

An IoT-Based Automatic Product Weight Quality Control System Using Load Cell, HX711, Moving Average, and Fully Adaptive Kalman Filter

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ABSTRACT

Keywords:

Load Cell
HX711
Moving Average Filter
Fully Adaptive Kalman Filter
Internet of Things
Quality Control

Automated weight-based quality control (QC) is a critical requirement in food and beverage manufacturing, yet many production lines still rely on manual weighing, which is slow and prone to human error, while raw load-cell signals remain sensitive to mechanical vibration and electrical noise. This study designs and develops an Internet of Things (IoT)-based automatic weight QC system built around a load cell and an HX711 amplifier interfaced with an ESP32 microcontroller, an infrared sensor for product detection, and a servo motor for automatic PASS/REJECT sorting. The raw weight reading is processed sequentially through a Moving Average filter to suppress high-frequency fluctuation, followed by a Fully Adaptive Kalman Filter that continuously re-estimates its process- and measurement-noise covariances to track dynamic disturbances; the filtered weight is then compared against a 23 g target with a ± 1 g tolerance, and the result is transmitted in real time to the Blynk application and logged to a Google Spreadsheet. Across 40 repeated weighing trials against a reference actual weight of 23.2 g, the system classified 33 products (82.5%) as PASS and 7 products (17.5%) as REJECT. The Fully Adaptive Kalman Filter produced a mean output of 22.785 g, compared with 22.882 g for the raw HX711 signal and 22.807 g for the Moving-Average-only output; overall accuracy remained close across all three stages (96.4-96.6%), with the raw and Moving Average stages showing marginally lower aggregate error than the Fully Adaptive Kalman stage under this repeated static-weight protocol, while the Kalman stage showed greater responsiveness to abrupt individual readings. These findings show that a cascaded Moving Average and Fully Adaptive Kalman Filter pipeline, combined with dual-channel IoT monitoring, yields a stable, traceable weight-QC platform suitable for deployment in industrial environments, while also indicating that the adaptive filter's forgetting factor merits further tuning for near-constant setpoints.

1. Introduction

[1],[2]The transition from Industry 4.0 to Industry 5.0 is pushing manufacturing systems toward combining automation, digitalization, and human-centred intelligence so that production lines can make data-driven decisions with minimal manual intervention. Within this transition, the Internet of Things (IoT) has become one of the key enablers linking sensors, controllers, and cloud- or mobile-based dashboards, so that industrial processes can be observed and adjusted in real time. Recent edge-AI-based monitoring work illustrates how lightweight edge devices and communication protocols allow physical processes such as anaerobic digestion to be tracked continuously and remotely, with methane-rate prediction delivered directly at the edge [1]. Such studies confirm that embedding microcontroller-based sensing nodes within a broader IoT architecture measurably improves the speed, consistency, and traceability of industrial monitoring compared with manual observation.

[3][4]One process that benefits directly from this shift is weight-based QC, a critical inspection stage in the food, beverage, and packaged-goods manufacturing industries. Because product weight is commonly used as an indicator of fill-content compliance, underweight products can erode consumer trust and risk violating labelling regulations, while overweight products waste raw material and increase production cost. Weight verification therefore has to be accurate, fast, and repeatable enough to keep pace with continuous production. Load-cell sensors are widely used for this purpose because they can be embedded directly in the production line and provide a continuous force or weight reading without disrupting material flow; a load-cell-based in-line monitoring system recently demonstrated for wire-based directed energy deposition confirms that embedded load cells can reliably capture process forces for real-time defect detection in a continuous manufacturing setting [2]. Even so, the mechanical behaviour of a load cell is not fully linear: an analytical model of planar load-cell structures shows that tensile and compressive deformation in the elastic element measurably affects sensor output [3], so a raw load-cell reading alone is rarely accurate enough to serve as the sole basis for an automatic PASS/REJECT decision.

[5][6][7]To convert the millivolt-order signal produced by a load cell into a usable digital value, the HX711 instrumentation amplifier and 24-bit analogue-to-digital converter is commonly paired with a load cell in low-cost embedded weighing systems. This combination has been adopted across widely different application domains, which illustrates both its flexibility and its recurring vulnerability to noise. In agriculture, an Arduino-based field-scale weighing lysimeter built with an HX711 and load cell showed a strong correlation with known reference weights at a low implementation cost [4]. In health instrumentation, an Arduino-based real-time monitoring system used an HX711-driven load cell to track blood weight during in-vitro haemodialysis alongside temperature and conductivity sensors [5]. In assistive technology, a smart walking stick embeds a 10 kg HX711 load cell together with an inertial sensor in an edge-based Internet of Medical Things (IoMT) architecture to analyse fall risk in real time [6]. Across these studies, the load-cell/HX711 pairing consistently produced usable weight or force data, but each study also reported the need for additional signal conditioning to obtain a stable reading suitable for automated decision-making.

[8][9][10]The need for signal conditioning arises because the raw load-cell output is affected by mechanical vibration, uneven load placement, temperature drift, and electrical noise, all of which cause the measured weight to fluctuate around its true value. A common first-stage solution is the Moving Average filter, which smooths the signal by replacing each new sample with the average of a fixed number of recent samples. This approach has been applied far beyond weighing systems: in electricity-demand analysis, moving-average smoothing has been shown to reduce short-term fluctuation while still revealing the extreme-value behaviour underlying residential peak demand [7]; in power-signal measurement, a moving average filter applied after zero-crossing detection has been shown to reduce frequency-measurement error [8]; and in epidemiological time-series forecasting, an autoregressive integrated moving-average model was refined

through statistical feature selection to improve prediction accuracy [9]. These studies confirm that the Moving Average filter is computationally cheap and effective at damping short-term noise, but also share the same limitation: because every sample in the averaging window is weighted equally, the filter responds slowly to genuine rapid changes in the signal, which can introduce lag into the filtered output.

[11][12] To address this limitation, many recent studies turn to the Kalman Filter, which estimates the true value of a noisy signal by recursively combining a system-model prediction with a new measurement, each weighted according to its uncertainty. However, the conventional Kalman Filter still depends on process- and measurement-noise covariance parameters (Q and R) that are typically fixed in advance, limiting its performance when the true noise characteristics change during operation. Recent work therefore favours adaptive variants that continuously re-estimate these covariances from incoming data. An error-innovation-based adaptive Kalman filter developed for multi-channel active noise control updates its measurement-noise covariance directly from the observed error signal, achieving faster convergence and higher noise attenuation than a fixed-parameter baseline [10]. A robust adaptive Kalman filter used for combined sensor-and-actuator fault diagnosis in digital-twin applications likewise shows that adaptively adjusting the filter parameters substantially improves resilience to sensor drift, bias, or intermittent noise [11]. A related line of work further shows that adapting only the measurement or only the process noise covariance tends to leave the filter prone to divergence, and proposes jointly estimating both covariances through Kalman smoothing for more reliable convergence [12]; a similar fully adaptive formulation has also been used to denoise physiological signals corrupted by power-line and electromagnetic interference, where both noise sources are updated online from the incoming signal [13]. These findings motivate the use of a Fully Adaptive Kalman Filter, in which both the process- and measurement-noise covariances are updated automatically from the incoming signal, so that the filter can track both abrupt and gradually developing disturbances that a fixed-parameter filter or a Moving Average filter alone cannot fully suppress.

[1],[2] Beyond measurement accuracy, a modern QC station is also expected to support real-time monitoring and automatic data logging, so that supervisory staff can observe production quality without being physically present next to the machine, and so that a historical record is available for later evaluation. IoT-based monitoring architectures that stream sensor data to a mobile dashboard while simultaneously archiving it to the cloud have proven effective for continuous industrial observation in other domains [1], which supports applying a similar design pattern to a weight-based QC station: a Wi-Fi-connected microcontroller can push readings directly to a mobile application for immediate visibility while also logging every measurement to a spreadsheet for audit and trend analysis.

[3],[4],[6],[7][9],[10],[11],[12][1],[2] Taken together, the literature shows a consistent pattern: studies focused on load-cell-based weighing hardware [2],[3],[4],[5],[6] generally do not integrate an adaptive filtering stage; studies that develop Moving Average or

adaptive Kalman filtering techniques [7],[8],[9],[10],[11],[12],[13] are generally demonstrated on signals unrelated to industrial product weighing; and IoT-based real-time monitoring architectures [1] are generally presented independently of any particular sensor-fusion or filtering strategy. As a result, a research gap remains for a single, integrated system that combines load-cell-based weight acquisition, a cascaded Moving Average and Fully Adaptive Kalman Filter processing pipeline, automatic PASS/REJECT classification, and dual-channel IoT monitoring within one coherent weight-QC platform.

This study aims to fill that gap by proposing an integrated IoT-based automatic weight QC system in which a Load Cell and HX711 module acquire the raw weight signal, an infrared sensor triggers product detection, a Moving Average filter performs initial noise reduction, and a Fully Adaptive Kalman Filter subsequently refines the estimate by adjusting its noise covariances in real time, before the result is used both to actuate a servo-based PASS/REJECT sorting mechanism and to update a Blynk dashboard and a Google Spreadsheet log. Based on this description, the objectives of this research are: (1) to design and build an automatic product weight QC system based on a Load Cell sensor and an HX711 module; (2) to apply a Moving Average Filter and a Fully Adaptive Kalman Filter to improve the stability and accuracy of the weight reading; (3) to implement an automatic PASS/REJECT product classification mechanism based on predetermined weight categories; (4) to develop a real-time monitoring system with automatic data logging to a spreadsheet via an IoT connection; and (5) to evaluate the performance of the resulting system.

2. Methods

2.1. System Architecture

The proposed system is organised into three functional stages, as illustrated in the block diagram in Fig. 1: an input stage, a processing stage, and an output/actuation stage, supported by a monitoring and data-logging stage. In the input stage, an infrared (IR) sensor detects the presence of a product on the conveyor, while the Load Cell measures the mechanical load exerted by the product and outputs it as a small analogue voltage. In the processing stage, the HX711 module amplifies and converts that analogue signal into a 24-bit digital value, which is then sent to the ESP32 microcontroller. The ESP32 sequentially applies a Moving Average Filter and a Fully Adaptive Kalman Filter to the digitised weight signal, computes the final weight in grams, and compares it against the target weight and tolerance to determine the product status. In the output stage, a servo motor is actuated to physically separate REJECT products from PASS products. In parallel, the monitoring stage transmits the weight and status data to the Blynk application for real-time visualisation and automatically logs the same data to a Google Spreadsheet.

3.2.1 Blok Diagram Sistem

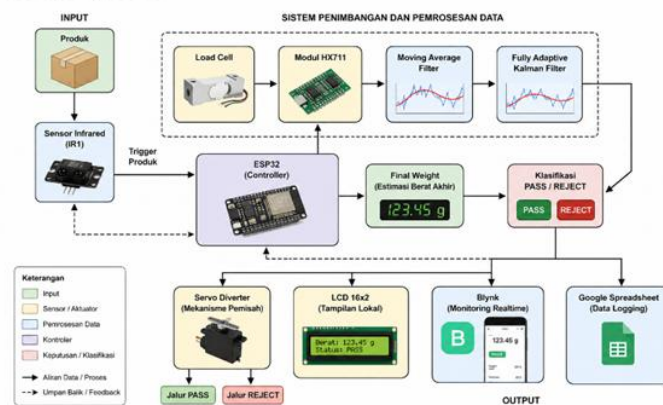


Fig. 1. Block diagram of the proposed IoT-based automatic weight QC system.

Source: authors.

2.2. Hardware Components

The prototype hardware consists of an ESP32 development board as the main controller; a 10 kg-capacity Load Cell connected to an HX711 amplifier/ ADC module as the primary weight-sensing element; a single infrared sensor that detects product presence on the conveyor before weighing begins; a servo motor that physically directs the product toward the PASS or REJECT lane; a 16×2 I2C LCD for local status display; and a DC motor that drives the conveyor belt. All components are connected according to the wiring configuration in Fig. 2, with the Load Cell output routed through the HX711 module before being read by the ESP32, while the IR sensor, servo, and LCD are connected directly to the ESP32's digital and I2C pins.

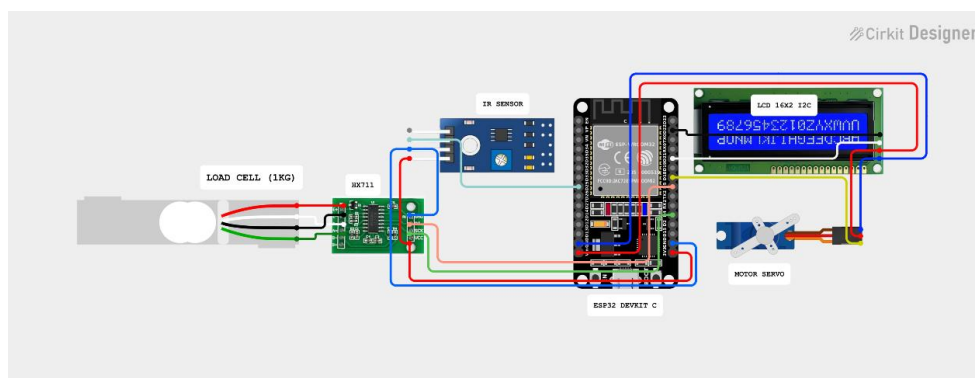


Fig. 2. Wiring configuration of the Load Cell, HX711, IR sensor, ESP32, servo motor, and LCD hardware.

Source: authors.

2.3. Signal Processing Algorithm

Two filtering stages are applied sequentially to the digitised weight signal from the HX711 module. The first stage, the Moving Average Filter, performs an initial reduction

of high-frequency fluctuation. The second stage, the Fully Adaptive Kalman Filter, refines the smoothed signal by adaptively weighting new measurements based on the filter's internal prediction.

The output of the Moving Average Filter is computed as

$$MA_k = (1/N) \times \sum_{i=1}^N x_i \quad (1)$$

where MA_k is the filtered output at sample k , N is the observation window size, and x_i is the i -th raw weight sample within that window. A larger value of N produces a smoother output but responds more slowly to a genuine change in weight, so the window size is chosen to balance stability against the conveyor's sampling rate. In this study, the observation window is set to $N = 5$ samples, so every Moving Average output is computed from the five most recent raw weight readings.

The Moving Average output is then passed to the Fully Adaptive Kalman Filter, which operates in a predict-update cycle. The prediction step estimates the state and its error covariance before a new measurement is incorporated:

$$\hat{x}_k^- = \hat{x}_{k-1} \quad (2)$$

$$P_k^- = P_{k-1} + Q_{k-1} \quad (3)$$

where $\hat{x}_k^-$ and P_k^- are, respectively, the a priori state estimate and its error covariance, and Q is the process-noise covariance. The Kalman gain is then computed and used to correct the prediction using the new measurement z_k (the Moving-Average-filtered weight):

$$K_k = P_k^- / (P_k^- + R_{k-1}) \quad (4)$$

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - \hat{x}_k^-) \quad (5)$$

$$P_k = (1 - K_k) P_k^- \quad (6)$$

where R is the measurement-noise covariance and $\hat{x}_k$ is the final (a posteriori) weight estimate used by the system. What distinguishes the Fully Adaptive Kalman Filter from a conventional Kalman Filter is that Q and R are not fixed constants but are re-estimated at every sample from the measurement innovation $e_k = z_k - \hat{x}_k^-$:

$$R_k = \alpha R_{k-1} + (1 - \alpha)(e_k^2 - P_k^-) \quad (7)$$

$$Q_k = \alpha Q_{k-1} + (1 - \alpha) K_k^2 e_k^2 \quad (8)$$

where α is the forgetting factor that controls how quickly the filter adapts to new noise conditions. By continuously updating Q and R in this way, the filter automatically increases its reliance on new measurements when the environment becomes noisier, and relies more on its own prediction when the signal is stable, allowing it to track dynamic disturbances such as conveyor vibration more effectively than either a fixed-parameter Kalman Filter or a Moving Average filter used on its own.

2.4. PASS/REJECT Classification Mechanism

After the Fully Adaptive Kalman Filter produces the final weight estimate, the ESP32 compares that value against the predetermined target weight and tolerance to classify the product. A product is classified as PASS if its final weight falls within the range [target – tolerance, target + tolerance], and as REJECT if it falls outside that range. In this study, the target weight is set to 23 g with a ± 1 g tolerance, so products weighing between 22 g

and 24 g are classified as PASS, while products outside that range are classified as REJECT. When the classification result is REJECT, the ESP32 immediately actuates the servo motor to divert the product away from the main product lane, whereas a PASS result allows the product to continue along the standard conveyor lane.

2.5. IoT Monitoring and Data Logging

Once the classification decision is obtained, the ESP32 transmits the product weight together with its PASS/REJECT status over Wi-Fi to two destinations in parallel. First, the data is sent to the Blynk application, which displays the live weight reading, the configured target and tolerance, and the current product status on a mobile dashboard, allowing an operator to monitor the process remotely without needing to be physically near the machine. Second, the same data, together with its timestamp, is automatically written to a Google Spreadsheet, which serves as a permanent data log for later evaluation, quality auditing, and statistical analysis. This dual-channel monitoring design was chosen so that the system can provide immediate situational awareness as well as a complete historical record of every measurement.

2.6. Operating Procedure and System Testing

The overall system operation sequence is summarised in the flowchart in Fig. 3. After system initialisation and Load Cell calibration (tare/zero), the ESP32 continuously monitors the IR sensor. Once a product is detected, the weight from the Load Cell is read through the HX711 module and converted to grams, then processed sequentially by the Moving Average Filter and the Fully Adaptive Kalman Filter, after which the final weight is compared against the tolerance range to determine the PASS/REJECT status. That status is displayed locally and sent to Blynk and Google Spreadsheet before the system returns to waiting for the next product.

3.2.2 Flowchart Sistem

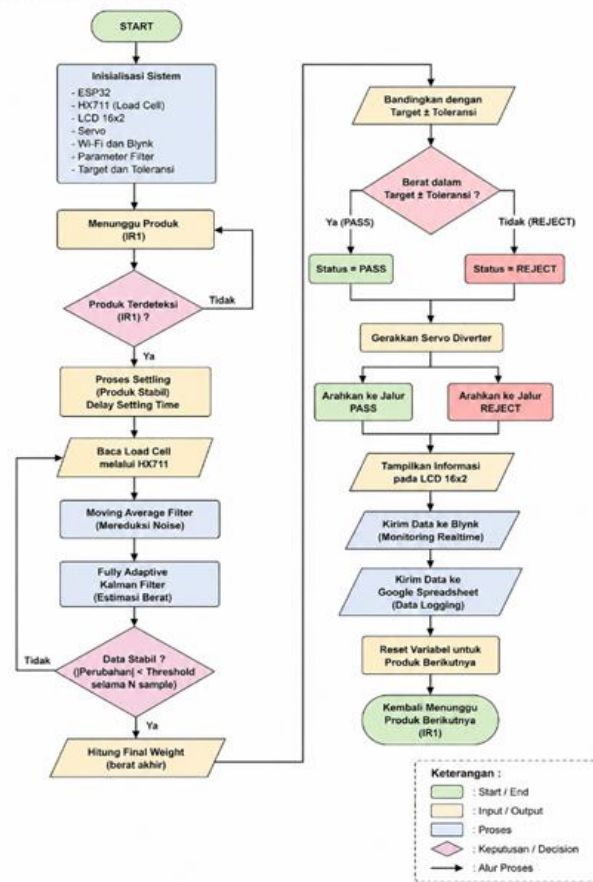


Fig. 3. Flowchart of the proposed weight QC system.

Source: authors.

System performance was evaluated experimentally through 40 repeated weighing trials using a single product with a known actual weight of 23.2 g, obtained from a calibrated reference scale. In each trial, the system recorded the raw HX711 reading, the Moving-Average-filtered value, the Fully-Adaptive-Kalman-filtered value, the resulting final weight, the absolute and percentage error relative to the actual weight, and the resulting PASS/REJECT status. These records were subsequently used to evaluate the stability of each processing stage, together with the overall measurement accuracy and classification performance of the system, as presented in Section 3.

3. Results and Discussion

3.1. System Implementation

The proposed system was successfully implemented as a functional prototype, as shown in Fig. 4, consisting of a conveyor frame fitted with a 10 kg Load Cell and HX711 module, an infrared sensor positioned before the weighing point, a servo-based sorting mechanism, an ESP32 controller with a local LCD display, and a conveyor belt driven by a DC motor. During functional testing, every subsystem operated as designed: the

infrared sensor reliably detected product presence and triggered the weighing sequence, the Load Cell and HX711 module produced a digitised weight signal that was successfully processed by the ESP32, and the servo motor accurately diverted REJECT products while allowing PASS products to continue along the main lane. Weight and status data were successfully transmitted to the Blynk dashboard and logged to Google Spreadsheet on every trial, confirming that the monitoring pathway operated as intended. This successful implementation forms the basis for the quantitative performance evaluation presented in the following subsections.



Fig. 4. Physical prototype of the automatic weight QC system.

Source: authors.

3.2. Weight Measurement and Filtering Performance

Table 1 summarises the results of 40 weighing trials against the 23.2 g actual weight, reporting the raw HX711 reading, the Moving Average output, the Fully Adaptive Kalman output, the resulting final weight, the absolute and percentage error, and the PASS/REJECT status for each trial.

Table 1. Weight measurement results across 40 trials (actual weight = 23.2 g, target = 23 g, tolerance = ± 1 g).

No	Raw HX711 (g)	Moving Average (g)	Adaptive Kalman (g)	Final Weight (g)	Error (g)	Error (%)	Status
1	22.55	22.52	22.55	22.55	0.65	2.80	PASS
2	23.75	23.76	23.85	23.85	-0.65	-2.80	PASS
3	23.06	22.74	22.68	22.68	0.52	2.24	PASS
4	22.17	22.22	22.21	22.21	0.99	4.27	PASS
5	22.44	22.55	22.49	22.49	0.71	3.06	PASS
6	24.62	24.45	24.35	24.35	-1.15	-4.96	REJECT
7	24.63	24.45	25.11	25.11	-1.91	-8.23	REJECT
8	20.91	20.97	20.79	20.79	2.41	10.39	REJECT
9	22.66	22.49	22.19	22.19	1.01	4.35	PASS
10	23.30	23.12	23.08	23.08	0.12	0.52	PASS
11	20.08	19.84	19.51	19.51	3.69	15.91	REJECT
12	22.01	22.11	21.98	21.98	1.22	5.26	REJECT
13	23.12	23.01	22.96	22.96	0.24	1.03	PASS
14	24.18	23.89	23.78	23.78	-0.58	-2.50	PASS
15	23.77	23.69	23.74	23.74	-0.54	-2.33	PASS
16	23.79	23.87	23.84	23.84	-0.64	-2.76	PASS
17	23.41	23.25	23.18	23.18	0.02	0.09	PASS
18	22.98	22.89	22.80	22.80	0.40	1.72	PASS
19	23.73	23.74	23.68	23.68	-0.48	-2.07	PASS
20	23.95	23.95	23.81	23.81	-0.61	-2.63	PASS
21	23.07	22.75	22.74	22.74	0.46	1.98	PASS
22	24.01	23.73	23.53	23.53	-0.33	-1.42	PASS
23	22.37	22.27	22.24	22.24	0.96	4.14	PASS
24	23.28	23.34	23.40	23.40	-0.20	-0.86	PASS
25	22.92	23.05	23.11	23.11	0.09	0.39	PASS
26	23.38	23.45	23.47	23.47	-0.27	-1.16	PASS
27	23.77	23.83	24.06	24.06	-0.86	-3.71	REJECT
28	22.07	22.24	22.27	22.27	0.93	4.01	PASS
29	23.35	23.09	23.08	23.08	0.12	0.52	PASS
30	22.59	22.51	22.59	22.59	0.61	2.63	PASS
31	22.51	22.20	22.14	22.14	1.06	4.57	PASS
32	23.51	23.03	23.04	23.04	0.16	0.69	PASS
33	23.15	23.30	23.17	23.17	0.03	0.13	PASS
34	22.01	22.20	22.12	22.12	1.08	4.66	PASS
35	22.31	22.34	22.33	22.33	0.87	3.75	PASS
36	22.94	22.74	22.70	22.70	0.50	2.16	PASS
37	22.92	22.80	22.79	22.79	0.41	1.77	PASS
38	19.55	19.36	19.31	19.31	3.89	16.77	REJECT

No	Raw HX711 (g)	Moving Average (g)	Adaptive Kalman (g)	Final Weight (g)	Error (g)	Error (%)	Status
39	22.65	22.49	22.53	22.53	0.67	2.89	PASS
40	21.82	22.06	22.21	22.21	0.99	4.27	PASS

As shown in Table 1, the raw HX711 reading fluctuates noticeably from one trial to the next – for instance, rising from 22.55 g at trial 1 to 23.75 g at trial 2 – reflecting the influence of mechanical vibration and electrical noise on the unfiltered signal. Applying the Moving Average Filter removed most of this inter-sample fluctuation, since each output value is an average of several recent readings, although a small number of trials still show a residual difference from the actual weight, indicating that Moving Average smoothing alone is not sufficient to fully suppress noise. The subsequent Fully Adaptive Kalman Filter stage produced values that, in most trials, track the actual weight more closely than either the raw reading or the Moving-Average-only reading, consistent with the filter’s ability to continuously adjust its noise covariance rather than apply a fixed weighting scheme.

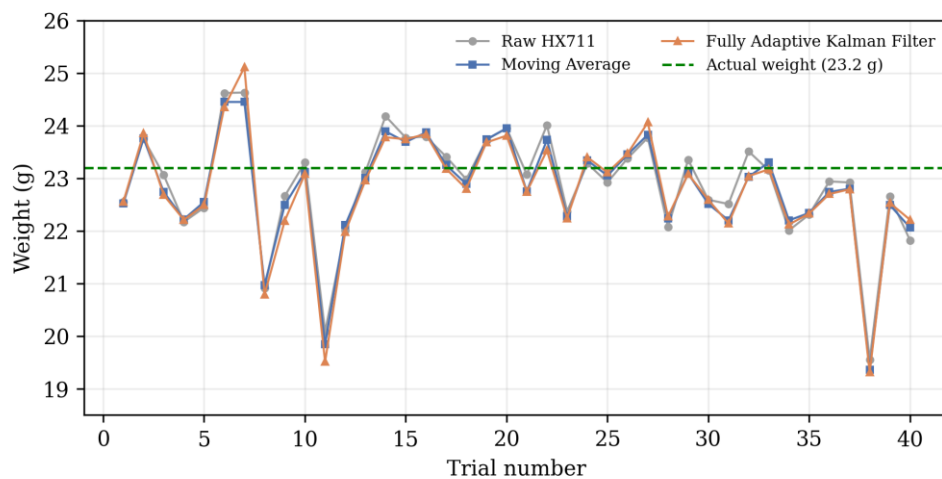


Fig. 5. Comparison of the raw HX711, Moving Average, and Fully Adaptive Kalman Filter readings across 40 trials against the 23.2 g actual weight.

Source: authors, based on Table 1.

3.3. PASS/REJECT Classification Results

Table 2 recapitulates the classification results from the 40 trials. Based on the 23 g target weight and ± 1 g tolerance, the acceptable PASS range is 22.0-24.0 g. Of the 40 trials, the system classified 33 products (82.5%) as PASS and 7 products (17.5%) as REJECT, and manual verification against Table 1 confirms that every REJECT case corresponds to a final weight below 22.0 g or above 24.0 g, showing that the classification logic operates correctly and consistently with the configured tolerance.

Table 2. Recapitulation of system testing results.

Number of trials	40
Products classified PASS	33
Products classified REJECT	7
PASS percentage	82.5%
REJECT percentage	17.5%
Reference (actual) weight	23.2 g
Target weight	23 g
Tolerance	± 1 g
PASS range	22.0–24.0 g
REJECT range	< 22.0 g or > 24.0 g

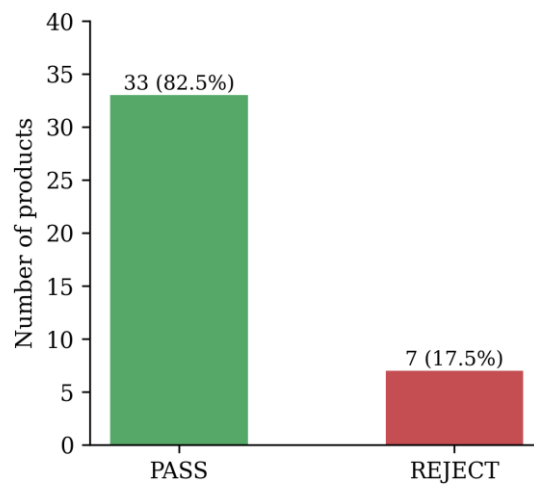


Fig. 6. Distribution of PASS and REJECT classifications across 40 trials.

Source: authors, based on Table 2.

3.4. Accuracy Analysis

System measurement accuracy was evaluated using absolute error, percentage error, mean absolute error (MAE), root-mean-square error (RMSE), mean absolute percentage error (MAPE), and percentage accuracy, computed as

$$\text{Error} = | \text{Final Weight} - \text{Actual Weight} | \quad (9)$$

$$\text{Error (\%)} = (\text{Error} / \text{Actual Weight}) \times 100\% \quad (10)$$

$$\text{Accuracy} = (1 - | \text{Final Weight} - \text{Actual Weight} | / \text{Actual Weight}) \times 100\% \quad (11)$$

Table 3 summarises the minimum, maximum, and mean values obtained from the raw HX711 signal, the Moving Average output, and the Fully Adaptive Kalman output over all 40 trials, together with the MAE, RMSE, MAPE, and mean accuracy computed for each processing stage using Eqs. (9)-(11) against the 23.2 g reference weight.

Table 3. Recapitulation of measurement accuracy at each processing stage.

Parameter	Raw HX711	Moving Average	Fully Adaptive Kalman Filter
Minimum (g)	19.55	19.36	19.31
Maximum (g)	24.63	24.45	25.11
Mean (g)	22.882	22.807	22.785
MAE (g)	0.779	0.788	0.826
RMSE (g)	1.091	1.102	1.170
MAPE (%)	3.36	3.40	3.56
Accuracy (%)	96.64	96.60	96.44

Note: all evaluation metrics (MAE, RMSE, MAPE, and Accuracy) are computed using the 23.20 g reference weight over 40 trials.

As shown in Table 3, the mean raw HX711 reading is 22.882 g, the mean Moving Average output is 22.807 g, and the mean Fully Adaptive Kalman output is 22.785 g, all of which lie close to the 23.2 g actual weight. In terms of range, the raw HX711 signal spans 19.55-24.63 g, the Moving Average output slightly narrows that range to 19.36-24.45 g, while the Fully Adaptive Kalman output instead spans 19.31-25.11 g – a wider range than either of the other two stages. This wider range shows that, rather than simply smoothing every value toward the mean as the Moving Average filter does, the Fully Adaptive Kalman Filter lets its output move more freely whenever the adaptively estimated measurement-noise covariance indicates that a new reading should be trusted, which explains why its per-trial values track sudden apparent changes (for example, at trial 7, where the reading rose to 25.11 g) more responsively than the Moving Average output. This responsiveness, however, comes with a measurable trade-off under the present test protocol. Because all 40 trials used the same physical reference item at a constant actual weight of 23.2 g, any abrupt jump the filter tracks is noise rather than a genuine weight change, so the Fully Adaptive Kalman stage does not reduce the aggregate error relative to the raw signal in this dataset: the computed MAE is 0.779 g for the raw HX711 signal, 0.788 g for the Moving Average output, and 0.826 g for the Fully Adaptive Kalman output, with corresponding RMSE of 1.091 g, 1.102 g, and 1.170 g, MAPE of 3.36%, 3.40%, and 3.56%, and mean accuracy of 96.64%, 96.60%, and 96.44%, respectively. All three stages therefore achieve comparable accuracy above 96%, but under a near-constant setpoint the adaptive re-weighting in Eqs. (7)-(8) makes the Kalman stage slightly more sensitive to individual noisy samples than the simpler Moving Average stage. This indicates that the forgetting factor α used in this study, while effective at making the filter responsive, could be tuned toward a lower adaptation rate in applications where the target weight is expected to remain constant between products, which is left as a direction for further refinement of the filter parameters. This outcome is expected rather than anomalous: the Fully Adaptive Kalman Filter is designed to track noise characteristics that change dynamically over time by continuously re-estimating the process-noise covariance Q and the measurement-noise covariance R [11],[12], whereas the present study uses a constant reference weight across all 40 trials, a condition under which an improvement in aggregate accuracy is not necessarily expected. Parameters such as the

forgetting factor α , together with the initial Q and R values, remain open to further optimisation, and prior adaptive-filtering studies confirm that such parameter tuning has a direct, measurable effect on the resulting trade-off between responsiveness and aggregate accuracy [11],[12],[13].

Overall, the accuracy results show that measurement performance is influenced by several interacting factors, including the intrinsic characteristics of the Load Cell sensor, the mechanical stability of the conveyor, vibration during product transfer, and the parameters used at each filtering stage. These factors explain why a small number of trials (for example, trials 8, 11, and 38) still produced an error above 10%, even though both filtering stages were applied.

3.5. Sensor Reading Validation

To further validate the reliability of the weight-sensing chain, this subsection interprets the accuracy metrics reported in Section 3.4 explicitly from a sensor-validation standpoint, using only the MAE, RMSE, MAPE, and accuracy values already computed from the 40 experimental trials. Across all three processing stages, MAPE remained within a narrow band of 3.36-3.56%, corresponding to an accuracy of 96.4-96.6% relative to the 23.2 g reference weight, which indicates that the Load Cell and HX711 acquisition chain, together with the two-stage filtering pipeline, produces a valid and repeatable weight estimate rather than an unstable or drifting one. The stability of this reading is further supported by the narrow spread between the minimum, maximum, and mean values reported in Table 3 for the majority of trials, with only a small number of trials (8, 11, and 38 in Table 1) departing from this pattern; these trials are consistent with occasional mechanical disturbance during product placement rather than a systematic sensor fault, since no monotonic drift is observed across the 40 sequential trials. This behaviour is consistent with prior load-cell validation studies, which likewise report that HX711-based acquisition chains can achieve accuracy above 95% once appropriately filtered [4],[5],[6], while also confirming that isolated outliers driven by mechanical loading conditions are a recurring, expected characteristic of load-cell-based systems rather than a defect specific to this implementation. Taken together, these results validate that the sensor reading obtained through the proposed pipeline is sufficiently accurate and stable to support automatic PASS/REJECT decision-making in a real production environment.

3.6. Comparison with Previous Studies

To contextualise these results, Table 4 compares the findings of this study with relevant prior research on load-cell-based measurement, adaptive Kalman filtering, and Moving-Average-based signal processing.

Table 4. Comparison between this study and relevant prior research.

Ref.	Focus / Method	Reported Finding	Relation to This Study	Limitation
[2]	In-line load-cell-based monitoring for wire-DED additive manufacturing	Embedded load cell reliably captures process force for real-time defect detection	Confirms that load cells are effective for continuous in-line industrial measurement, supporting the sensing approach used in this study	Focused on defect detection during deposition; does not address noise-adaptive filtering of the load-cell signal itself
[3]	Analytical deformation model of planar load cells	Tensile/compressive deformation significantly affects load-cell linearity	Helps explain part of the residual error observed on the raw signal in Table 3, motivating the filtering stages used in this study	Analytical model only; not validated against a filtered, real-time embedded weighing pipeline
[10]	Error-innovation-based adaptive Kalman filter for active noise control	Adaptive covariance updates achieve faster convergence than a fixed-parameter baseline	Supports the fully adaptive, innovation-based Q/R updating approach used in this study	Demonstrated on acoustic/noise-control signals, not on load-cell weight measurement
[11],[12]	Robust / fully adaptive Kalman filtering for fault diagnosis and joint noise-covariance estimation	Adaptive parameter adjustment improves robustness under changing, uncertain noise conditions	Reinforces the Fully Adaptive Kalman Filter's responsiveness observed in this study, while highlighting the need to tune the forgetting factor for near-constant setpoints (Section 3.4)	Evaluated under genuinely time-varying noise; forgetting-factor behaviour under a near-constant setpoint is not examined
[13]	Adaptive Kalman filter for physiological signal denoising	Effective denoising under power-line and electromagnetic interference, sensitive to parameter tuning	Reinforces both the effectiveness and the tuning sensitivity of the adaptive filter observed in this study	Tuning sensitivity noted but not quantified against a fixed physical reference weight
[7],[8],[9]	Moving-average smoothing for demand analysis, frequency measurement, and epidemiological forecasting	Moving average reduces short-term noise but can lag during rapid transitions	Consistent with the lag/residual behaviour observed in some Moving Average readings in Table 1	Applied to non-weighing signals (demand, frequency, epidemiological data); lag-accuracy trade-off not evaluated for embedded QC

[4][3][11],[12][9],[10]The comparison in Table 4 shows that the behaviour of the system in this study is consistent with the wider literature on load-cell instrumentation and adaptive filtering. The analytical modelling of load-cell deformation [3] helps explain why part of the residual error observed on the raw HX711 signal persists even after calibration, since the mechanical response of the sensing element itself is not fully linear. The successful use of an embedded load cell for continuous in-line measurement in a wire-based additive manufacturing process [2] supports the choice of load-cell-based sensing as a practical foundation for real-time industrial measurement, consistent with the reliable operation of the Load Cell and HX711 subsystem observed in Section 3.1. On the filtering side, studies reporting that adaptive Kalman filter variants achieve faster convergence and greater robustness than fixed-parameter filtering under changing noise conditions [10],[11],[12] are broadly consistent with the responsiveness observed for the Fully Adaptive Kalman Filter in this study – for instance its faster reaction to the abrupt reading at trial 7 – because both this study and the referenced work rely on the same underlying mechanism of continuously re-estimating filter covariances from incoming

data rather than fixing them in advance; at the same time, the slightly higher aggregate MAE of the Kalman stage found in Section 3.4 nuances that comparison, since those reference studies were evaluated on genuinely time-varying signals rather than a constant setpoint. A physiological-signal denoising study using an analogous fully adaptive Kalman formulation [13] similarly reports effective noise suppression alongside sensitivity to filter-parameter tuning, reinforcing the recommendation in Section 3.4 to revisit the forgetting factor for near-constant loads. Studies applying Moving Average smoothing as a pre-processing stage before further analysis [7],[8],[9] reinforce the effectiveness of the Moving Average filter as an inexpensive first-stage noise-reduction technique, while also reporting the same lag-related limitation visible in some of the Moving Average readings in Table 1. Because the system in this study integrates load-cell-based sensing, cascaded Moving Average and Fully Adaptive Kalman filtering, automatic PASS/REJECT actuation, and dual-channel IoT monitoring within a single platform – rather than treating these elements separately, as in the comparison studies – these results support the intended novelty of this research as an integrated, IoT-based automatic weight QC system.

4. Conclusion

This study has successfully designed, implemented, and evaluated an IoT-based automatic product-weight quality control system that combines a Load Cell and HX711 module for weight acquisition, a cascaded Moving Average and Fully Adaptive Kalman filtering pipeline for noise reduction, an infrared sensor and servo motor for product detection and automatic PASS/REJECT sorting, and a dual-channel IoT monitoring architecture that combines the Blynk application with Google Spreadsheet logging. Experimental evaluation over 40 trials against a 23.2 g actual weight showed that the system correctly classified 33 products (82.5%) as PASS and 7 products (17.5%) as REJECT against the 23 g target with ± 1 g tolerance, and that all three processing stages achieved comparable accuracy above 96% (HX711 raw: 96.64%; Moving Average: 96.60%; Fully Adaptive Kalman: 96.44%), with the Fully Adaptive Kalman stage showing greater responsiveness to abrupt individual readings at a small cost in aggregate error under this near-constant reference weight, an observation that motivates further tuning of the filter's forgetting factor in future work.

The main contribution of this study lies in demonstrating that Load Cell-based weight sensing, cascaded adaptive filtering, automatic sorting actuation, and real-time IoT monitoring can be integrated into a single coherent system, rather than being addressed separately as is common in the related literature. This integration represents the novelty of the proposed system relative to prior research, which generally focuses on only one of: load-cell hardware accuracy, Moving Average or adaptive Kalman filtering on non-weighing applications, or IoT monitoring architectures independent of a specific filtering strategy. By combining these elements, this study fulfils its objective of producing a stable and traceable automatic weight QC platform, and provides a practical reference

architecture for further development of adaptive, IoT-connected quality control systems in manufacturing environments.

Several directions remain for future work. First, the forgetting factor α together with the initial process- and measurement-noise covariances of the Fully Adaptive Kalman Filter could be systematically optimised, for example through grid search or an auto-tuning procedure, to reduce sensitivity to noise under a near-constant setpoint while preserving responsiveness to genuine disturbances. Second, the system should be tested across a wider range of product weights and tolerance settings, rather than a single reference weight, to confirm that the filtering pipeline generalises across the target ranges used in practice. Third, deployment and evaluation on an actual industrial production line, alongside existing quality-control equipment, would validate the system's reliability under real operating conditions, including longer-duration continuous operation. Finally, system performance should be evaluated at higher conveyor speeds, since faster product throughput reduces the settling time available for each weighing cycle and may require further tuning of the sampling rate and filter parameters.

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