained.

1. Introduction

Using Adaptive Filtering techniques transient effects are shortened but are still present [1-4]. Another work on this topic is undertaken using the NLR method for fitting of a second order time domain model to output waveform of the platform in short time. This method is faster than the adaptive filtering techniques [5].

Further work on this topic is undertaken using simpler sub-model where they have indicated that the number of unknown parameters can be reduced and therefore a good initial guess could be made for fast weighing [6-9]. Using this kind of classical model based techniques and having limitation that they require an accurate model of dynamic weighing system. Difficulty might occur in real-time operation. Another new approach based on using a neural network is applied for mass prediction successfully [10]. The main objectives of this study are as follows:

- Application of the NLR method for determination of dynamic weighing system parameters,
- Modeling of weighing system and reducing its computational complexity,
- High speed correct sub-model selection,
- Determination of the initial conditions,

- Identification / calibration of the platform parameters,
- High speed and accurate mass prediction.

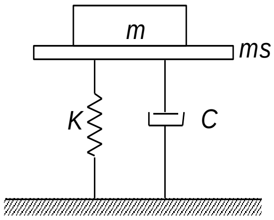

Figure 1. Weighing platform.

The weighing platform (see Fig.1) response is governed by the solution to the second order differential equation

$$(m+ms)\frac{\partial^2 y(t)}{\partial t^2}+C\frac{\partial\, y(t)}{\partial\, t}+K\,y(t)=g\cdot(m) \qquad (1)$$

The weighing system parameters are the constants *K*, *C* and the variable *m*. The applied mass *m* is a step input and the platform mass, *ms* is assumed to be zero for simplification.

The weighing platform response is governed by the solution of the second order differential equation and is modeled in the most general form by a constant term and plus a transient term which can be under damped, critically damped or over damped, depending on the mass of the applied object [1-10]. Thus

$$y(t)=F(\theta,t)\equiv\theta_0+\{F_u(\theta_u,t),F_c(\theta_c,t)\text{ or }F_o(\theta_o,t)\} \qquad (2)$$

where,

$$F_u(\theta_u,t)=e^{-\theta_{u1}t}\,\theta_{u2}\sin(\theta_{u3}t+\theta_{u4})$$

$$F_c(\theta_c,t)=e^{-\theta_{c1}t}(\theta_{c2}+\theta_{c3}t) \qquad (3)$$

$$F_o(\theta_o,t)=e^{-\theta_{o1}t}\,\theta_{o2}+e^{-\theta_{o3}t}\,\theta_{o4}$$

A single compound model needs 12 parameters, which results in a high computational complexity and lack of robustness in the NLR method. This can be overcome by automatically identifying the appropriate response mode from the data, since a simpler sub-model can then be used, and a good initial guess provided for the unknown parameters [6].

Several new approaches are described in the literature [5-10] and some results are given to demonstrate the success and robustness of the NLR method over a range of conditions including noisy data.

2. New Approaches for Dynamic Weighing Systems

In this study, new approaches are based on reducing the number of unknown model parameters by factors of up to 125 successfully [5-8].

-*New sub-modeling approach*: The correct sub-model can be identified by first performing one iteration starting with critical model [5-7]. The predicted mass from this one iteration thereby provides a close initial guess for subsequent iterations with the identified sub-model. When the correct mode of the response is identified from the data then a simplified model can be employed by inserting the appropriate sub-model. So, the number of unknown parameters is now reduced from 12 to 5. Noise-free data with sample intervals at 10 milliseconds are generated for a weighing platform with parameters K=10000, C=2000, ms=0, which is critically damped at 100 Kg. The results of applying one iteration are shown in Fig.2 for a range of under damped and over damped applied masses. This new sub-modeling approach is proposed that provides robustness of convergence and a good initial guess provided for the unknown parameters.

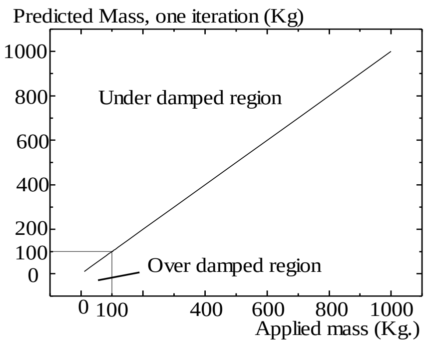

Figure 2. Model estimation using noise-free data.

The number of parameters can be reduced to 3 if the constant parameters C and K are known for the platform. These parameters can be identified by off-line calibration, or if parameter drift is present then they can be found on-line by reverting to under-damped model (4) for a proportion of the NLR runs.

-Platform parameters identification: Throughout the parameters identification process, it will be assumed that the weighing platform response is under-damped and the model uses the following format of equation;

$$Fu(\theta,t) = \theta_0 - e^{-\theta_1 t_n}\theta_2 \sin(\theta_3 t_n + \theta_4) \qquad (4)$$

where θ is the array of implicit model parameters, t_n is the discrete time intervals. It is assumed that by assigning some values for constant explicit parameters for the identification process used in this study; the applied mass m is be known and therefore only K and C need to be identified [6, 9].

The Transient Analysis (TA) method [11-14] can be used to provide good guesses of platform parameters K and C for the accurate parameter identification using the NLR method. The NLR method can give accurate estimates of the weighing platform parameters iteratively for noise-free and noisy data reducing from 5 to 3, which are applied mass, initial displacement and the velocity of the platform response.

-Estimation of initial conditions: A further reduction in computational complexity can be obtained by estimating the initial displacement and velocity from the data by a different means than non-linear regression [5-8]. This can be done by fitting a polynomial curve (5) of degree R to the data,

$$y_m(t) = \sum_{r=0}^{R} b_r t^r \qquad (5)$$

which is a relatively low complexity operation. Coefficients b_0 and b_1 give estimates of the displacement and velocity. This allows expressions for the model parameters to be passed to the NLR procedure, which are functions of just one unknown, the applied mass m.

-High speed mass prediction: An explicit-model approach is developed, for the case where the platform parameters and the initial conditions are known that provides a further improvement in computational time [5].

3. Non-linear Regression

The NLR method [15-18] is used for fitting a specified non-linear model to observed values by using iterative regression steps to reduce the sum of squares error (*sse*) between the model and observations. This method applies linear-regression techniques to the solution of the non-linear model. The non-linear model is

$$y_m(t_n) = F_u(\theta, t) + e(t_n) \tag{6}$$

where $e(t)$ is the modeling error. Measured data y_m is obtained at discrete time intervals t_n., which describes the measured displacement of a weighing platform when the new mass is applied on the platform. The derivatives of the model with respect to the parameters θ, is defined as

$$Z_{i,n} = \partial F(t_n) / \partial \Theta_i \tag{7}$$

which is called Jacobian matrix over a set of N data points, and from an initial θ^*, an iterative refinement is performed:

$$\theta = \theta^* + (Z^T Z)^{-1} Z^T [y_m(t) - F(\theta^*, t)] \tag{8}$$

These iterations are continued until a suitable criterion is met and iterations are stopped when either η is bigger then the new *sse*, or a specified number of iterations or allotted computer time is exceeded. Where η is the convergence criterion [15]. To the modification of the Gauss-Newton method, halving method is used for improving the estimated platform parameters. In this work, the halving limit n is typically set to 10 [5, 6].

4. Platform Parameters Identification[8]

Throughout the parameter identification process, it will be assumed that the weighing platform response is under-damped, the applied mass m is be known and therefore only K and C need to be identified. The weighing model structure is known and therefore data can be generated via simulation and recorded for the purpose of subsequent identification.

It is possible to obtain good initial values by using the Transient Analysis (TA) method. This method in practice often can only be applied off-line, because data preparation for parameter estimations becomes time-consuming. This approach is also very sensitive to noise but can give approximate parameter values [14].

For the purposes of illustrating the NLR method, the outputs computed from the model, θ, so that the modeling error $e(t_n)$ is minimized in the least-squares sense. The NLR method is iterative and requires initial guesses for the values of K and C. Therefore the TA method is used to provide good guesses of platform parameters for the accurate parameter identification by the NLR method. The NLR iterative process, which generates successively improved estimates by linearising the model equations about existing parameters values.

5. Simulated Results

The model structure for a weighing system is known and therefore simulated data is used for identification of the model parameters. Sampled data is simulated for the weighing platform result. It is important to note that the results obtained by using the identification method are highly dependent on the choice of the sampling interval for obtaining the data. Increasing the number of sampling intervals can improve the accuracy of the estimates; difficulties also arise when the sampling interval is either too large or too small [12].

Simulations are carried out on a dynamic weighing system in which, K=1000 N/m, C=50 N/(m/s), ms=0 Kg. g=10 m/s^2, m=100 Kg is applied at t=0. The weighing platform response is simulated, generating 100 data points at the sampling intervals of 0.04 sec. and initial conditions are assumed y(0)=0, y'(0)=0. The input is a step function. In this work, the platform response takes a long time to reach steady-state position as seen in Fig. 3. The noise sequences added to the states are uniformly distributed with amplitude of 5% relative to the steady state conditions. The applied mass is known and only K and C are required for the subsequent prediction process.

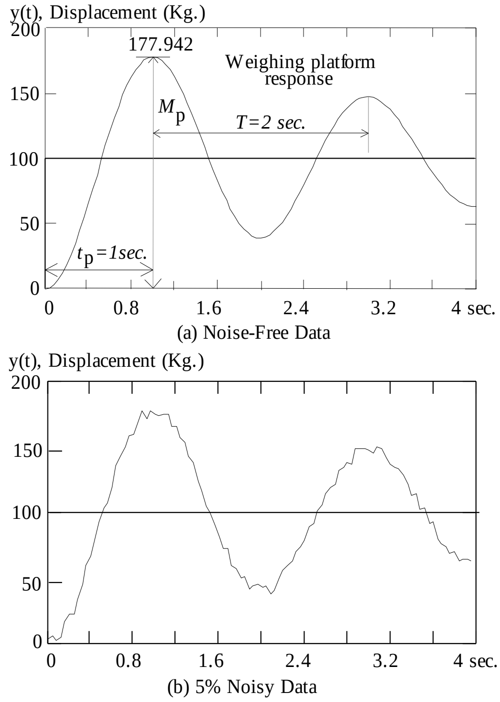

Fig.3 The simulated response of the weighing platform with noise-free and 5% noisy data.

In real life situations, the input-output data of a system usually contain certain kinds of noise, or measurement errors. In general, weighing systems are considerably sensitive to their environment that includes sources of noise, measurement errors and at intervals due to parameters drift with age affecting the accuracy of the system [1-6, 13].

The first guesses of the platform parameters K and C obtained using the analytical method are 990 N/m, and 45 N/(m/s) respectively with zero initial conditions. For noisy data with non-zero initial conditions, different platform parameter values obtained using this method. These values are assumed as a guess of the platform parameters for the NLR requirements to be identified accurately.

Using the weighing platform parameter identification, the NLR procedure is repeated until the sum-squared modeling error (sse) is acceptable. The platform parameters are obtained iteratively for noise-free and noisy data and are listed in Table 1.

From the results obtained for noise-free case, it can clearly be seen that the non-linear identification method of the NLR can give accurate estimates of platform parameters when the input-output data do not contain any noise or measurement errors shown in Fig.4 [5, 9].

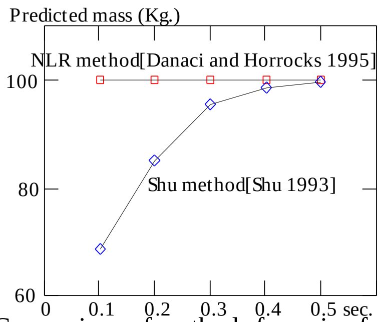

Fig.4 Comparison of methods for noise-free data.

The results confirmed that the identification approach works very well for the noise-free case. When the correct model is known, the minimum number of $y_m(t_n)$ data points required is equal to the number of unknown parameters in the model [5]. As shown in Fig.4, the NLR method immediately gives the exact mass and in fact does so from sample n=5. However, in practice measurements will be noisy and more points than the min. are needed.

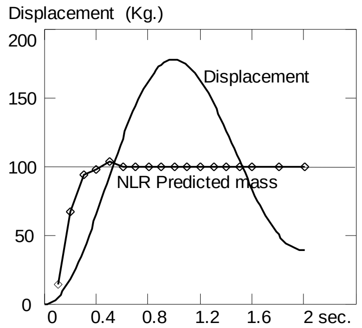

Fig. 5 Platform response and the NLR result.

Fig.5 shows the NLR result for K=1000, C=50 and t_s=0.02 sec. for m=100 Kg and added white noise that is uniformly distributed with a peak value of 2%. The mass is predicted for increasing record lengths to 100. The error effects of the meas. noise are quickly reduced to very low levels in only the time it takes the platform to oscillate one quarter of a period. The results obtained for noise-free and noisy data with non-zero initial case is that the NLR method seemed to work better than the analytical methods shown in Table 1.

The NLR approach works well even when initial guess values are sometimes poor. Therefore it is not necessary to use of the analytical method for obtaining the initial values. This is seen from the results of the Table 2 for running the NLR algorithm alone to determine the platform parameters [8].

Table 1 The Model Parameters determination of the weighing platform using noise-free, 1-5% noisy data.

No. of Iterations	System Parameters					*sse*
	θ_0	θ_1	θ_2	θ_3	θ_4	
First Guess	1.01010	0.22500	1.01269	3.138371	1.499225	0.0805273812
1	0.99998	0.24904	1.00293	3.151245	1.492385	0.0000857514
2	1.00000	0.25000	1.00314	3.152377	1.491659	0.0000000003
3	1	0.25	1.00314	3.152380	1.491656	0
Actual values	1	0.25	1.00314	3.152380	1.491656	

Platform parameters	Initial guess values	Final converged values	Actual values
Noise-free data (K, C)	990, 45	1000, 50	1000, 50
1% Noisy data (K,C)	990, 45	1000.2995, 49.92248	1000, 50
5% Noisy data (K,C)	990, 45	1001.5007, 49.6130	1000, 50

N=100, ts=0.04 sec. The initial conditions: y_0=0.012, y'_0=0.6 m/sec

5% Noisy data (K,C)	953, 44	1001.547, 51.012	1000, 50

Table 2. The weighing platform parameters determination by the NLR method using 2% added noisy data.

No. of Iterations	System Parameters					*sse*
	θ_0	θ_1	θ_2	θ_3	θ_4	
First Guess	0.5555	0.1	0.5635	4.24146	1.55026	76.840554704
1	1.0110	1.1448	0.8944	4.44339	0.34048	21.811449426
2	1.0217	0.5374	0.7359	3.17552	1.10450	10.813993398
3	1.0090	0.2759	0.8191	3.25361	1.35904	1.7879925302
4	1.0002	0.2520	1.0079	3.15126	1.49408	0.0174246688
Actual values	1	0.25	1.00314	3.15238	1.49165	

N=150, ts=0.02 seconds the initial conditions: y_0=-0.0072, y'_0=0.007 m/seconds

Platform parameters	Initial guess values	Final converged values	Actual values
2% Noisy data (K,C)	1800, 20	999.75, 50.41	1000, 50

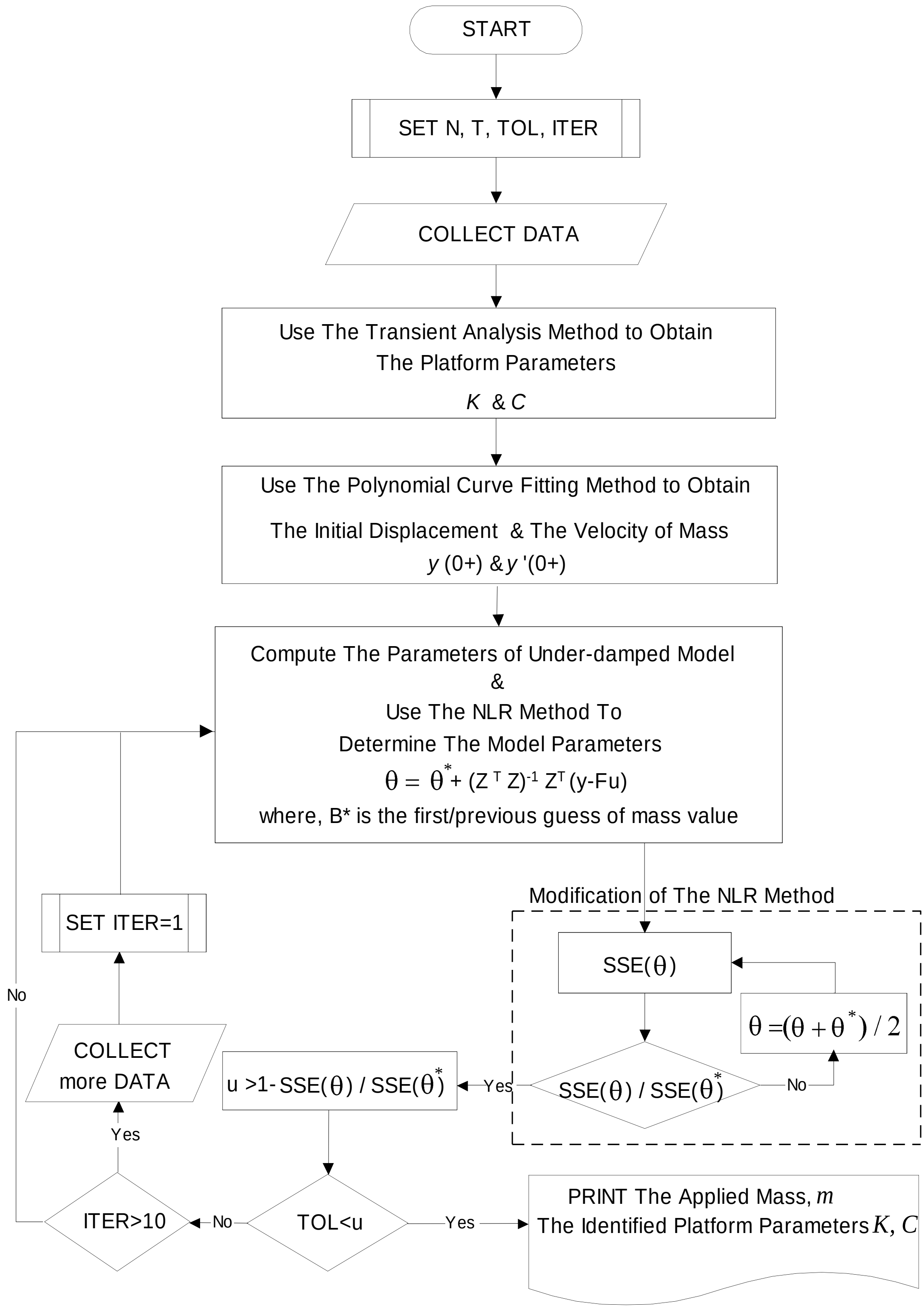

Fig. 6 Identification /(Calibration) of The Dynamic Weighing Platform Parameter(s).

parametric (adaptive) methods and the analytical methods [5].

A program using the 5 parameters implicit model with the NLR approaches (see Fig.6) can be used also re-calibration to the *K* and *C* when required and thus reduces the errors induced by the environment [8].

6. Conclusions

In this paper, the Non-parametric TA method is first considered for the off-line identification of the weighing system parameters from samples of input-output data, but the results obtained are noisy and inaccurate and alternative ways can be found to provide preliminary parameters. Secondly the NLR method is applied for estimating the dynamic weighing system parameters, which is based on the NLR signal processing method for fitting of a time-domain model to the output waveform of the weighing platform. This method provides more accurate estimates than the other parametric methods and TA method. In the presence of white noise, it is shown that the NLR method can still provide good parameter estimates.

The use of the modified NLR method for dynamic weighing also allows rapid real-time identification of the weighing system parameters and prediction of the steady-state applied mass in the presence of noisy data even noise becomes larger, the NLR methods can still produce reasonable estimates for the system parameters. It is confirmed by simulation results that the identification and prediction procedure work very well for the dynamic weighing system. This method is more reliable, robust and gives fast and accurate results.

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