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Research Article

IOT-ENABLED CYBER-PHYSICAL ASSEMBLY SYSTEM FOR SEAL DETECTION IN ELECTRIC VEHICLE CHARGING CONNECTORS

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Abstract

The reliability of electric vehicle charging connectors depends on correct seal installation, since the seal protects the interface from dust and moisture. This study developed an IoT-enabled cyber-physical assembly system integrating fiber-optic and photoelectric sensors, a programmable logic controller, pneumatic actuation, a Raspberry Pi edge gateway, and a human-machine interface. The system was evaluated on an industrial production line using the same connector model, machine, operating procedure, and inspection criteria as the baseline. The baseline rejection rate, drawn from routine production records before implementation, was 19.18%. After calibration, 600 consecutive connectors were assembled during a continuous five-hour validation run, with manual inspection by experienced quality personnel serving as the reference standard. The post-implementation rejection rate fell to 2.80%, an 85.41% relative reduction (16.38 percentage points), yielding a production yield of 97.17%. The detection system achieved 99.50% accuracy, 88.89% precision, 94.12% recall, 99.66% specificity, and a 91.43% F1-score. Average cycle time was 30 seconds per unit, with a repeatability error of ±0.10 mm across 30 repeated press-depth measurements. These results indicate improved defect prevention, assembly consistency, and traceability under the evaluated conditions, with remaining defects mostly outside the seal-sensing scope.

Keywords: Assembly Automation, Cyber-Physical System, EV Charging Connector, IoT, Quality Control, Smart Manufacturing

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INTRODUCTION

The growth of electric vehicles has increased the need for dependable charging hardware. An EV charging connector is repeatedly exposed to mechanical loading, humidity, dust, temperature variation, and handling by users. Its sealing components are therefore essential to maintaining ingress protection and reducing the risk of moisture intrusion, short circuits, overheating, and premature failure. Small assembly errors, including a missing seal, two seals installed together, a reversed seal, or an incomplete lock, may not be obvious during rapid manual production but can compromise product reliability.

Industry 4.0 provides a framework for addressing this problem through cyber-physical systems (CPS), the Industrial Internet of Things (IIoT), and data-driven quality control. A CPS connects physical equipment with computational control through sensing, communication, decision logic, and actuation. In manufacturing, this integration allows a process to verify its own condition, stop when requirements are not satisfied, and record production data for later analysis (Colombo et al., 2017; Kusiak, 2018; Lee et al., 2015; Lu, 2017; Monostori, 2014; Wang et al., 2015; L. D. Xu et al., 2018; Zhong et al., 2017). IIoT connectivity extends these functions by linking controllers, gateways, operator interfaces, and databases so that quality information is available in real time (Boyes et al., 2018; Ryalat et al., 2023; Sisinni et al., 2018; Tao et al., 2018; H. Xu et al., 2018).

Automated quality assurance is especially relevant for small components whose presence and orientation must be verified before pressing or locking. Fiber-optic sensors can detect small targets with high sensitivity, while photoelectric sensors can confirm object position and sequence. Combining several sensor signals can reduce the weaknesses of a single sensing method and improve decision robustness (Andronie et al., 2021; Hall & Llinas, 1997; Khaleghi et al., 2013). PLC-based logic is also suitable for machine-level inspection because it provides deterministic control, rapid response, and straightforward integration with pneumatic mechanisms and safety devices.

Previous research has described CPS architectures, automotive quality monitoring, smart in-process inspection, and autonomous defect-control systems (Bankar & Nandurkar, 2023; Castillo et al., 2024; Lee et al., 2018; Neal et al., 2021; Wang & Jiao, 2024; Weiss et al., 2024; Yousef et al., 2025). Machine-vision research further shows that image-based methods can broaden defect recognition beyond fixed binary sensor rules, although they require representative datasets, computational resources, and controlled validation (Czimmermann et al., 2020; He et al., 2016; Ren et al., 2017; Xie, 2008). Related Industry 4.0 research identifies explainable AI, predictive maintenance, edge computing, and digital twins as important extensions for adaptive and traceable manufacturing systems (Adadi & Berrada, 2018; Bokrantz et al., 2017; Carvalho et al., 2019; Jones et al., 2020; Moosavi et al., 2024; Shi et al., 2016; Tao et al., 2019; Wuest et al., 2016). However, fewer studies report a low-cost industrial prototype that integrates seal-presence sensing, component-position verification, automated pressing, edge data acquisition, and operator traceability in one EV connector assembly station. Moreover, improvement claims are difficult to interpret when baseline and post-implementation data are obtained from different lines, products, or operating periods.

This study therefore develops and validates an IoT-enabled CPS for EV charging connector seal installation. The research is designed to provide a controlled before-and-after comparison by using the same production line, connector model, assembly procedure, equipment, and inspection criteria, with the baseline recorded immediately before implementation. Performance is assessed using rejection rate, defect-category reduction, process yield, confusion-matrix metrics, cycle time, and press-depth repeatability. The contribution is a practical machine-level architecture that links defect prevention with real-time monitoring and traceable production records.

RESEARCH METHOD

Research Design

This study used an industrial prototype validation design to develop and evaluate an Internet of Things (IoT)-enabled Cyber-Physical System (CPS) for seal installation in electric vehicle charging connectors. The design combined system development with a controlled before-and-after production comparison. The research stages consisted of requirements analysis, mechanical and control design, hardware-software integration, calibration, industrial validation, and performance evaluation. To improve comparability, the baseline and post-implementation observations were conducted on the same production line using the same connector model, unchanged assembly procedures, and the same inspection criteria. The baseline rejection rate was obtained from routine production records immediately before CPS installation. Although this approach reduced differences related to product type, equipment, and production timing, it remained a before-and-after validation rather than a randomized experiment.

Research Target/Subject

The research was conducted at an automotive component supplier in Bekasi Regency. The research subject was the seal-installation process for an EV charging connector, including missing seals, double seals, reversed or misaligned seals, and incomplete locking. The industrial validation involved 600 consecutive connector assemblies produced during a five-hour production run. All units were manufactured using the same production line, connector model, assembly sequence, and acceptance criteria. Every CPS decision was compared with manual inspection by quality inspectors as the reference standard. Mechanical repeatability was evaluated separately using 30 repeated press-depth measurements under identical machine settings.

Research Procedure

The procedure began with analysis of the existing seal-installation process and defect categories. A machine-level CPS was then designed with three integrated layers. The physical layer consisted of the positioning jig, connector fixture, linear guide, pneumatic cylinder, solenoid valves, reed switches, and safety devices. The cyber layer used an Omron CP1E programmable logic controller to process sensor inputs, execute rule-based decisions, and control actuator movement. The communication layer consisted of an Omron NB7W human-machine interface and a Raspberry Pi 5 edge gateway for monitoring and data storage.

After mechanical assembly and electrical wiring, the sensors, pneumatic mechanism, PLC logic, safety interlocks, HMI, and gateway were calibrated and tested. Each production cycle consisted of connector loading, seal and component detection, PLC decision-making, pneumatic pressing, inspection processing, and unloading. Pressing was permitted only when the required seal-presence, position, press-depth, and lock conditions were satisfied and no double-seal condition was detected. Unsafe conditions or invalid sensor combinations stopped the process. Following CPS inspection, each connector was manually verified to determine whether the classification was correct. Figure 1 presents the integrated CPS architecture and the relationship among its physical, cyber, and communication layers.

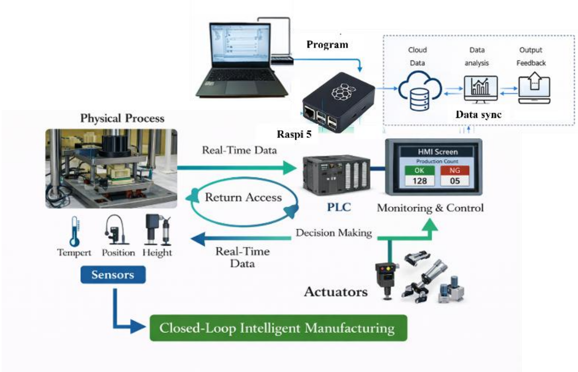

Figure 1. Integrated CPS architecture for the seal-installation station.

Instruments, and Data Collection Techniques

Seal presence was detected using a Keyence FS-N11N fiber-optic sensor, while connector presence and position were verified using an Autonics BEN300-DFR photoelectric sensor. The pneumatic mechanism included a cylinder, solenoid valve, air preparation unit, flow controls, and reed switches. An area sensor curtain, emergency stop, guarded press zone, and PLC interlocks were used for operator safety. The Raspberry Pi gateway collected timestamps, product identifiers, sensor states, OK/NG decisions, defect categories, cycle times, alarms, and machine status at 10 Hz. Data were stored in CSV files and an SQLite database, while information was displayed through the HMI.

Production data included total units, accepted units, rejected units, defect categories, and cycle duration. Manual visual inspection provided paired reference labels for constructing the confusion matrix. Press depth was measured with a calibrated digital displacement gauge having 0.01 mm resolution. Table 1 summarizes the variables, data sources, sample sizes, and performance indicators.

Table 1. Validation measures, data sources, and reported indicators

Measure	Data source and sample	Reported indicator
Baseline rejection	Routine records immediately before CPS	Rejection rate
Validation production	CPS and HMI logs; 600 units	Yield, cycle time, rejects
Detection performance	Paired CPS and manual inspection; 600 units	Accuracy, precision, recall, specificity, F1-score
Press-depth repeatability	Digital gauge; 30 repeated measurements	Range and repeatability error

Data Analysis Technique

The data were analyzed descriptively. Rejection rate was calculated by dividing rejected units by total production, while process yield was calculated from accepted units divided by total production. Relative defect reduction was determined by comparing baseline and post-implementation rejection rates, and the absolute change was reported in percentage points. Detection performance was evaluated using accuracy, precision, recall, specificity, and F1-score derived from true-positive, false-positive, false-negative, and true-negative classifications. Average cycle time was calculated from loading, detection, pressing, inspection-processing, and unloading durations. Press-depth repeatability was expressed as half of the maximum-to-minimum range. Continuous data were summarized using means, ranges, and repeatability values, whereas categorical data were reported as frequencies and percentages. No inferential hypothesis testing was performed because the study used one continuous prototype-validation run rather than replicated experimental blocks.

RESULTS AND DISCUSSION

The proposed system completed the 600-unit validation run and produced 583 accepted connectors and 17 rejected connectors, corresponding to a process yield of 97.17%. The overall rejection rate decreased from the baseline value of 19.18% to 2.80%. This is a relative reduction of 85.41% and an absolute decrease of 16.38 percentage points. Because the baseline was collected immediately before implementation on the same line and the validation used the same connector model, equipment, operating procedure, and inspection criteria, the comparison is more credible than a comparison based only on unrelated historical records. Nevertheless, the study remains a before-and-after industrial validation rather than a randomized experiment, so minor differences in operators, material batches, or environmental conditions may still have affected the observed result.

The defect-category results show that the CPS eliminated observed missing-seal and double-seal rejects during the validation run. Reverse-seal defects decreased from 3.99% to 0.30%, and not-locked defects decreased from 3.23% to 0.70%. These improvements are consistent with the system logic: the fiber-optic sensor confirms the presence of the small rubber seal, the photoelectric sensor verifies connector positioning, and the PLC prevents pressing when the required combination of inputs is not satisfied. The result supports the use of sensor fusion for assembly inspection, because multiple signals provide complementary evidence and reduce dependence on one measurement channel (Hall & Llinas, 1997; Khaleghi et al., 2013).

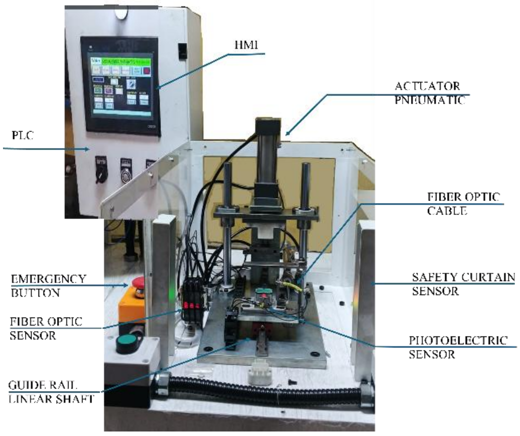

Figure 2. Industrial prototype of the CPS-based seal-installation machine.

The “others” category increased from 1.33% to 1.80%. Inspection records indicated that these defects were mainly related to mixed models or conditions originating from an earlier process and were not directly represented in the current seal-detection logic. This finding is important because the reduction in total rejects should not be interpreted as complete elimination of assembly risk. The present CPS is effective for the predefined seal-related modes, but its rule-based architecture cannot classify every unexpected appearance, material defect, or upstream process variation. Machine vision and learning-based classification may extend the inspection scope, although such methods require representative image datasets, additional computing resources, and validation against changing production conditions (Czimmermann et al., 2020; He et al., 2016; Moosavi et al., 2024; Ren et al., 2017; Weiss et al., 2024; Wuest et al., 2016; Xie, 2008).

Manual quality inspection was used as the ground truth for 600 paired classifications. The confusion matrix contained 16 true positives, two false positives, one false negative, and 581 true negatives. These values produced 99.50% accuracy, 88.89% precision, 94.12% recall, 99.66% specificity, and a 91.43% F1-score. The high specificity indicates that acceptable products were rarely rejected by the CPS, while the single false negative shows that sensor-based control did not identify every defective assembly. Detection accuracy must therefore be distinguished from production yield: accuracy evaluates agreement with the reference inspection, whereas yield represents the share of manufactured products accepted after assembly. Reporting both prevents an inflated interpretation of system effectiveness.

Table 2. Manufacturing and detection performance after CPS implementation

Indicator	Result	Interpretation
Rejection rate	19.18% to 2.80%	85.41% relative reduction
Process yield	583/600 (97.17%)	17 units rejected
Detection accuracy	99.50%	597 correct classifications
Recall / specificity	94.12% / 99.66%	One false negative; two false positives
Cycle time	30 s/unit	600 units in approximately 5 h
Press-depth repeatability	±0.10 mm	14.90-15.10 mm range

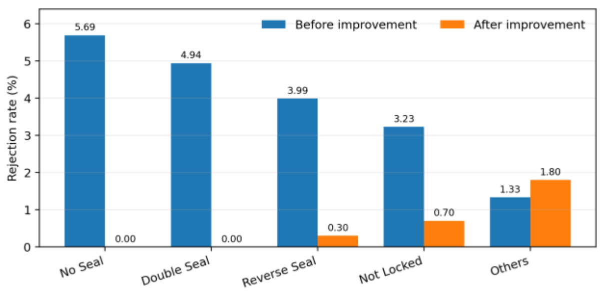

Figure 3. Defect-category rejection rates before and after implementation

The recorded cycle consisted of approximately eight seconds for loading, five seconds for sensor detection, ten seconds for pressing, four seconds for inspection processing, and three seconds for unloading. The total cycle time was therefore 30 seconds per unit, which is consistent with the five-hour production duration for 600 units. Integration of inspection within the assembly station removed the need for a separate immediate seal-checking step and reduced operator-dependent variation. This machine-level coordination reflects the core CPS principle in which sensor feedback influences actuation before the product advances (Lee et al., 2015; Lee et al., 2018; Castillo et al., 2024).

Mechanical performance was stable during calibration. Thirty repeated press-depth measurements ranged from 14.90 mm to 15.10 mm, giving a repeatability error of plus or minus 0.10 mm. Stable press depth is important because insufficient insertion can leave the seal unlocked, while excessive movement may deform the connector or seal. The pneumatic mechanism provided a practical balance of speed, simplicity, and maintenance requirements, while the reed switches and PLC sequence limited uncontrolled travel.

The Raspberry Pi gateway and HMI recorded production status, sensor signals, cycle time, alarm information, and OK or NG outcomes. This traceability enables supervisors to review defect patterns and supports continuous improvement, which is a central advantage of IIoT-enabled manufacturing (Boyes et al., 2018; Ryalat et al., 2023). The prototype demonstrates that a relatively low-cost combination of industrial sensors, PLC control, edge data storage, and pneumatic actuation can translate a general CPS concept into a specific shop-floor quality application. Future validation should use repeated production runs, confidence intervals, controlled material lots, and a clearly classified "others" category to establish the stability and generalizability of the improvement.

CONCLUSION

This study developed and industrially validated an IoT-enabled cyber-physical system for seal installation in EV charging connectors. The comparison used the same production line, connector model, assembly procedure, equipment, and inspection criteria, with baseline records collected immediately before implementation. During a continuous five-hour run, the system processed 600 connectors, accepted 583 units, and reduced the rejection rate from 19.18% to 2.80%, equivalent to an 85.41% relative reduction and a 16.38 percentage-point decrease. Missing-seal and double-seal defects were eliminated in the observed run, while reverse-seal and not-locked defects were substantially reduced. Against manual inspection, the CPS achieved 99.50% accuracy, 94.12% recall, 99.66% specificity, and a 91.43% F1-score. The machine maintained a 30-second cycle time and a press-depth repeatability error of plus or minus 0.10 mm. These outcomes support the conclusion that the integrated sensors, PLC logic, pneumatic pressing, edge gateway, and HMI improved seal-related defect prevention, consistency, and traceability under the evaluated conditions. The increase in the "others" defect category and the use of one continuous before-and-after trial limit broader generalization. Further work should replicate the validation across production lots and add inspection capability for upstream or visually complex defects.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During manuscript preparation, the authors used ChatGPT to assist with language editing and citation formatting. The authors reviewed and edited the resulting text and take full responsibility for the content of the publication.

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AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation; Formal analysis; Methodology; Writing - original draft.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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