Research Article GU J Sci 38(4): 1835-1844 (2025) DOI: 10.35378/gujs.1569752

Gazi University

Journal of Science

http://dergipark.org.tr/gujs

Combination of FIR and Kalman Filters to Increase Measurement Accuracy in Dynamic Weighing

Sena ZENGIN[1], Bayram AKDEMIR[2]

[1]Gebze Technical University, Faculty of Engineering, 41400 Kocaeli, Türkiye
[2]Konya Technical University, Faculty of Engineering and Natural Science, 42250, Konya, Türkiye

Highlights

- This paper focuses on a prediction algorithm for items with unknown weight.
- In this study, Kalman filter and FIR filter combinations were proposed for the prediction algorithm.
- A highly accurate prediction algorithm is designed through a combination of filters.

Article Info

Received: 18 Oct 2024
Accepted: 9 Jul 2025

Keywords

Kalman filter
FIR filter
Estimation algorithms

Abstract

This study investigates the application of a combination of Finite Impulse Response (FIR) and Kalman filters to improve measurement accuracy in dynamic weighing processes. Dynamic environments, characterized by moving objects and varying conditions, pose challenges such as noise and signal losses, which can adversely affect measurement results. To address these issues, FIR filtering is employed to preprocess the data, effectively removing low-frequency noise. The cleaned data is then processed using a Kalman filter, minimizing errors at each step. The Kalman filter has proven effective in improving measurement accuracy by making predictions on noisy data. Consequently, the combined use of FIR and Kalman filters enables the achievement of reliable and accurate measurement results in dynamic weighing processes. This approach offers practical solutions to dynamic weighing problems in various application areas.

1. INTRODUCTION

Scales are products that we frequently use in our daily lives, significantly easing our tasks. Throughout history, scale models have undergone significant changes, and today, there are models equipped with the latest technologies, making them suitable for practical use. With technological advancements, scales range from analog models to precision balances, designed to meet various needs.

Weighing operations are classified into two main categories: static and dynamic weighing. Static weighing refers to measuring an object in a fixed system and is preferred for obtaining accurate results, although it can cause time delays. Dynamic weighing, on the other hand, involves measurements under moving or variable conditions, providing faster results. The two primary applications of this method are Checkweighers and weigh-in-motion (WIM) systems. Checkweighers weigh objects on a moving belt, while WIM systems measure the weight of vehicles in motion. Dynamic weighing methods are widely used in various sectors, including services, industry, commerce, and transportation, as they save time and reduce workload. However, dynamic weighing operations can lead to issues like low-frequency noise, necessitating the development of various filtering methods to achieve more accurate results.

A system developed by Meixedo et al. [1] was designed to measure the weight applied by trains to the rails while in motion. This system, placed on the rails, continuously monitors the durability of the rails and alerts for maintenance needs before damage occurs, thereby enhancing transportation safety and reducing maintenance costs. Guo et al. [2] investigated the application of an adaptive Kalman filter approach for

*Corresponding author, e-mail: senazengin@gtu.edu.tr

predicting short-term traffic flow rates and measuring uncertainty. In this study, the adaptive Kalman filter algorithm was employed to predict the expected number of vehicles in the next time interval. Real-world traffic flow data were collected and analyzed at 15-minute intervals. The results demonstrated that the adaptive Kalman filter approach could produce viable predictions and prediction intervals, showing promise for improving traffic flow prediction and proactive traffic control systems. In a study by Gülbaş [3], noise resulting from dynamic weighing was filtered using an IIR filter, increasing the accuracy of the measured weight. Li et al. [4] aimed to measure vehicle load on highways more accurately and quickly by using the Back Propagation (BP) algorithm, reporting increased measurement accuracy in dynamic weighing. Rehman et al. [5] developed a weight estimation algorithm using a Kalman filter for dynamic weighing. This algorithm achieved optimal filtering and precise mass flow estimation in a conveyor belt system. Another study aimed to predict people's next moves by detecting their movements using a Kalman filter, to prevent potential accidents [6]. In a paper by Pitawala [7], objects with different weights were placed in a moving area, and the next fruit weight was predicted using a Kalman filter. In a similar study published by Ying et al. [8], KF, FIR, and IIR filters were used and compared.

The Kalman filter is a state estimation algorithm that is widely used because it makes predictions about the past, present, and future. It produces estimates of hidden variables based on uncertain or inaccurate measurements. Weighing operations are critically important in various application areas, and accuracy is a significant problem, especially in dynamic and moving environments. These environments can lead to measurement errors due to unstable conditions and various environmental factors.

The combination of FIR and Kalman filters represents a significant advancement in dynamic weighing systems, effectively addressing both high-frequency noise and model-based estimation errors that are often inadequately managed by standalone methods. Unlike traditional approaches that apply either FIR filtering for noise reduction or Kalman filtering for state estimation separately, this hybrid method synergistically integrates both techniques to enhance signal quality and prediction accuracy. Recent studies have demonstrated that this approach substantially improves measurement reliability, particularly in high-speed and heavy-load scenarios where conventional filters tend to underperform. By smoothing raw sensor data before recursive state estimation, the FIR-Kalman filter combination accelerates convergence and reduces estimation variance, resulting in more precise and robust weight predictions. Consequently, this method fills a critical gap in the literature by providing a practical, adaptive, and high-performance solution suitable for real-time, industrial-scale dynamic weighing applications requiring both precision and responsiveness.

This study examines the application of combinations of FIR and Kalman filters in weigh-in-motion systems and explores how these methods can enhance measurement accuracy. This study highlights the potential of combining classical digital filtering with model-based estimation techniques to enhance system performance in noisy measurement environments.

2. MATERIAL METHOD

The workflow of this study is illustrated in Figure 1. Data obtained from the Load Cell and HX711 were processed using MATLAB to create the dataset. The study compared three different methods. In the first approach, the dataset is estimated using a Kalman Filter (KF). Noise was then added to the data. A second estimation algorithm was obtained by first applying the KF and then a Finite Impulse Response (FIR) filter to the noisy data. In the final method, the noisy data was first filtered using the FIR filter, followed by the application of the KF, and an estimation algorithm was obtained. Three approaches were compared.

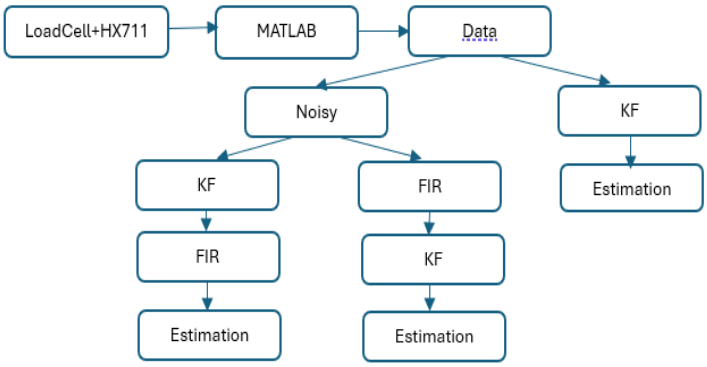


Figure 1. *Flow diagram for the study*

In the conducted study, the weight data were obtained via a load cell. The load cell consists of a metal chassis, known as the spring element, and a Wheatstone bridge setup with strain gauges. When a force is pushed on the spring, it creates an electrical signal in the Wheatstone bridge. This signal is sent to a microprocessor, which then shows the force or weight measurement.

The general structure of the Wheatstone bridge is as shown in Figure 2. When the Wheatstone bridge is balanced, the voltages Vd and Vc are equal. Assuming that the supply voltage V1 fluctuates and changes by ΔV, the balance at points Vc and Vd remains unchanged.

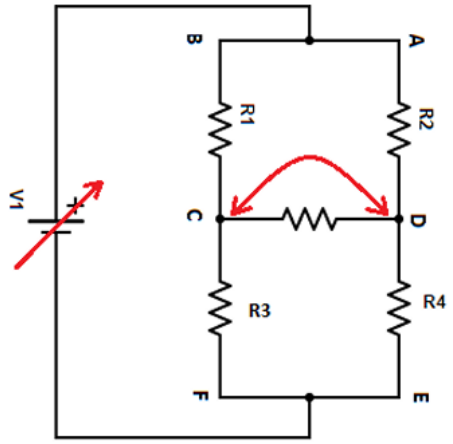


Figure 2. *General structure of the Wheatstone bridge*

The system can continue to operate smoothly. The strain gauge in the Wheatstone bridge can measure changes in length caused by an external force. As the strain gauge is stretched or compressed, a change in resistance occurs. This change in resistance allows for the measurement of voltage.

The HX711 amplifier, known as a weight sensor, is a highly sensitive board designed to interface directly with a bridge sensor for weighing scales and industrial control applications. It is used in projects such as weight measurement, process control, and weight sensing.

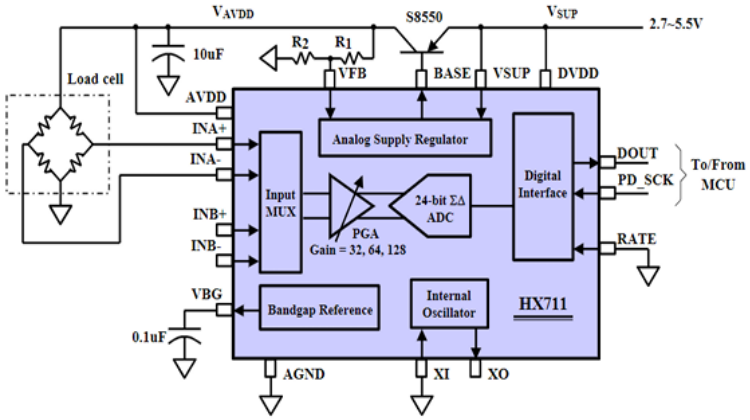


Figure 3. *Implemented HX711 amplifier circuit design*

The HX711 amplifier used in the study is given in Figure 3. The Delta-sigma analog-to-digital converters (DS-ADCs) within the amplifiers consist of a high-speed sampling modulator followed by a digital/decimation filter that produces a high-resolution data stream output. The DS modulator is responsible for digitizing the analog input signal and reducing noise at low frequencies, using a decimator filter to slow down the output data rate. The modulator samples the analog input signal by converting it into a high-speed, single-bit, modulated pulse wave. The digital/decimation filter then takes this sampled data and converts it into a high-resolution, slower digital code. Additionally, it removes high-frequency noise and reduces the device's data output rate to a usable frequency.

2.1. FIR Filter

The Finite Impulse Response (FIR) filter is a filtering method used to process digital signals. In this study, the designed FIR filter's characteristics are determined based on the desired frequency response in the frequency domain. The passband and stopband frequencies, as well as the filter coefficients, are established. By using the designed filter, noise-reduced data is obtained. The mathematical equation of the FIR filter is given in Equation (1).

$$y(n) = \sum_{k=0}^{N} b(k)x(n-k). \quad (1)$$

This equation represents the convolution sum of the finite impulse response b(k) with the input signal x(k), resulting in the filter output y. The structure of the FIR filter is shown in Figure 4.

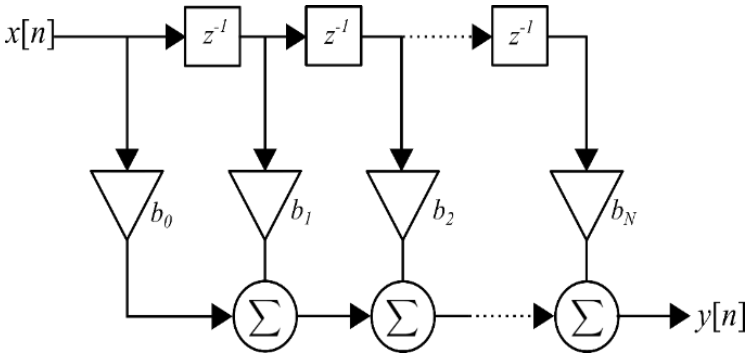


Figure 4. *Structure of the FIR filter*

Here, z^{-1} represents the unit delay element. In FIR filters, the digitized signal passes through delay elements. NNN denotes the number of unit delay elements. When a unit delay is applied to the signal x[n], it becomes x[n−1]. The signal x[n−1] is multiplied by the filter weight coefficient, and the results of each multiplication are summed to form the filter output. The time interval for the input signal to reach the output after the FIR filter is applied is referred to as the delta delay. Delta delay depends on the filter coefficient.

As the filter coefficient increases, the delta delay also increases. The delay time is a crucial factor in analyzing system response. In FIR filters, the settling time is a crucial factor in determining the filter's stability and dynamic response. This study selects appropriate parameters to minimize delta delay, ensuring faster settling time and more stable results.

2.2. Kalman Filter

Many modern systems are equipped with a series of sensors that enable the estimation of unknown variables based on various measurements. One of the algorithms that enables the estimation of these unknown variables is the Kalman filter. The Kalman filter is known as a linear optimal state estimation method and is highlighted as one of the Bayesian filter theories [9]. In systems where data flow is regular, the Kalman filter predicts the next data point by using the previous data point as input and generates instant predictions through the state update Equation [6].

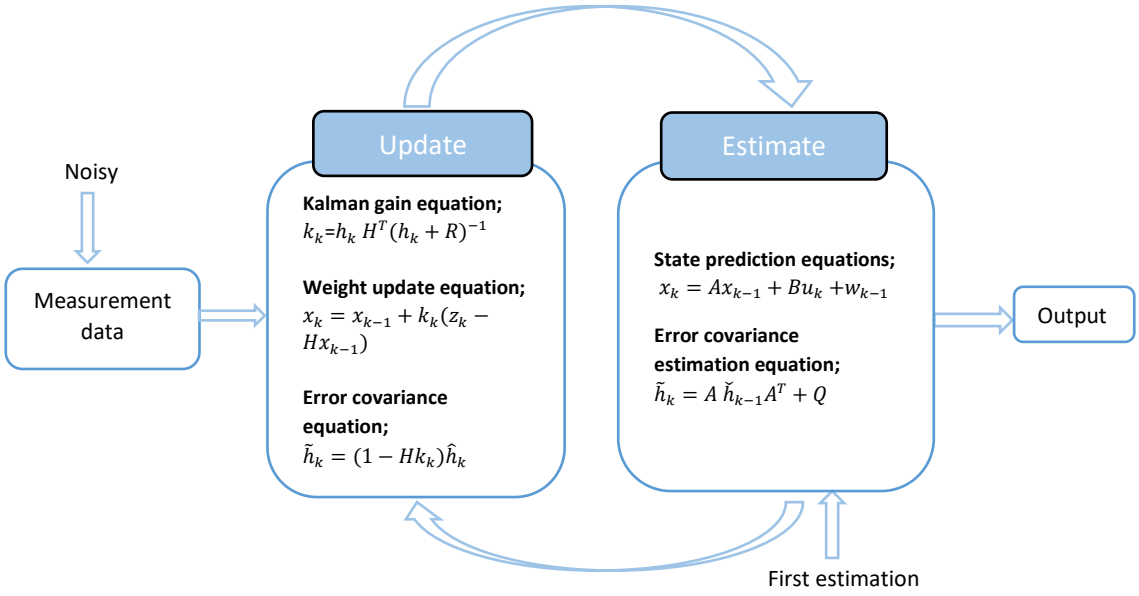


Figure 5. *KF Estimation algorithm and mathematical equation*

When examining the mathematical algorithm of the Kalman filter, it can be observed that the prediction process is compared with the observed data. The difference obtained from this comparison is scaled by a factor called the Kalman gain. To improve the accuracy of the predictions, this difference is applied to the model as feedback. The predicted output is used as the input for the following prediction in the mathematical formula. These operations continue cyclically.

The equations used in the Kalman filter are given in Figure 5 $x_k \in \boldsymbol{R^n}$, is an n-dimensional state vector with an initial state value x_0, mean value m_0, and error covariance $\tilde{\boldsymbol{h}}_{\boldsymbol{0}}$ ($x_0 \sim \mathbf{N}(m_0, \tilde{\boldsymbol{h}}_{\boldsymbol{0}})$). Elements A and B are representations of matrices. $\mathbf{A} \in \boldsymbol{R^{nxn}}$ is the state matrix, and $\mathbf{B} \in \boldsymbol{R^{nxm}}$ is the input matrix. Since our signal data is one-dimensional, these elements are numeric values. $\boldsymbol{u_k}$ is the control signal and also the system input $\mathbf{u} \in \boldsymbol{R^m}$, $\mathbf{w} \in \boldsymbol{R^n}$represents the noise in the signal, and $\boldsymbol{w_{k-1}}$ is the previous process noise.

The Kalman gain is the most critical parameter for the estimation method. The value H is the result of the combination of the measurement state value and the noise, and it is generally assumed to be 1 [10].

3. THE RESEARCH FINDINGS AND DISCUSSION

The data collected by the load cell is directed to the amplifier through pins, generating a dataset. The obtained data is processed using the Kalman-FIR filter in MATLAB, and a prediction algorithm is developed.

In this study, a Kalman filter-based prediction algorithm was developed to estimate the next weight of objects with different weights. To enhance the accuracy of the prediction algorithm, a FIR filter was utilized.

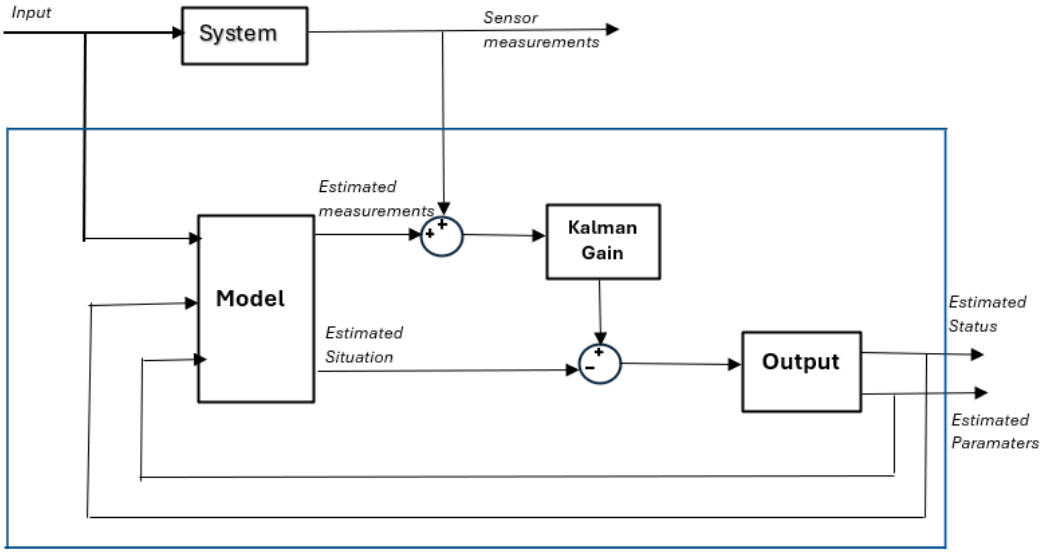


Figure 6. *Design prediction algorithm [11]*

When examining the working system of the KF prediction algorithm in Figure 6:

- The system, as defined, consists of the weight measurement setup we established using the HX711 amplifier and load cell. The collected data is processed in MATLAB.
- The developed model uses the measured value and previous prediction parameters as inputs. In each step, these inputs are rescaled with the Kalman gain to produce a new prediction result.
- The KF (Kalman Filter) part is where the prediction algorithm is implemented. The KF operates in a continuous loop and, when used for measuring a specific weight, recalculates.

The Kalman gain at each measurement minimizes errors and achieves accurate measurements. To reduce the white noise added to the weight signal and obtain more precise results, the KF, KF-FIR, and FIR-KF algorithms were utilized.

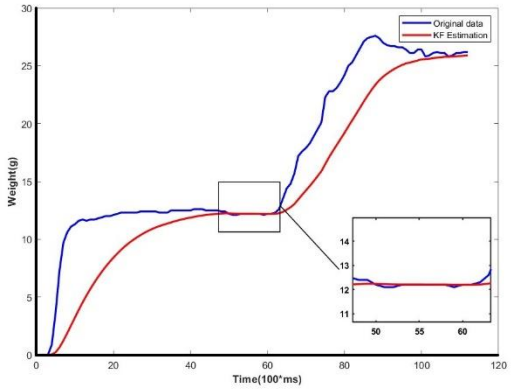


Figure 7. *Noiseless KF estimation graph*

As illustrated in Figure 7, when the measured values remain constant, the Kalman filter effectively reduces the error rate by bringing the predicted value closer to the actual value. The blue line represents the measured values, and the red line represents the expected values. After adding white noise to the original data using MATLAB, the noisy data was processed with the Kalman Filter. As shown in Figure 8, there is more fluctuation compared to the noiseless data.

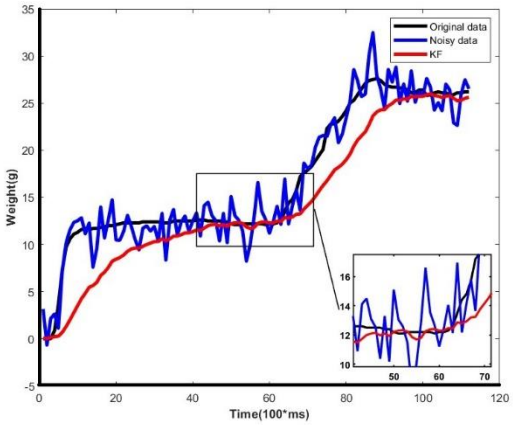


Figure 8. *Noisy KF estimation graph*

To apply the FIR filter to the noisy signal, the FIR characteristics and filter coefficients were first calculated. After designing the FIR filter, it was applied to the noisy data. The filtered signal was then further processed using the Kalman Filter (KF), and the prediction results are presented in Figure 9. The section drawn in blue represents the result predicted by the FIR, while the section drawn in red shows the outcome of the KF filtering applied to the FIR-processed signal.

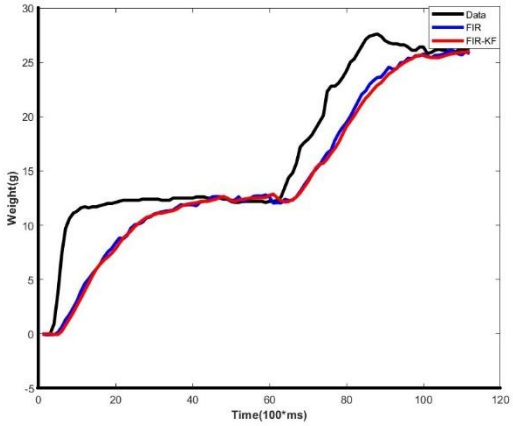


Figure 9. *FIR-KF estimation graph*

In Figure 10, the noisy signal was first subjected to the Kalman Filter (KF), and then the predicted signal was filtered using the FIR filter. The error rate of the KF-FIR algorithm was found to be 0.802%. The FIR filter reduced the fluctuations in the KF prediction results. The section drawn in blue represents the result predicted by the KF, while the section drawn in red shows the outcome of the FIR filtering applied to the KF-processed signal.

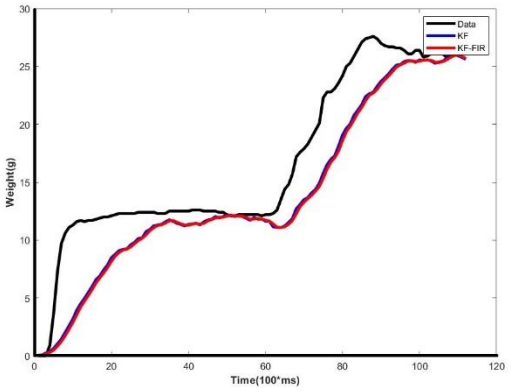


Figure 10. *KF-FIR estimation graph*

In each scenario, actual weights were compared with the estimated values. The error was calculated by subtracting the estimated value from the actual value. The average error values for each method are listed in Table 1.

Table 1*. Algorithm results*

Filtering Method	KF	KF-FIR Algorithm	FIR-KF Algorithm
Error rate	%3.35	%0.802	%0.134

In this study, three different filtering scenarios were compared to assess their effectiveness in estimating dynamic weights using noisy signals. In the first scenario, only the Kalman filter was used without any prior filtering. Although this approach offers computational simplicity, it proved to be the least effective in noisy conditions, as it struggled to compensate for measurement disturbances on its own. In the second scenario, the Kalman filter was applied first, followed by FIR filtering on the predicted signal. While this method showed some improvement in signal stability, initial inaccuracies due to raw noise input reduced its overall effectiveness compared to the first method. In the third scenario, applying FIR filtering before the Kalman filter significantly improved prediction accuracy by effectively suppressing high-frequency noise and providing the Kalman filter with a cleaner input. This approach yielded the most stable and precise results, especially in environments with heavy noise and rapidly changing conditions. Overall, the FIR-Kalman hybrid method proved to be the most robust and accurate, particularly suitable for industrial-scale applications where both high precision and real-time performance are essential.

4. RESULTS

In this study, the dynamic weighing of objects with varying masses was addressed in the presence of measurement noise, a common challenge in real-time signal acquisition systems. To enhance prediction accuracy, a two-stage filtering approach was proposed, combining a Finite Impulse Response (FIR) filter for preliminary noise attenuation with a Kalman filter (KF) for model-based state estimation. The Kalman filter, known for its recursive estimation capability, was employed to iteratively update the predicted weight values, adapting to changes in the measurement environment by adjusting the Kalman gain at each time step. This adaptive gain mechanism contributed to a significant reduction in estimation error, thereby improving the stability and reliability of the predictions. Furthermore, experimental evaluations revealed that the hybrid FIR-KF filtering approach yielded superior performance compared to standalone Kalman filtering or unfiltered raw data, particularly under high-noise conditions. The FIR filter effectively suppressed high-frequency components and outlier spikes, allowing the Kalman filter to operate on a smoother signal with reduced variance. As a result, the proposed FIR-KF method demonstrated a notable improvement in prediction accuracy, achieving minimal error rates across various test scenarios. The results were validated through comparative analysis and visualized with graphical representations, confirming that the FIR-KF algorithm offers a robust and practical solution for real-time dynamic weighing applications.

The implementation of the Kalman filter for predicting the weights of dynamically moving objects yielded promising results, particularly in estimating average weights with high accuracy. However, the algorithm's performance in tracking rapid, instantaneous weight fluctuations was relatively limited, indicating a need for further refinement, potentially through adaptive or extended Kalman filter variants. To enhance the robustness and applicability of the system, future studies should evaluate its performance under industrial-scale conditions. Additionally, incorporating product classification capabilities within the dynamic weighing process may enable more versatile usage across various sectors. The integration of artificial intelligence techniques could further extend the system's functionality by enabling real-time monitoring of the physical state of the items, facilitating intelligent classification, anomaly detection, and context-aware decision-making within automated weighing systems.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

REFERENCES

[1] Meixedo, A., Gonçalves, A., Calçada, R., Gabriel, J., Fonseca, H., and Martins, R., "Weighing in motion and wheel defect detection of rolling stock", 3rd Experiment International Conference, 86-90, (2015), DOI: 10.1109/EXPAT.2015.7463220

[2] Guo, J., Huang, W., and Williams, B.M., "Adaptive Kalman filter approach for stochastic short-term traffic flow rate prediction and uncertainty quantification", Transportation Research Part C: Emerging Technologies, 43: 50-64, (2014), DOI: 10.1016/j.trc.2014.02.006.

[3] Gülbaş, M., "Dynamic Weighing Method for Checkweigher", MSc. Thesis, Istanbul Technıcal Unıversıty Institude of Science, Engineering and Technology, İstanbul, (2022).

[4] Chen, N., Li, Q., Li, F., and Jia, Z., "A data processing algorithm based on vehicle weigh-in-motion systems", Ninth International Conference on Natural Computation (ICNC), IEEE, 227-231, (2013), DOI: 10.1109/ICNC.2013.6817975

[5] Rehman, T., Tahir, W., and Lim, W., "Kalman filtering for precise mass flow estimation on a conveyor belt weigh system", In Mechatronics and Robotics Engineering for Advanced and Intelligent Manufacturing, Springer International Publishing, 329-338, (2017), DOI: 10.1007/978-3-319-33581-0_25

[6] Vural, C., "Adaptif Kalman Filtresi Kullanımı ile Gerçek Zamanlı Yaya Takibi", Istanbul Technical University Institude of Science Engineering and Technology, İstanbul, (2022).

[7] Pitawala, S., "State estimation for dynamic weighing using Kalman filter", In Journal of Physics: Conference Series, IOP Publishing, 1489(1): 7-10, (2020), DOI: 10.26686/WGTN.17142506

[8] Ying, Z., Yunbin, H., and Min, L., "The research on data processing for dynamic batching-weighing system", 6th International Conference on Computer Science & Education (ICCSE), IEEE, 888-890, (2011).

[9] Woods, J., and Radewan, C., "Kalman filtering in two dimensions", IEEE Transactions on Information Theory, 23(4): 473-482, (1977), DOI: 10.1109/TIT.1977.1055750

[10] Çayıroğlu, I., "Kalman filtresi ve programlama", Fen ve Teknoloji Bilgi Paylaşımı", 1, (2012).

[11] Zengin S., Akdemir B., "Hareketli Tartımda Dijital Filtre Kullanımı", International Science and Art Research Center 1.Internatıonal Trakya Scıentıfic Research Congress, Tekirdağ, 215-221, (2023).