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## Optimization measurement method for checkweigher

### Abstract

The paper presents a new measurement method for checkweighers, where the measurement result is obtained by solving a simple optimization problem. The method assumes that the mass of constant geometry and a small masses spread is measured. The measurement accuracy changes as a function of noise-eliminating low-pass filter frequency was investigated. The state of knowledge about the filtration of checkweigher signal is also summarized.

**Keywords:** Checkweigher, optimization, weighing methods, filter.

### 1. Introduction

Checkweighers are widely used in industry applications, especially on production lines. They are used for fast and precise control of the product mass. Their measurement speed can reach a couple hundred units per minute, and measurement accuracy is as high as 0.01 g [12].



Fig. 1. Checkweigher [1]

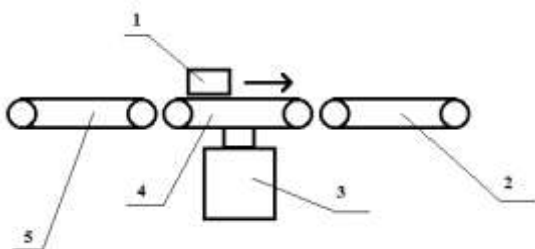


Fig. 2. Checkweigher diagram. 1) weighed object, 2) output belt, 3) weigh module with mass transducer, 4) middle belt, where the mass measurement takes place, 5) input belt

Increasing demand for more efficient production processes is forcing the product control to be done more effectively.

In the case of weighing, it is done by measurement of mass of moving objects. The lack of object stopping necessity greatly speeds up the measurements, but also adds additional noise to the

measurement signal, caused by the dynamic forces [13]. Possible causes are, for example, vibrations of the moving parts, their residual unbalance, and transient states caused by the entry of weighed objects on the belt, often with impacts.

With the increase in measurement output performance, dynamic influence also increases, and singular measurement time decreases. This entails the need to use increasingly better signal processing algorithms.

Estimation of the weighted mass is usually done on the base of the signal smoothed with a specified filter. In the Figs 3, 4, 5 and 6 the ideal measurement signal, as well as comparison of ideal and real signal are shown.

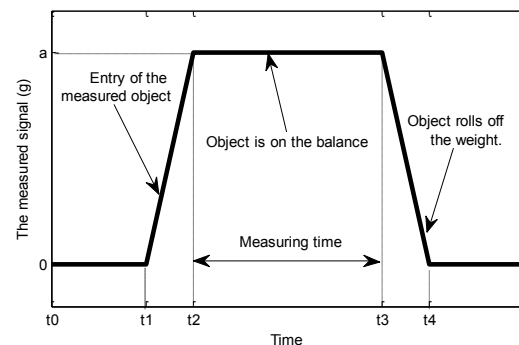


Fig. 3. Model of ideal weight measurement in checkweigher

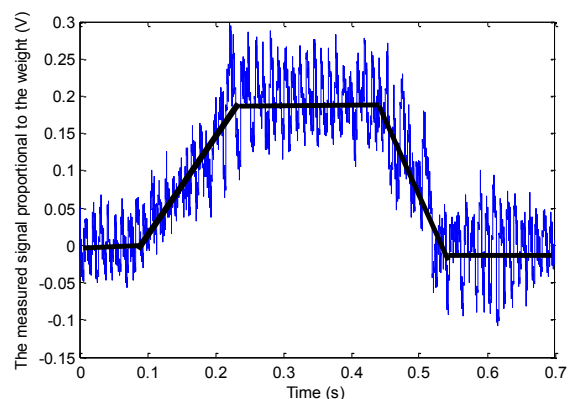


Fig. 4. The actual measurement signal (blue) and assumed ideal signal (black)

As can be seen in the Fig. 4, the interferences generate considerable amount of signal noise. Additionally, one can observe that there is only 0.3 s of measurement time available in this particular example. All this causes considerable difficulties with the precise determination of the measured mass.

The classic solution is the use of a low-pass filter with parameters constant in time. In such a filter, setting the lowest possible cutoff frequency would be desirable, but it would increase the response time and, consequently, force the need to reduce the frequency of measurements.

In recent years, a number of methods to reduce this time was presented. One of them is a system of two or more low-pass filters with different cut-off frequencies proposed by R. Maier et al. [1]. In this solution, the filter switching is based on the steady-state criterion.

Another solution [2] involves the use of a filter with cut-off frequency changing linearly in time (from highest to lowest). The major difference between these filters is that the first works on discrete signals, and the other on continuous. However, in both cases parameters are variable in time and the response time limitation occurs.

The discrete time-variant low pass filter described in [3] allows for further decrease of the response time and lower noise susceptibility. The examples of other filters can be found in [4-8]. The algorithms presented there are based on the weighing scale model based on the system with one degree of freedom [4, 5], but there are also algorithms that don't use the models. There are adaptative analog and digital filters, Kalman filters [5], solutions based on neural networks [6-7], recursive filters [8] and others.

Information about which signal part is subjected to estimation comes from the optical sensors located at the beginning and end of the conveyor belt. Works [9,10] are based on these solutions. Another method proposes K. Fukuda et al. [11]. According to this method, characteristic points of entry and exit of the weighted object are determined directly from the differentiated measurement signal, which is first smoothed using the specified filter.

## 2. Developed measurement method

As it was mentioned earlier, checkweighers tend to measure weight of one specific product, with more or less unchanging weight and permanent size. This means that each passage will be similar to one another and the weight will react similarly to objects entry and exit, where the highest vibration are generated, caused by the falling of the pack on conveyor belt or the impact on construction.

With these issues in mind, one can propose a measurement method, which will be based on the identified model fitting to the given measurement signal. Then, the calculated ratio will be converted to the mass of a specific object.

### 2.1. Preprocessing

Before starting the analysis of the collected data some operations should be carried out. These include:

1. The removal of the DC component
2. The conversion of the values read by the ADC to grams by using an appropriate coefficient
3. Filtering the measurement signal by the appropriate low-pass filter

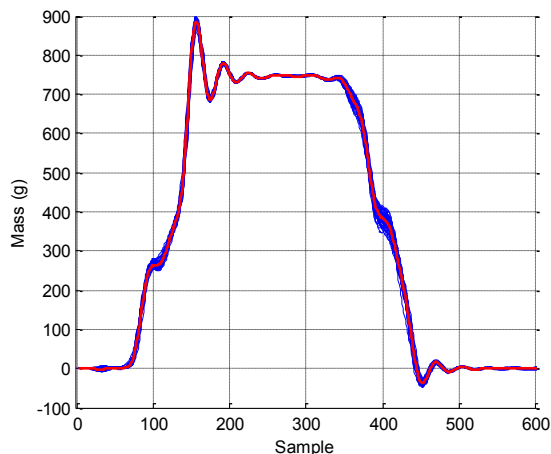


Fig. 5. Filtered measurement signals for 747 g object, using the 8-order Butterworth filter with 30Hz cut-off frequency (blue). The model is marked in red

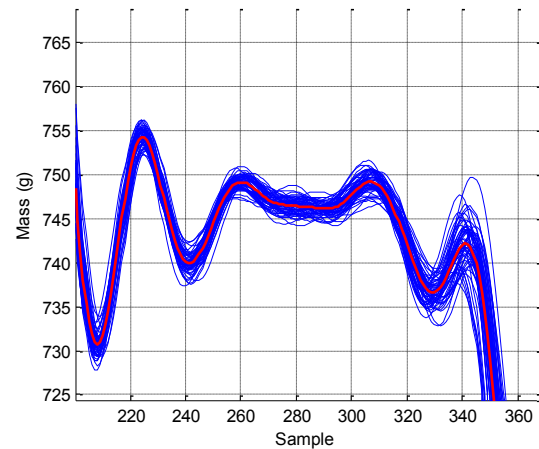


Fig. 6. Zoom-in of the high part of the signal from Fig. 4

Especially the last point is very important: it allows for the elimination from the waveform the distortions generated by motors, and other vibrations transmitted by the weight. Unfortunately, filter order, cut-off frequency and filter type must be chosen experimentally, and too strong filter will result in too strong waveform distortion, while too weak will be insufficient to filter out the noise.

### 2.2. Model build

Model build is simple: multiple passing (>10) through the checkweigher of the same object is needed, and then the signal is averaged. Synchronization of the waveforms is done by the signal from built-in photocell, which informs about entering object.

It should be noticed, that the model fits to the envelope of the measurement signals. One can also see the negative effects of the use of standard low-pass filters that need some time to stabilize under the sudden change of input signal.

### 2.3. Mass measurement

Using the obtained model of measurement signal for given object, deviations of individual waveforms can be tested with respect to the model. With these deviations the weight of the objects can be approximated.

It was assumed in the project, that individual measurements differ from the model by the scaling factor. The measurement in grams is calculated by multiplication of the scaling factor and the mass of the object used for the model development.

In this way, a single-variable optimization problem occurs, which can be written in the following form:

$$\min_k \sum_{n=from}^{to} [w(n) * k - m(n)]^2$$

subject to:

$$0.01 \leq k \leq 2 \quad (1)$$

where:  $k$  – scaling factor,  $w$  – the measured signal, for which the object mass has to be calculated,  $m$  – model signal for known mass,  $from, to$  – the range of the curve fitting.

The limitation in optimization (1) can be omitted by reference to the unambiguous local minimum of a quadratic function, thereby speeding up the selected algorithm.

In turn, the range in which the optimization function works is searched by the algorithm that for all possible ranges within set limits calculates the standard deviation between samples, and then it sums them up. Looking for a minimum we find the best possible range for optimization function. This process is relatively long, but it is performed once during the build of a model. The

optimization process itself, eg. for the range where there are about 200 points, is performed very quickly and on average it takes a medium class computer about 6ms using Matlab 'lsqcurvefit' functions

Then the unknown mass is calculated from the following formula:

$$\text{measurement} = \text{mass of model object} * k \quad (2)$$

As can be seen, quite good results were obtained in view of the fact that the belt was moving close to the maximum speed. Standard deviation of the results was 0.11 g.

### 3. The influence of the low-pass filter cutoff frequency on the measurement accuracy

It was stated earlier that the filter order and the filter cut-off frequency must be chosen manually, unfortunately, by an experimental method. However, for the purpose of testing it was decided to calculate the characteristics of the error depending on the filter cutoff frequency.

It was done for the two different masses, 115 and 747 g, with 60 passes registered for each of them. For every filter change the model was built again, and the range of the model fitting was adjusted. The 8-order filter was designed using the Butterworth method.

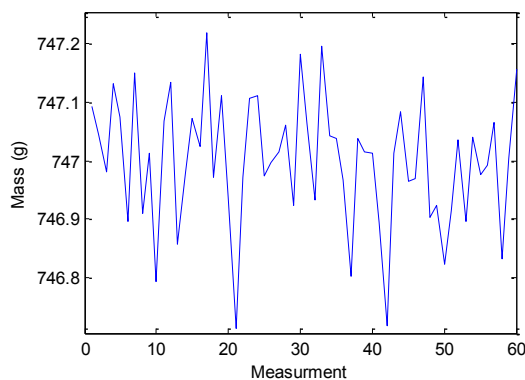


Fig. 7. The results of the analysis of 60 runs series measurement of the same object with automatic range adjustment and using a 8 order Butterworth filter with a cutoff frequency of 30 Hz

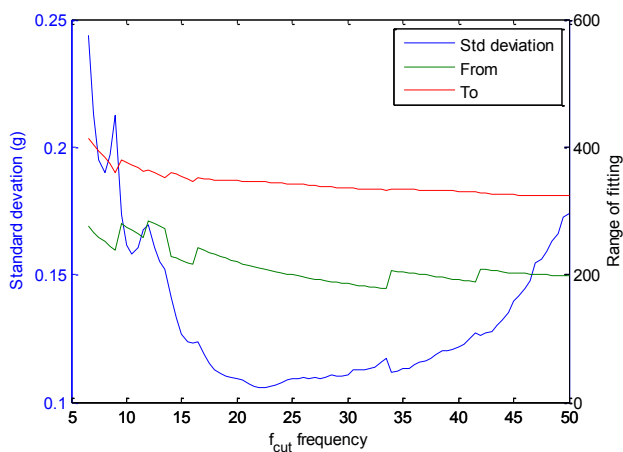


Fig. 8. Analysis for the 747g mass. Minimum in  $f_{\text{cut}} = 22\text{Hz}$

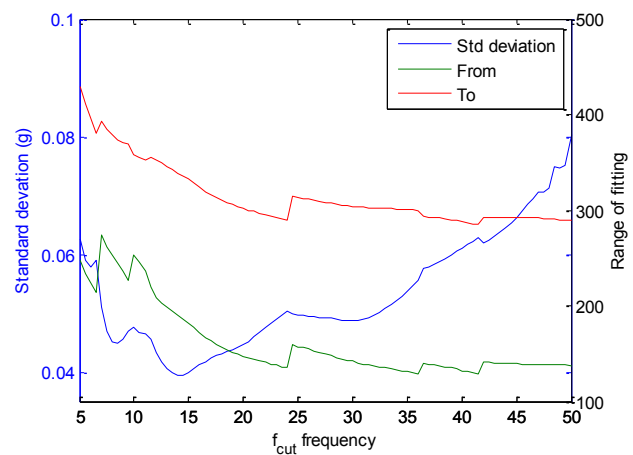


Fig. 9. Analysis for the 115g mass. Minimum in  $f_{\text{cut}} = 14\text{Hz}$

From the above graphs one can see that choosing the appropriate filter cut-off frequency has a large impact on the accuracy of the results. Further work will go towards improved search algorithm of the best segment for the fitting and to test various functions that minimize the search time of the best segment.

It can also be noted that the error/cut-off frequency dependence has many local minima, and therefore the only algorithm which could be used here and would accelerate the process of finding a suitable cut-off frequency is a genetic algorithm.

### 4. Summary

The developed measurement method already achieves better accuracy than the ones used so far, and makes the further improvement possible after additional work.

The described solution is recommended when the measured objects are similar in terms of weight and size, and we only want to know the weight deviations between the individual objects. It is especially important on production lines with the control of completeness of the package, with low-mass objects inside.

Further work will be carried out towards the improvement of the algorithm seeking out optimal fitting section, and a wider range of filters will also be tested.

*RADWAG Company is kindly acknowledged for their help and providing checkweighers for experiments.*

*The research presented in this work has been supported by the European Union within the European Regional Development Fund program no. POIG.01.03.01-14-086/12.*



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Received: 29.09.2014

Paper reviewed

Accepted: 05.01.2015

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