LOAD CELL RESPONSE CORRECTION USING ANALOG ADAPTIVE TECHNIQUES

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ABSTRACT

Load cell response correction can be used to speed up the process of measurement. This paper investigates the application of analog adaptive techniques in load cell response correction. The load cell is a sensor with an oscillatory output in which the measurand contributes to response parameters. Thus, a compensation filter needs to track variation in measurand whereas a simple, fixed filter is only valid at one load value. To facilitate this investigation, computer models for the load cell and the adaptive compensation filter have been developed and implemented in PSpice. Simulation results are presented demonstrating the effectiveness of the proposed compensation technique.

1. INTRODUCTION

Load cells are used in a variety of industrial weighing applications. Since information processing and control systems cannot function correctly if they receive inaccurate input data, compensation of the imperfections of the sensors is one of the most important aspects of sensor research. Influence of unwanted signals, non ideal frequency response, parameter drift, non-linearity, and cross-sensitivity are the five major defects in primary sensors [2]. In the new generation of sensors, called intelligent or smart sensors, the influence of these imperfections has been dramatically reduced by using signal processing techniques.

Some sensors such as load cells have an oscillatory output, which need time to settle down. For dynamic measurement, it is important to make a decision on the measurand as fast as possible. Dynamic measurement refers to the ascertainment of the final value of a sensor signal while its output is still in oscillation. It is used to speed up the process of measurement. One example of processing that can be done on the sensor output signal is filtering to achieve response correction. Several methods have been reported addressing this problem. Software techniques for sensor compensation are reviewed in [1]. Digital adaptive techniques have been used in [7] for load cell response correction. An artificial neural network has been proposed for dynamic measurement which needs a learning phase [8]. Other methods such as employing kalman filter [5] and estimation with recursive least square (RLS) procedure [6] have also been applied for dynamic weighing systems. Almost all the above reported methods are based on digital signal processing techniques which need analog-to-digital convertors and powerful signal processors. Although digital techniques have been used efficiently, the aim of this paper is to investigate the possibility of using analog adaptive techniques for load cell response correction. The potential benefits of analog adaptive techniques compared to digital methods include higher signal processing speeds, lower power dissipations, and smaller integrated circuit areas. It should be noted that most applications of analog adaptive techniques have focused on communications and digital magnetic storage [3] and there has been little or no work on application of analog adaptive techniques to intelligent sensors which is the main focus of this paper.

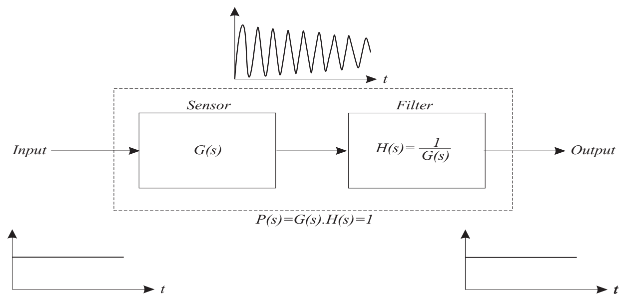

Figure 1: General principle of load cell response correction

2. LOAD CELL RESPONSE CORRECTION

The primary sensor is considered as a system with transfer function $G(s)$. The general principle for eliminating the transient time is shown in Fig.1. A filter having the reciprocal characteristic of the sensor is cascaded with it. Therefore, the transfer function of the whole system is *"unity"* which means that any changes in the input transfer to the output without any distortion. The response of a load cell can change for different measurands. For example, the characteristic of a load cell changes when a load is applied to it because the mass of the load contributes to the inertial parameters of the system. Therefore the transfer function of the filter should change accordingly. In other words, a fixed filter can be used only for one specific load value.

The general equation for the dynamic response of the load cell is given by [7]:

$$(m+m_0)\cdot\frac{d^2y(t)}{dt^2}+c\cdot\frac{dy(t)}{dt}+k\cdot y(t)=F(t) \qquad (1)$$

Where m is the mass being weighed, m_0 is the effective mass of the sensor, c is the damping factor, k is the spring constant, and $F(t)$ is the force function. The Laplace transfer function of this sensor is

$$G(s) = \frac{Y(s)}{F(s)} = \frac{\frac{1}{m+m_0}}{s^2 + \frac{c}{m+m_0}s + \frac{k}{m+m_0}} = \frac{g}{s^2 + \frac{\omega_0}{Q}s + \omega_0^2} \tag{2}$$

This shows that m affects all inertial parameters of the sensor such as gain factor , g , quality factor , Q , and natural frequency , ω_0.
Eq. 2 yields a pair of complex conjugate poles $a \pm jb$ where

$$a = -\frac{c}{2(m+m_0)} \tag{3}$$

and

$$b = \sqrt{\frac{k}{(m+m_0)} - \frac{c^2}{4(m+m_0)^2}} \tag{4}$$

Thus the zeros of the adaptive filter, which are the poles of the sensor can be obtained.

In general, assume $\boldsymbol{w}$ is defined as a vector that contains all of the parameters of adaptive filter i.e.

$$\boldsymbol{w} = [w_1\ w_2\ w_3\ \ldots]^T \tag{5}$$

The elements of $\boldsymbol{w}$ can be calculated for different values of the measurand. To emphasise that $\boldsymbol{w}$ depends on m, it can be written as $\boldsymbol{w}(m)$. m is unknown in the first instance when a new measurement begins. Therefore the parameters of the adaptive filter can not be set to appropriate values in order that the filter behaves as an inverse system. Hence, an adaptive rule is required to modify the parameters of the adaptive filter according to the value of measurand. This rule is a crucial element but there is not a straightforward solution for it. Usually, in classic adaptive techniques, an adaptive algorithm, such as LMS, updates $\boldsymbol{w}$ to minimize a cost function. However, Eq.(2) shows that, for a load cell, the suitable filter has a pair of conjugate zeros, $z_{1,2} = a \pm jb$, which, a and b can be considered as the parameters of adaptive filter and the relationship between them and load can be modelled as in Eqs.(3) and (4). The real-time measurement operation is shown in Fig.2. In this block

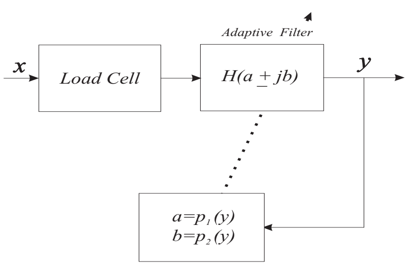

Figure 2: Block diagram showing the adaptive load cell response correction method

diagram m has been substituted with y, the output of the whole system, which is proportional to m. Initially the zeros of the filter are set to arbitrary values. Then the the output y is calculated. This new value of y is used to calculate the zeros of the filter once again. Repeating these steps results in a rapid approach to obtain the steady state value of y.

So far the zeros of a 2nd-order compensation filter have been examined. In order that the analog filter can be realised, it is necessary to add at least two poles to the filter. The values of these poles can be determined practically. For simulation purposes, these poles are selected by trail and error so that the output of the filter quickly reaches its steady-state value with minimum oscillation. The transfer function of the compensation filter is

$$H(s) = \frac{(m+m_0)}{10^{-5}} \cdot \frac{s^2 + \frac{c}{m+m_0}s + \frac{k}{m+m_0}}{s^2 + 600s + 10^5} \tag{6}$$

The transfer functions of the load cell (Eq. 2) and its compensation filter (Eq. 6) are biquadratic functions. There now exists a wealth of theoretical and experimental information on the design of fixed or non-adaptive analog biquads [4]. The problem is how to make a biquad adaptive and it is necessary to have only one filter component to track changes in m without any influence on the other parameters such as damping factor, c, and the spring coefficient, k.

3. LOAD CELL MODEL

Amongst the various biquad structures, the state-variable lowpass filter [4], shown in Fig.3, can be used to model the behaviour of the load cell.

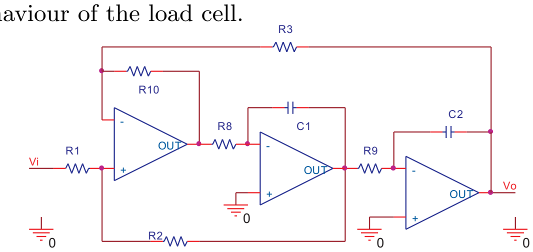

Figure 3: State-variable lowpass filter

The state-variable filter transfer function is:

$$T_{sv}(s) = K1 \frac{\frac{1}{R_8 R_9 C_1 C_2}}{s^2 + K1(\frac{R_1}{R_2 R_8 C_1})s + \frac{R_{10}}{R_3 R_8 R_9 C_1 C_2}} \tag{7}$$

where

$$K1 = \frac{R_2(R_3 + R_{10})}{R_3(R_1 + R_2)} \tag{8}$$

Comparing this transfer function with the load cell transfer function, Eq.(2), shows that R_8 can model $(m + m_0)$. R_8 has to be split into a fixed resistor equal to m_0 and a resistor proportional to m. Since m is the mass being weighed and in the model it is equivalent to stimulating voltage (V_i), the resistor has to be a voltage-controlled device whose resistance can be varied with V_i. With analog behavioural modeling facility in PSpice, it is possible to simulate such a resistor. This is achieved by using the G component(a voltage-controlled current source) and "TABLE" which allows the user to enter different resistors for different voltages. Using this voltage-controlled resistor in the lowpass filter (Fig.3) produces an analog biquadratic filter which can model the behaviour of the load cell. The complete model is depicted in Fig.4. From experimental data for a

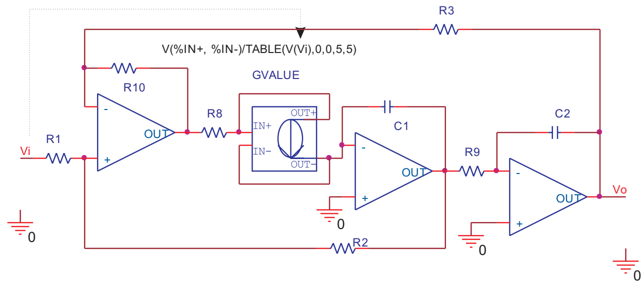

Figure 4: Load cell model

particular load cell [8] the damping factor c, spring constant k, and the effective mass of the load cell m_0, are 3.5, 2700 Pa, and 0.5 kg, respectively. These numbers are used to determine the values for resistors and capacitors in Fig.4.

For step excitation, the input voltage of the model is a step function whose amplitude is proportional to m. The simulation results for two different values of m are shown in Figs.5 and 6 which indicate that changing the input, similar to the practical case, varies all inertial parameters of the output waveform such as the steady state value, resonant frequency and damping factor.

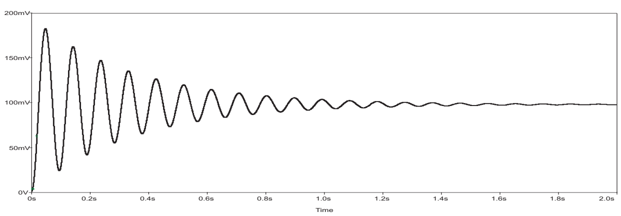

Figure 5: Output of the load cell model for $m = 0.1kg$

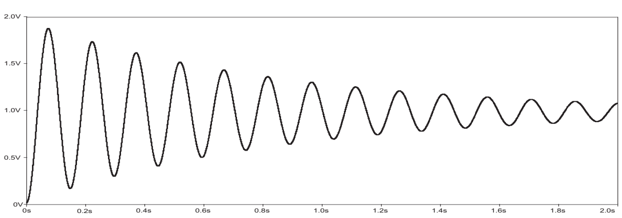

Figure 6: Output of the load cell model for $m = 1kg$

4. ADAPTIVE COMPENSATION FILTER MODEL

Since the transfer function of the compensation filter (Eq. 6) is a biquadratic function, different scaled outputs in the state variable filter, shown in Fig.3, need to be added to form a complete biquad. To make this biquad adaptive, as described in the block diagram of Fig.2, the filter's zeros have to be changed by the output of the biquad. Similar to the sensor model approach, it is possible to use a voltage-controlled resistor in the compensation filter. The filter output voltage is used to control this resistance. The complete adaptive biquad is shown in Fig.7. The transfer

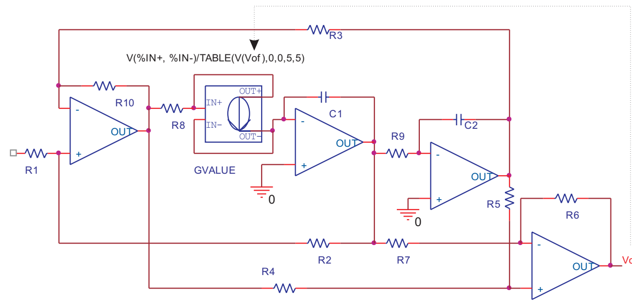

Figure 7: Adaptive compensation filter model

function of this filter is

$$H(s) = K\frac{s^2 + \frac{R_6(R_4+R_5)}{R_5R_8C_1(R_6+R_7)}s + \frac{R_4}{R_5R_8R_9C_1C_2}}{s^2 + K1(\frac{R_1}{R_2R_8C_1})s + \frac{R_{10}}{R_3R_8R_9C_1C_2}} \qquad (9)$$

where

$$K = K1\frac{R_5(R_6+R_7)}{R_7(R_4+R_5)} \qquad (10)$$

and $K1$ was previously defined in Eq.(8). Similar to the sensor model, R_8 consists of a fixed resistor and a voltage-controlled resistor whose resistance is controlled by the filter's output voltage. In other words R_8 models $(m + m_0)$.

The adaptation sequence can be described as follow. Before stimulating the load cell, filter output voltage is zero and the initial transfer function of the filter will be

$$H_0(s) = g \cdot \frac{(s - a_0 - jb_0)(s - a_0 + jb_0)}{(s - d - je)(s - d + je)} \qquad (11)$$

Where g is the gain factor of the filter, a and b are the real and imaginary parts of filter's zeros respectively, d and e are real and imaginary parts of filter's poles respectively, and the subscript ($_0$) denotes the initial values. The zeros of the filter need to cancel the poles of the sensor i. e. a and b are the same as eqs.(3) and (4). Since a and b depend on m (the output of the filter) which is unknown at first, they cannot be fixed values. The initial values for a and b are:

$a_0 = -\frac{c}{2(0+m_0)}$ and $b_0 = \sqrt{\frac{k}{(0+m_0)} - \frac{c^2}{4(0+m_0)^2}}$

When the input is applied to the filter with initial transfer function of $H_0(s)$, it produces an output, say m_1. Since the zeros of the filter change with the output voltage, the new values for a and b will be a_1 and b_1 and then the transfer function of the filter changes to

$$H_1(s) = g \cdot \frac{(s - a_1 - jb_1)(s - a_1 + jb_1)}{(s - d - je)(s - d + je)} \qquad (12)$$

With this new transfer function, the filter produces a new output that changes the filter's zeros again and this procedure continues until a and b converge to their final values.

It should be noted that the poles of this compensation filter (Eq. 9) vary as m varies, which is not the case with the filter model (Eq. 6). However, this does not represent a problem because the load cell does not have any zeros and for pole-zero cancellation only the zeros of the filter are important. In addition, the variation of filter's poles can be tolerated as long as the filter remains stable and does not create significant oscillation in the output. To examine the stability of the adaptive compensation filter, its transfer function is considered as follow

$$H(s) = g \cdot \frac{s^2 + \frac{c}{m+m_0} \cdot s + \frac{k}{m+m_0}}{s^2 + \frac{600}{m+m_0} \cdot s + \frac{10^5}{m+m_0}} \tag{13}$$

The poles of the filter are : $p_{1,2} = d \pm je$ where $d = -\frac{600}{2(m+m_0)}$ and $e = \sqrt{\frac{10^5}{(m+m_0)} - \frac{600^2}{4(m+m_0)^2}}$

As m varies from its initial value, $m = 0kg$, to its final value, for example $m = 1kg$, the real and imaginary parts of the filter's poles, d and e will change. The root locus of the filter's poles in s-plane is shown in Fig.8. This figure

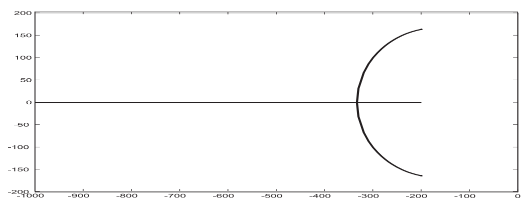

Figure 8: Filter poles root-locus for m from 0 to $1kg$

shows that the poles of the filter remain in the left hand side of $j\omega$ axes for all values of m from 0 to 1kg. Moreover, when $m \longrightarrow \infty$, the real part of poles are still negative and hence the filter remains stable for all values of m.

5. SIMULATION RESULTS

In this section the load cell and the adaptive compensation filter models will be used to examine how analog adaptive techniques can be used for load cell response correction. Fig.9 shows the load cell output and the compensation filter output for $m = 0.1kg$. To illustrate the capability in tracking changing in m, Fig.10 shows the results when $m = 1kg$. Clearly the simulation results show that analog adaptive biquad filter, shown in Fig.7, can be applied for response correction of the second order sensors.

To indicate the necessity for using an adaptive filter, a fixed filter is used for compensation. The filter is adjusted for $m = 0.1kg$. If the sensor is stimulated with $m = 0.1kg$, the result is the same as Fig.9, but for $m = 1kg$ stimulation, the input and output of the filter is depicted in Fig.11, which shows that the fixed filter is unable to perform response correction when m varies.

6. CONCLUDING REMARKS

This paper has addressed response correction of the load cell sensor using analog adaptive techniques. It has been shown that the state-variable biquadratic filter provides accurate and flexible sensor and adaptive compensation filter models. The load cell model in addition to tracking the variation in the mass being weighed, allows the user to vary the other parameters including damping factor and spring coefficient. The effectiveness of the models has been validated by simulation. Further work is aimed at practical implementation of the analog adaptive filter for load cell response correction.

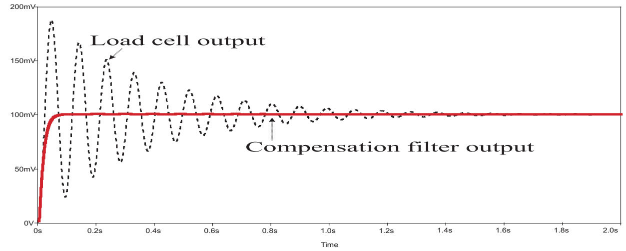

Figure 9: Result of adaptive compensation for $m = 0.1kg$

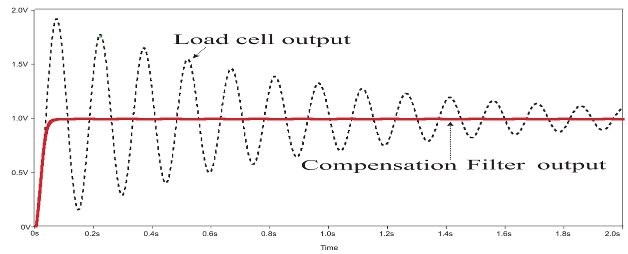

Figure 10: Result of adaptive compensation for $m = 1kg$

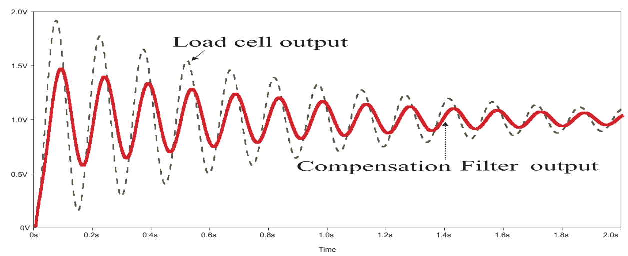

Figure 11: Fixed filter for load cell response correction when m varies from 0.1 to 1kg

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