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Enhancing The Performance of Dynamic Weighing Systems using Kalman Filter

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ABSTRACT

In automated production lines, were the mass of single product must be maintained within predefined weight narrow range; a dynamic weight system is required to attain this objective. Checkweigher is integrated in the production line to reduce the overweight and underweight of the product by acquiring the weight signal from the load cell which affected by different sources of noise and vibration and extracts the correct weight. The main objective of this thesis is to design and implement a Kalman filter that reduces the fluctuation and vibration of product weight and enhance the dynamic weighing system performance, which is observed in the real time, and extract the correct weight of the product. This will increase weighing accuracy while maintaining or increasing the production speed. Furthermore, a mathematical model of the checkweigher and load cell is derived and presented.

The simulation and experimental results are presented and compared. The results achieved, show that the Kalman filter may provide effective alternative to the conventional methods especially when the system is nonlinear and low frequency noise is incorporated in the bandwidth of the useful signal.

Keywords: checkweigher, load cell, MATLAB, Kalman filter.

ملخص

تحسين أداء أنظمة الوزن الديناميكية باستخدام مرشح كالمان

في خطوط الإنتاج المؤتمتة هناك حاجة ماسة للمحافظة على وزن المنتج ضمن نطاق محدد يمنع من الزيادة أو النقصان في الوزن, حسب معايير الجودة و الإنتاج.

يستخدم نظام "فحص الوزن" ضمن خطوط الإنتاج للوصول الى الغاية المطلوبة و ذلك من خلال الحصول على إشارة الوزن و تتأثر هذه الإشارة من العديد من مصادر التشويش و الضجيج مما يؤثر على القراءة الحقيقية للوزن. تهدف هذه الدراسة إلى دراسة و تطبيق نظام ترشيح للإشارة بإستخدام Kalman Filter للتخلص من التشويش و الحصول على الوزن الحقيقي للمنتج المتحرك على نظام فحص الوزن, و هذا سوف يساهم في زيادة دقة قياس الوزن مع المحافظة على سرعة عملية التوزين و الإنتاج.

ضمن عملية التصميم , تم الحصول على النموذج الرياضي لنظام فحص الوزن و خلايا الوزن, بالإضافه لعرض النتائج لعملية التحليل و المحاكاة, ومقارنتها مع النتائج التي تم الحصول عليها، وتبين أن Kalman Filter قد توفر بديلا فعالا للأساليب التقليدية وخاصة عندما يكون النظام غير خطي و يحتوي على ضوضاء منخفضة التردد في عرض النطاق الترددي للإشارة مفيدة.

To My Parents,

My Wife,

And my kids

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At the very outset, all my prayers and thankfulness are to Allah the almighty for facilitating this work and for granting me the opportunity to be surrounded by great and helpful people at IUGAZA and PTC.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

$w(t)$	Mass of the desired item.
m_l	The equivalent mass of the load cell.
c	Damping coefficient.
θ	The position of the weigh table.
$x(t)$	the system input
$u(t)$	Controller transfer function
$z(t)$	Stochastic disturbances (system noise with covariance Rv).
$y(t)$	System output (position of balance beam).
$v(t)$	measurement noise
F	Force in (N)
K	Stiffness in (N/m).
δx	The deflection

ABBREVIATIONS

SPM	Signal Processing Module.
JIT	Just In Time.
WIN	Weight in Motion
LSM	Low Speed Motion
HSM	High Speed Motion
LQG	Linear Quadratic Gaussian
P	Prismatic
GUI	Graphical User Interface
DWS	Dynamic Weighing System
RMS	Root Mean Square

CHAPTER 1 INTRODUCTION

1.1 Motivation

The process of product weighing is an essential part of modern industry. There is a constant need for knowing the exact weight of many items, e.g., food, ingredients for production, pharmacology, chemistry, technology, etc.[1]. The type and the number of products that require weight control are increasing. Consequently, the legal requirements of government bodies need developing to guarantee the exact weight. In production, this means high accuracy and efficiency of weighing. Continuation of this trend brings benefits for both the customer and the producer. That is, manufacturing efficiency is increased; hence, profitability whilst package quality and quantity are assured to the customer's satisfaction.

The weighing process and weighing instruments are very crucial to the industrial and public sectors in Gaza. Electronic weighing based systems are replacing the mechanical, volumetric and time based mass and quantity measurements; with increasing demand on performance and accuracy. The weighing systems have applications in almost all local industries in Gaza Strip such as retail, automation, logistic & transport, postal & courier, R&D, health etc.

1.2 Background

A weighing scale is a measuring instrument that is used for determining the weight or mass of an object. Many traditional instruments are used as weighing scales such as scale spring and balance spring. Weighing scales are used in many industrial and commercial applications, and products such as loaded tractor-trailers and medical scales.

In the area of mass production, products are weighed using industrial weighing systems, which are machines that weigh a package dynamically. The weight of the package is estimated while the product has been carried over a loadcell weigh-table by a transport system. Normally the transport system is of a conveyer belt type. The weigh-table is mounted on a load cell, which is the uncontrollable weighing device capable of weighing an item. A signal-processing module (SPM) acquires the electrical signal from weighing device and estimates a value of weight for the passing product as its output.

Development of software and technological innovations in manufacturing activities have changed the face of the weighing balance industry in Gaza Strip. This industry is moving towards developing integrated weighing solutions instead of stand-alone weighing balances. Weighing solutions include weighing balances that are integrated to the manufacturing and inventory systems of an enterprise. These solutions can provide various benefits such as enabling advanced inventory management, Just-in-time "JIT" manufacturing, reduction in inventory holding cost and inventory holding period, e-ordering, vendor and customer relationship management. These solutions also enable automatic and accurate recording of transactions.

Weight in motion (WIM) systems fall into two groups [2]:

- Low speed motion (LSM) which the speed less than 15km/h.
- High speed motion (HSM) which the speed faster than 15km/h.

The two main reason for LSM and HSM systems are functionality and accuracy. The functional requirement is simply aimed at fulfilling low or high-speed applications. The accuracy requirement is based on the current technical inability of high-speed systems to weigh accurately enough for enforcement or fee payment purposes. In this thesis, we will be applying the first method practically.

The checkweigher is one of the most common dynamic weighing system used in almost all modern production lines, different types of products will be passed on the conveyor with different infeed velocities to collect enough data for analysis and simulation. A digital weight indicator is required to interface the weight transducer.

Checkweigher system components

A typical checkweigher dynamic weight system incorporates a series of conveyor belts. Checkweighers are known also as belt weighers, in-motion scales, conveyor scales, dynamic scales, and in-line scales. In filler applications, they are known as check scales. Generally, checkweigher has three belts or chain beds:

- **Infeed Conveyor**: An infeed belt that may change the speed of the package and bring it up or down to a speed required for weighing. The infeed is also sometimes used as an indexer, which sets the gap between products to an optimal distance for weighing. It, sometimes, has special belts or chains to position the product for weighing.
- **A Weigh Belt**. This is typically mounted on a weight transducer which can typically be a strain-gauge load cell or a servo-balance (also known as a force-balance), or sometimes known as a split-beam. Some older machines may pause the weigh bed belt before taking the weight measurement. This may limit line speed and throughput.
- **A Reject Belt** that provides a method of removing an out-of-tolerance package from the conveyor line. The reject can vary by application. Some require an air-amplifier to blow small products off the belt, but heavier applications require a linear or radial actuator. Some fragile products are rejected by "dropping" the bed so that the product can slide gently into a bin or other conveyor.

Weigh table Consists of the conveyor belt attached with a module for weight measurement, which includes transducer and the signal conditioner unit to feed the weight signal to the computerized control. Figure (1.1) shows the checkweigher in production environment.

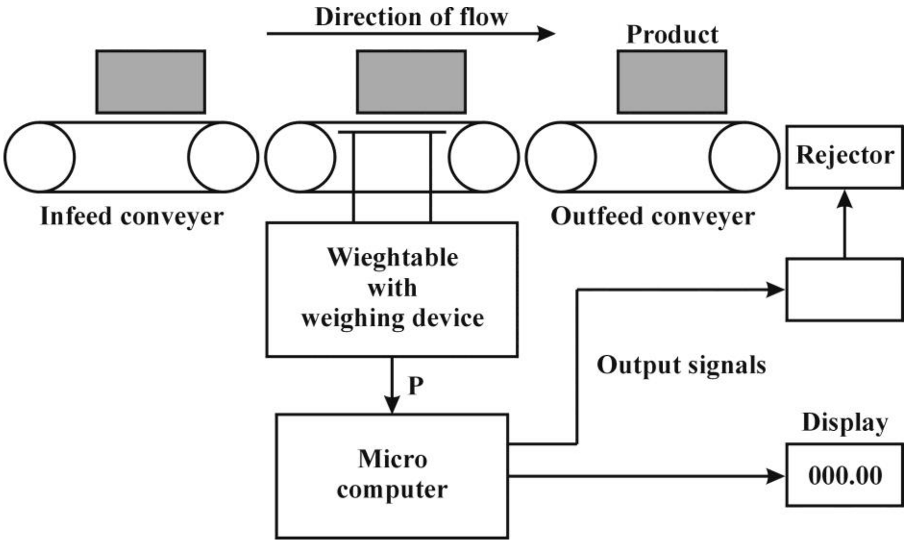

Figure (1.1): Product Flow in Typical Checkweigher

1.3 Previous Study

Through many years, many papers proposed and discussed the weighing systems and checkweigher in motion and investigated in many ways how to filter the electrical signal from the associated noises. Some of them proposed various filters such as Kalman filter, LQG filter and fuzzy logic estimator. These filter techniques gave satisfactory results for their authors. The next paragraph discusses proposed solutions since 1965.

Tariq and Balachandran [3] presented two-checkweigher systems. The first is a robot checkweigher and the second is a conventional checkweigher system. The former is considered as an intelligent system compared to the later in transporting and weighing the objects, which the latter is a conveyor belt driven system. They proved that the robot checkweigher is an interesting method in sorting the products without any significant reduction in the product rate. The solution to filter the signal from load cell based dynamic weighing system is proposed based on Kalman filter. Simulations performed on the model of the dynamic weighing system showed that Kalman filter can be employed in a practical system.

This method was successfully implemented on a specific system setup, however it not suitable for general industrial dynamic weighing systems. It requires tuning the entire system and conducting repeated measurement cycles. In addition, this method did not explaining how to integrate the measured signal into the system controller, and uses complicated embedded control systems, which is the current trend in modern industrial control systems, and needs simplification and modification for a proper hardware realization.

Balachandran et al [3] presented two main aims to improve the weighing process: (1) increase the speed of weighing process and (2) achieve good measurement accuracy. They used an integrated control and filtering approach. The Linear Quadratic Gaussian (LQG) was used to combine the design of control and filtering the weighing process. Finally, a simulation result showed that the LQG design method was suitable for practical dynamic weighing systems.

Halimic, et al [4] presented an optimal integrated control and filtering approach to improve the performance of a weighcell based dynamic weighing system. They were derived an analytical solution for weigh filter. Finally, the results in this paper was compared to the results of [3] and the comparison showed that an improved performance could be achieved by adopting the LQG design method.

Halimic, et al [5] fuzzy logic estimator for dynamic weighing system was designed. Applying this type of filter increased the precision of weighing; hence, improving the results for repeated measurement. However, increase in the accuracy for the single measurement depended heavily on the granularity of the filter. This method depended heavily on the characteristics of product, the initial settings of dynamic weighing system needs to be modified for each product.

Correia and Couto [6] presented a data acquisition solution using RISC type microcontroller. The weighing test showed error below 100 g in 400 kg for an industrial platform of 8 smart load cells. In [7] Fukuda, Tottori, Kameoka, Ono, and Yoshida were proposed method to improve the accuracy of measured axle weight of an In-motion vehicle. They confirmed by processing the simulated results that the new method is superior to conventional method concerning the range and standard deviation in the error of the estimated axle weight taking into account the transient vibration. In this paper they clarified that the new method depends on processing the output signal that obtained from the axel weighing system contaminated with the noise due to the vibration of the vehicle.

Halimic, et al [8] presented an adaptive deconvolution filter to suppress the noise within the Bandwidth of the desired signal. The obtained results shows an improvement of the accuracy , but there were less improvement in the signal measurement results. Therefore an additional noise filter was employed to improve the signal measurement.

In order to suppress the noise, classical signal processing techniques were extensively used in [9]**.** Higino and Couto based on linear and stationary mathematical models. However, practical dynamic measurement systems are inherently non-linear and their characteristics vary with time. Yamazaki, et all [10] suggested a continuous weighing by multi-stage conveyor belt scale, in this method, raising throughput of the conveyor line without increasing the conveyor belt speed by the use of two or three conveyor belt scale (called a multi-stage conveyor belt scale) that were arranged in the line in direct sequence to each other. Through the new measuring technique, a weighing scale can be created which adjusts the conveyor belt length to the product length. This method added extra cost on the system, and had a limit on its maximum throughput.

1.4 Problem Statement

Generally, the weighing process has nonlinear characteristics, large time-delay and noticeable uncertainty. As an example, the checkweigher influences by many factors such as sensitivity to temperature, noise contributed by low frequency and airflow which causes error readings. Therefore, we must reduce and eliminate these factors using various filtering methods.

The traditional measuring principle and feeding method cannot satisfy the increasing control requirements; the noise superimposed on the weight signal will cause a great distortion in the output signal. On the other hands, the increased performance of the position control loop (smaller steady-state error) improves the accuracy of a dynamic weighing system. However, high performance of the position control loop slows down the overall transient response.

To eliminate these sources of inaccuracy and resolve the contradictory effects we propose an integrated digital control and filtering design module, which will be placed between the weigh-table and the microcomputer module. It can be implemented in the weighing control software.

1.5 Thesis Objective

The overall objective is to design, simulate and implement a load cell based dynamic weighing system with improved throughput and accuracy. This work is undertaken in the following developments stages: first, analyze the main factors that affect the accuracy of the dynamic weighing system. Then derive and present the exact model of the load cell based dynamic weighing system. The next stage is studying different approaches to identify, minimize or extract error signal from weighing signal. The fourth stage is to Implement the selected approach (Kalman/PID) using MATLAB and simulate the system with a friendly graphical user interface (GUI), where we can change the system parameters.

Finally develop a prototype for the designed system with onboard algorithm for error extracting. Then discuss the results and compare with previous methods.

1.6 Thesis Contribution

This study contributes to the area of practical application of weighing systems, and implements a working model for dynamic weighing noise filtering and correct weight extraction. The system is based on a general type Loadcell to reach the required accuracy without any additional electronic or mechanical modules.

The main contribution of this research is to study how to reduce and filter noise in dynamic weight systems using general typed load-cell without any special modules to reduce mechanical noise such as oil damper used in high profile and expensive load-cells. In addition, any load-cell can be defined and implemented as part of the checkweigher by using the mass, stiffness and damping parameters of the load-cell.

The study includes design and implementation of Kalman filter integrated dynamic weight controller for any commercial loadcell. The research includes simulation and hardware implementation on real time system. The weight signal and the effect of several noise types are investigated. The developed model is tested and the results will be compared with standard weight tests.

CHAPTER 2 WEIGHING SYSTEMS AND MATHEMATICAL MODELING

2.1 Introduction

Measuring load is an important and essential part of many industrial and commercial operations. It is crucial to have accurate measurements of the load, as small errors, occurring repeatedly, and lead to substantial loss of revenue. Therefore, weighing systems have an important device; it is denoted as load cell [11]. A load cell is uncontrollable weighing device capable of weighing an article. It is used in a variety of industrial weighing applications.

The weight used for weighing at check weighing, called a ribbon weight or tape weight and consists primarily of a mechanical transport system and an electronic weighing system. The mechanical transport system used to transport the subject across the weight and further in the production system. The electronic weighing system is used to measure the weight of the item when the item transported across it. An image of a weighing conveyor is shown in Figure 2.1. Weighing unit consists of a conveyor system and the electronic weighing system.

In this chapter the hardware components of the electronic checkweigher is presented, in addition to the mathematical model of the loadcell .

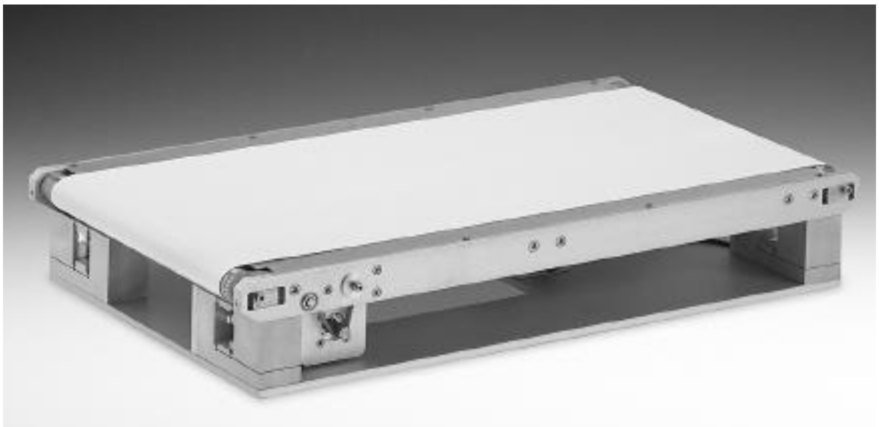

Figure (2.1): Weighing Unit in Tape Weight.

2.2 Checkweigher System.

A checkweigher is a system that weighs items as they pass through a production line, classifies the items by preset weight zones, and ejects or sorts the items based on their classification. Checkweighers weigh 100% of the items on a production line. Typically, an infeed section, scale section, discharge section, rejecter or line divider, and computerized control comprise the physical checkweighing system. Checkweighers and their components vary greatly according to how they are used, the items being weighed, and the environment surrounding them.

2.2.1. Typical Uses of a Checkweigher

Many possible uses for a checkweigher include:

- Check for under and/or overweight filled packages.
- Insure compliance with net contents laws for prepackaged goods
- Check for missing components in a package including labels, instructions, lids, coupons, or products
- Verify count by weight by checking for a missing carton, bottle, bag, or can in a case.
- Check package mixes against weight limits to keep the solid to liquid ratio within established standards.
- Reduce product giveaway by using checkweigher totals to determine filler adjustments
- Classify products into weight grades.
- Measure and report production line efficiency
- Keep production printouts as a record of settings for management and regulatory agencies.
- Analyze filler head performance for both single and multi-head fillers
- Print production totals for a day, shift, hour, batch or product run
- Monitor short and long-term filler performance through statistics.
- Provide Statistical Process Control (SPC) charts for manual feedback and process adjustments.
- Provide SPC for closed loop control, feedback, and automatic process adjustments
- Link packaging line data to upstream control and information systems
- Interface with computers and Programmable Logic Controllers (PLCs) to link the checkweigher to the production process, including controlling the checkweigher through a remote PLC station
- Save Quality Control labor

2.2.2. Statistical Uses of a Checkweigher:

Today’s technology makes checkweighers more reliable and accurate than ever before. The information that a quality team had to collect by hand can now be collected in the blink of an eye by the checkweigher system. The primary value in checkweighing is in achieving “100% sampling” compared to intermittent sampling off-line.

Statistical uses of a checkweigher include:

- Analyze production by weight zone or classification.
- Use 5 or more zones to get detailed fill weight information.
- Monitor overall production efficiency through total count and total weight.
- Monitor overall production speed efficiency (items per minute)

- Monitor standard deviation to alert operator or filler of an out of tolerance condition

2.3 Checkweigher Electronic System

Weigh scales have wide range of uses in industrial, commercial and consumer applications. Electronic weight scales design is based on using a load cell as the primary transducer. Load cell designs can be distinguished according to the type of output signal generated (pneumatic, hydraulic, electric). Strain-gage load cells convert the load acting on them into electrical signals with the output in range of mV/V. The signal chain has to handle the small signal accurately in presence of noise. The signal then has to be processed for non-linearity, temperature dependency and offset errors and drifts. Hence, the signal chain consists of appropriate excitation technique, signal conditioning, signal acquisition and processing and interface and communication.

The most important parameters to consider when designing a weigh-scale system are internal count, ADC dynamic range, noise-free resolution, update rate, system gain, and gain-error drift. The system must be designed to be ratio metric, hence independent of supply voltage.

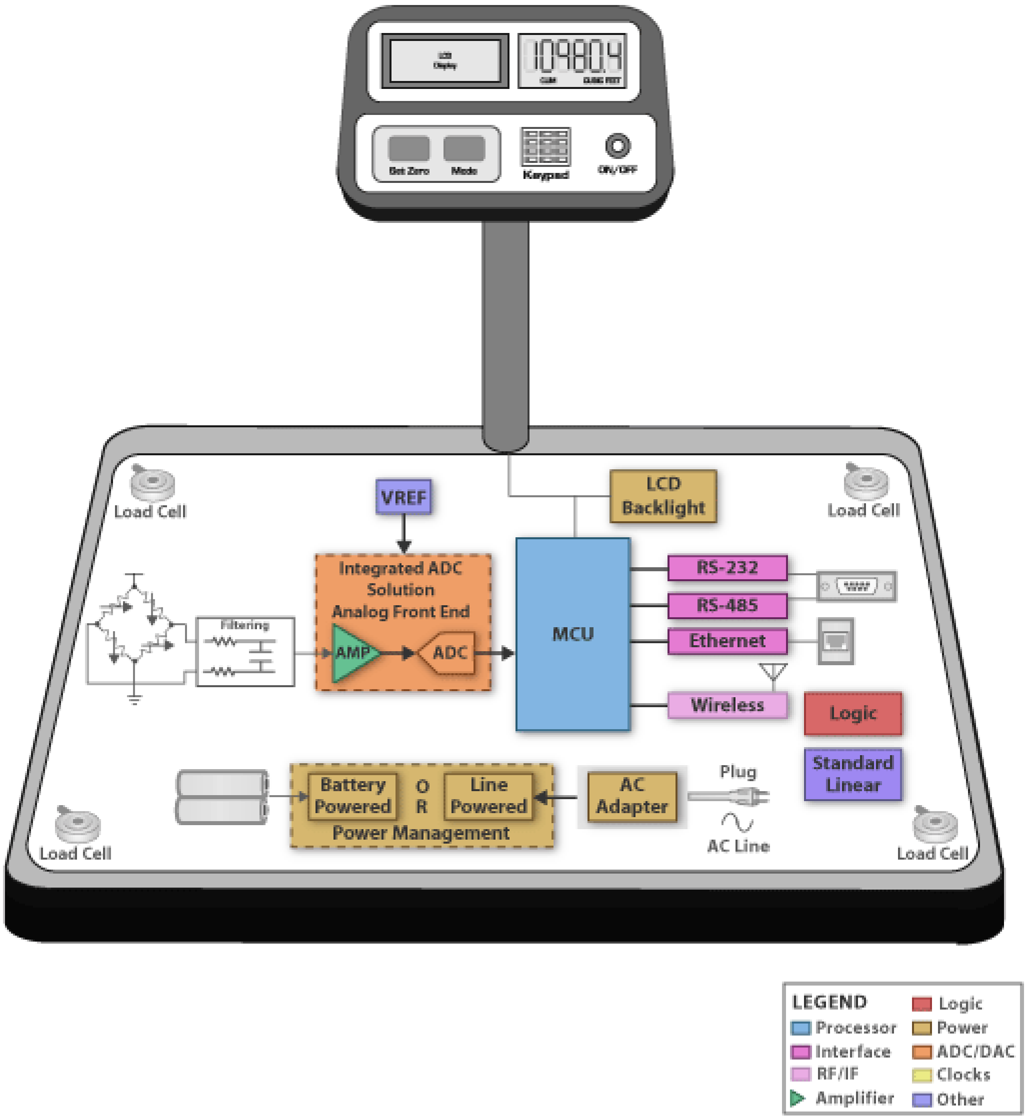

Figure (2.2): Checkweigher Electronic System.

Excitation Technique: The sensor needs an accurate and a highly stable excitation source. Many pressure sensor designs use the same common reference for the excitation circuitry and the ADC for better accuracy and the thus the sensor output is ratio metric.

Signal Conditioning: In most Load cells, the output range of a strain gauge is very small and thus the signal needs to be amplified before processing to prevent introduction of errors. The Signal Conditioner module should provide a wide selection of Low Noise Amplifiers with high CMRR and high gain at low frequencies to be suitable for the small signal output of the sensor. Additionally, since the signal bandwidth is low, the 1/f noise of the amplifiers can introduce errors

Signal Acquisition and Processing: Modern high resolution differential ADCs have low temperature and offset drifts required for Weigh Scale application before it is sent to a MCU. Modern 8bits or 32 bits microcontroller can be used to perform calibration and compensation in addition to using the on-chip data converters for data acquisition. It also provides functions including calculation and signal processing, friendly user interface such as LCD display and keypad control, and wireless/wired data transfer and connectivity interfaces.

Interface and Communication: Traditional RS-232/RS-485 interfaces remain popular choices for weigh scale application. Special application based weigh scales include wired options of Ethernet or USB connectivity and wireless options based on IEEE 802.15.4 protocols

Power: The Weigh Scale can be Line Powered (AC Mains supply) or Battery Powered. power management portfolio includes LDOs, DC/DC converters and buck boost regulators giving flexibility to the user to configure a power solution that meets the system requirements. The DC/DC buck converters offer over 95% efficiency over a wide battery voltage range, even with input voltage down to 1.8 volts extending battery life. Special Buck-Boost converters generate a stable required output voltage, supply constant current for over- and under-input voltage conditions, and support various battery configurations.

2.4 Micro computer controlled load cell digitizer

Almost all modern weighing instruments are utilizing microcomputers to control the operations and to calculate the weights, and the principles of operation for a typical load cell digitizer will be described around the block diagram in Figure 2.3. The digitizer can be divided into four main blocks:

- Front end analogue signal conditioning
- Analogue/Digital conversion
- Microcomputer and digital processing.
- Front panel control and display block

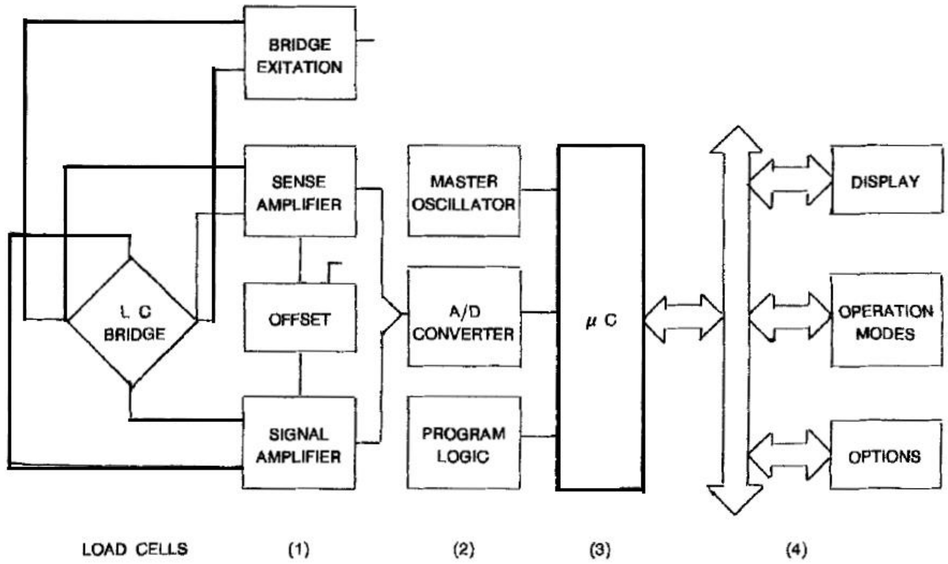

Figure (2.3): Block Diagram of typical Load Cell Digitizer.

2.4.2. Front End Analogue Signal Conditioning

The analogue front-end functions are performed in the blocks:

- Bridge supply (Excitation of the load cells),
- Sense amplifier,
- Offset (of zero) and
- Signal amplifier.

These blocks together generate two signals:

- a scaled , off-set corrected DC signal input, and
- a reference DC signal,

Which alternatively are switched to the input of the dual slope integrating A/D converter.

The **bridge supply unit supplies** stabilized 10-15 volts DC to the load cell system.

The **sense amplifier block** senses the voltage level at the load cells and generates reference voltages of 2 V for use by the A/D converter.

The **zero offset blocks** develop a calibrated voltage to compensate for the user application dead load. The offset voltage is obtained from the sense amplifier so that it will "track" the changes in load cell excitation at the load cell connection box terminals.

The **signal amplifier block** receives the load cell signal output and the offset voltage (from the zero offset blocks) and scales the combined voltages according to the SPAN gain calibration. The resulting DC signal is the input to the A/D converter unit.

2.4.3. Analog/Digital conversion

ADC Internal Count : The resolutions of typical weigh-scale systems, as seen by the user, range from a count of 1:3,000 at the low end up to 1:10,000 for high-end solutions. For example, a weigh scale that can measure up to 5 kilograms with a count of 1:10,000 has a weight resolution of 0.5 grams. This resolution, as seen on the LCD display, is generally referred to as the external count. In order to guarantee that this resolution is met accurately, the internal resolution of the system must be better by at least an order of magnitude. In fact, some standards dictate that the internal count of the system be a factor of 20 times better than that of the external count. For the example above, the internal count would need to be 1:200,000.

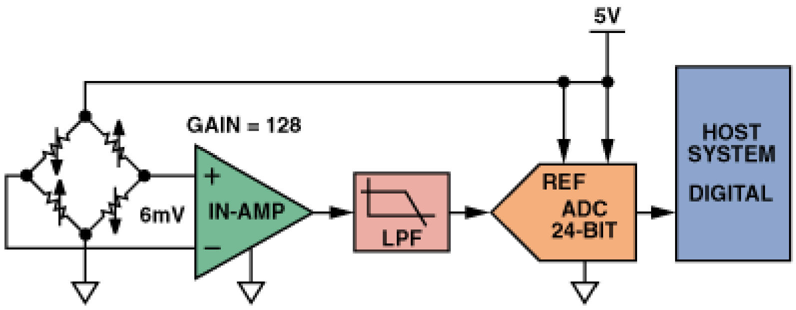

Figure (2.4): Typical Weigh-Scale System ADC Interface

ADC Dynamic Range

In weigh-scale applications using standard high-resolution A/D converters, the entire full-scale range of the ADC is unlikely to be used. In real applications if the load cell has a 5-V supply and a full-scale output of 10 mV. The linear range is 6 mV. Using a gain-of-128 stage on the front end, the ADC input will see about 768 mV full-scale. If a standard 2.5-V reference is used, only 30% of the ADC's dynamic range is used.

If the internal count needs to be 1:200,000 accurate for the full-scale range of 770 mV, the ADC therefore needs to be of the order of 3× to 4× better in order to meet the performance requirements. In this case, for a count of 1:800,000, the ADC would require 19 bits to 20 bits of accuracy. The practical challenge posed by the signal-processing requirement can now be understood.

Gain and Offset Drift

Industrial weigh-scale systems typically operate over a 50-degree (Celsius) temperature range. Designers must consider the accuracy of the system at temperatures beyond room temperature, since gain drift with temperature can be a dominant source of error. For example, a 20-bit stable system with a 1-ppm/°C gain-error drift will have 50 LSBs of error over a 50-degree range. Even though the system may be 1-LSB stable at 25°C, it is in effect only 50-LSBs accurate over the full temperature range. Choosing an ADC with low gain drift is thus a very important consideration when designing weigh scales.

Offset drift is not as big a consideration. Most sigma-delta ADCs are designed with inherent chopping-mode techniques, which give the advantage of lower drift and better immunity to 1/f noise—useful features for weigh-scale designers. For example, the AD7799 A/D converter has an offset drift specification of 10 nV/°C. In a 20-bit system, this would contribute a total of only 1/4-LSB error over the full 50-degree operating range.

Noise-Free Resolution

One common mistake when reading data sheets is lack of attention as to whether noise is specified as root mean square (rms) or peak-to-peak (p-p). For weigh-scale applications, the most important specification is p-p noise, which determines noise-free-code resolution. The noise-free-code resolution of an ADC is the number of bits of resolution beyond which it is impossible to distinctly resolve individual codes due to the effective input noise—associated with all ADCs. This noise can be expressed as an rms quantity, often as a number of LSB units (counts, 2–n of full scale). Multiplying by 6.6 (to capture 99.9% of all values in a standard distribution) provides a reasonable equivalent peak-to-peak value (expressed in LSBs). Data sheets for most Analog Devices sigma-delta ADCs specify both the rms- and the p-p, or noise-free, codes.

Update Rate

In Figure 4, it can be seen that the noise-free resolution of the system depends on the update rate of the ADC. For example, using a 2.5-V reference and an update rate of 4.17 Hz, the resolution is 20.5 bits p-p (gain of 128); whereas at 500 Hz, the resolution decreases to 16.5 bits. In weigh-scale systems, the designer needs to balance the lowest update rate at which the ADC can be sampled with the output data rate needed to update the LCD display. For high-end weigh scales, a 10-Hz ADC update rate is generally used.

2.4.4. Weigh-Scale Reference Design

The best ADC architecture to use for weigh-scale applications is sigma-delta, due to its low noise and its high linearity at low update rates. A further benefit is that noise shaping and digital filtering are implemented on-chip. The integration in the high-frequency modulator shapes the quantization noise so that the noise is pushed toward one half of the modulator frequency. The digital filter then band-limits the response to a significantly lower frequency. This greatly reduces the need for complex post-processing of the ADC data by the user.

The ADC should also contain a low-noise programmable-gain amplifier (PGA) with high internal gain to magnify the small output signal from the load cell. An integrated PGA can be optimized to give low temperature drift, as compared to a discrete amplifier with external gain resistors. With a discrete configuration, any errors due to temperature drift will get amplified through the gain stage. The AD7799, specifically designed for weigh-scale applications, has an excellent noise specification (27 nV/rt-Hz) and a front-end gain stage with a maximum gain of 128 mV/mV. The load cell can be directly interfaced to this ADC.

Figure 2.5 is a block diagram of a reference design, a weigh-scale system evaluation board designed at Analog Devices. It consists of an AD7799 ADC, controlled by an ADuC847 microcontroller. Besides providing, the digital interface to the AD7799 and implementing the post processing, the ADuC847 microcontroller itself also contains a 24-bit, high-performance sigma-delta ADC. This will allow users to compare test results between a system containing the AD7799 ADC, and a completely self-contained system using the ADuC847 ADC, with the same hardware connections, so as to choose a design that best meets the requirements.

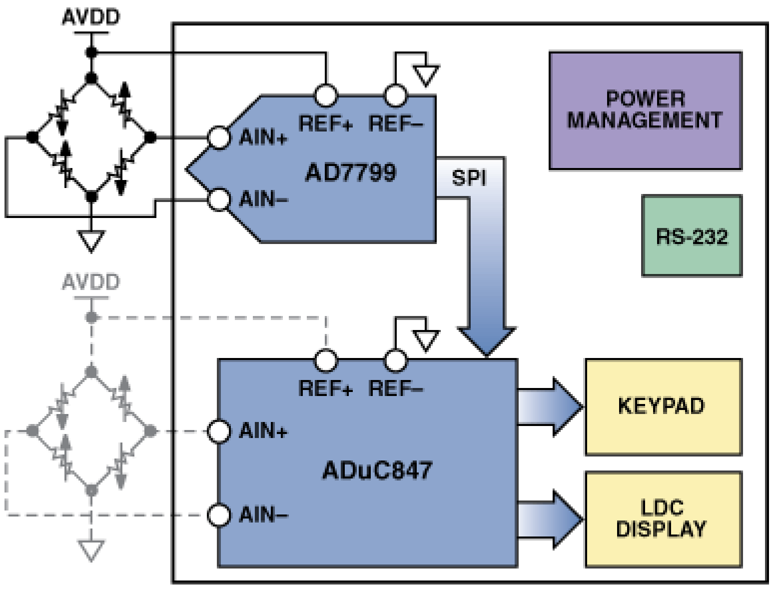

Figure (2.5): Weigh Scale Reference-Design Block Diagram

2.5 Load Cell Description

An electronic weighing system is the electronic system used for dynamic weighing. A weighing system consists of one or more sensors and an intelligent module. The sensor is usually called a load cell and is available in several different types. In industrial weighing systems, there are three types of load cell: Magnetic transducer which measures change in magnetic permeability, oscillating string transducer which measures changes in frequency and the third one is the strain gauge transducer which measure changes in resistance [12]. The three types of load cell are called transducers because it converts the force into a measurable data. In the weighing system used in this thesis we will use the third type.

Majority of the industrial weighing systems use the strain gauge load cell in various types such as bending beam, shear beam, canister, and S beam load cell, etc., as shown in Figure 2.2. It is considered the most common type of load cells in industry due to their low price and great loads area. In addition, it is suitable to be used in the dusty and moist workshop environments.

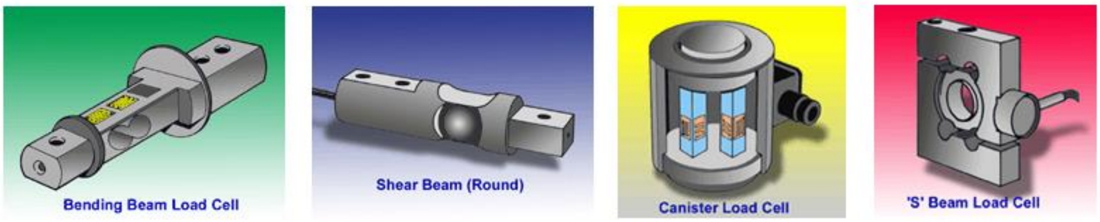

Figure (2.6): Load Cell Types

Figure 2.3 shows the structure of the load cell. It has four arms Whetstone bridge.

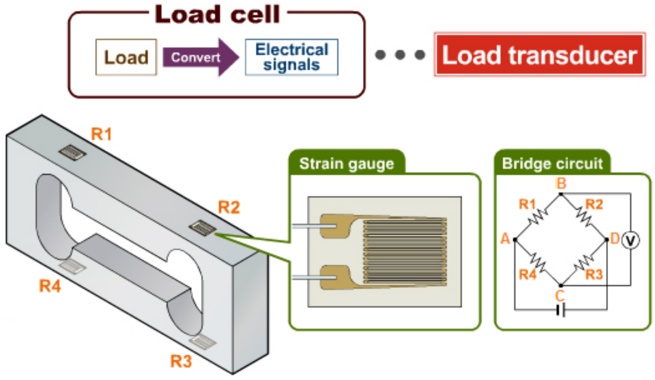

Figure (2.7): Wheatstone Bridge Load Cell

This configuration allows for temperature compensation and cancellation of signals caused by forces not directly applied to the axis of the applied load. A regulated 5 to 20 volt DC is required as input that applied between points A and D. When force is applied to the transducer, the Whetstone Bridge is unbalanced which causing an output voltage between points B and C. The emerging voltage between point B and C is proportional to the applied force on steal body, which is measured very precisely.

As mentioned above load cells are blocks of metal that have been machined in such a way that specific areas are put under high strain when weight is applied to them. These areas have strain gauges attached to them with a high strength adhesive. The most common materials used to manufacture loadcell are Aluminum Alloy, Steel Alloy, and Stainless steel. Strain gauges themselves consist of thin wire or foil elements that are glued to the loadcell body. Strain gauge load cell are cunningly shaped so that even very small movements or “stretching” of the gauge results in comparatively large changes in resistance.

The loadcell usually have four or six wires coming out of them. Two of these wires are to power the loadcell. This is called the excitation, whereas the excitation voltage of the loadcell ranges from 5 volts to 15 volt DC. Two of the other wires return a signal to the weight indicator. These are called the signal wires. If the loadcell has a 6-wire connection, the extra two wires are called sense wires. The weight indicator to compensate for voltage drop in the excitation over long distances uses these. The sense wires are connected to the same point as the excitation wires.

2.6 Load cell modeling

In order to control checkweigher system, it is necessary to have a model that describes its dynamic behavior. Therefore, if we consider up and down motion of the conveyer belt of the checkweigher, we may apply two-spring mass to model this system as shown in Figure (2.4).

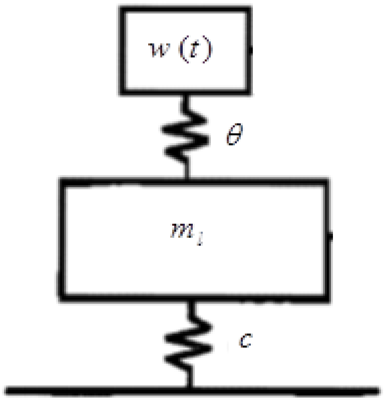

Figure (2.8): Load Cell Modeling

When a product comes onto the weightable, it causes the weighable to move, and this can be described by the following differential equation:

$$w(t)g = (w(t)+m_l)\theta^{\bullet\bullet}(t) + c\theta^{\bullet}(t) + k\,\theta(t) \tag{2.1}$$

Or

$$\theta^{\bullet\bullet}(t) + \frac{c}{w(t)+m_l}\theta^{\bullet}(t) + \frac{k}{w(t)+m_l}\theta(t) = \frac{w(t)g}{w(t)+m_l} \tag{2.2}$$

where:

$w(t)$ = mass of the desired item.

m_l = the equivalent mass of the load cell.

c = damping coefficient.

θ = the position of the weigh table.

$\theta^{\bullet}$ = the velocity.

$\theta^{\bullet\bullet}$ = the acceleration.

Defining the state variables $\zeta_1(t) = \theta(t)$ and $\zeta_2(t) = \theta^{\bullet}(t)$, the state differential equation of the system combined with equation (2.2) becomes:

$$\dot{\zeta}_2(t) + \frac{c}{w(t)+m_l}\zeta_2(t) + \frac{k}{w(t)+m_l}\zeta_1(t) = \frac{w(t)g}{w(t)+m_l} \tag{2.3}$$

Equation (2.3) becomes:

$$\zeta_2^{\bullet}(t) = -\frac{c}{w(t)+m_l}\zeta_2(t) - \frac{k}{w(t)+m_l}\zeta_1(t) + \frac{w(t)g}{w(t)+m_l} \tag{2.4}$$

Equation (2.4) may be rewritten as state space equation as follows:

$$\begin{bmatrix} \dot{\zeta}_1(t) \\ \dot{\zeta}_2(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\dfrac{k}{w(t)+m_l} & -\dfrac{c}{w(t)+m_l} \end{bmatrix} \begin{bmatrix} \zeta_1(t) \\ \zeta_2(t) \end{bmatrix} + \begin{bmatrix} 0 \\ \dfrac{g}{w(t)+m_l} \end{bmatrix} w(t) \tag{2.5}$$

Let $x(t)=\begin{bmatrix}\zeta_1(t)\\ \zeta_2(t)\end{bmatrix}, \alpha(t)=-\dfrac{k}{w(t)+m_l}, \beta(t)=-\dfrac{c}{w(t)+m_l}$ and $\gamma(t)=\dfrac{g}{w(t)+m_l}$ and the controlled variable *y(t)* be the position of the weightable.

Then the state differential equation in the matrix form is:

$$\begin{aligned}\dot{x}(t)&=\begin{bmatrix}0 & 1\\ \alpha(t) & \beta(t)\end{bmatrix}x(t)+\begin{bmatrix}0\\ \gamma(t)\end{bmatrix}u(t)+z(t)\\ y(t)&=\begin{bmatrix}1 & 0\end{bmatrix}x(t)+v(t)\end{aligned} \tag{2.6}$$

Where *u(t)* = *w(t)*

The above equation rewritten in another form as follows:

$$\begin{aligned}\dot{x}(t)&=A(t)x(t)+B(t)u(t)+z(t)\\ y(t)&=Cx(t)+v(t)\end{aligned} \tag{2.7}$$

Where:
x(t) is the state space of the mechanical system.
u(t) is the system input (*w(t)* unknown mass of a product).
z(t): stochastic disturbances (system noise with covariance Rv).
y(t): system output (position of balance beam).
v(t): measurement noise (Gaussian zero mean white noise with covariance &).
A(t) & B(t) time varying matrices, and C is a constant matrix.

The performance of a load cell depends primarily on its ability to deflect under highly repeatable conditions when load is applied or removed. Through this thesis, we will use 10kNF207 loadcell. The typical deflection for a 10kN F207 loadcell at full rated load is 9µm, or 9 microns.

The relation between the stiffness and deflection in load cell determined by the equation:

$$F = K\,\delta x \tag{2.8}$$

where:

F= force (N).

K= stiffness (N/m).

δx is the deflection.

From eq (2.8) the stiffness K is equal $1.1\times10^{9}\ N/m$

CHAPTER 3 KALMAN FILTER

3.1 Kalman Filter

Kalman filter method is an estimation method that widely applied in real time applications such as tracking objects, economics, navigation, and others. It used to estimate the state of the dynamic model (system) or part of it based on the measurement of the system inputs and output, and the relation between them [13].

Dynamic model estimation has two steps: prediction and correction. In the first step, the state is predicted with the dynamic model describing the behavior of the state vector of the system. The second step is the correction was the observation model establishes the relationship between the measurement and the state vector. Therefore, the error covariance of the estimator is minimized. These steps are repeated each time with the state of the previous time as initial value.

Kalman filter is a model that combines measured data and prediction of data to find the optimal estimate of the state of a system or state. The filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements [14]. The general state-space model can be written as (3.1).

$$\begin{aligned} x_{t+1} &= A_t x_t + B_t u_t + \varepsilon_t \\ y_t &= C_t x_t + D_t u_t + \upsilon_t \end{aligned} \tag{3.1}$$

Where A_t, B_t, C_t, and D_t are matrices, which describe the model. x_t is the state vector, describes the state of the system. y_t is observations vector describing measured data from system, u_t is an external input. Two different noises ε_t and υ_t added to the state and observation equations respectively. The state equation has covariance matrix $R_v(x)$ and the observation matrix has covariance matrix $R_w(x)$. The two random variable $R_v(x)$ and $R_w(x)$ assumed to be independent of each other. In addition, they are used to characterize the uncertainty in the state and observation model.

Kalman filter works with a prior estimate of the state vector $\hat{x}^-$, and a posteriori estimate of the state vector $\hat{x}$. Note the difference in the minus sign. A priori estimate can be considered as a prediction of state vector from the model in equation 3.1, and a posteriori estimate can be considered as the reconstruction of the actual state vector from the information in the observation, resort, and the model in equation 3.1. $\hat{x}^-$ and $\hat{x}$ are random vector with covariance $\hat{P}^-$ and $\hat{P}$ are given by equation 3.2:

$$\begin{aligned} P_t^- &= E\left[\left(x_t - \hat{x}_t^- \right) \left(x_t - \hat{x}_t^- \right)^T \right] \\ P_t &= E\left[\left(x_t - \hat{x}_t^- \right) \left(x_t - \hat{x}_t \right)^T \right] \end{aligned} \tag{3.2}$$

Where $e_t^- = \left(x_t - \hat{x}_t^-\right)$ and $e_t = \left(x_t - \hat{x}_t\right)$.

Kalman filter equations are divided into two groups: time update equations and measurement update equations. The two groups of equation are divided into the next equations.

The time update equations or prediction are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the *a priori* estimates for the next time step. They are based on the following equations:

$$\hat{x}_t^- = A\hat{x}_{t-1} + Bu_t \tag{3.3}$$

$$P_t^- = AP_{t-1}A^T + Q \tag{3.4}$$

The measurement update equations or corrector are responsible for the feedback as example, for incorporating a new measurement into the a priori estimate to obtain an improved *a* posteriori estimate. In addition, it based on the following equations:

$$K_t = P_t^- C^T (CP_t^- C^T + R)^{-1} \tag{3.5}$$

$$\hat{x}_t = \hat{x}_t^- + K_t (y_t + C\hat{x}_t^-) \tag{3.6}$$

$$p_t = (1 - K_t C)P_t^- \tag{3.7}$$

Figure 3.1 shows Kalman filter cycle using time update and measurement update states.

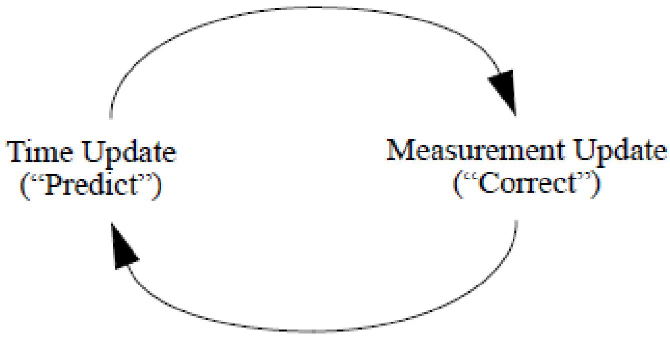

Figure (3.1): Kalman Filter Cycle

The term in equations (3.5) and (3.6) corresponds to the previously mentioned linear projection and (3.7) is A calculation of the variance of the estimate of the state vector, which is obtained by the measurement equation. The difference in equation (3.6) is called the measurement innovation, or the residual. The residual reflects the discrepancy between the predicted measurement and the actual measurement. A residual of zero means that the two are in complete agreement.

The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as corrector equations. The predictor equation has a state estimate x_t and error covariance P_t . Both of them propagated at each time step. After that, the corrector equation provides feedback with new measurement to improve the previous estimation.

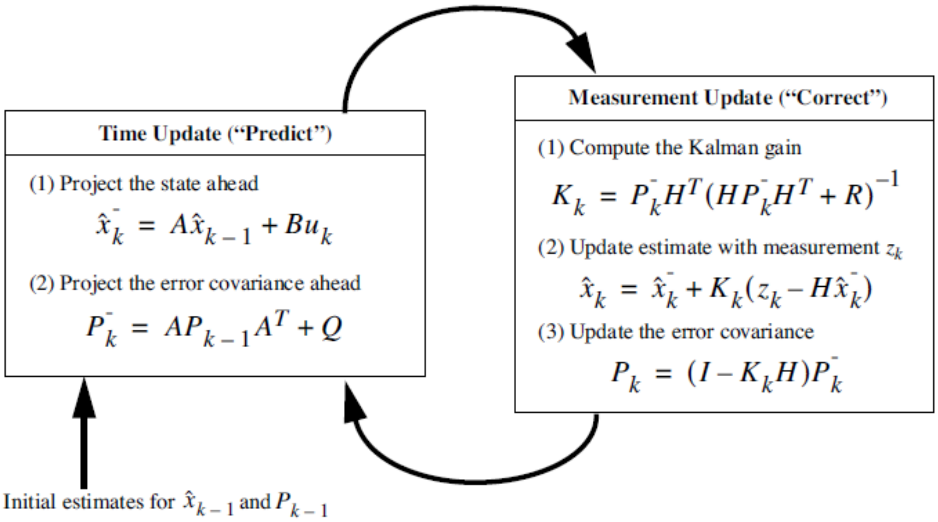

Figure (3.2): A Complete Picture of the Operation of the Kalman Filter

3.2 Simple Kalman Filter

Simple Kalman filter was presented in [4]. The model is shown as:

$$\begin{aligned} m_{t+1} &= m_t + \varepsilon_t \\ y_t &= m_t + \upsilon_t \end{aligned} \tag{3.8}$$

Where y_t indicates the sum of the four load cells and m_t is the mass of the subject. The problem in this model that it estimates the position of the object not the object weight. Kalman filter denoted as an attractive method to estimate the weight of the object not only reducing the signal noise that accompanying the signal as this is done by simple filter.

The filter can be initialized and started every time and the final estimate can be taken when the object starts moving on the belt again, as it must be assumed that the best estimate is obtained if all samples from the weighing are used to obtain the estimate.

It can be expected that a pre-filter is required to remove the heavy vibrations at the resonance frequency of the simple model. The pre-filter is used the same way as used for the low-pass filtering. Figure 3.3 shows the use of model on a weighing of a 35 kg subject. It appears that the method immediately appears to provide a good estimate of the mass, but it can also be seen that the remaining vibrations can be seen in estimates. This is because it is a poor assumption that the vibrations can be modeled as white noise.

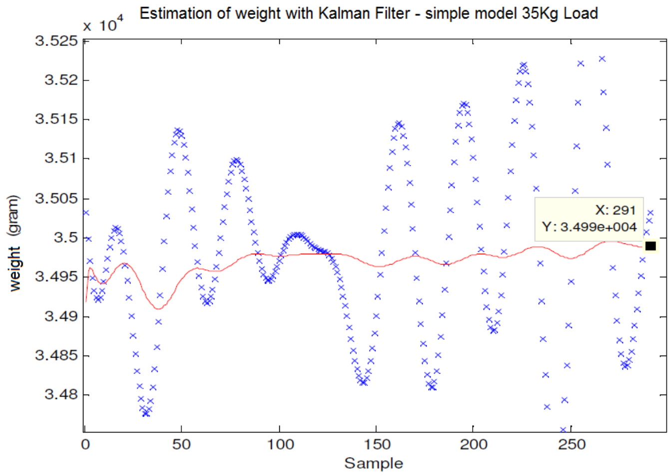

Figure (3.3): Estimation of Weight with Kalman Filter- Simple Model 35Kg load

3.3 Kalman Filter 4 Phases:

The weighing process on a weighing conveyor can be divided into four phases. The first phase is before the package enters the weighing area and this is considered the zero point, so you have a reference for weighing. In the second phase the package moves into the weigh feeder, in the third phase the package runs over the weigh feeder and in the fourth and final phase, the package leaves the weigh feeder. The model used in the Kalman filter will look different for each of the three phases, the Kalman filter is to be used in all phases.

A solution to this problem is to implement the Kalman filter using a finite state machine, where the model changes depending on which state you are in. Photo sensors can be used to switch between states, and Figure 3.4 shows a diagram of the state machine.

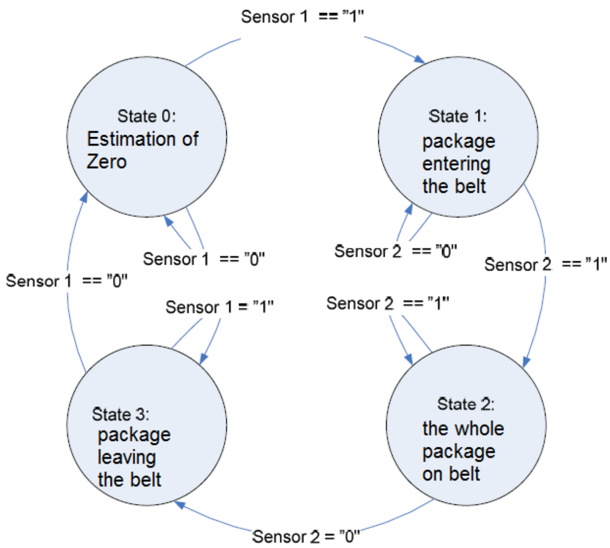

Figure (3.4): Overview of the Requirements for Changing the Phases of the State Machine

State-vector in the Kalman filter extended with two states. One is dm_t , indicating an estimate of the change in mass on the weighing plane per sample, when the subject is moving on the weighing belt. The other is η_t indicates the estimate of the zero point. The new states are state-vector in the Kalman filter is given $\begin{bmatrix} n_t & m_t & dm_t & \eta_t \end{bmatrix}^T$.

3.3.2. State "0" - No Package on Belt

In the first phase, called state "0" in the state machine, the zero point is estimated to achieve a reference point for weighing. The following model is used:

$$\begin{bmatrix} n_{t+1} \\ m_{t+1} \\ dm_{t+1} \\ \eta_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & A_{SF} \end{bmatrix} + \varepsilon_t$$
$$y_t = \begin{bmatrix} 1 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} n_{t+1} \\ m_{t+1} \\ dm_{t+1} \\ \eta_{t+1} \end{bmatrix} + \upsilon_t \tag{3.9}$$

The model describes a zero, which is changed only by white noise. In addition, a shaping filters in the model to describe the vibrations from weighing belt. The observation is the sum of zero and the vibrations from weighing belt.

3.3.3. State "1" – Package Moving into the Weighing Belt

In the second phase, called state "1" in the state machine, the Kalman filter depends on the mass. While the subject is entering the belt, a rough estimate is obtained when the subject is brought into the belt. In this state, it is assumed that the mass of the subject is evenly distributed over the whole subject, and that the derivative of the measured mass will thus be approximately constant while the subject is moving.

$$\begin{bmatrix} n_{t+1} \\ m_{t+1} \\ dm_{t+1} \\ \eta_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & A_{SF} \end{bmatrix} \begin{bmatrix} n_t \\ m_t \\ dm_t \\ \eta_t \end{bmatrix} + \varepsilon_t$$
$$Y_t = \begin{bmatrix} 1 & 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} n_t \\ m_t \\ dm_t \\ \eta_t \end{bmatrix} + \upsilon_t \tag{3.10}$$

The model describes mass as the final estimated mass plus the estimated derivative of the mass. The zero point and the vibrations described as in state 0 The observation is the sum of belt vibrations, zero and the mass of the belt.

3.3.4. State "2" - The Whole Package on the Weighing Belt

The third stage is called state "2" in the state machine. This state is used to estimate the mass of the subject when the subject is on the belt. In this state, we have the following model.

$$\begin{bmatrix} n_{t+1} \\ m_{t+1} \\ dm_{t+1} \\ \eta_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & A_{SF} \end{bmatrix} \begin{bmatrix} n_t \\ m_t \\ dm_t \\ \eta_t \end{bmatrix} + \varepsilon_t$$

$$Y_t = \begin{bmatrix} 1 & 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} n_t \\ m_t \\ dm_t \\ \eta_t \end{bmatrix} + \upsilon_t \tag{3.11}$$

In this state, it is assumed that the item weight does not change. The model for the zero point and belt vibration is the same as in the other two states. The observation is the sum of zero, weight and belt vibration.

3.3.5. State "3" –The Package Leaving the Weighing Belt

In the fourth phase, called state "3" in the state machine, the Kalman filter depends on the mass weight on the belt changing down to zero, while the subject is moving on the weighing belt. This state is very similar to state "1" and it is assumed again that the mass of the subject is evenly distributed over the subject, and that the derivative of the measured mass will thus be approximately constant while the subject moving of the weighing belt.

$$\begin{bmatrix} n_{t+1} \\ m_{t+1} \\ dm_{t+1} \\ \eta_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & A_{SF} \end{bmatrix} \begin{bmatrix} n_t \\ m_t \\ dm_t \\ \eta_t \end{bmatrix} + \varepsilon_t$$

$$Y_t = \begin{bmatrix} 1 & 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} n_t \\ m_t \\ dm_t \\ \eta_t \end{bmatrix} + \upsilon_t \tag{3.12}$$

The model describes mass as the final estimated mass minus the estimated derivative of the mass. The zero point and the vibrations described as in the other states. The observation is the sum of belt vibration, zero and the mass of the belt.

Figure 3.5 shows the use of the Kalman filter with four stages on data from a 12.4 kg item that is filtered with a pre-filter.

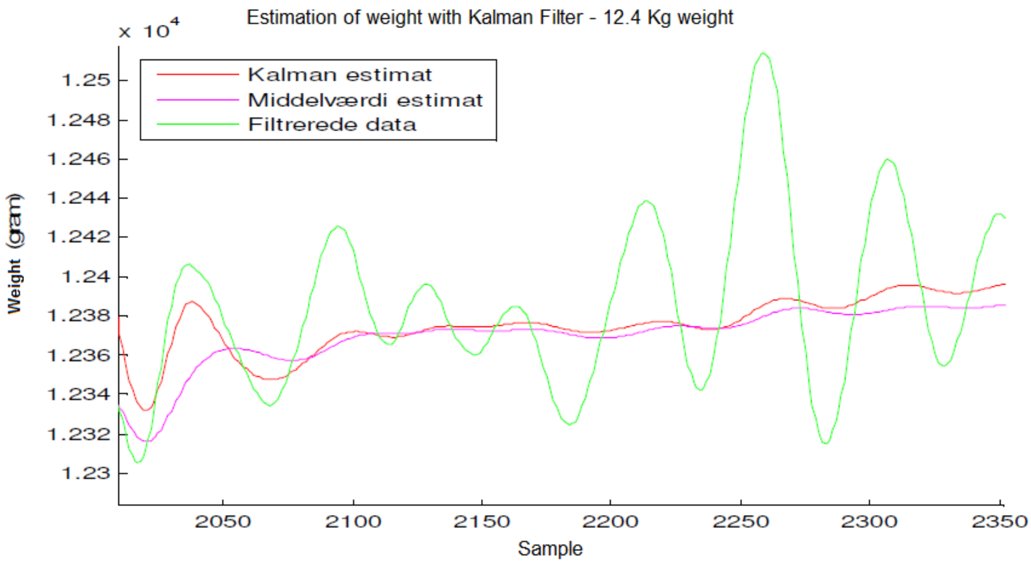

Figure (3.5): Estimate of Weight with Kalman Filter - 12.4 Kg Weight

3.4 Tracking of zero

The zero point in the model can cause problems during the use of data. This is due to zero constant shifts upwards with a few grams when the item is moving on the weighing belt unless the variance of the noise on the zero point is set very low. The actual origin of the electronic system is as stable as zero in the model introduces a constant error in the form of a variable offset rather than to compensate for a small almost negligible error if not zero point variance is set very low or zero.

3.5 Kalman smoothing

Kalman filter is causal, but as the result of the balance is not needed immediately after subject is moving on the weighing belt, then a non-causal Kalman smoother is used to update the current estimates of the weight. You can choose between three different types of smoother [15].
- Fixed lag smoother
- Fixed point smoother
- Fixed interval smoother

A fixed layer smoother updates all metrics based on a certain number of measurement points out in "the future". A fixed-point smoother retrieve a specific measuring point relative to the available data, and a fixed interval smoother updates all endpoints in the range of use of all measuring points. If a fixed interval smoother is chosen, it is not known in advance when smooth transferee obtains the best result. Smoothing requires all state vector x_t and variance matrices P_t stored and smooth transferee initialized with [15].

$$\begin{aligned} \hat{x}_{s,N} &= \hat{x}_N \\ P_{s,N} &= P_N \end{aligned} \tag{3.13}$$

Then all the measurement points' recursively with the following updates [5].

$$\begin{aligned} \hat{x}_{s,t} &= \hat{x}_t + C_t(\hat{x}_{s,t+1} - \hat{x}_{t+1}) \\ C_t &= P_t A^T P_{t+1}^{-1} \end{aligned} \tag{3.14}$$

Smoothing calculates the result is:

$$E[x_t \mid y(1:N)] \text{ for } 1 \le t \le N \tag{3.15}$$

The model used for the Kalman filter, describes the mass as a constant mass. Kalman smooth transfer is the expected value of this constant conditional on all measurements y (1: N), as described in equation (3.14). This means that all the Kalman smooth estimates of the mass will be the same if the process noise is set to zero, and this estimate will be the same as the last estimate in the Kalman filter. This means that there is no reason to apply Kalman smooth transfer provided the process noise of the mass is set to zero or close to zero.

CHAPTER 4 SIMULATION AND ANALYSIS

Matlab program has been written to simulate weight graphs and to apply Kalman filter method to extract the weight of an item. Graphical User Interface (GUI) is shown in Figure (4.1).

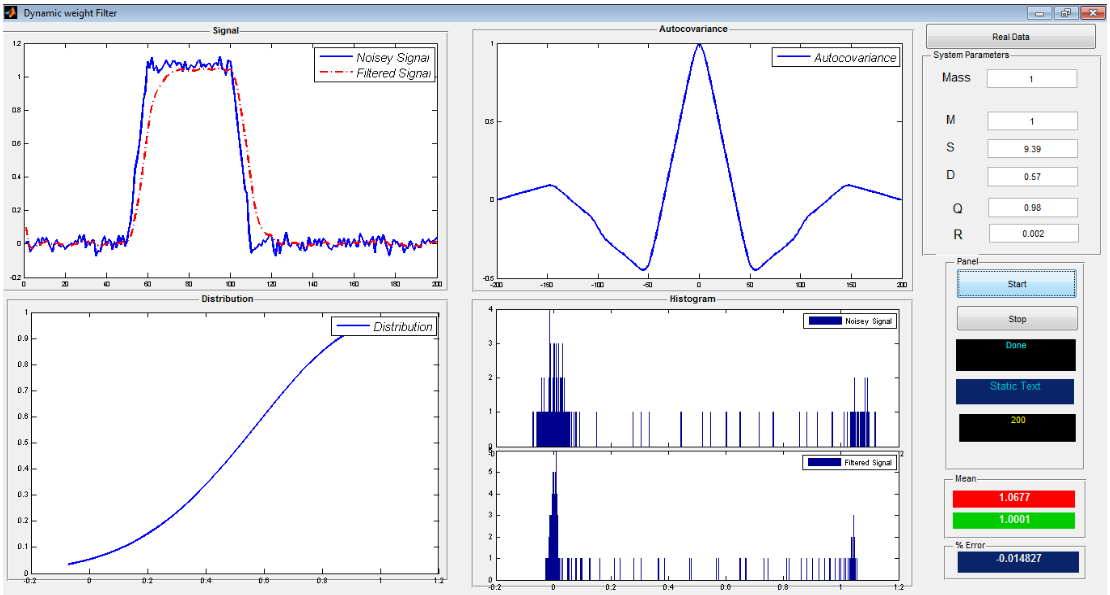

Figure (4.1): GUI Screen

The GUI system has four screens, signal, autocovarience, distribution and histogram respectively. These four screens show the form of input and output signal of the object and the effect of the load cell parameters. The result displayed at GUI for calculates the weight from the output graph using Kalman filter method.

Through GUI the user enters the product mass and then runs simulation to get the information about noise effects and how Kalman filter reduces the noise and improves the signal.

Matlab was used as it encompasses a numerical computing environment which allows the implementation of algorithms, plotting of functions and data, creation of user interfaces and interfacing with programs written in other languages (Mathworks, 2012).

Load cell has three parameters the load cell mass (M), spring constant (S) and damping factor (D). These parameters are entered. For investigating the effect of different load cell, the damping effect and spring, constant values were varied. Fig (4.2) compares two outputs of two different values of load cells for the same weight.

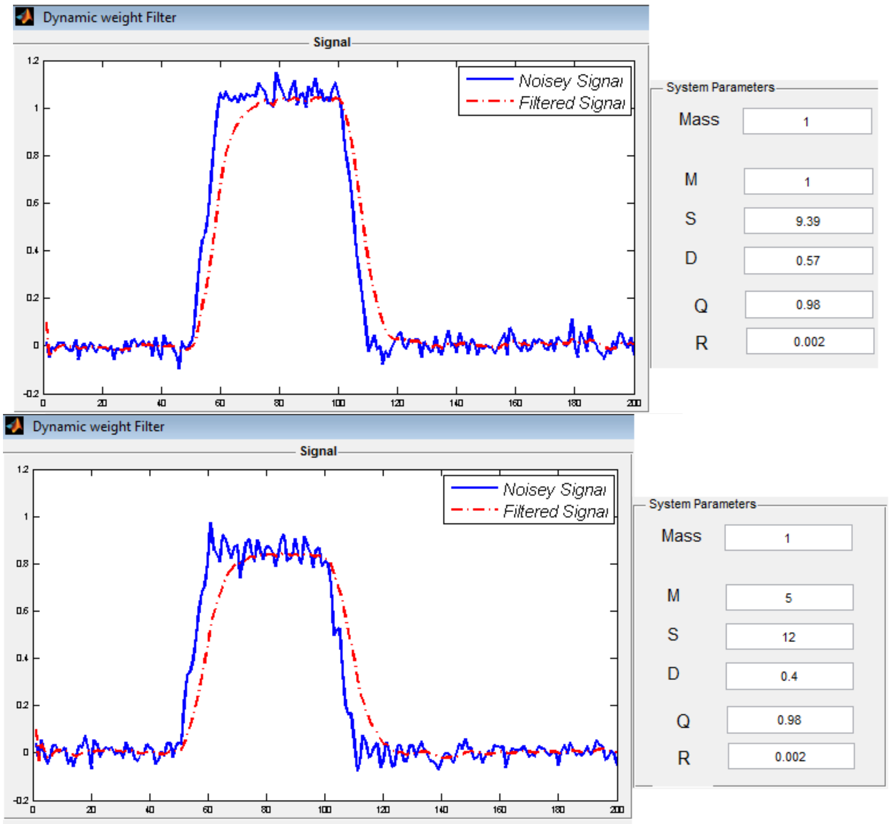

Figure (4.2): Load Cell Output

The first quart of GUI shows the input or noisy signal (Blue) and the signal after filtering using Kalman filter (Red). The weight signal was generated to simulate a passing object over a checkweigher; this was implemented by feeding a rectangular pulse u(k) to the system mathematical model of the checkweigher, and adding measurement and process noise. Figure (4.3) shows block diagram of the Kalman filter in Simulink.

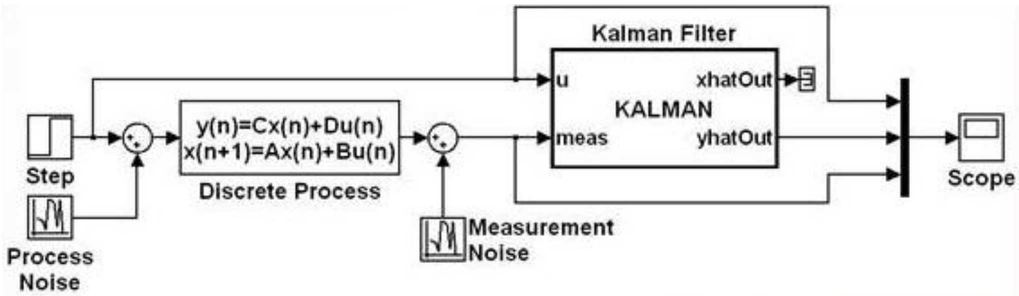

Figure (4.3): Block Diagram of Kalman Filter

We consider here the common case of noisy sensor measurements. There are many sources of noise in such measurements. For example, each type of sensor has fundamental limitations related to the associated physical medium, and when pushing the envelope of these limitations the signals are typically degraded. In addition, some amount of random electrical noise is added to the signal via the sensor and the electrical circuits. The time varying ratio of "pure" signal to the electrical noise continuously affects the quantity and quality of the information. The result is that information obtained from any one sensor must be qualified as it is interpreted as part of an overall sequence of estimates, and analytical measurement models typically incorporate some notion of random measurement noise or uncertainty as shown above.

There is the additional problem that the actual state transform model is completely unknown. While we can make predictions over relatively short intervals using models based on recent state transforms, such predictions assume that the transforms are predictable, which is not always the case. The result is that like sensor information, ongoing estimates of the state must be qualified as they are combined with measurements in an overall sequence of estimates. In addition, process models typically incorporate some notion of random motion or uncertainty as shown above.

The second shows the autocovarience. Practical implementation of the Kalman filter is often difficult due to the inability in getting a good estimate of the noise covariance matrices Q and R. Extensive research has been done in this field to estimate this covariance from data. Varying Q and R affect the performance of the output signal.

The third quart shows the distribution. A Gaussian distribution can be used to model the error in a system where the error is caused by relatively small and unrelated events. This distribution is a curve which is symmetric about the mean (i.e. a Bell shaped curve) and has a range measured by standard deviations above and below the mean of the data set.

Figure (4.4) shows possible Gaussian distribution, where the mean (μ) is 10 and standard deviation (σ) is 2. F(x) is the number of times a certain value of x occurs in the population. The mean is simply the numerical average of all the samples in the population, and the standard deviation is the measure of how far from the mean the samples tend to deviate.

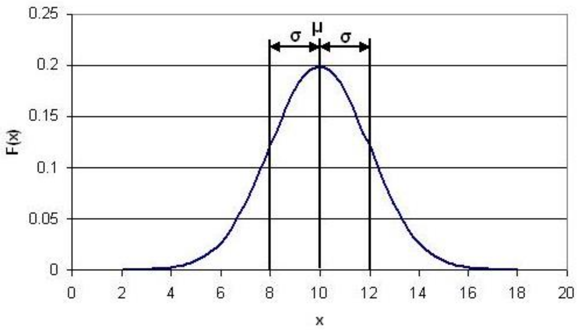

Figure (4.4): Gaussian Distribution Function

The following sections explain how and why a normal distribution curve is used in control and what it signifies about sets of data.

Distribution curves can be used to determine the probability, P(x), of a certain event occurring. When this is done, the distribution curve is known as a Probability Density Function (PDF). In the figure (4.4), the x-axis represents the range of possible events (the magnitude of noise generated by the loadcell sensor). The y-axis represents the number of times a certain x value occurs in a population. The PDF can be described mathematically as follows:

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} * e^{-(x-\mu)^2/2*\sigma^2} \tag{4.1}$$

Note that one standard deviation of a Gaussian noise distribution is equivalent to the rms noise of the distribution.

The last quart is the histogram. Histogram use to computes the frequency distribution of the elements in the input and output signal. From the plot one can easily see that the data exhibits a Normal (also called Gaussian or bell-shaped distribution) which is what should be expected if one is observing thermal noise. The histogram shows that there are two bell shaped distributions, the first around the zero weight value which represents the checkweigher without the weight of the object and the second distribution when the object is passing over the checkweigher. We can observe the difference between the noisy weight signal before and after the Kalman filter applied.

As example we will enter 2Kg as product weight and load cell parameters M=1Kg, S=9.39N/m and damping ratio D=0.57 respectively. Figs 4.5 show the results after simulation.

GUI shows that the product of the weight associates with noise equal 2.12Kg. After using Kalman filter the signal is filtered and the weight becomes 1.997Kg. This means that the error is reduced 0.123%.

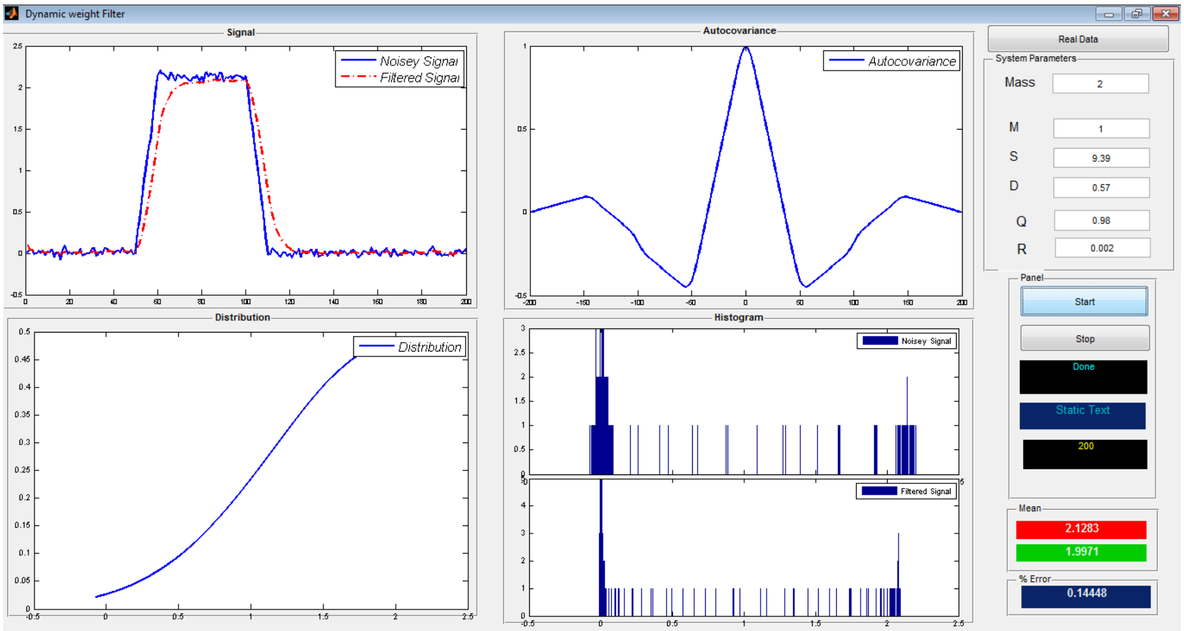

Figure (4.5): Simulation of Load Cell Measurement

The following tables show the results for testing and varying mass of product and load cell parameter. As example in table (4.1) fixing load cell parameters and varying product mass. The results in Table (4.1) show that Varying Mass Product will not have much effect on the Kalman filter output.

Mass (Kg)	**0**	**0.5**	**1**	**2**	**3**	**5**	**10**
M (Kg)	**1**						
S (N/m)	**9.659**						
D (kg/s)	**0.57**						
Error %		**0.0003**	**0.0055**	**0.0032**	**0.006**	**0.0067**	**0.009**

For investigating the effects of different load cells, the damping coefficient and spring constant values were varied , Table (4.2) shows that by changing the loadcell mass the system output error will increase. As example in Table (4.2) when product Mass =1Kg and M=100 the error equal 5.087. This means that when the object passing through the conveyer the load cell cannot recognize the mass.

Table (4.2) Varying Load Cell Mass

Mass (Kg)	**1**						
M (Kg)	**1**	**0.5**	**1**	**10**	**20**	**50**	**100**
S (N/m)	**9.659**						
D (kg/s)	**0.57**						
Error %		**0.0486**	**0.0055**	**-1.263**	**-1.835**	**0.466**	**5.087**

To simulate load cells with different stiffness values, Table (4.3) illustrates running a fixed load over load cells with different spring constant values. The results show running a 1kg product weight over a 1kg load cell with a damping coefficient of 0.57kg/s. The stiffer load cell has less deflection as expected

Table (4.3) Varying Spring Constant

Mass (Kg)	**1**						
M (Kg)	**1**						
S (N/m)	**9**	**9.3**	**9.659**	**9.7**	**9.9**	**10**	**11**
D (kg/s)	**0.57**						
Error %	**-7.101**	**-2.8**	**0.0055**	**0.4496**	**2.619**	**3.706**	**14.651**

To simulate the effect of changing the damping coefficients of the loadcell , table (4.4) compares different damping coefficient on a 1kg load cell with 9.659N/m spring constant using a 1kg load

Table (4.4) Varying Damping Factor

Mass (Kg)	**1**						
M (Kg)	**1**						
S (N/m)	**9.659**						
D (kg/s)	**0.5**	**0.54**	**0.57**	**0.6**	**0.63**	**0.66**	**0.7**
Error %	**-0.288**	**-0.120**	**0.0055**	**0.1321**	**0.2590**	**0.3863**	**0.5565**

For example by entering 0.5Kg as product weight and load cell parameters M=1Kg, S=9.39N/m and damping ratio D=0.57 respectively. Fig 4.6 shows the results after simulation.

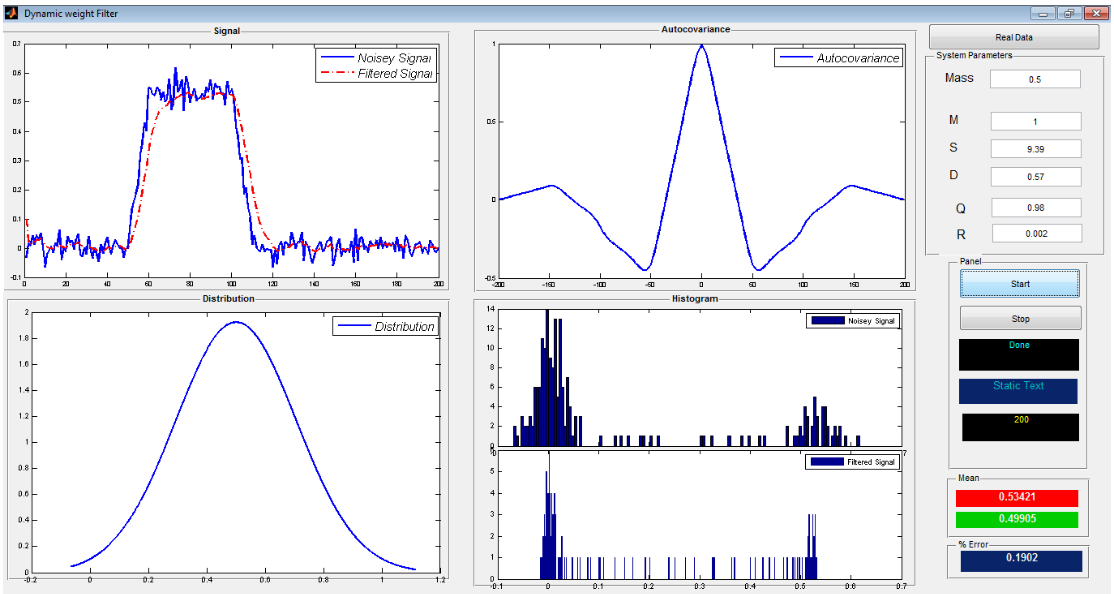

Figure (4.6): Simulation of Load Cell with Mass= 0.5Kg, M=1kg, S=9.39N/m and D=0.57

Figure (4.6) shows that the Kalman filter could be used for optimal filtering in dynamic weighing systems. The uncontrollable input signal in the dynamic weighing system, which represents the weight input on the weightable (Blue). And the output signal (Red) which represent the controllable signal using Kalman filter.

The covariance of the system noise, R, is considered a measure of the level of confidence in the given model of the load cell. It arises from the state error covariance between the system and the model of the system. Its value will be determined using performance indices as quality of filter Q. In our case, the values of the covariance matrices for system and measurement noise are Q= 2 and R= 1, respectively. If a particular application needs a faster system response or smaller steady-state error, it can be achieved by changing the values of the weighting matrices. Finally, increasing the value of Q and/or decreasing the value of R, the system response and steady-state error are improved. The above figure shows that the best values for Q and R. there values are 0.98 and 0.002 respectively.

CHAPTER 5 WEIGHING SYSTEM TESTING & ANALYSIS

5.1 Introduction

An experiment setup was designed to acquire the weight raw signal from a Checkweigher with single load cell; a block diagram that describes the signal flow is shown in Figure 5.1

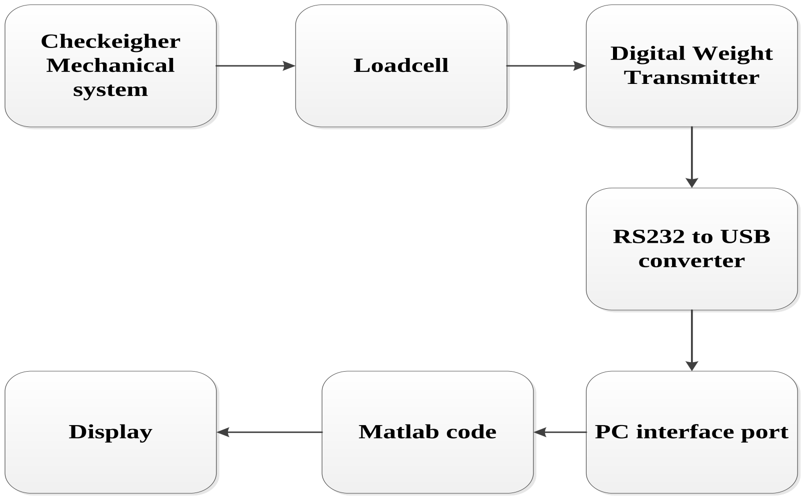

Figure (5.1): Experimental System Setup

5.2 Checkweigher Mechanical system

A general type checkweigher machine was used to test the filtering algorithm, the machine design is suitable for testing different sizes of product, in addition of product feed speed, the machine in Figure 5.2 has a built in digital weight transmitter which has a communication interface to transmit the weight signal to the computer running the filtering code.

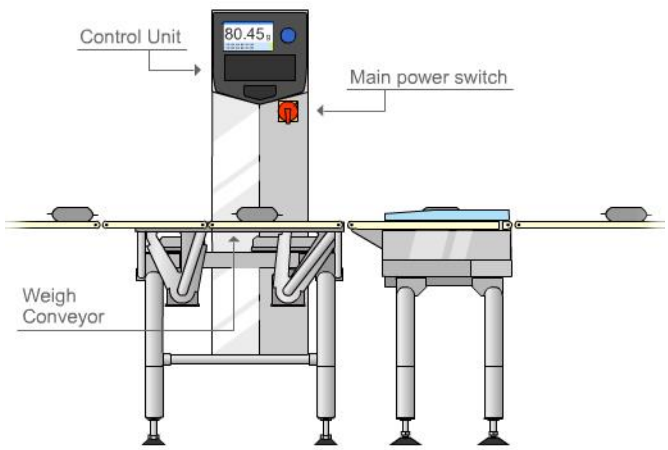

Figure (5.2): Checkweigher machine setup

Different weight samples were tested on the checkweigher Figure 5.3 ,and in different conditions especially in the noisy industrial environment with different sources of mechanical vibration from nearby machines.

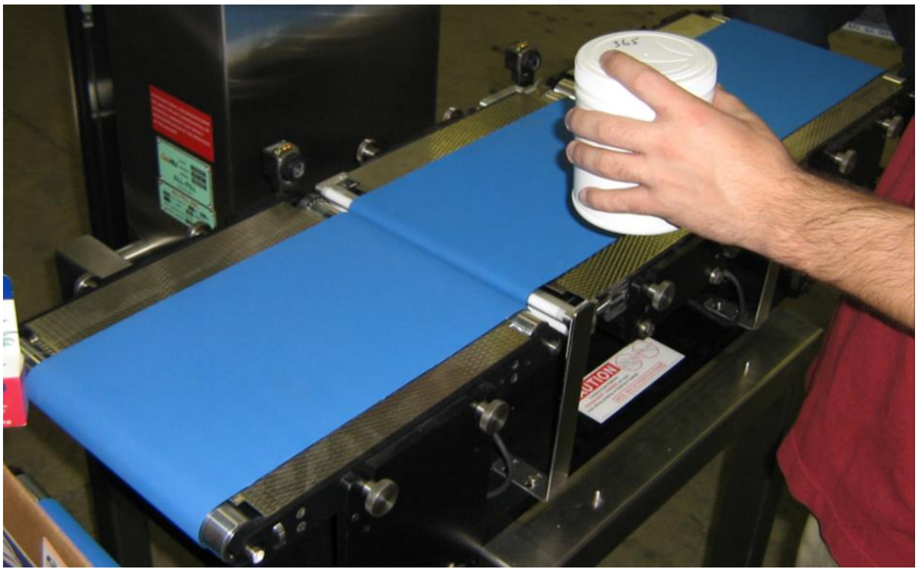

Figure (5.3): Checkweigher weight sample testing

5.3 Digital Weight Transmitter

A digital weight transmitter is used to convert the loadcell signal to a digital form, and store it in the device's memory, the unit has a built in RS232/RS485 converter which allow for direct connection to PC or PLCs Figure 5.4.

The weight data is sent continuously to the computer via Rs232/RS485 interface, or sent on demand using ASCII format.

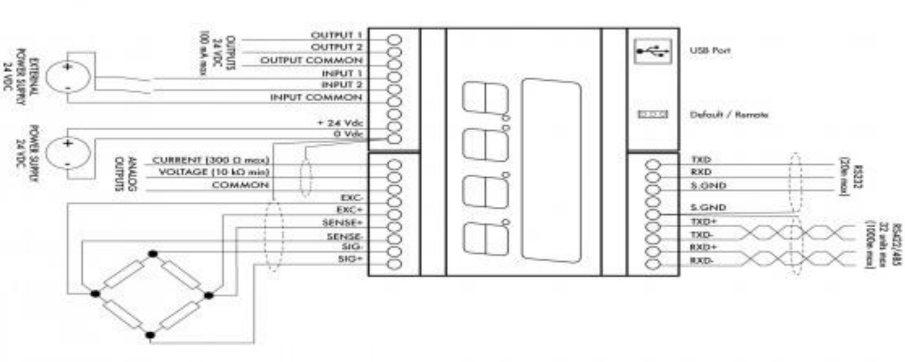

Figure (5.4): Digital Weight Transmitter interfacing

5.4 Checkweigher signal display

After capturing and storing the checkweigher signal in the Matlab 'mat' file format, we can plot this data before filtering as shown in Figure 5.5.

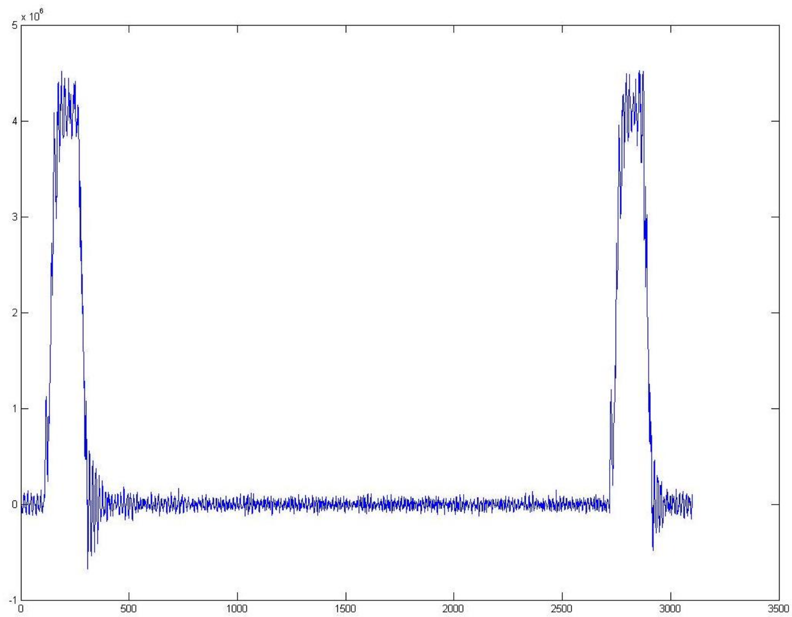

Figure (5.5): Checkweigher Signal before Filtering

In Figure 5.6 we plot the weight signal after implementing the Kalman filter algorithm.

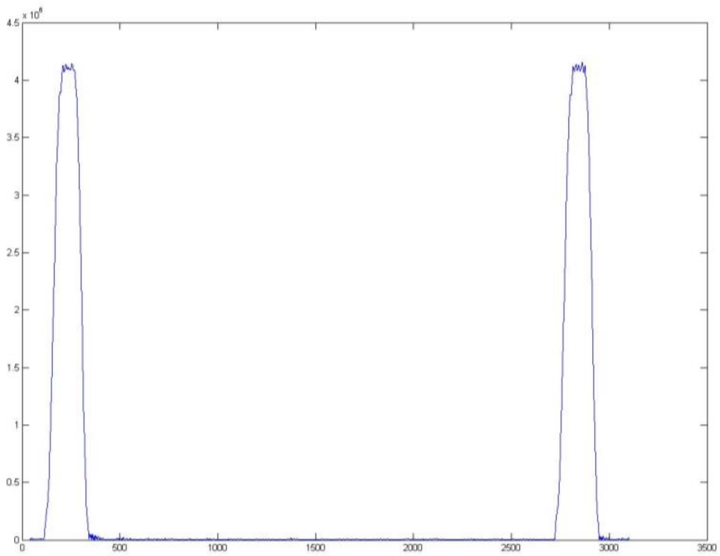

Figure (5.6): Checkweigher Signal after Filtering

CHAPTER 6 RESULTS AND DISCUSSIONS

This chapter presents simulations and results. Mathematical modeling of a commercial checkweigher was carried out in this study. The loadcell was mathematically modeled with spring-mass-damper approximation method. Simulation and practical experiments were carried out to test the Kalman filtering algorithm. The Kalman filter technique was introduced to reduce the noise and distortion in the weight signal. The developed software included a simulator part to test the loadcell model and to show the relevant result to the hardware model. A typical example, calculated with the generated software, was included.

6.1 Simulation results

The simulation method allowed the testing and investigating of loadcell parameters on the stability and performance of the system model, changing these parameters is based on the construction of the loadcell.

The simulations were successful in providing an easy and quick comparison for different load cell parameters while presenting a visual graph of the load cell output for the weight applied. The real world testing allowed for a better understanding of external and internal variables unaccounted for using the simulations.

Simulations done on Matlab of different weigh graphs running with different weights between 0.5 and 10kg. It show that the Kalman filter output error and error percentage is between 0.0003 and 0.009%. The error is slightly increased with increasing product weight, while any change to the loadcell parameters from the actual values resulted in large error. The Kalman method implemented on the simulation model proved to improve the weighing accuracy.

We compare our out values with the output values in [16] for six weights of 57g, 145g, 197g, 242g, and 378g were run through simulation. The results are presented in Table (6.1), Table (6.2) and Figure 6.1, Figure 6.2.

Table (6.1) Simulation results of Kalman filter compared with three method

Actual weight	Frequency method	Averaging method	Damping method	Kalman filter method
57 gm	57.122	56.709	57.179	57.2
145 gm	144.66	144.050	145.5990	144.9
197 gm	197.640	194.780	196.270	197.102
242 gm	242.690	245.490	241.1	242.12
272 gm	272.560	267.400	272.960	272.4
378 gm	377.170	366.730	376.360	377.5

Table (6.2) Simulation results of Kalman filter error compared with three method

Actual weight	Frequency method error	Averaging method error	Damping method error	Kalman filter method error
57 gm	0.122	0.291	0.179	0.2
145 gm	-0.43	-0.95	0.5990	-0.1
197 gm	0.640	-2.22	-0.73	0.102
242 gm	0.690	3.490	-0.9	0.12
272 gm	0.560	-4.6	0.960	0.4
378 gm	-0.83	-11.27	-1.64	-0.5

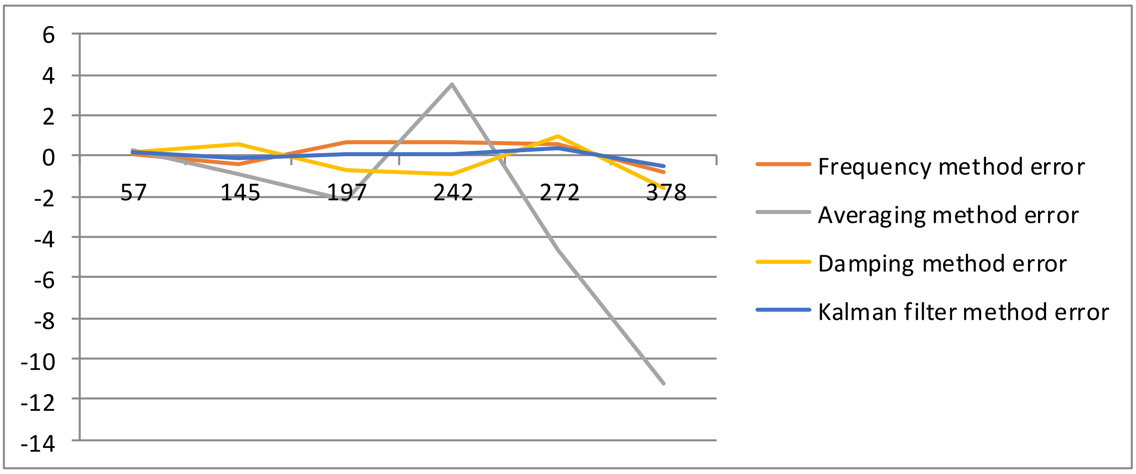

Figure (6.1): Object Weight error comparison

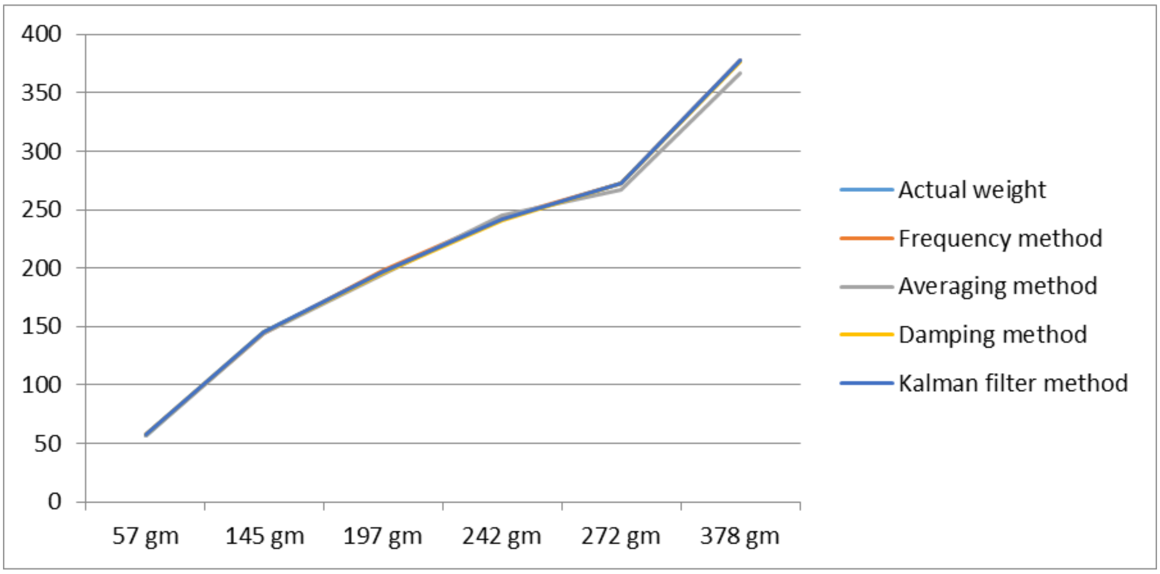

Figure (6.2): Actual Weight VS measured weight

6.2 Experimental Results

After implementing the developed model using single point of load cell with DGTQ data acquisition card and Kalman, filter on the computer, the experimental results of the checkweigher system showed a great dependence of the system on the loadcell parameters. Without having, the correct parameters of the loadcell used in the system would result in a very bad performance of the filtering algorithm.

In our study, we had the approximated parameters of the load cell after trying different implemented techniques, which gave a good performance of the Kalman filter algorithm.

A comparison of the implemented model and three other methods for six weights of 57g, 145g, 197g, 242g, and 378g. The results are presented in Table (6.3), Table (6.4) and Figure 6.3, Figure 6.4.

Table (6.3) Experimental results of Kalman filter compared with three method

Actual weight	Frequency method	Averaging method	Damping method	Kalman filter method
57 gm	57.122	56.709	57.179	56.88
145 gm	144.66	144.050	145.5990	145.14
197 gm	197.640	194.780	196.270	197.16
242 gm	242.690	245.490	241.1	241.9
272 gm	272.560	267.400	272.960	271.7
378 gm	377.170	366.730	376.360	378.25

Table (6.4) Experimental results of Kalman filter error compared with three method

Actual weight	Frequency method error	Averaging method error	Damping method error	Kalman filter method error
57 gm	0.122	0.291	0.179	-0.22
145 gm	-0.43	-0.95	0.5990	0.14
197 gm	0.640	-2.22	-0.73	0.16
242 gm	0.690	3.490	-0.9	-0.1
272 gm	0.560	-4.6	0.960	-0.3
378 gm	-0.83	-11.27	-1.64	0.25

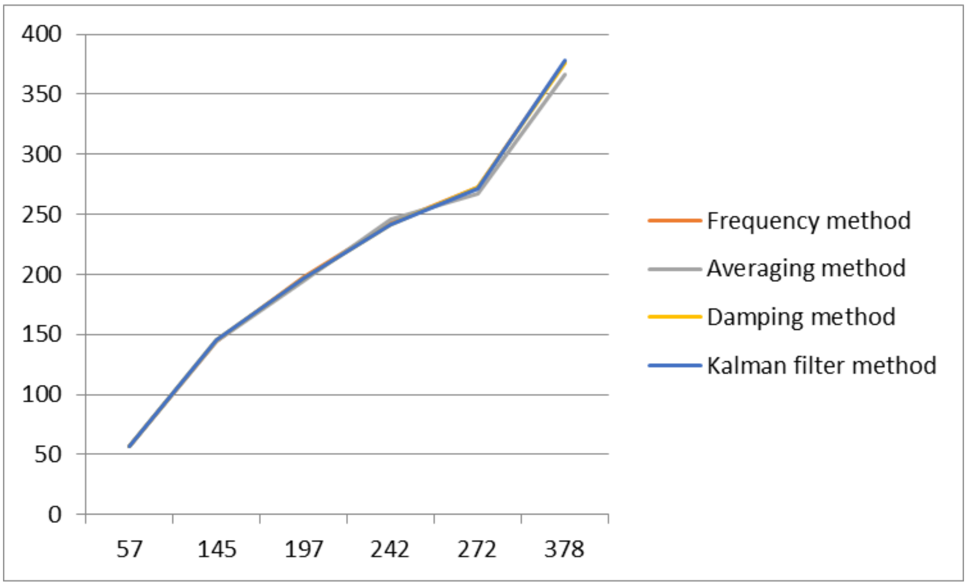

Figure (6.3): Actual Weight VS measured weight

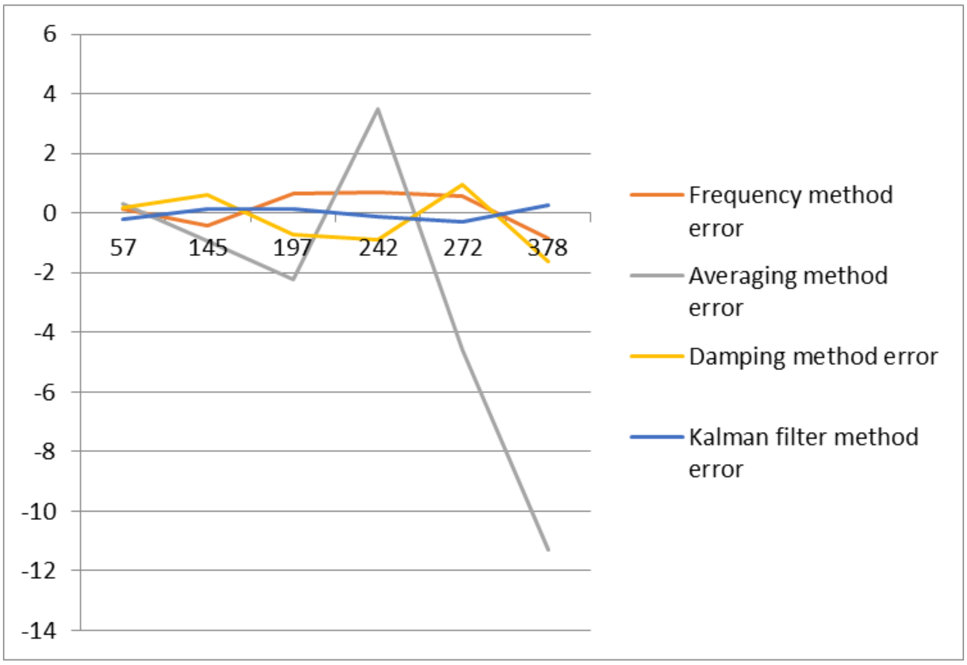

Figure (6.4): Object weight error comparison.

CHAPTER 7 CONCLUSION

In dynamic weighing systems conventional control and filtering methods employed have limitation in improving the accuracy and throughput rate. In this study, Kalman filtering technique has been explored to find a solution that will enable measurement accuracy and throughput rate of article weighing to be increased.

The simulation for a Dynamic Weighing System (DWS), was successfully implemented, with the model of the checkweigher is described in detail. The results generated by the simulator were compared to the ones obtained in the real system and they were quite alike. The mathematical model was approximated by a spring-mass-damper system, and the model parameters were identified by the experimental data for open-loop response.

A GUI was designed to simulate Kalman filtering for a real load cell signal. The parameters can be entered and changed according to the load cell type. It is possible to discover and to quantify improvements in the DWS, without having to make unnecessary and expensive changes in the real process. The simulator can manipulate parameters of the system model used in signal generation and filter design.

Future work will be on solving the load cell parameters identification problem, using more theoretical approach.

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APPENDIX A: DYNAMIC WEIGHING SYSTEM

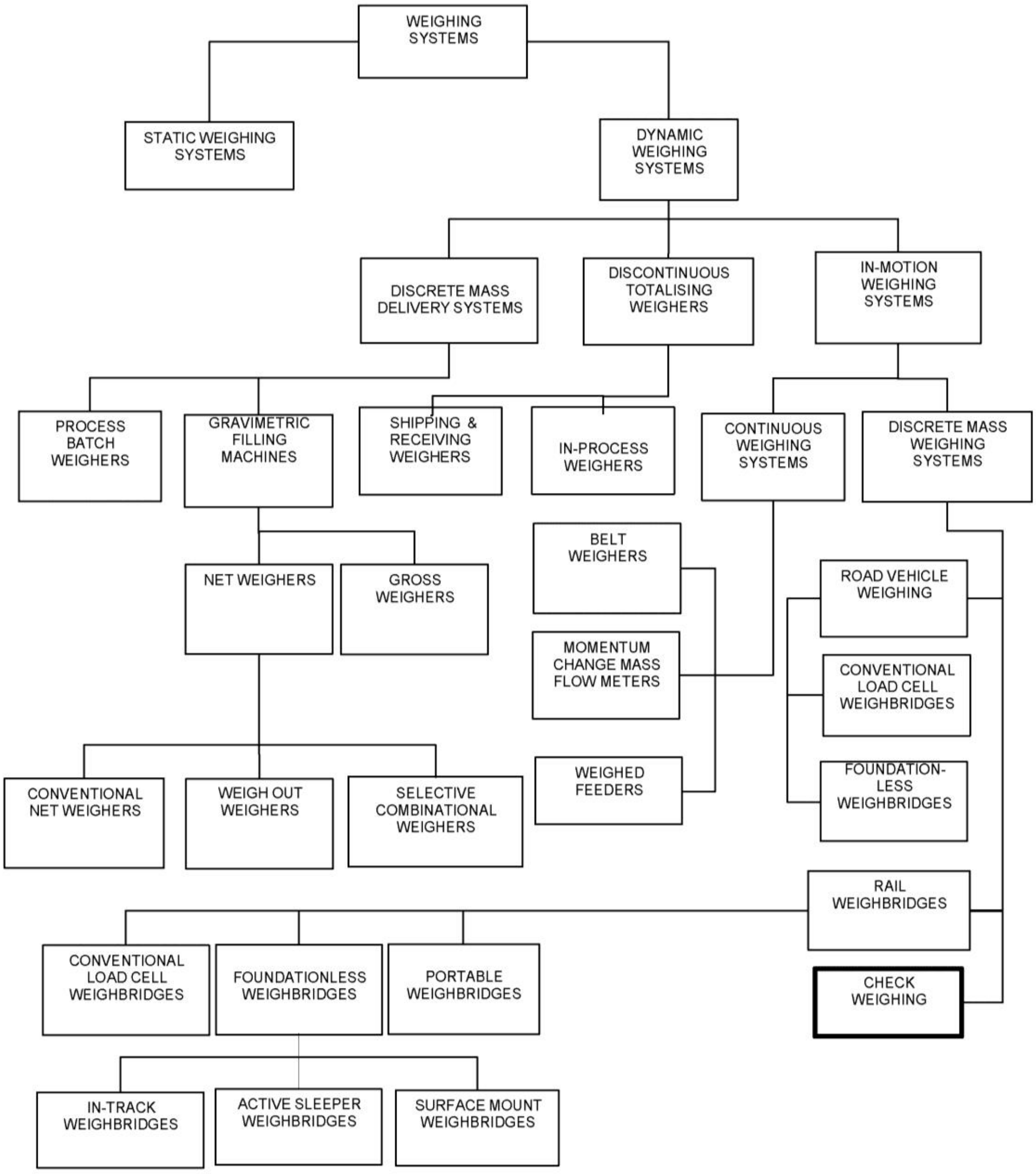

Figure (A.1) General Hierarchy of Weighing Systems

APPENDIX B: ECONOMIC COST AND MATLAB FUNCTIONS

Economic Cost

Economic cost of the project is listed in Table (B.1) showing the software cost and hardware cost.

Table (B.1) Software Cost And Hardware Cost.

	Item	Cost ($)
1	Damped Load Cells Tedea-Huntleigh Model 240	1000
2	Digital Weight indicator	1000
3	NI- USB DAQ	1000
4	Personal Computer	800
5	Checkweigher Hardware	2400
6	Mathworks Matlab software student package	300
7	Miscellaneous expenditure	500
	Total	7000

MATLAB function description

MATLAB File	Description
DWS.m	Main MATLAB file
DWS.fig	Main GUI file
DWS_Init.m	Initialize System parameters
SerStart.m	Start Serialport capture loop
SerStop.m	Stop Serialport capture loop
KMB.m	Loadcell dynamic simulation
LoadDWS.m	Load saved capture file
KalmanFilter.m	Kalman filter Algorithm