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Smart Hydraulic Press with Real-Time Force and Stroke Monitoring Using Embedded Sensors

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Abstract: *Hydraulic presses generate two critical process variables: applied force and ram stroke. In many small and medium manufacturing units, these variables are either observed through analog gauges or logged in systems that remain isolated from operator identity, shift assignment, attendance status, and supervisory approvals. This paper presents a complete smart hydraulic press monitoring architecture that integrates embedded force and stroke sensing with a secure workforce-governance platform. A load cell or pressure-derived force channel and a linear displacement channel are conditioned, digitized, calibrated, segmented into pressing cycles, and transmitted to a backend application using authenticated APIs. MongoDB collections store raw sensor samples separately from summarized press-cycle records so that engineering diagnostics and dashboard performance can be supported at the same time. The administrative layer includes JWT authentication, refresh-token rotation, role-based access control, departments, shifts, employee profiles, attendance records, correction approvals, leave requests, holidays, announcements, notifications, CSV exports, and audit logging. The evaluation uses a controlled simulated dataset of 12,000 press cycles, 25 employees, four departments, five shifts, and 30 working days. Results show mean peak-force error of 1.8 percent of full scale, mean maximum-stroke error of 1.2 percent of full scale, cycle detection accuracy of 98.7 percent, median dashboard latency of 310 ms, and complete blocking of tested unauthorized administrative API attempts. Additional diagrams, result dashboards, metric visualizations, data-flow figures, and a future deployment roadmap are included to make the design reproducible and technically clear. The system is positioned as an operational monitoring and governance platform, not as a certified safety controller or metrology substitute.*

Keywords: Smart hydraulic press, real-time force monitoring, stroke sensing, embedded sensors, load cell, linear displacement sensor, Industry 4.0, MongoDB, role-based access control, attendance management, audit logging, cyber-physical systems.

I. INTRODUCTION

Hydraulic presses are widely used in metal forming, punching, deep drawing, compression molding, riveting, bearing fitting, sheet forming, and assembly operations because they provide high controllable force over a defined stroke. The mechanical process is usually stable, but the monitoring environment in small and medium factories is often weak. Operators may read analog gauges, estimate ram travel visually, record production manually, and manage attendance or shift records in separate spreadsheets. When a quality dispute, overload incident, short-stroke event, or production-count mismatch occurs, the factory may not have a reliable record that links the machine event to the responsible operator and approved shift. [1], [2]

Modern smart-manufacturing literature treats production equipment as cyber-physical resources that combine sensing, computation, networking, and decision support. Smart hydraulic press concepts and automatic press-cycle generation show that hydraulic equipment can be integrated with digital-twin, manufacturing-execution, and intelligent-control layers. However, those works primarily emphasize process intelligence. They do not fully address routine governance problems such as who was operating the press, whether the operator was on an assigned shift, whether the attendance record was later modified, and whether an approval trail exists for the modification. [1], [2], [9]

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This paper therefore draws a wider system boundary. The press event is not treated only as a sensor record; it is treated as a machine-operator-workflow record. Each cycle is connected to machine identity, operator identity, shift identity, department identity, attendance state, leave state, authorization policy, and audit history. The purpose is not merely to show force and stroke curves on a screen, but to create a traceable operational record that can support supervision, maintenance review, quality investigation, employee accountability, and administrative compliance.

The technical contribution of the paper is threefold. First, it specifies an embedded force-stroke acquisition and calibration layer using a force sensor and linear displacement sensor. Second, it defines a backend data model that separates raw sensor samples from summarized press cycles while linking both to workforce records. Third, it embeds the monitoring system inside an administrative platform with authentication, RBAC, attendance locking, leave approval, audit logging, and indexed database queries. This integration responds to the broader Industry 4.0 requirement that machines, people, data, and cyber-security controls must be considered together. [5], [6], [7]

II. OBJECTIVES AND SCOPE

The primary objective is to design a practical monitoring platform for a smart hydraulic press that records force and stroke in real time and attaches each cycle to the correct operator and administrative context. The scope includes sensing architecture, calibration equations, cycle segmentation logic, backend data modeling, dashboard visualization, administrative workflows, security controls, and simulation-based evaluation. The system is intended for supervisory monitoring and governance in small or medium factory environments.

The system is outside the scope of certified functional safety. It does not replace emergency-stop circuits, safety-rated PLCs, pressure relief valves, certified load measurement instruments, or formal metrology equipment. The claim is operational rather than safety-certified: the proposed platform improves observability, traceability, record consistency, and accountability under defined conditions.

Table 1. Research objectives and technical scope

Objective	Implementation focus	Expected outcome
Real-time force and stroke monitoring	Load cell or pressure sensor, stroke sensor, conditioning, ADC, timestamping	Cycle-level peak force, maximum stroke, and anomaly flags
Cycle traceability	Machine ID, operator ID, shift ID, department ID, cycle timestamps	Every press cycle can be queried with workforce context
Administrative integration	Attendance, corrections, leave, holidays, announcements, notifications	Machine evidence and HR state are stored in one governed system
Security and governance	JWT, refresh-token rotation, backend RBAC, audit logging, input validation	Reduced broken-access-control and tampering risk
Performance evaluation	Simulated 12,000 cycles and authenticated workflow tests	Architecture-level evidence before field deployment

III. LITERATURE SURVEY

Jankovic, Simic, and Herakovic proposed a smart hydraulic press concept in which conventional press operation is extended through Industry 4.0, digital-twin reasoning, real-time parameter monitoring, and manufacturing-execution integration. Their work supports the idea that hydraulic presses can become cyber-physical production resources instead of isolated machines. [1]

Jankovic, Novak, Simic, and Herakovic further examined automatic generation of hydraulic press cycles from tool, product, RFID, and production-plan data. This shows that press-cycle behavior can be formalized and represented

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digitally, which motivates the structured cycle record used in the proposed system. However, the work remains centered on production-cycle generation rather than workforce governance. [2]

Makansi and Schmitz presented data-driven condition monitoring of a hydraulic press using supervised learning, feature extraction, and neural networks on simulated hydraulic press data. Their results show that multivariate cyclic data can support fault-state classification. In the present paper, machine-learning diagnosis is treated as future work, while the current implementation focuses on reliable capture, calibration, governance, and dashboard delivery of the fundamental force-stroke stream. [3]

König and Helmi used convolutional neural networks and sensitivity analysis to evaluate sensor relevance in hydraulic condition monitoring. Their work demonstrates that sensor channels do not contribute equally to diagnostic performance. This supports a measured architecture that begins with the most operationally meaningful variables, force and stroke, before adding pressure, temperature, vibration, current, acoustic, or oil-quality sensors. [4]

Ryalat, ElMoaqet, and AlFaouri designed a smart factory based on cyber-physical systems and IoT, showing that the physical layer, communication layer, and application layer must operate as a unified system. Their approach aligns with the proposed layered architecture in which embedded sensing, networked APIs, and dashboards operate with shared database state. [5]

Security research on industrial cyber-physical systems emphasizes that interconnectivity expands the attack surface. Kayan et al. review cyber-security issues in industrial cyber-physical systems, while NIST SP 800-82 provides guidance for securing operational technology under performance, reliability, and safety constraints. OWASP identifies broken access control as a leading web-application risk. These works justify backend authorization, token rotation, audit logging, input validation, rate limiting, and the decision not to trust frontend route guards as security controls. [6], [7], [8]

Industry 4.0 and IoT surveys provide the broader theoretical base for this work. Cyber-physical system architectures describe how machines, analytics, and services can be connected in manufacturing environments, while industrial IoT surveys explain the value of sensor networks, data acquisition, and service integration. The proposed system applies these ideas to a hydraulic press and extends them with workforce and administrative state. [9], [10], [11]

IV. METHODOLOGY

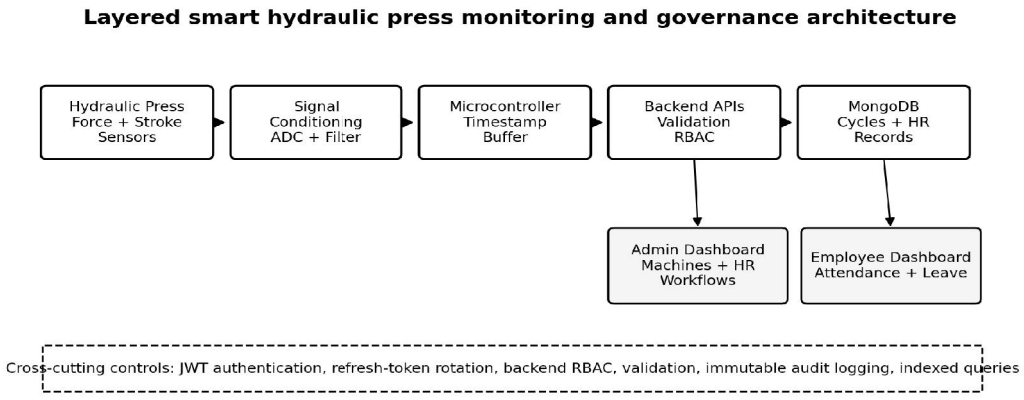

Figure 1. Proposed system architecture connecting force-stroke sensing, embedded acquisition, secure APIs, MongoDB, dashboards, RBAC, and audit logging.

The proposed methodology is organized into five layers: sensing, embedded acquisition, backend ingestion, database persistence, and role-specific dashboard presentation. The sensing layer obtains physical measurements. The embedded

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layer conditions, digitizes, timestamps, buffers, and segments the stream. The backend validates records and attaches machine and workforce context. MongoDB stores raw sensor samples and summarized cycle records in separate collections. The dashboard layer visualizes real-time and historical information according to user role.

The monitoring path is evaluated as an end-to-end latency chain. A physical sample is useful only after it has moved through acquisition, preprocessing, network transmission, backend validation, persistence, and dashboard rendering. The total latency is expressed as follows:

$$L_{total} = t_{acq} + t_{pre} + t_{net} + t_{db} + t_{ui} \quad (1)$$

where L_total is the end-to-end monitoring delay, t_acq is sensor acquisition delay, t_pre is embedded preprocessing delay, t_net is communication delay, t_db is backend validation and database persistence delay, and t_ui is dashboard rendering delay.

4.1 Sensor Acquisition and Calibration

Two sensor channels are used. The force channel can be implemented using a load cell mounted in the press frame or by using a pressure transducer and hydraulic area conversion where the installation makes direct load-cell mounting difficult. The stroke channel can be implemented using a linear potentiometric transducer, LVDT, magnetostrictive linear sensor, or encoder aligned with ram travel. Both channels require zeroing, scaling, signal conditioning, and periodic verification before their readings should be trusted for trend analysis.

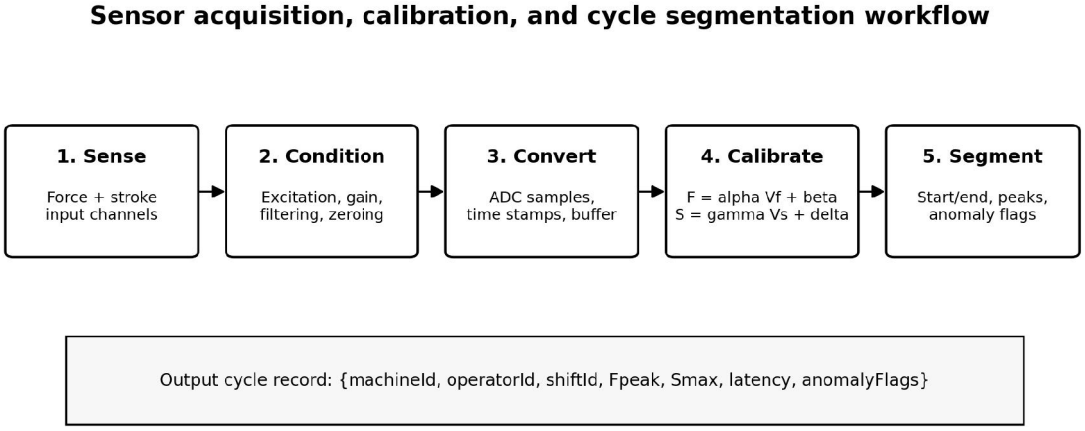

Figure 2. Sensor acquisition, calibration, and cycle segmentation workflow for the proposed smart press.

A linear calibration model is adopted for the supervisory prototype. The estimated force is calculated from the conditioned force-channel voltage or ADC-normalized value:

$$F(t) = alpha * V_f(t) + beta \quad (2)$$

where F(t) is estimated press force at time t, V_f(t) is the conditioned sensor value, alpha is the gain derived from reference loading, and beta is the zero-offset correction.

Similarly, stroke displacement is calculated as:

$$S(t) = gamma * V_s(t) + delta \quad (3)$$

where S(t) is ram displacement, V_s(t) is the conditioned stroke-sensor value, gamma is the displacement scaling coefficient, and delta is the mechanical zero offset. More complex polynomial or lookup-table calibration can be introduced later if field testing reveals nonlinearity, hysteresis, or temperature effects.

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4.2 Cycle Segmentation and Feature Extraction

A press cycle is defined as a bounded sequence of sensor samples. Cycle start is detected when stroke crosses a configurable motion threshold above the idle vibration band. Cycle end is detected when stroke returns below a reset threshold or when ram motion remains below a configured velocity threshold for a defined dwell time. Thresholds are stored at machine level rather than globally because idle vibration, stroke length, and operating behavior vary from press to press.

For each detected cycle, the backend calculates the peak force and maximum stroke as:

$$F_{peak,j} = \max(F_i) \text{ for samples } i \text{ in cycle } j \quad (4)$$

$$S_{max,j} = \max(S_i) \text{ for samples } i \text{ in cycle } j \quad (5)$$

The cycle record stores machineId, operatorId, shiftId, departmentId, startTime, endTime, F_peak, S_max, cycleDuration, overloadFlag, shortStrokeFlag, calibrationVersion, ingestionTime, and audit references. Raw samples and summarized cycles are intentionally separated. Raw samples preserve diagnostic detail, while summaries keep dashboard and reporting queries fast.

4.3 Backend Data Model

MongoDB collections linking telemetry, operator identity, attendance, leave, and audit state

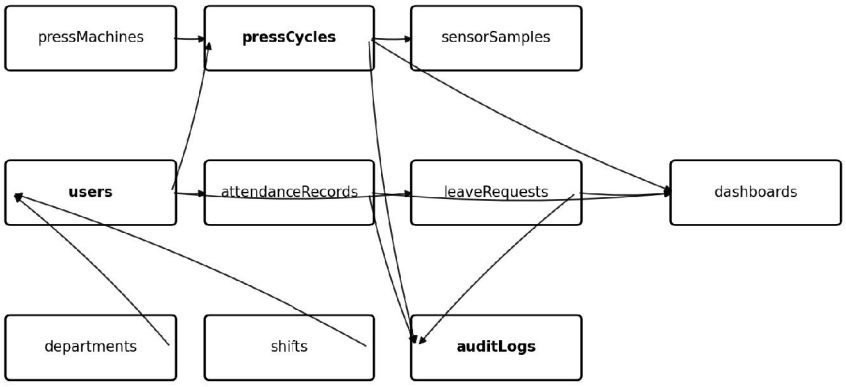

Figure 3. Data model linking press-machine telemetry with employees, attendance, leave workflow, and audit logs.

The MongoDB schema includes users, departments, shifts, attendanceRecords, attendanceCorrections, leaveTypes, leaveBalances, leaveRequests, holidays, announcements, notifications, pressMachines, pressCycles, sensorSamples, refreshTokens, and auditLogs. Compound unique indexes enforce one attendance record per employee per date, unique employee email, unique employee ID, and department-code uniqueness. Sensor samples are indexed by machineId, cycleId, and timestamp. Leave requests are indexed by employee, status, and date interval so that overlap checks are efficient.

Table 2. Main collections and indexing strategy

Collection	Purpose	Important indexes / constraints
pressMachines	Stores machine configuration, thresholds, calibration version	machineCode unique; active flag; threshold settings
sensorSamples	Stores dense time-series samples for	machineId + cycleId + timestamp

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Collection	Purpose	Important indexes / constraints
	force and stroke	
pressCycles	Stores summary of each completed cycle	machineId + startTime; operatorId + shiftId; anomaly flags
users	Stores employee and admin identities	employeeId unique; email unique; role; active status
attendanceRecords	Daily attendance status and lock state	employeeId + date unique; status + date
attendanceCorrections	Employee correction request and approval trail	employeeId + date + status
leaveRequests	Leave application workflow and decision state	employeeId + status + date range
auditLogs	Immutable sensitive-state-change history	actorId + timestamp; entityType + entityId

4.4 Security, RBAC, and Governance Controls

Authentication uses password hashing, short-lived JWT access tokens, refresh-token rotation, refresh-token revocation, and login blocking for deactivated employees. Authorization is enforced at the backend API layer. Frontend route guards improve user experience but are not treated as security boundaries. Privileged functions such as shift modification, password reset, attendance unlocking, CSV export, leave approval, announcement publication, and department deletion are revalidated on every request. [6], [7], [8]

The threat model includes CSRF, XSS, injection-like payloads, credential stuffing, token theft, refresh-token replay, direct API calls bypassing the frontend, unauthorized object access, and tampering with attendance or press-cycle records. Mitigations include HTTP-only cookies where applicable, CSRF tokens for cookie-authenticated flows, input validation, output encoding, parameterized access patterns, token rotation, rate limiting, least-privilege RBAC, and immutable audit entries.

Table 3. Validation rules, data invariants, and enforcement points

Module	Rule or invariant	Enforcement point
Department	Name and code must be unique	MongoDB unique index and API validation
Department	Cannot be deleted while employees or cycles reference it unless archived or reassigned	Service-layer referential check
Shift	Start time, end time, working days, and active flag must be valid	API validation and assignment service
Employee	Email and employee ID must be unique; deactivated employee cannot authenticate	Unique index and authentication middleware
Attendance	One record per employee per date; locked record cannot be modified except by authorized unlock flow	Compound index, attendance service, audit log
Leave	Overlapping approved leave for the same employee is blocked; balance cannot go negative unless policy permits	Date-interval query and approval service
Sensor data	Every cycle must reference a valid machine and valid time interval	Press-cycle ingestion service
Access control	Frontend route protection must be backed by	RBAC middleware and route policy

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Module	Rule or invariant	Enforcement point
	backend authorization	

V. IMPLEMENTATION DESIGN

The implementation is designed as a web-based application with embedded data ingestion. A microcontroller receives analog or digital force and stroke signals, applies local conditioning logic, and sends samples or buffered cycle packets to the backend. The backend validates the machine identifier, calibration version, timestamp sequence, and operator assignment before creating press-cycle records. Employees and admins interact with the same database through different dashboards and route policies.

The admin dashboard provides machine overview, peak-force trend, stroke trend, recent anomalies, attendance status, employee list, shift configuration, correction queue, leave approval queue, holiday management, announcements, notifications, CSV export, and audit history. The employee dashboard limits the view to personal profile, today attendance, monthly attendance, correction requests, leave balance, leave request status, assigned shift, holidays, and notifications. This separation supports usability while the backend enforces the actual access boundary.

The proposed application does not depend on external email, SMS, or third-party notification services. Notifications remain internal to reduce delivery failure points and to keep operational records within the same controlled platform. The trade-off is that users who are not logged in may miss alerts; this is addressed in future work through optional locally managed push or gateway integration subject to security approval.

VI. RESULTS AND ANALYSIS

A full-scale factory deployment was not available at the time of writing. Therefore, the paper evaluates the proposed system through controlled simulation. The simulation is not presented as certified metrology or field validation. It is used to verify architecture behavior, workflow consistency, authorization logic, indexing strategy, cycle-detection behavior, and dashboard-level performance under reproducible conditions.

Table 4. Simulation setup and workload parameters

Parameter	Configured value
Hydraulic press count	1 press
Sensing channels	2 channels: force and stroke
Employees	25 registered users
Departments	4 departments
Shifts	5 shift definitions
Working period	30 working days
Synthetic press cycles	12,000 cycles
Force range	0 to 100 kN
Stroke range	0 to 250 mm
Noise model	Zero-mean additive disturbance with higher force-channel transient noise
Workflow tests	Authenticated admin and employee requests, leave approvals, attendance corrections, CSV export, invalid role attempts

Combined normalized monitoring error is computed with equal force and stroke weights unless stated otherwise:

$$E_m = (1/N) * \sum_{j=1}^{N} [w_f |F_j - F\_hat_j| / F_{max} + w_s |S_j - S\_hat_j| / S_{max}] \quad (6)$$

where E_m is the normalized monitoring error, N is the number of evaluated cycles, F_j and S_j are reference peak force and maximum stroke for cycle j, F_hat_j and S_hat_j are measured estimates, F_{max} and S_{max} are full-scale ranges, and w_f and w_s are non-negative weights that sum to one.

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The simulated force-stroke curves in Figure 4 show how normal, high-force, and short-stroke behavior can be separated visually before more advanced diagnosis is introduced. The overload trend crosses the configured force threshold, while the short-stroke trend fails to complete the expected displacement range.

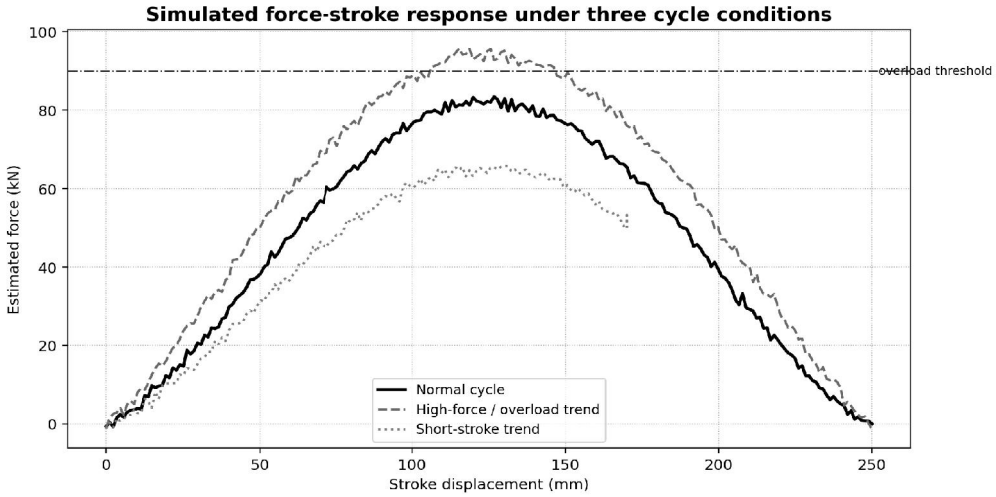

Figure 4. Simulated force-stroke curves for normal, overload, and short-stroke operating conditions.

Figure 5 shows the result dashboard concept added to the evaluation section. It combines live cycle traces, KPI cards, latency distribution, attendance status, leave and correction queues, and indexed query response times. This figure demonstrates the central design argument: process telemetry and administrative state should be interpreted together rather than in separate systems.

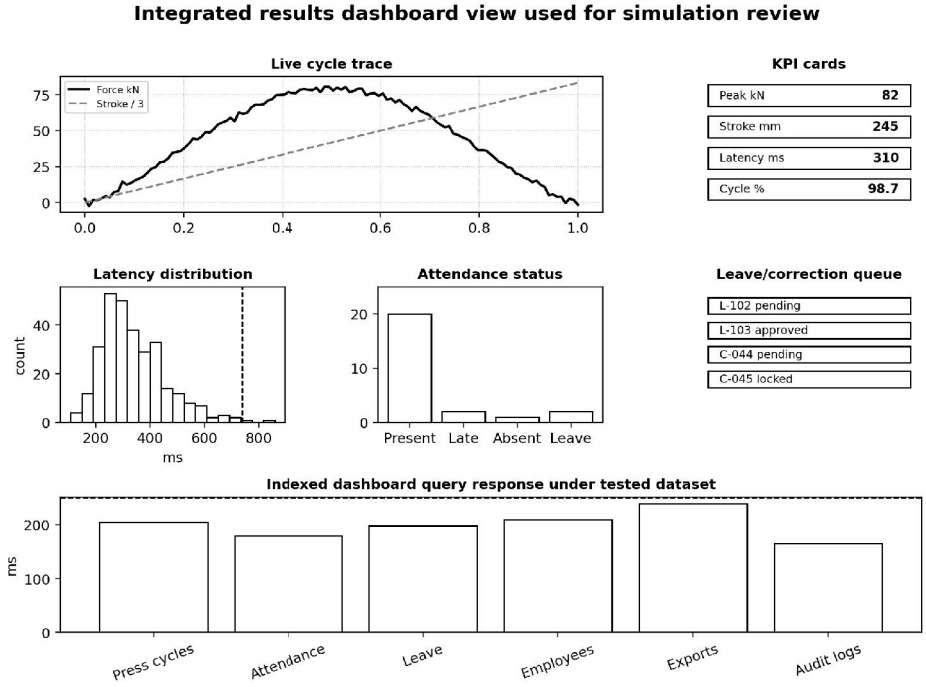

Figure 5. Results dashboard and metric visualization integrating force-stroke trends, latency, attendance status, leave workflow, and indexed dashboard queries.

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The main simulated results are summarized in Table 5 and Figure 6. Mean peak-force error remained 1.8 percent of full scale under correct calibration. Mean maximum-stroke error was 1.2 percent of full scale. Cycle detection reached 98.7 percent when the stroke threshold was above the idle vibration band. Median monitoring latency was 310 ms and the 95th percentile latency was 740 ms. Unauthorized administrative API attempts, locked attendance edits, and duplicate leave approvals were blocked in all designed test cases.

Table 5. Simulated evaluation metrics and principal findings

Evaluation dimension	Metric	Simulated result	Interpretation
Force monitoring	Mean peak-force error	1.8% of full scale	Acceptable for supervisory monitoring after calibration
Stroke monitoring	Mean maximum-stroke error	1.2% of full scale	Stable because stroke signal is smoother than force transients
Cycle segmentation	Cycle detection accuracy	98.7%	Threshold tuning required for maintenance movements
Real-time performance	Median end-to-end latency	310 ms	Suitable for dashboard-level observation
Real-time performance	95th percentile latency	740 ms	Tail latency dominated by network and rendering delays
Authorization	Unauthorized admin API attempts blocked	100% in designed test cases	Backend RBAC prevented route-bypass attacks
Attendance integrity	Locked attendance edits rejected	100% in designed test cases	Locking preserved finalized records
Leave consistency	Double approval prevented	100% in concurrent tests	Version checks avoided duplicate balance deduction
Database access	Indexed dashboard query response	Under 250 ms for tested dataset	Compound indexes improved filtered dashboard views
Export function	CSV generation field match	100% in sample tests	Export reflected filtered and locked attendance records

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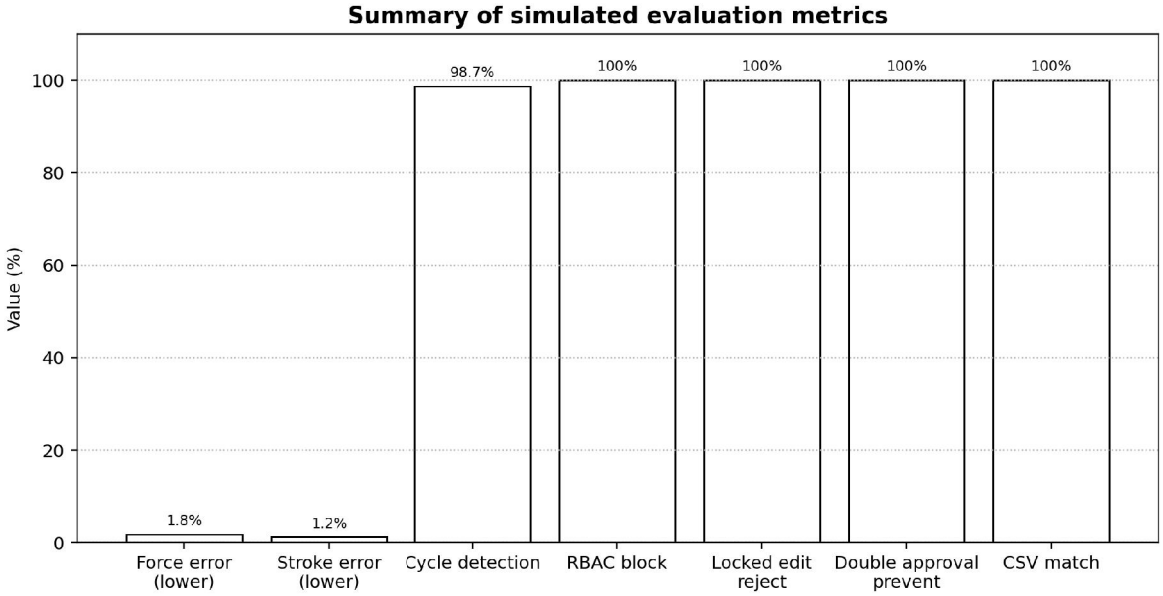

Figure 6. Summary of simulated evaluation metrics used to compare sensing, segmentation, workflow, and authorization behavior.

Dashboard performance was most sensitive to indexing strategy. Attendance queries filtering by date, department, shift, and employee performed well when compound indexes were defined on employee and date fields and when department and shift were resolved through employee assignment references. Press-cycle queries showed the same pattern: indexing by machineId, cycleId, and timestamp kept recent-cycle retrieval and historical force-stroke traces responsive.

Workflow tests confirmed that admin and employee modules stayed within their access boundaries. Employees could view their own attendance, correction requests, leave balances, shifts, holidays, announcements, and notifications. They could not approve corrections, modify departments, toggle shifts, reset passwords, or export CSV reports. Admins could manage departments, shifts, employees, corrections, leave approvals, holidays, notifications, announcements, audit review, and machine records subject to validation constraints. The tested RBAC decision matrix is shown in Figure 7.

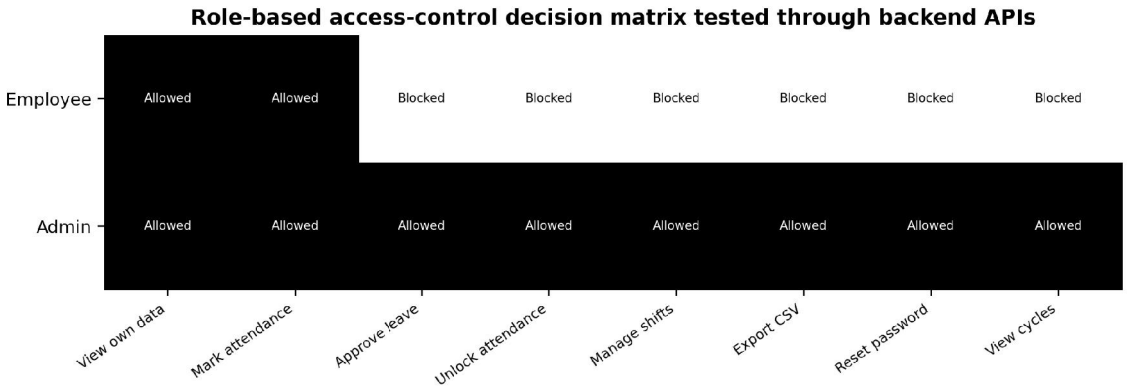

Figure 7. Role-based access-control matrix tested through backend API workflow cases.

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The results support the architecture-level claim that real-time force-stroke observability and administrative consistency can be implemented under one security model. The two concerns are not in conflict as long as raw samples, summarized cycles, workforce records, and audit logs are modeled separately but linked through stable identifiers.

VII. DISCUSSION

The simulation indicates that the system should not be understood as a simple sensor add-on. The physical force and stroke channels produce valuable evidence, but their operational meaning depends on surrounding context. A peak-force event has limited value if it cannot be linked to machine identity, operator identity, shift assignment, attendance state, and audit history. This integration separates the proposed platform from dashboard-only monitoring tools.

Sensing accuracy depends on calibration state, sensor mounting quality, hydraulic pressure stability, cable noise, temperature, mechanical alignment, and ADC resolution. A calibrated load-cell or pressure-derived channel is suitable for supervisory monitoring, overload detection, and trend comparison, but field deployment would require traceable calibration before the system could be used for formal acceptance testing. Stroke monitoring is less sensitive to sharp force transients but still depends on zeroing and alignment.

Latency is a full-path property. A high sample rate alone does not guarantee real-time monitoring. Acquisition, preprocessing, network transmission, backend validation, database write time, and UI rendering all contribute. The separation of raw sensorSamples from summarized pressCycles reduces avoidable query overhead and preserves diagnostic data for later investigation.

Security overhead is justified because industrial cyber-physical systems face risks from connectivity, unauthorized access, credential abuse, and data tampering. The design follows the principle that every privileged action must be checked at the API layer. This is especially important because a malicious user can bypass frontend routes and call backend endpoints directly. [6], [7], [8]

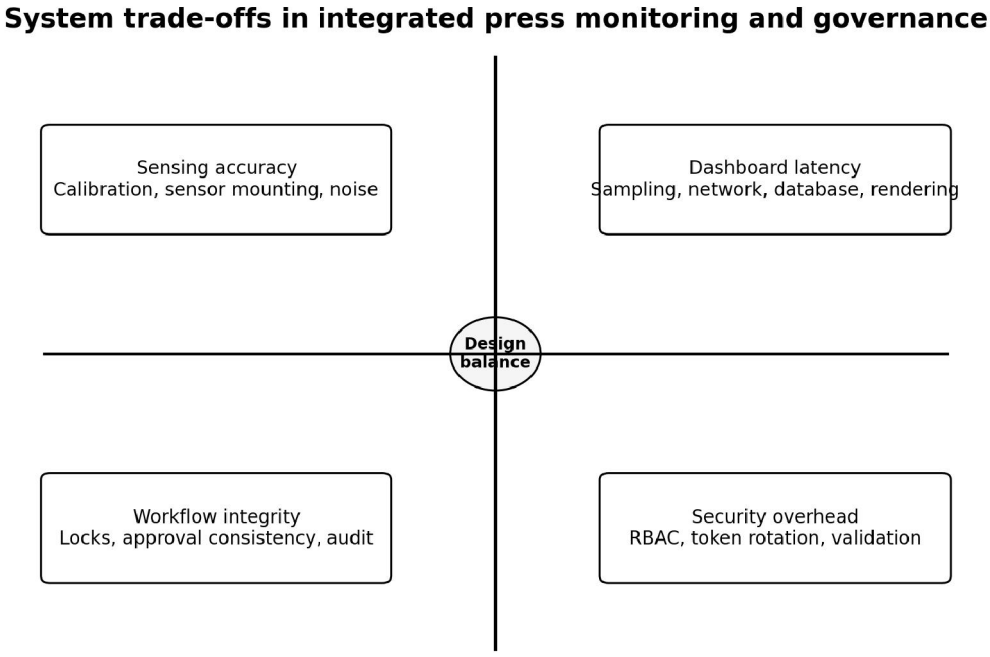

Figure 8. Discussion of system trade-offs among sensing accuracy, dashboard latency, workflow integrity, and security overhead.

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The main limitation is that all results are simulation-based. The dataset and workload are adequate for architectural verification, but they cannot prove performance under factory noise, electromagnetic interference, sensor drift, vibration, operator behavior, network instability, and long-duration mechanical wear. Field deployment is therefore required before claiming production readiness.

VIII. CONCLUSION AND FUTURE SCOPE

This paper presented a complete smart hydraulic press monitoring system that combines embedded force-stroke acquisition with workforce-governance workflows. The architecture ties each pressing cycle to machine identity, operator identity, shift assignment, attendance state, leave state, authorization policy, and audit history. This design expands the traditional boundary of press monitoring from process visualization to operational accountability.

The simulated evaluation showed 1.8 percent mean peak-force error, 1.2 percent mean maximum-stroke error, 98.7 percent cycle detection accuracy, 310 ms median end-to-end latency, and consistent enforcement of tested authorization, attendance-locking, leave-approval, and CSV-export workflows. These results provide architecture-level evidence that the proposed integration is feasible. They do not replace physical calibration, safety certification, or production trials.

System readiness can be expressed as a weighted combination of measurement reliability, workflow consistency, and security correctness:

$$R_s = \lambda_m * M_r + \lambda_w * W_c + \lambda_s * S_c \quad (7)$$

where R_s is system readiness, M_r is measurement reliability, W_c is workflow consistency, S_c is security correctness, and λ_m, λ_w, and λ_s are non-negative weights that sum to one.

Future work should include physical calibration rigs, long-duration sensor drift testing, hydraulic vibration and electromagnetic-noise testing, pilot deployment on an actual press, predictive anomaly detection, encrypted telemetry, signed firmware, device identity, network segmentation, high-volume archival testing, and multi-press fleet analytics. The proposed roadmap is shown in Figure 9.

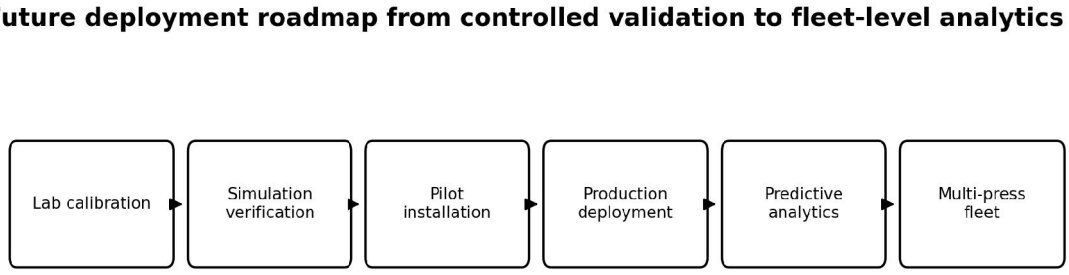

Figure 9. Future deployment roadmap from laboratory calibration to multi-press fleet integration.

The system is not a certified safety controller and should not be positioned as one. Its contribution is operational: it gives a small or medium factory a single auditable platform where a force reading, a stroke trace, an operator record, and an approval history can be queried together.

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IX. REPRODUCIBILITY CHECKLIST

Table 6. Reproducibility checklist for field implementation

Item	Required action
Calibration records	Store sensor model, calibration date, calibration coefficients, reference loads, and responsible engineer
Machine thresholds	Configure force limit, expected stroke, idle vibration band, short-stroke threshold, and dwell time per press
Data retention	Define retention periods for raw samples, cycle summaries, attendance, leave, audit logs, and CSV exports
Role policy	Document which actions are allowed for admin, supervisor, employee, and disabled account states
Security review	Verify token storage, refresh rotation, RBAC enforcement, rate limits, validation, and audit immutability
Pilot acceptance	Compare system readings against reference instrumentation before production use

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