Mathematical & Computational Applications, Vol. 4, No. 1, pp. 53-59, 1999.

DETECTION OF THE STARTING OF THE NEWLY APPLIED MASS FOR SUCCESSIVE WEIGHING

Mustafa DANACI, Adem KALINLI

Erciyes University, Engineering Faculty, Control & Computer Eng. Dept.
38039 - Kayseri / TURKEY

Abstract - In this study, new approaches are proposed over a range of conditions with unknown loading time to determine the initial conditions and identify the explicit model parameters of successive weighing system in the early part of the transient response. When a new mass is applied to the platform, the starting of the newly applied mass is detected by modelling error approach and then predicted automatically using the Non-Linear Regression (NLR) method and the detection process is repeated for successive continuous weighing. Simulation results are provided to indicate the improvement in both speed and accuracy of the model and the mass prediction.

1. INTRODUCTION

Accurate and fast weighing is an important requirement throughout the modern world [1-6]. The platform parameters must be known for fitting the system dynamic model to the early part of the platform transient response and determining the model parameters which provide the high speed mass prediction. Signal processing methods have been studied to estimate the weight dynamically while still in the transient mode, and more recently adaptive filtering has been used [1-4]. This paper presents new approach to successive continuous (non-stop) weighing. It is based on the NLR [7] signal processing approach of fitting of a time-domain model to the early part of the dynamic weighing platform response. This method can be faster than the adaptive filtering methods proposed so far because no filter adaptation time is required [5-6].

The approach is applied over a range of dynamic conditions including noisy data with unknown loading time for prediction of the applied mass. This is the most difficult task of the dynamic weighing problem. In successive continuous weighing, when the new mass is applied to the weighing platform due to non-periodic or unknown loading time, then the starting time of the newly applied mass should be detected as soon as possible. When a new applied mass is detected, this mass is then predicted automatically using the NLR method and the detection processes are repeated for successive weight measurements [6].

2. MODELLING OF DYNAMIC WEIGHING

The weighing platform response is governed by the solution of the second order differential equation (1) and is modelled in the most general form by a constant term and over-damped, critically-damped or under-damped transient [8-10].

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

The speed and accuracy of mass prediction are major considerations for successive continuous weighing; therefore, an explicit model is developed for improved accuracy and fast mass prediction [5-6]. This new model contains 5 unknown parameters, which are the applied mass m to be predicted, the platform parameters K and C, the initial displacement $y(0)$ and the initial velocity $y'(0)$ of the applied mass, where ms is the self mass of the platform.

In general, weighing systems are considerably sensitive to their environments, which includes sources of noise and measurement errors affecting the accuracy of the system. The number of unknown explicit model parameters can be reduced from 5 to 3 if the constant platform parameters K and C are known for the given platform.

The platform parameters can either be found by an off-line calibration, or found on-line by reverting to the 5 parameter implicit model for a proportion of the NLR runs [6]. Thus, re-calibration reduces the errors induced by the environment. Assuming that any variation in K and C is slow, since the platform parameters were determined in an earlier identification process, these values can be set as constant parameters for the high speed mass prediction process.

3. ESTIMATION OF THE INITIAL CONDITIONS

A further reduction in computational complexity can be obtained by estimating the initial displacement and the initial velocity from the data by different method other than the NLR [5, 6, 11-13]. This can be done by fitting a polynomial curve of degree R to the data using only one iteration,

$$y_{m}(t) = \sum_{r=0}^{R} a_r t^r \tag{2}$$

which is a relatively low complexity operation. The coefficient a_0 and a_1 give estimates of the initial displacement and the velocity. These values are substituted into the explicit model, so the unknown number of explicit model parameters is reduced from 3 to 1. Subsequently leaving only the applied mass to be predicted quickly by the NLR method providing accuracy and decreased computation time. Using the model equation (as given in Appendix) for the mass prediction stage therefore improving the prediction of mass significantly (see Figure 1 and Table-1).

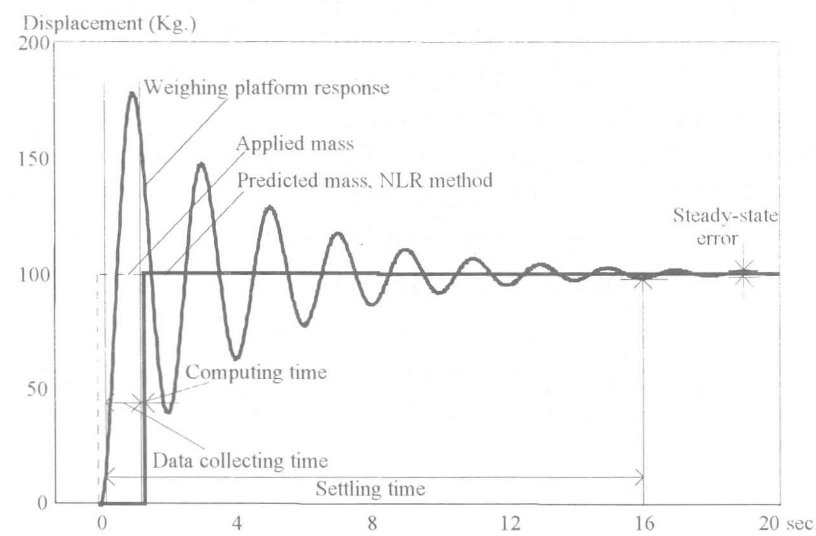

Figure 1. Weighing platform response and the NLR result [6]

Table 1 Further improvement of the initial conditions and mass prediction.

Initial conditions: y(0)	y'(0)	Initial Guess (Kg)	Final Predicted mass (Kg.)	Actual applied mass (Kg.)
-0.00003	2.04153	100	999.287	1000

Determination of the initial conditions using model equation, and mass prediction by NLR method simultaneously				
Initial conditions: y(0)	y'(0)	Initial Guess (Kg)	Final Predicted mass (Kg.)	Actual applied mass (Kg.)
-0.0003	2.0097367	999.287	999.598	1000
-0.0003	2.009627	999.598	999.605	1000

The present approach requires a correct sub-model selection. The model identification process has been found to be reliable if the initial guess of mass value is set to the value for critical damping [5-6]. Performing one iteration of the NLR algorithm automatically identifies the correct sub-model, and then a selected explicit model is used for all subsequent iterations.

Therefore, the computational complexity of the NLR procedure is $O(M^3)=5^3$ a significant speed-up for high speed mass prediction by a factor of 125 is obtained. This approach provides robustness of convergence and gives accurate results.

4. NEW APPROACHES FOR MODEL DETECTION

In general, automatic weighing systems require reliable detection of the starting time of the new applied mass on the platform [1-6]. This is so that data from the previous mass can be eliminated from the process to obtain the updated model, which assumes only one mass (that is the new mass) is present in the signal. This assumption will be explained in the following paragraphs.

A conceptionally simple way would be to use a threshold technique [4, 6, 12, 14] on the platform signal, see Figure 2. But two difficulties can arise. One occurs if a low-level threshold is used to detect the starting of the applied mass at the earliest time. However there is then an increased danger of false detection due to any noise in the signal. The second difficulty can arise, if the platform is still oscillating from the previously applied mass and also if the new applied mass differs only by a small amount. It can then happen that the change in amplitude of the signal due to the new applied mass is not greater than the oscillation still remaining. However reliable detection the threshold must be set greater than the amplitude of the remaining oscillation, but less than the amplitude of the signal change due to the new applied mass [6]. Hence this method can only be considered for large change in applied mass.

A more reliable way is to continuously monitor the modelling error during the previously applied mass. It is very easy to calculate the modelling error. This new approach enables to overcome threshold approach problem, and to calculate the modelling error over a defined data window, which constantly moves forward as time progresses [6]. The window length is chosen so as to provide adequate noise averaging. A shorter window preferred to reduce calculation time. This means that a constant threshold can be set. To test this approach, simulated responses for the detection of new applied masses are given in Figures 5.

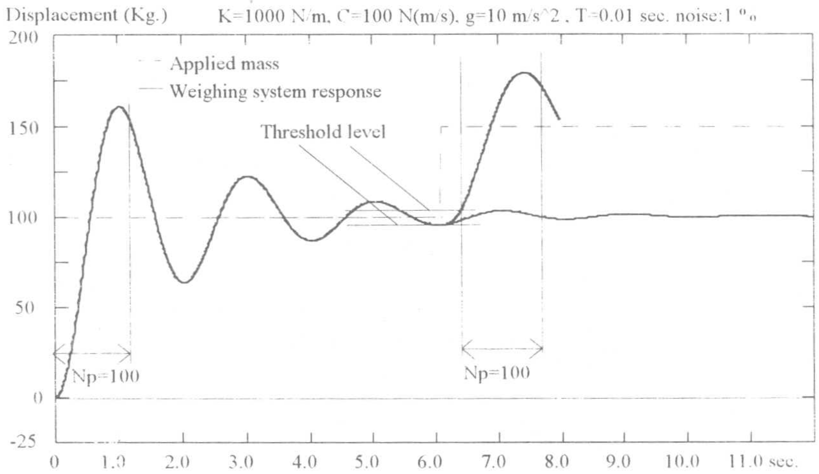

Figure 2. Detection of the starting of the new applied mass by threshold approach.

5. SIMULATION RESULTS

This section presents simulation results for the prediction of different applied mass values under various noisy amplitudes with unknown loading time. Simulations were carried out on a weighing system in which, K=1000 N/mm, C=50 N/(mm/s), ms=0 Kg. The gravity was assumed to be g=1000 mm/s^2 and the mass m=100 Kg was applied at t=0. The signal was sampled at intervals of 0.02 sec. The predicted mass for noise-free data is shown in Figure 3 together with Shu's method [4] that the NLR method immediately gives the exact mass and in fact does so from sample n=5. The speed advantage of NLR is clear. The noise was taken to be uniformly distributed with amplitude of 2% relative to the steady state conditions.

For the noisy signal the predicted mass shows a random deviation about the exact value which diminishes with increasing numbers of samples due to the averaging effect of the model fitting. The mass predicted by the NLR method for data containing 2% noise is plotted in Figure 4.

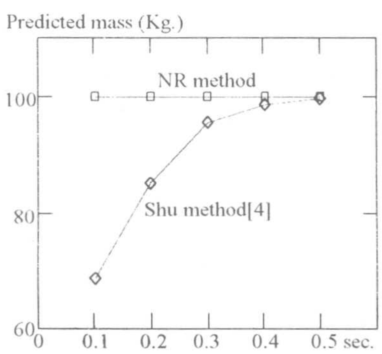

Figure 3 Comparison of methods for noise-free data[5].

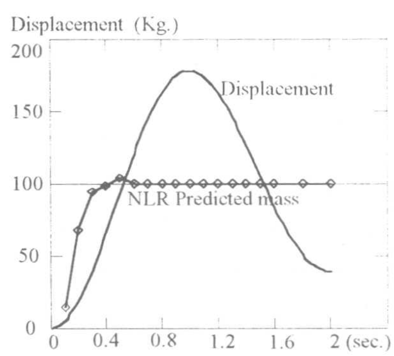

Figure 4 Weighing system displacement with noisy data and the NLR results [5].

In order to improve the accuracy of mass prediction, highly accurate values for initial velocity should be used. This can be achieved by switching from the polynomial curve fitting method to the model equation approach, providing that the mass prediction value has reached a significantly close value to the actual applied mass.

Figure 5 shows the response of the weighing platform to two consecutively applied masses, starting at 100 Kg and then adding 50 Kg. Figure 5(a) shows in more detail the effect of adding the 50 Kg to the 100 Kg. The signal is sampled at intervals of 10 milliseconds for Np=100 samples, the time of application 100 Kg applied mass is predicted by NLR method taking only a few milliseconds. A threshold error level is set a value of 0.1 that adding some safety margin on the mean squared error (*MSE*) of the previous model that is sufficient to indicate start of the new mass. Initially the threshold level was set to minimum value. The detection process then proceeds for the new applied mass by comparing between the previous *MSE* of the predicted 100 Kg and the present *MSE* of the new collected data (Nd=10 in this example, where Nd is number of test sample for detection process).

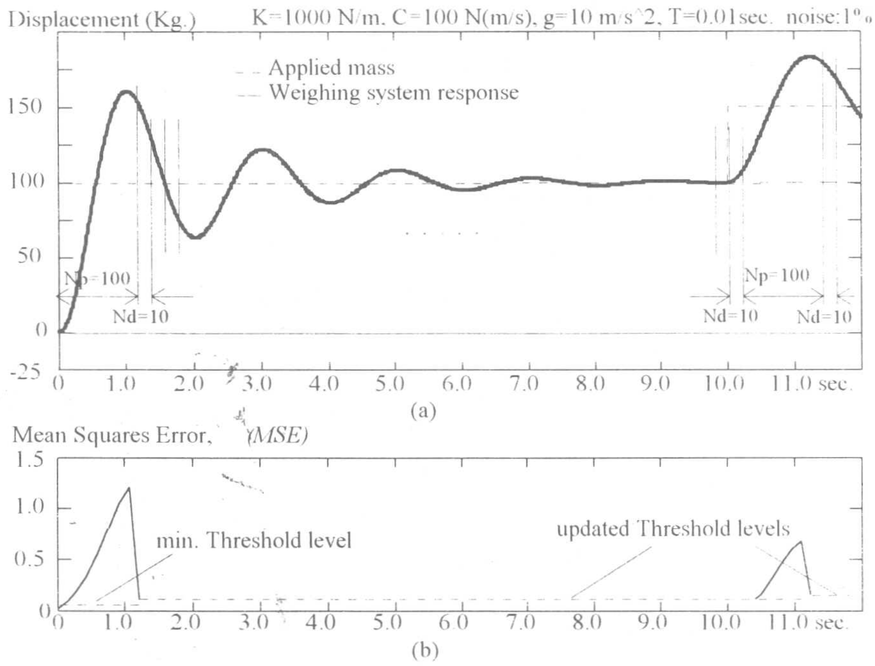

Figure 5 Simulated responses for detection of the new applied mass: (a) Expanded horizontal axis, (b) Mean squares error (*MSE*).

The new applied mass is indicated by significant error to an increase in *MSE*, over the previous steady value as shown in Figure 5(b). Here a 15% increase was used as the criterion. The previous steady value is that due to the measurement noise and would be updated at times between applies masses.

If the threshold level is too short, the method will too sensitive to individual noise fluctuations. If it is too long it is going to be come over the time. The modelling error method cannot be used, while collecting a longer data set (Np) and then performing the mass prediction process. This is because, after the new mass is being applied, the main algorithm needs longer data set and time to compute new indicated mass. During that period there is a high modelling error, therefore modelling error process should be stopped, otherwise it will falsely indicate the new mass. A tolerance level of accuracy must first be established for the particular application concerned. Therefore the sampling interval for prediction process should be taken as fairly short compared with the time constants expected for the system [9]. Increasing the number of sample can improve the accuracy of the estimates but its time consuming [10, 12, 13, 15].

The flow chart for the implementing the approaches described in this paper is given in Figure 6. Software has been developed for successive continuous weighing, which is applicable for small to large dynamic weighing systems, provides real-time implementation.

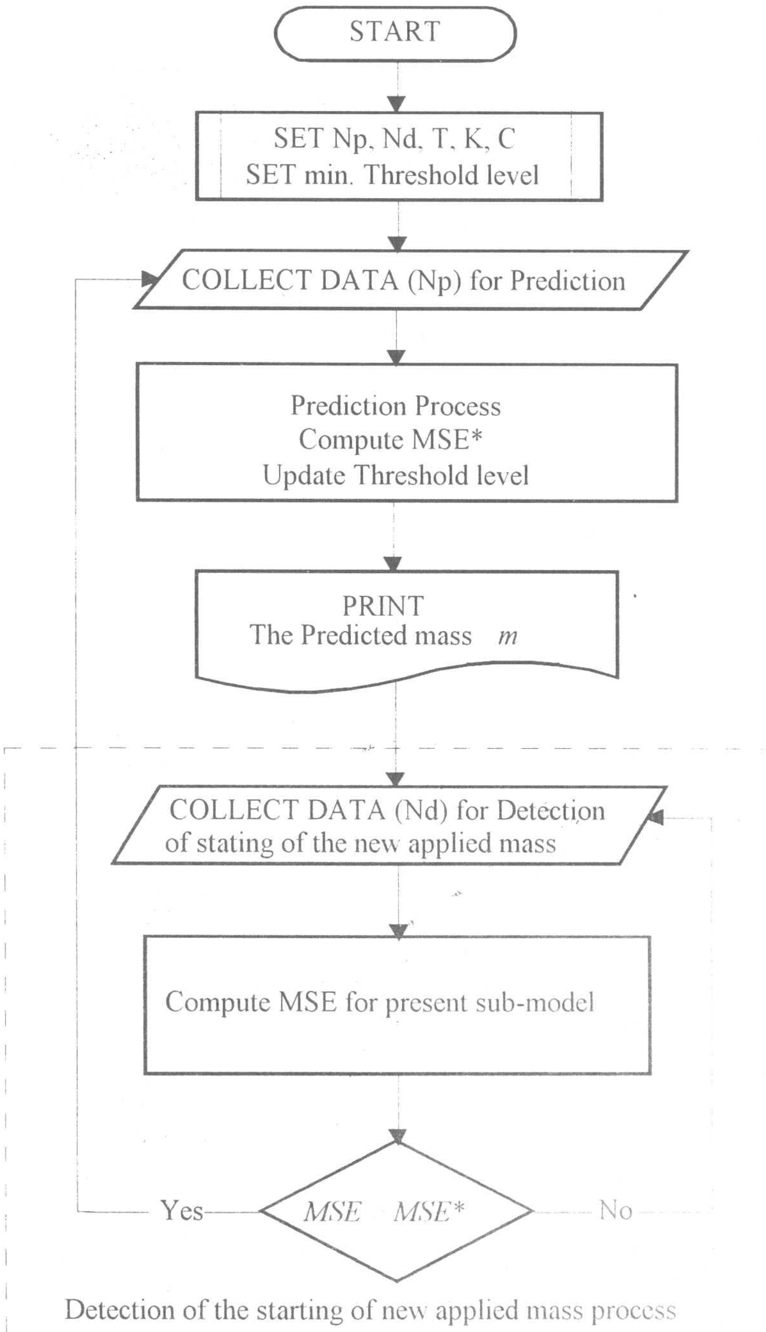

Figure 6. Flow chart of successive continuous weighing process.

6. CONCLUSIONS

In this study, the NLR method is applied successively in modelling, identification and prediction tasks for a dynamic weighing system. The application of NLR signal processing method provides high speed parameter identification of dynamic weighing and fast prediction of the steady state value of the applied mass with significantly improved accuracy. Simulation results confirm that over a range of conditions, when a new mass is applied to the platform, the starting of the newly applied mass is detected by modelling error approach and then predicted automatically using the NLR method and the detection process is repeated for successive continuous weighing. Simulation software for successive continuous weighing ensuring real-time implementation has been used to indicate that fast and accurate results can be obtained.

Acknowledgements - The co-operating of W. & T. Avery Ltd in providing access to a weighing platform is gratefully acknowledged. Thanks are due to Dr. D.H.Horrocks for useful discussions while at the School of Engineering, Cardiff University of Wales, UK.

APPENDIX

Here the model parameters are defined for the weighing system platform constants K, and C, the applied mass $m(t)$, platform mass ms, the initial platform displacement b_0 and initial velocity b_1. For the under-damped case [5-7];

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

$$\theta_0 = (m+ms)g / K, \qquad \theta_1 = 0.5C / (m+ms),$$

$$\theta_2 = \sqrt{B_1^2 + B_2^2}, \qquad \theta_3 = \omega_d = \sqrt{K(m+ms)^{-1} - \theta_1^2},$$

$$\theta_4 = \tan^{-1}(B_1 / B_2),$$

where, $B_1 = \theta_0 - b_0$, $B_2 = b_1 + B_1\theta_1 / \theta_3$, and ω_d is the natural damped frequency.

REFERENCES

[1] K. E. Norden, Electronic Weighing in Industrial Processes, Granada Technical Books, London, 1984.
[2] A. King (Fellow), In Introduction to Weighing Systems, Electronic Technology, 21, 25-29, 1987.
[3] W. J. Shi, N. M. White and J. E. Brignell, Adaptive Filters in Load Cell Response Correction, Sensors and Actuators A, 37, 280-285, 1993.
[4] W. Q. Shu, Dynamic Weighing Under Non-zero Initial Conditions, IEEE Transactions on Inst. and Meas., 42 (4), 806-811, 1993.
[5] M. Danacı and D. H. Horrocks, A Non-linear Technique for Improved Dynamic Weighing, ECCTD'95, European Conf. on Circuit Theory and Design, 1, 507-510, Istanbul, Turkey, 1995.
[6] M. Danacı, Non-linear Regression Techniques For Dynamic Weighing Systems, Ph.D Thesis, Cardiff University of Wales, UK., 1996.
[7] M. N. Ediger, A Gauss-Newton Method for Nonlinear Regression, J. of The Mathematica, 1 (2), 42-44, 1990.
[8] J. Golden and A. Verwer, Control System Design & Simulation, McGraw-Hill Book, UK, 1991.
[9] J. A. Spriet and G. C. Vansteenkiste, Computer Aided Modelling & Simulation, Academic Press, London, 1982.
[10] J. Schwarzenbach and K. F. Gill, System Modelling and Control, Chapman and Hall, NY, 1988.
[11] D. M. Bates and D. G. Watts, Non-linear Regression Analysis and Its Applications, John-Wiley and Sons, NY, 1988.
[12] L. Ljung, System Identification, Theory for The User, Prentice-Hall, New Jersey, 1987.
[13] Soderstrom and Stoica, System Identification, Prentice-Hall, Englewood Cliffs, 1989.
[14] N. K. Sinha and G. P. Rao, Identification of Continuous-Time Systems, Kluwer Academic Publishers, London, 1991.
[15] M. R. Spiegel, Statistics, Schaum's Series, McGraw-Hill Book Company, 2nd Ed., 1988.