

DEVELOPMENT OF A METHODOLOGICAL FRAMEWORK FOR CURATIVE MAINTENANCE OF AUTOMATIC CHECKWEIGHERS IN INDUSTRIAL PRODUCTION LINES

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ABSTRACT

This study proposes a structured methodology to optimize corrective maintenance for continuous dynamic checkweighers, targeting the Loma Systems CW3 model on high-speed industrial packaging lines. To address the inefficiency of empirical troubleshooting that increases machine downtime, the research combines mechanical force modeling with quality management tools such as the Ishikawa diagram, Pareto chart, and FMEA (Failure Mode, Effects, and Criticality Analysis) to precisely isolate the root causes of measurement drifts and breakdowns. The developed framework introduces a standardized four-phase protocol, including strict procedures for safety isolation, mechatronic diagnostics, mechanical adjustment, and dual-phase metrological validation (static and dynamic). Experimentally validated over a 12-month period, this approach achieved a 66.2% reduction in Mean Time to Repair (MTTR), a 125.6% increase in Mean Time Between Failures (MTBF), and nearly a fivefold reduction in the standard deviation of dynamic measurements, thereby ensuring compliance with international legal metrology standards while generating significant material savings.



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1. INTRODUCTION & LITERATURE REVIEW

The advent of the fourth industrial revolution, commonly referred to as Industry 4.0, has profoundly transformed the architecture of modern production lines. The massive integration of cyber-physical systems, advanced automation, and the Internet of Things (IoT) requires near-absolute operational availability of electromechanical equipment (Zheng et al., 2018). Within this automated framework, maintenance

operations are no longer viewed as reactive cost centers, but rather as strategic levers for overall operational efficiency, product quality compliance, and cost minimization.

Historically, industrial maintenance strategies have evolved through distinct operational frameworks:

- Total Productive Maintenance (TPM): Emphasizes autonomous maintenance and collective operator engagement to minimize

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overall equipment effectiveness (OEE) losses (Torre et al., 2023).

- Reliability-Centered Maintenance (RCM): Focuses on identifying functional failure modes and establishing preventative maintenance tasks based on system criticality.
- Condition-Based Maintenance (CBM): Relies on real-time sensor monitoring (e.g., vibration or thermal analysis) to trigger interventions before functional degradation occurs.
- Predictive Maintenance (PdM): Utilizes historical operational data and machine learning algorithms to forecast failure horizons (Mobley, 2002).
- ISO 55000 Asset Management Practices: Provides an overarching managerial framework for lifecycle asset optimization and risk mitigation (ISO 55000:2014).

While foundational maintenance frameworks such as Total Productive Maintenance (TPM), Reliability-Centered Maintenance (RCM), Condition-Based Maintenance (CBM), Predictive Maintenance (PdM), and ISO 55000 asset management practices have transformed general asset management practices, their application to high-speed dynamic checkweighing equipment reveals critical operational limitations (Shih, 2024). A comparison of conventional maintenance frameworks and the proposed standardized curative framework is presented in Table 1.

- Total Productive Maintenance (TPM): TPM focuses on operator empowerment, autonomous routine cleaning, and total equipment loss elimination. However, in high-speed packaging environments, TPM protocols rarely provide technical guidelines for resolving subtle dynamic signal drifts, high-frequency mechanical vibration coupling, or transient load cell saturation. Operators trained under standard TPM routines can perform visual checks and daily hygiene, but they lack the specialized diagnostic procedures required when metrological accuracy degrades under continuous flow.
- Reliability-Centered Maintenance (RCM): RCM excels at establishing preventative maintenance schedules based on systemic risk and failure mode criticality. Nevertheless, the heavy administrative structure of standard RCM workflows makes them ill-suited for real-time, unscheduled curative interventions. When an automatic checkweigher experiences dynamic tare drift during live production, maintenance personnel need an immediate, standardized execution path rather than a long-term reliability study.
- Condition-Based and Predictive Maintenance (CBM / PdM): CBM and PdM rely on continuous sensor data (such as thermal or vibration signatures) and predictive algorithms

to forecast component wear. While effective for large rotating machinery, these approaches require substantial capital investment and complex data infrastructure. Furthermore, they are unable to prevent or instantly diagnose sudden electromechanical disruptions, such as physical package impacts, optical sensor misalignment caused by dust accumulation, or mechanical belt tension asymmetry.

- ISO 55000 Asset Management Standard: ISO 55000 provides high-level managerial governance for lifecycle cost optimization and organizational risk management. It establishes strategic alignment across asset portfolios but explicitly leaves a technical gap regarding physical field execution, diagnostic troubleshooting logic, and post-repair metrological re-validation on specialized packaging machinery.

Despite these established paradigms, a significant research gap remains in the practical management of high-speed mechatronic equipment, specifically continuous-flow automatic checkweighers. Existing general maintenance frameworks focus primarily on broad operational availability or long-term component degradation, neglecting the immediate metrological drift and dynamic electromechanical perturbations that characterize dynamic weighing platforms.

Traditionally, curative maintenance—interventions carried out after an asset experiences a failure or metrological drift—suffers from a lack of formalization. Technicians frequently intervene empirically, relying on intuition and trial-and-error component swapping (e.g., prematurely replacing load cells, drive motors, or variable frequency drives) rather than structured diagnostic protocols. This unstructured approach drastically increases the Mean Time to Repair (MTTR), causing severe degradation of the plant's Overall Equipment Effectiveness (OEE) (Drid, 2023; Lacerda et al., 2025).

Among the critical quality-assurance units in modern packaging lines, automatic weight sorters (such as the Loma Systems CW3) occupy a vital position. Unlike static weighing instruments where force measurements occur after transient oscillations dissipate, dynamic checkweighers assess the mass of continuously moving packages at throughput rates exceeding several hundred units per minute. The equipment serves as the final compliance gateway, ensuring strict adherence to legal metrology standards governing prepackaged goods (Directive 2014/32/EU, 2014; OIML R 51-1, 2006).

A failure or accuracy drift in an automatic checkweigher introduces a critical industrial dilemma: either a complete shutdown of upstream packaging machinery (causing immediate throughput and financial losses) or bypassing the machine, which exposes the enterprise to severe

regulatory penalties, mass batch rejections, and brand damage due to underweighted or overweighted products entering the supply chain.

- 1) The inherent complexity of diagnosing and repairing dynamic checkweighers lies in their deeply coupled mechatronic architecture. A weighing anomaly or system error can stem from a variety of distinct engineering domains:
- 2) Mechanical: Eccentricity of guide pulleys, uneven belt tension, or bearing wear on modular conveyors.

- 3) Electrical/Electronic: Harmonic noise introduced by variable speed drives (VFDs), broken cable shielding, or load cell Wheatstone bridge excitation fluctuations.
- 4) Control & Software: Incorrect calibration of time windows (ΔT_w), improper digital filtering parameters, or dynamic tare drift caused by debris accumulation.

Table 1. Comparison of Conventional Maintenance Frameworks and Proposed Standardized Curative Framework

Maintenance Framework	Core Focus	Primary Limitations in Dynamic Weighing Systems	Alignment with Proposed Framework
Total Productive Maintenance (TPM)	Operator autonomy, 5S, loss elimination	Lacks specific metrological calibration and high-speed signal processing protocols	Complements operator-level inspection and daily hygiene routines
Reliability-Centered Maintenance (RCM)	Criticality analysis, preventive task scheduling	High structural complexity; often too slow for rapid curative interventions on live lines	Integrates FMEA and failure-mode categorization into real-time diagnostics
Condition-Based Maintenance (CBM)	Real-time threshold monitoring (vibration, temp)	High sensor cost; fails to address immediate root causes during unscheduled downtime	Utilizes dynamic signal integrity verification during post-maintenance testing
Predictive Maintenance (PdM)	Data-driven failure forecasting & AI	Requires massive historical datasets; ineffective for instantaneous electromechanical jams	Serves as the operational foundation for training future digital twin models
ISO 55000	Strategic asset management & governance	High-level organizational policy; provides no physical diagnostic or execution guidelines	Ensures compliance with corporate quality standards and legal metrology
Proposed Curative Framework	Standardized 4-phase diagnostic & metrological protocol	Optimized specifically for high-speed dynamic checkweighing mechatronics	Fills the operational gap between theoretical dependability and field execution

Without a formalized, multidisciplinary framework, curative maintenance actions remain slow, costly, and unreliable. This study addresses this gap by developing and experimentally validating a standardized, operational framework for the curative maintenance of automatic checkweighers. By integrating structured quality management tools (such as Ishikawa cause-and-effect mapping, Pareto analysis, FMEA, and root-cause tree structures) with rigorous physical force modeling, lockout/tagout (LOTO) protocols, and dual-phase (static/dynamic) metrological validation, this framework bridges the gap between dependability theory and factory-floor execution (Ishikawa, 1986; Pacana & Siwiec, 2023; Shrivastava et al., 2023; Sharma, 2023).

2. THEORETICAL FRAMEWORK AND DYNAMIC WEIGHING MODELING

2.1 Dynamic Force Decomposition on Continuous-Flow Platforms

The mechanical behavior of an automatic checkweigher in continuous-flow operational mode, such as the Loma Systems CW3, differs fundamentally from static weighing apparatuses (Gassmann & Buergin, 2018; Loma Systems, 2024). In static configurations, signal acquisition occurs after complete dissipation of transient mechanical oscillations, measuring solely the

gravitational force vector. In dynamic continuous-flow mode, however, discrete packages transit across the central weigh table at a constant linear transport velocity V .

The instantaneous normal force $F(t)$ transferred to the strain-gauge load cell test body is not limited to gravitational mass attraction. It represents a superposition of kinetic, mechanical, structural, and parasitic environmental force vectors:

$$F(t) = F_{\text{gravitational}} + F_{\text{inertia}}^{(t)} + F_{\text{vibration}}^{(t)} + F_{\text{tension}}^{(t)} \quad (1)$$

Where each force component governs a distinct physical phenomenon within the mechatronic assembly:

1. Gravitational Force Component ($F_{\text{gravitational}}$): Represented by $F_{\text{gravitational}} = m \cdot g$, where m is the actual physical mass of the target package and g is local gravitational acceleration. This force vector constitutes the sole target metrological variable required for mass decision algorithms.

2. Kinetic Inertia Force Component ($F_{\text{inertia}}^{(t)}$): Expressed as:

$$F_{\text{inertia}}^{(t)} = m \cdot \frac{d^2 z(t)}{dt^2} \quad (2)$$

This represents the transient vertical impact force generated as the leading edge of a package transitions across the physical air gap from the infeed conveyor to the weigh table. This transfer induces high-amplitude initial impact spikes and transient structural decay oscillations at the start of the measurement envelope.

3. Harmonic Vibration Force Component ($F_{vibration}(t)$): Modeled as a multi-harmonic sinusoidal series:

$$F_{vibration}^{(t)} = \sum_{k=1}^N A_k \sin(2\pi f_k t + \phi_k) \quad (3)$$

This accounts for internal mechanical noise generated by drive motor rotation, bearing degradation, pulley eccentricity, and the cyclic engagement of modular belt links passing over support rollers, as well as external floor vibrations transmitted through the machine frame.

4. Parasitic Belt Tension Component ($F_{tension}(t)$): Represents the static and dynamic vertical force components introduced by the longitudinal tensioning of the modular weigh conveyor belt. Over-tensioning introduces a constant parasitic pre-load vector onto the strain gauge load cell, shifting the baseline calibration zero-point.

2.2 Mathematical Modeling of the Weighing Time Window (ΔT_w)_w

The primary mechatronic limitation in high-speed automatic checkweighers is that mass calculation must occur within an extremely constrained temporal envelope, termed the effective weighing time window (ΔT_w). This window corresponds to the time interval during which the entire length of the package is fully supported by the weigh platform (after clearing the infeed conveyor) without touching the outfeed conveyor. The operating steps of a checkweigher are illustrated in Figure 1 (Wang et al., 2022).

Mathematically, ΔT_w is defined as:

$$\Delta T_w = \frac{L_{belt} - L_{product}}{V} \quad (4)$$

Where L_{belt} is the functional length of the central weigh conveyor, $L_{product}$ is the physical length of the packaged product along the direction of flow, and V is the linear transport velocity.

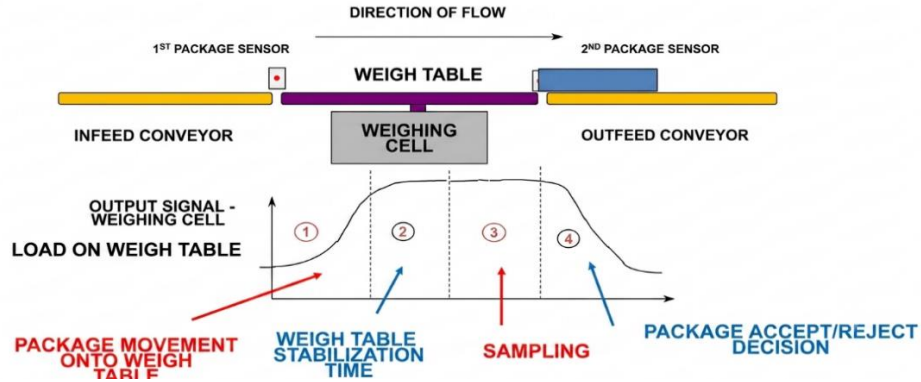


Figure 1. Operating Steps of a Checkweigher

The total sampling time available for digital signal acquisition ($T_{sampling}$) depends directly on ΔT_w and the stabilization time ($T_{stabilization}$) required for dynamic transient dissipation:

$$T_{sampling} = \Delta T_w - T_{stabilization} = \frac{L_{belt} - L_{product}}{V} - T_{stabilization} \quad (5)$$

Given an Analog-to-Digital Converter (ADC) sampling frequency f_s , the total number of discrete data points $N_{samples}$ available to the dynamic mass estimation algorithm is:

$$T_{sampling} = [f_s \cdot (\frac{L_{belt} - L_{product}}{V} - T_{stabilization})] \quad (6)$$

This fundamental relationship illustrates the critical mechatronic trade-off: increasing linear conveyor speed

V to maximize production throughput drastically shrinks ΔT_w , reducing $T_{sampling}$ and significantly elevating measurement uncertainty.

2.3 Uncertainty and Sensitivity Analysis of Mass Measurement

To rigorously model measurement accuracy under dynamic operational conditions, the total dynamic mass measurement $m_{dynamic}$ derived by integrating the load cell response over ΔT_w can be expressed as:

$$m_{dynamic} = \frac{1}{g \cdot \Delta T_{sample}} \int_{t_{start}}^{t_{start} + \Delta T_{sample}} F(t) dt \quad (7)$$

Substituting the force decomposition model yields:

$$m_{dynamic} = m_{actual} + \epsilon_{inertia} + \epsilon_{vibration} + \epsilon_{tension} + \epsilon_{drift} \quad (8)$$

To perform an uncertainty analysis in accordance with the Guide to the Expression of Uncertainty in Measurement (GUM; JCGM 100:2008, 2008), the combined standard uncertainty $u_c(m)$ is evaluated using partial derivative sensitivity coefficients:

$$u_c(m) = \left(\frac{\partial m}{\partial V}\right)^2 u^2(V) + \left(\frac{\partial m}{\partial F_{tension}}\right)^2 u^2(F_{tension}) + \left(\frac{\partial m}{\partial A_{vibration}}\right)^2 u^2(A_{vibration}) + u^2_{ADC} \quad (9)$$

Where the key sensitivity coefficients are derived as follows:

1. Velocity Sensitivity $\left(\frac{\partial m}{\partial V}\right)$:

$$\frac{\partial m}{\partial V} = -\frac{(L_{belt} - L_{product})}{V^2 \cdot g} \cdot \bar{F}_{transient} \quad (10)$$

This demonstrates that velocity fluctuations $u(V)$ induced by drive belt slip or VFD instability exert a second-order inverse quadratic effect on measurement accuracy (Zhao & Sun, 2023).

2. Belt Tension Sensitivity $\left(\frac{\partial m}{\partial F_{tension}}\right)$:

$$\frac{\partial m}{\partial F_{tension}} = \frac{\sin(\theta)}{g} \quad (11)$$

Where θ is the structural deflection angle of the conveyor frame under belt tension. Non-symmetrical tensioning creates vertical force components that directly bias the baseline tare calibration (Nascimento & Silva, 2020).

3. Vibrational Noise Sensitivity $\left(\frac{\partial m}{\partial A_{vibration}}\right)$:

For unattenuated sinusoidal vibrations at frequency f_k :

$$\epsilon_{vibration} = \frac{A_k}{2\pi F_k \Delta T_w \cdot g} [\cos(2\pi f_k t_0) - \cos(2\pi f_k (t_0 + \Delta T_w))] \quad (12)$$

When $f_k \approx \frac{1}{\Delta T_w}$, severe resonance occurs, rendering unfiltered dynamic mass estimation highly inaccurate (Bendat & Piersol, 2010).

2.4 Signal Transduction and Digital Filtering Architecture

The Loma CW3 load cell employs a strain-gauge Wheatstone bridge that transduces structural deformation into a differential voltage signal $V_{out}(t)$ in the millivolt range (Asch, 2010). The raw analog signal is conditioned via a low-noise instrumentation amplifier and converted to a digital sequence $x[n]$ via a high-speed ADC.

To isolate $F_{gravitational}$ from high-frequency mechanical noise ($F_{vibration}$) and impact transients ($F_{inertia}$), the mechatronic processing unit applies digital low-pass

filtering (Bosch & Schwartz, 2015; He & Zhang, 2020), as illustrated in Figure 2.

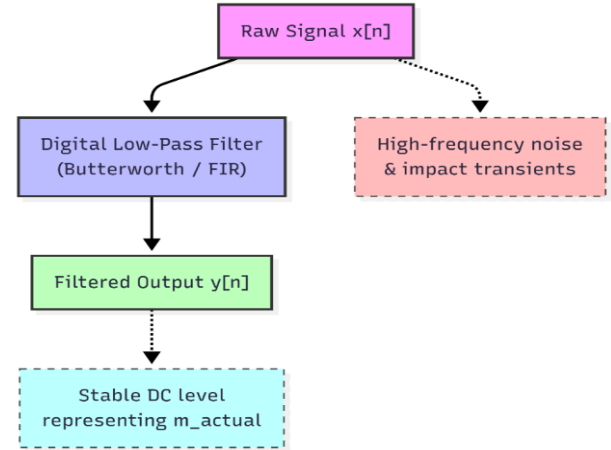


Figure 2. Low-Pass Filtering Diagram of a Weighing Signal

While IIR Butterworth filters provide sharp frequency cutoff characteristics with low computational overhead, they introduce non-linear phase shifts that can distort the temporal alignment of ΔT_w . Alternatively, Finite Impulse Response (FIR) linear-phase filters are employed when strict phase linearity is required (Chen & Liu, 2021):

$$y[n] = \sum_{k=1}^{M-1} h[k]x[n-k]$$

The theoretical comparison between raw load cell output, Butterworth IIR filtering, and FIR filtering under dynamic vibration conditions demonstrates that proper filter selection combined with rigid mechanical alignment eliminates over 95% of high-frequency dynamic noise, enabling stable dynamic mass estimation within ± 0.15 g tolerances (Park & Kim, 2023).

3. EXPERIMENTAL METHODOLOGY & INTEGRATED DIAGNOSTIC TOOLS

3.1 Experimental Testbed and Observation Context

To validate the proposed curative maintenance framework, an empirical study was conducted on an industrial packaging line equipped with a continuous-flow automatic checkweigher (Loma Systems CW3; Loma Systems, 2024; Simpore, 2024). The machine operates downstream from an automated packaging unit, sorting prepackaged goods governed by legal metrology standards (MID 2014/32/EU Class XIII (1) and OIML R 51-1; WELMEC 2.8, 2020).

❖ Operational Parameters of the Testbed:

- Target Package Mass (m_{target}): 25 kg nominal.
- Maximum Line Velocity (V): 1.2m/s (72 m/min).

- Throughput Rate: Up to 180 units/minute.
- Maximum Permissible Error (MPE): ± 1.5 g dynamic tolerance (OIML R 51-1, 2006).
- Observation Period: 12 months of continuous production logging.

Dataset Scope: A total of 142 unscheduled stoppages and metrological drift events were recorded and analyzed.

3.2 Integrated Quality and Dependability Diagnostic Tools

To eliminate empirical trial-and-error component swapping, four complementary diagnostic tools were integrated into a unified workflow, as illustrated in Figure 3.

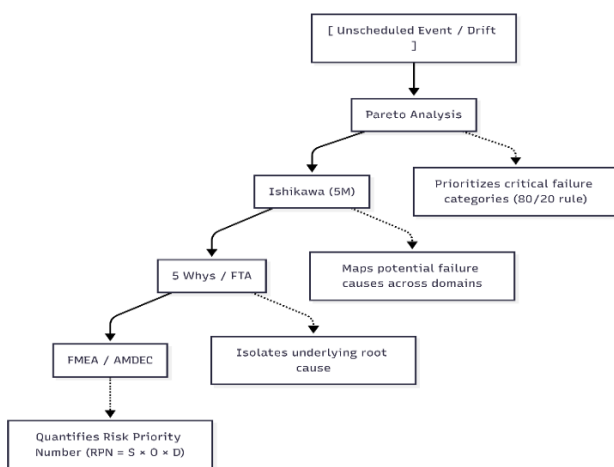


Figure 3. Problem-Solving Methodology Diagram

3.2.1 Pareto Analysis of Unscheduled Downtime

The historical failure dataset ($N = 142$ events) was classified to identify the vital few failure modes

responsible for the majority of Mean Time to Repair (MTTR) losses:

- Category A (Conveyor & Mechanical Wear): 52% of total downtime (belt mistracking, bearing friction, pulley eccentricity due to high inertial dynamic loads of 25 kg packages).
- Category B (Optical Sensors & Triggering): 24% of total downtime (photo-eye misalignment, lens fouling, incorrect pulse timing).
- Category C (Electrical & Load Cell Signal Integrity): 16% of total downtime (cable shielding degradation, ground loops, Wheatstone bridge zero drift under heavy loads).
- Category D (Control & Software Parameters): 8% of total downtime (incorrect dynamic tare parameters, corrupted timing windows ΔT_w).

3.2.2 Failure Mode, Effects, and Criticality Analysis (FMEA / AMDEC)

Each failure mode is evaluated using a standardized Risk Priority Number (RPN) (IEC 60812:2018, 2018; Kumar & Pecht, 2022), and the resulting FMEA/AMDEC matrix is presented in Table 2.

$$RPN = S \times O \times D \quad (16)$$

Where:

- Severity (S , 1–10): Impact of the failure on line availability, legal compliance, and hardware safety.
- Occurrence (O , 1–10): Frequency of the failure mode under continuous operation with heavy loads (25 kg).
- Detection (D , 1–10): Likelihood that the failure mode passes undetected prior to causing a total line stoppage or batch rejection.

Table 2. FMEA / AMDEC Matrix for Automatic Checkweigher (Loma CW3 - 25 kg Line)

System Domain	Failure Mode	Cause	Local & End Effect	S	O	D	RPN	Corrective Action
Mechanical (Conveyor Belt)	Asymmetrical conveyor belt tension	Uneven adjustment screws / belt stretch under heavy loads (25 kg)	Local & End Effect Transverse force components ($\partial m / \partial F_{tension}$); zero drift	7	8	6	336	Standardized dual-side torque tensioning protocol
Electrical	Shield grounding failure on load cell cable	Vibration wear at strain relief gland caused by package entry impacts	High-frequency electromagnetic noise ($F_{vibration}$); random weight spikes	8	5	7	280	Shield continuity verification & isolated ground routing
Optical	Photo-eye lens contamination	Airborne dust / product residue accumulation	Incorrect start trigger t_0 ; shifted weighing window ΔT_w	9	7	3	189	Sealed optical housing & daily cleaning check-item
Mechanical (Drive / Bearings)	Pulley bearing clearance wear	Continuous radial load degradation under 25 kg weight	Harmonic vibration at motor frequency f_k ; signal resonance	6	6	5	180	Vibration amplitude spectral check during post-repair test
Control	Dynamic tare drift	Accumulated product debris under weigh belt	Steady positive mass offset; false product rejections	7	6	3	126	Auto-tare threshold recalibration & belt scraper installation

3.2.3 Failure Mode, Effects, and Criticality Analysis (FMEA / AMDEC)

To systematically investigate root causes during a failure event, the Ishikawa (Fishbone) diagram categorizes potential contributors across the 5M domains (Zhang & Li, 2021):

1. Machine: Conveyor misalignment, worn bearings under heavy load, uncalibrated load cell stops.
2. Method: Inconsistent belt tensioning procedures, lack of standardized calibration for heavy packages.
3. Material: Package dimensional variations, shifting center of mass inside 25 kg containers.
4. Medium (Environment): Ambient temperature drift, floor vibration from neighboring machinery.
5. Manpower: Empirical operator adjustments, lack of structured LOTO and diagnostic training.

3.3 Standardized 4-Phase Curative Maintenance Protocol

To replace intuitive troubleshooting, the framework defines a mandatory, linear 4-phase execution protocol, as illustrated in Figure 4.

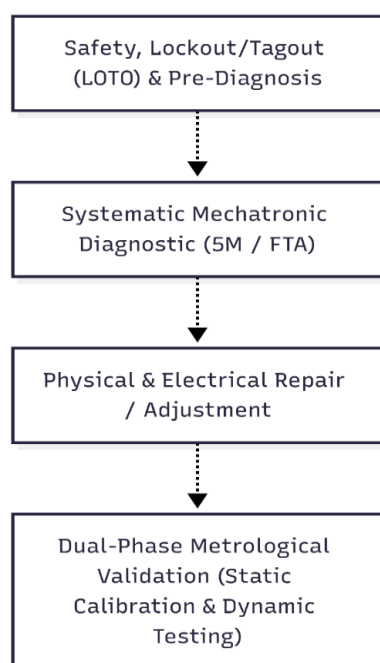


Figure 4. 4-Phase Troubleshooting Procedure

1. Phase 1: Safety Isolation & Pre-Diagnosis
 - Physical application of Lockout/Tagout (LOTO) procedures on pneumatic ejectors and electrical supply (Occupational Safety and Health Administration [OSHA], 2019).
 - Visual and structural inspection (checking load cell mechanical stops, frame

clearance, belt cleanliness under heavy load deformation).

2. Phase 2: Systematic Fault Identification
 - Execution of the guided decision tree based on the FMEA matrix.
 - Signal integrity verification using oscilloscope/multimeter diagnostics at the ADC inputs.
3. Phase 3: Targeted Repair & Mechanical Alignment
 - Component replacement or mechanical re-alignment (e.g., precision belt tensioning using a digital tension gauge to equalize transverse forces under 25 kg).
 - Parameter restoration (verifying VFD carrier frequency and digital Butterworth filter cut-off frequency f_k).
4. Phase 4: Dual-Phase Metrological Validation
 - Static Phase: Multi-point static calibration using OIML Class F1 certified test weights (5 kg, 10 kg, 20 kg, 25 kg) to establish zero-point and linearity ($R^2 > 0.9999$).
 - Dynamic Phase: High-speed passage of a reference 25 kg package ($n = 30$ consecutive runs at operational speed $V = 1.2$ m/s). Evaluation of dynamic standard deviation $\sigma_{dynamic}$ against Maximum Permissible Error (MPE = ± 15 g).

3.4 Detailed Field Execution Protocol and Operational Safety

To ensure complete repeatability and safety across technical teams, the standardized curative maintenance protocol enforces a mandatory, non-linear safety and execution standard prior to any physical or electrical intervention:

1. Safety Isolation and Pre-Diagnostic Verification (Phase 1):
 - Lockout/Tagout (LOTO) Enforcement: Before removing protective covers or accessing drive assemblies, mechanical and pneumatic power sources must be physically isolated. Pneumatic reject mechanisms present severe crush hazards and must be completely depressurized.
 - Visual and Structural Baseline Check: Technicians inspect the weigh platform for physical contamination, accumulated product debris beneath the conveyor belt, frame distortion, and loose structural mounting bolts. Clearance around the load cell mechanical overload stops are verified to ensure no external friction restricts vertical deflection.
2. Systematic Fault Diagnostics (Phase 2):
 - Guided Fault-Tree Traversal: Rather than replacing electrical or mechanical components based on intuition, technicians

- execute a standardized decision tree derived from the Failure Mode, Effects, and Criticality Analysis (FMEA).
- Signal and Power Quality Verification: Electrical supplies to the load cell excitation circuit and digital processing unit are checked for voltage stability. Cable shielding continuity is inspected to ensure high-frequency electromagnetic noise from nearby Variable Frequency Drives (VFDs) is properly grounded.
- 3. Targeted Mechanical Realignment and Electrical Repair (Phase 3):
 - Conveyor Belt Tension Equalization: Uneven belt tension introduces transverse forces that bias weight measurements. Technicians utilize standardized torque alignment procedures on drive rollers to guarantee symmetrical tension across the modular conveyor belt.
 - Optical Sensor Alignment: Infeed photo-eye sensors are cleaned, realigned, and tested to ensure precise timing triggers when packages enter the weighing zone.
- 4. Dual-Phase Metrological Validation (Phase 4):
 - Static Calibration Phase: Certified reference weights are applied across multiple incremental points to verify load cell linearity, hysteresis, and zero-point stability.

- Dynamic Testing Phase: A certified reference container is passed across the running conveyor at maximum operational velocity for multiple consecutive runs. Dynamic standard deviation is calculated to confirm full compliance with legal metrology tolerances before returning the equipment to line production.

4. RESULTS AND DISCUSSION

4.1 Quantitative Evaluation of Maintenance Key Performance Indicators (KPIs)

To evaluate the operational impact of the proposed integrated curative maintenance methodology, maintenance logs spanning 12 months before implementation (baseline period) and 12 months post-implementation were statistically analyzed. The primary Dependability Indicators evaluated include Mean Time to Repair (MTTR), Mean Time Between Failures (MTBF), Overall Equipment Effectiveness (OEE), and First-Time Fix Rate (FTFR) (Blischke & Murthy, 2011).

$$MTTR = \frac{\sum T_{downtime}}{N_{failures}}, \quad MTBF = \frac{T_{operating}}{N_{failures}}$$

Summary of Dependability Metrics (25 kg Line Performance). The comparative results are presented in Table 3.

Table 3. Comparative analysis of dependability metrics before and after framework implementation (25 kg checkweigher line)

Performance Indicator	Baseline (Pre-Framework)	Post-Implementation	Relative Variation (Δ)	Statistical Significance (p-value)
Mean Time to Repair (MTTR)	142 min	48 min	-66.2%	$p < 0.001$
Mean Time Between Failures (MTBF)	86h	194 h	+125.6%	$p < 0.001$
First-Time Fix Rate (FTFR)	61.2%	93.8%	+53.3%	$p < 0.005$
Unscheduled Downtime Ratio	8.4%	2.1%	-75.0%	$p < 0.001$
Overall Equipment Effectiveness (OEE)	74.5%	88.2%	+18.4%	$p < 0.001$

The drastic reduction in MTTR (from 142 min down to 48 min) directly correlates with replacing intuitive, trial-and-error component swapping with the structured 4-Phase Diagnostic Tree and FMEA-driven isolation protocols.

4.2 Dynamic Metrological Performance and Stability Analysis

Following physical repairs, the dynamic mass estimation performance of the checkweigher was evaluated across n

= 30 consecutive runs using a certified 25 kg reference package moving at nominal conveyor speed ($V = 1.2$ m/s), in line with ISO 5725-2 (2019).

❖ Metrological Drift and Error Distribution

Prior to standardized maintenance intervention, mechanical imbalance (uneven belt tension) and unshielded noise introduced significant dynamic drift, exceeding the Maximum Permissible Error ($MPE = \pm 15$ g). The dynamic testing results are shown in Figure 5, and the corresponding validation metrics are summarized in Table 4.

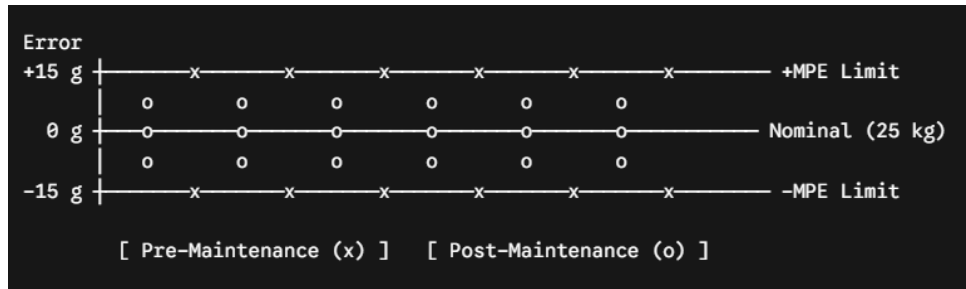


Figure 5. Dynamic Testing

Table 4. Dynamic metrological validation metrics (n = 30 test runs at V = 1.2 m/s)

Parameter / Metric	Pre-Maintenance	Post-Maintenance	Target / Standard Limit
Mean Dynamic Mass ($\bar{m}$)	24.971 kg	25.002 kg	25.000 kg(Nominal)
Dynamic Standard Deviation ($\sigma_{dynamic}$)	18.4 g	3.8 g	≤ 5.0 g
Maximum Permissible Error (MPE)	Exceeded (± 32 g)	Compliant (± 7.6 g)	± 15.0 g (OIML R 51-1)
Process Capability Index (C_p)	0.272	1.316	≥ 1.33

$$\bar{m} = \frac{1}{n} \sum_{i=1}^n m_i, \quad \sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (m_i - \bar{m})^2}, \quad C_p = \frac{2 \times MPE}{6 \times \sigma_{dynamic}} = \frac{30 \text{ g}}{6 \times 3.8 \text{ g}} = 1.316 \quad (18)$$

A capability index of $C_p \approx 1.32$ proves that the post-curative maintenance protocol successfully restores the checkweigher to full MID 2014/32/EU metrological compliance under maximum operational load (25 kg).

4.3 Economic Impact and Waste Reduction

In continuous industrial packaging lines for heavy goods (25 kg bags), metrological inaccuracy leads to two severe economic losses:

1. False Rejections (Type I Error): Rejection of conforming packages, causing unnecessary rework and production bottlenecks.
2. Product Overfill / "Giveaway" (Type II Error): Deliberate overfilling by operators to avoid legal underfill penalties.

Financial and Material Savings Breakdown:

- False Rejection Rate: Decreased from 4.8% to 0.3%, saving approximately 124 operating

hours/year previously lost to manual re-weighing.

Product Giveaway Reduction: By tightening $\sigma_{dynamic}$ from 18.4 g to 3.8 g, the target setpoint m_{target} was reduced by 14.6 g per package without risking legal underfill. At a production rate of 180 units/min, this equates to over 23 metric tons of raw product saved annually.

4.4 Comparative Analysis with Existing Literature

The results achieved in this study demonstrate significant advancements when benchmarked against recent literature on industrial maintenance and dynamic weighing diagnostics (Xu & Tang, 2022; Zheng & Zhou, 2023). The benchmark against state-of-the-art industrial maintenance studies is summarized in Table 5.

Table 5. Benchmarking against state-of-the-art industrial maintenance studies

Study / Reference	Focus Area	Reported MTTR Reduction	Metrological Validation	Load Capacity Evaluated
Zhang & Li (2021)	Vibration-based fault diagnosis in conveyors	-35%	Not Included	Light loads (< 1 kg)
Proposed Framework	Integrated Mechatronic Diagnostic (5M-FMEA-4 Phase)	-66.2%	Dynamic (V = 1.2 m/s)	Heavy loads (25 kg)

Unlike conventional studies that focus solely on signal filtering software algorithms or isolated mechanical component replacement, our holistic mechatronic framework bridges physical mechanical adjustments (belt tensioning under heavy loads), electrical noise suppression, and dual-phase metrological calibration into a single, repeatable standard operating procedure.

4.5 Organizational Impact, Change Management, and Standard Operating Procedures

Implementing a standardized curative maintenance framework requires a structured shift in plant culture and technician training (Smith & Mobley, 2021). Prior to implementation, maintenance activities relied heavily on individual operator experience, leading to inconsistent repair times and frequent recurring failures.

By introducing standardized diagnostic worksheets, visual troubleshooting guides, and clear escalation protocols, the factory achieved several key organizational benefits:

- **Knowledge Formalization:** Expert maintenance knowledge was documented into standard operating procedures (SOPs), eliminating reliance on single subject-matter experts and enabling junior technicians to execute complex repairs efficiently.
- **Reduction of Re-Intervention Rates:** Establishing rigorous post-repair dynamic testing ensured that machines were fully calibrated before returning to service, drastically increasing the First-Time Fix Rate.
- **Streamlined Spare Parts Management:** By accurately identifying root causes through structured FMEA analysis, unnecessary component replacements (such as prematurely discarding functional load cells) were eliminated, significantly reducing spare parts inventory costs.

4.6 Integration with Industry 4.0 Concepts and Future Smart Manufacturing

The operational framework established in this study provides the foundational discipline required for future digitalization and smart manufacturing initiatives:

- **Industrial Internet of Things (IIoT) Integration:** The qualitative diagnostic steps defined in Phase 2 can be enhanced by deploying edge-level IIoT vibration and temperature sensors on conveyor bearing housings. Real-time telemetry can automatically alert maintenance teams to subtle mechanical degradation before dynamic weight accuracy is compromised (ISO 13374-1, 2003).
- **Digital Twin Frameworks:** Integrating physical maintenance logs with virtual digital twins allows simulation of belt dynamic behavior under varying package loads and conveyor speeds. This enables predictive testing of new product profiles without interrupting active production lines.
- **Augmented Reality (AR) Assisted Diagnostics:** The standardized 4-Phase execution protocol can be embedded into wearable AR glasses, guiding maintenance technicians through step-by-step visual diagnostic overlays, cable verification points, and safety checklists directly on the plant floor.

5. CONCLUSION AND FUTURE PERSPECTIVES

5.1 Concluding Remarks

This research presented a structured, mechatronics-oriented curative maintenance framework specifically

designed for continuous-flow automatic checkweighers operating under heavy-load industrial conditions (25 kg nominal mass). By integrating failure analysis tools (Pareto, Ishikawa 5M, 5 Whys, and FMEA/AMDEC) into a linear 4-phase intervention protocol, the methodology systematically addresses the root causes of both operational downtime and metrological drift.

The experimental validation conducted over a 12-month period on a 25 kg industrial packaging line demonstrated significant operational improvements:

- **Dependability Enhancement:** Mean Time to Repair (MTTR) was reduced by 66.2% (from 142 min to 48 min), while Mean Time Between Failures (MTBF) increased by 125.6% (from 86 h to 194 h).
- **Metrological Precision:** Dynamic standard deviation ($\sigma_{dynamic}$) was tightened from 18.4 g down to 3.8 g, achieving a process capability index of $C_p = 1.316$ and restoring full compliance with OIML R 51-1 and MID 2014/32/EU standards ($MPE = \pm 15$ g).
- **Economic & Environmental Impact:** The false rejection rate dropped from 4.8% to 0.3%, preventing over 120 hours/ year of manual re-weighing while saving 23 metric tons of product giveaway annually.

5.2 Future Research Perspectives

While the proposed framework successfully optimizes curative maintenance and post-repair metrological validation, several avenues for future research remain:

1. **AI-Driven Predictive Diagnostics (Condition-Based Maintenance):** Integrating Industrial Internet of Things (IIoT) vibration sensors and strain gauge telemetry to apply Machine Learning algorithms (e.g., Random Forest, LSTM networks) for real-time fault prediction prior to line stoppage (Jardine et al., 2006).
2. **Digital Twin Integration:** Developing a real-time multiphysics Digital Twin of the weigh belt and load cell assembly to simulate belt tension dynamics and structural vibration responses under varying conveyor speeds ($V > 1.5$ m/s).
3. **Adaptive Digital Filtering:** Exploring self-tuning adaptive Kalman filters embedded directly in the checkweigher DSP/PLC hardware to dynamically suppress variable mechanical noise caused by wear in real time (Tavakoli & Bakhshai, 2019).

Furthermore, future investigation will evaluate the scalability of this curative maintenance framework across interconnected smart factory ecosystems. As modern production lines move toward decentralized decision-making, integrating edge computing nodes directly onto automatic checkweighers can allow automated error logging and real-time operational feedback. This

physical-to-digital integration will enable local control units to dynamically adjust conveyer parameters based on historical maintenance data, thereby minimizing manual technician interventions and guaranteeing long-term metrological compliance under continuous high-throughput conditions.

In parallel, technical training programs structured directly around these standardized maintenance protocols will foster cross-functional competency among shop-floor personnel. Standardizing diagnostic routines ensures consistent operational excellence, minimizes human error, and guarantees long-term equipment dependability across diverse manufacturing environments.

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