

Application Research of Intelligent Robots in the Assembly of Battery Modules for New Energy Vehicles

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Abstract: Given the problems of cell surface reflection, unstable incoming material position, damage susceptibility during contact, difficulty in achieving closed-loop fastening and welding quality control, and low efficiency of multi-model mixed-flow switching in new energy vehicle battery module assembly, this paper proposes an intelligent robot application framework that integrates 3D visual positioning, visual-force state fusion, Cartesian impedance control, and digital twin scheduling. Based on publicly available statistical data from the International Energy Agency and the International Federation of Robotics, this study analyzes the industry demand and incorporates research on robot assembly and battery automation over the past three years to build a closed-loop system of "perception-planning-execution-detection-traceability". It also offers models for pose estimation, compliant control, process capability evaluation and multi-objective scheduling, and sets engineering design goals and verification schemes for twelve-cell square modules. Based on the scenario calculation, assuming a theoretical cycle time of 45 seconds and the conditions of set equipment availability, performance rate and quality rate, the system can produce about 69 qualified modules per hour. The proposed framework provides an engineering basis for robot selection, control parameter setting, quality gating and digital operation-and-maintenance of a flexible automated battery module production line. Verification is divided into offline simulation, single-station test and full-line continuous-cycle validation, and the acceptance criteria include pose accuracy, contact-force limits, process capability, cycle time, traceability and recipe changeover. The staged scheme supports pilot-line acceptance and factory validation without substituting scenario calculations with actual enterprise production data.

1 Introduction

The development of power batteries for new-energy vehicles has moved away from the original goal of capacity expansion and is now focused on safety, cost, cycle life and traceability. Battery modules are situated between cell production and the whole pack assembly process, and generally include steps such as identifying incoming materials, inspecting polarity and appearance, sorting and stacking cells, adding heat insulation or cushioning materials, side-plate pressing, busbar

placement, bolt tightening or laser welding, electrical testing, and code traceability. These processes are generally high-repetition, high-load, fast-cycle-time, and have a high safety risk; therefore, they are suitable for robotic operation. However, due to factors such as cell-surface reflectivity, accumulated dimensional errors, susceptibility to deformation of pouch or prismatic cells, small terminal gaps, and frequent model changes, the traditional rigid automation method of "fixed fixtures + teaching trajectory" cannot be used reliably.

According to the International Energy Agency's Global EV Outlook 2026, the scale of global electric vehicle battery deployment was about 1.2 TWh in 2025 and increased significantly from 2024 [1]. With the increase in demand for module assembly lines, their capacity needs to be expanded; at the same time, the risk of low-probability but high-consequence events such as contact damage, polarity misinstallation, insufficient tightening torque, welding misalignment and insulation failure should be reduced. At the same time, according to statistics from the International Federation of Robotics, the automotive industry was still the largest customer sector for industrial robots in 2023, with 135,461 new installations [2]. Therefore, the key path for battery module assembly to move from "mechanical automation" to "cognitive and adaptive automation" is to introduce visual perception, force control, intelligent end-effectors, online detection and digital twins in a unified closed-loop system.

Most of the previous research has focused on dismantling old batteries, general-purpose high-precision assembly or single-item sensing and control. Research on the coupling of "multi-process quality chains, strong safety constraints and mixed-flow cycle time" in new battery module production is lacking. Therefore, this paper aims to: first, analyze the development of technology based on public data and review English literature from the past three years; second, identify the main engineering problems in battery module robot assembly; third, build an all-encompassing solution that integrates visual positioning, visual-force fusion, compliant control and digital twin scheduling; and finally, propose design objectives and evaluation methods directly applicable to the acceptance of a pilot production line. This study does not use real enterprise test data for the scenario parameters; instead, public data, process constraints and verifiable indicators are employed to build an application research system for engineering.

2 Current Status Analysis of the Research Topic

2.1 Industry Demand and Scale of Robot Applications

The demand for and deployment of EV batteries globally increased steadily from 2023 to 2025. In 2023, the demand was more than 750 GWh; in 2024, it reached approximately 950 GWh; and in 2025, the deployment was about 1.2 TWh. As individual cells, module structures, cooling solutions and electrical connection methods have all been continuously developed, an increase in production volume does not necessarily require extending the production of the same model on a single line. Therefore, the manufacturing system will need to be adjusted more frequently and be subjected to stricter quality control at a high-production-volume level.

As shown in Figure 1, the scale of electric vehicle battery production increased from more than 750 GWh in 2023 to about 1200 GWh in 2025, an increase of about 60% over the two years. The expansion has increased the demand for module assembly equipment and raised the economic cost of production downtime, rework and quality defects. Therefore, when evaluating robot solutions, one should consider cycle time, first-pass yield, changeover time and traceability integrity simultaneously, rather than focusing solely on the repeatability accuracy of robotic arms.

In terms of the structure of the robotics industry, the main application scenarios for industrial robots have long been in the automotive and electronics industries. Between 2021 and 2023, the number of robots in the automotive industry increased from 117,303 to 135,461; in 2022, the

electronics and electrical industry reached 156,920 units and then fell to 125,804 units in 2023; at the same time, the metal and machinery industry rose to 76,831 units. The above structure shows that automotive assembly is still relatively insensitive to changes in automation investment, and battery modules combine the characteristics of both automotive assembly and electronics and electrical assembly.

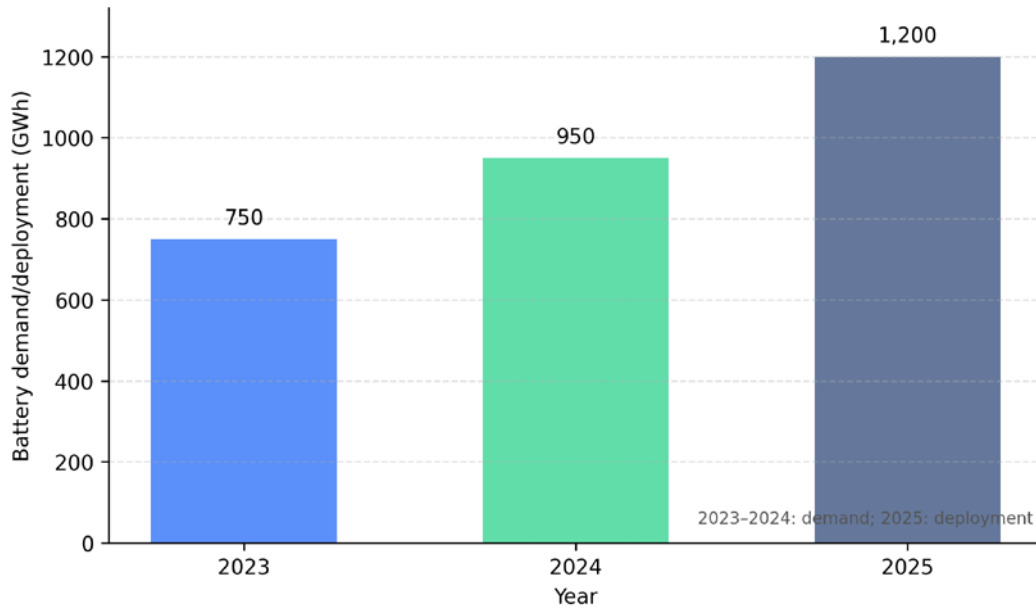


Figure 1: Global Electric Vehicle Battery Demand and Deployment Scale, 2023-2025

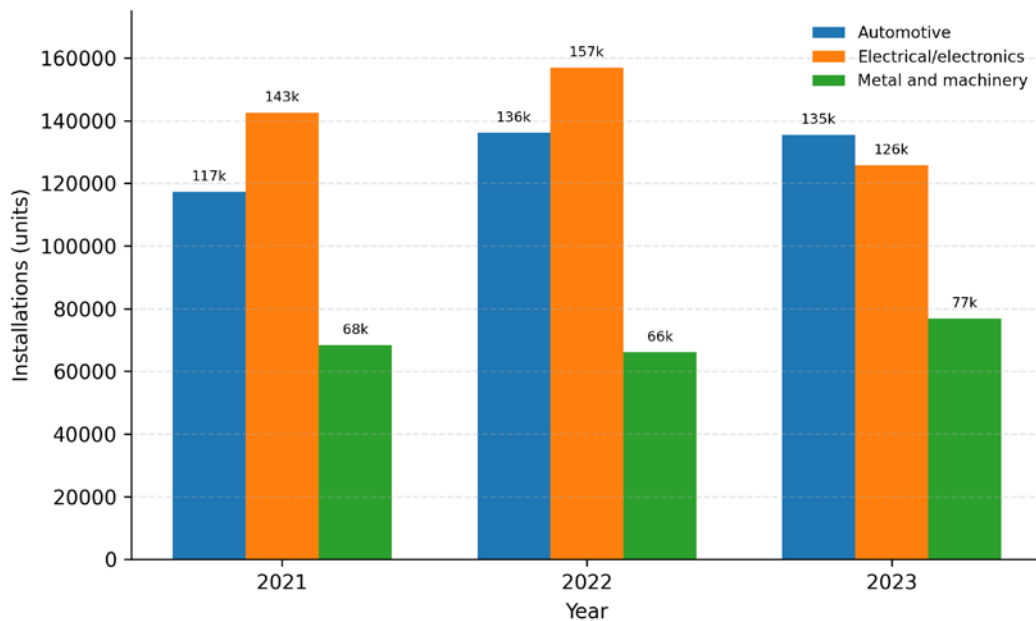


Figure 2: Global Industrial Robot Installations by Major Customer Industries, 2021-2023

As shown in Figure 2, robot installations for the automotive industry were relatively high in 2022 and remained high in 2023; however, the electronics and electrical industry was more susceptible to cyclical fluctuations. The production line for the battery module is at the intersection of the two industries' technologies, so it needs both the load-bearing, cycle-life and safety

engineering capabilities of the automotive industry and the high-precision positioning, terminal protection and electrical testing capabilities of electronic assembly. Therefore, a single handling robot is not suitable for the entire process.

2.2 Research Progress on Battery Robotics and Intelligent Assembly

Kaarlela and others have provided an organised review of electric vehicle battery robot disassembly and pointed out that the main obstacles to automation are differences in product structure, various connection methods, uncertain states and safety risks [3]. Although disassembly is in the opposite direction to new module assembly, the conclusions on component identification, tool switching, contact operation and safety isolation are equally relevant to module assembly; that is, the robot system must have the ability to recognize differences in model and state online. Zang and others have listed the prospects for perception, planning, end-tools and human-machine cooperation in battery robot disassembly, and have emphasized the need for task-level planning and skill reuse [4]. That is to say, module assembly should not turn each model into an independent program, but rather encapsulate stacking, pressing, fastening and testing into parameterised skills.

Liang and others designed and built an experimental robot disassembly unit for square battery cell modules, verified the importance of modular subsystems, general tools and quantitative performance evaluation for cross-product adaptation [5]. Wang and others proposed force-vision fusion fuzzy control for batch precision assembly of flexible adsorption parts, corrected the reference position using visual features, determined the contact state based on force information, and dynamically adjusted control parameters [6]. For the assembly of new modules, this approach directly corresponds to processes that are prone to jamming, such as terminal plugging, side plate pressing, insulation embedding and thread initiation.

Table 1: Main Assembly Processes and Robot Capability Requirements for Battery Modules.

Process stage	Main operation	Critical quality characteristics	Typical risk	Required robot capability
Cell feeding	Pick and place	Polarity and surface integrity	Reverse placement or collision	3D vision, soft gripping
Cell sorting	Measure and classify	Capacity and resistance consistency	Wrong grade mixing	Data binding, dynamic routing
Cell stacking	Align and compress	Gap and stack geometry	Tilt, scratch, cumulative error	Visual serving, force limiting
Adhesive dispensing	Apply thermal or structural material	Bead width and continuity	Break, overflow, contamination	Path tracking, flow monitoring
Busbar positioning	Place conductive connector	Terminal overlap and clearance	Short circuit or offset	Fine vision, compliant insertion
Fastening or welding	Join terminals and frame	Torque or weld quality	Loose joint, spatter, overheating	Process feedback, interlock
Electrical inspection	Measure insulation and voltage	Safety and traceability	Escape of hidden defect	Automatic test, MES linkage

Ota and others have built an autonomous system for scattered-part supply in precision assembly using vision, touch and six-dimensional force/torque sensors, and have carried out grasping, hand adjustment and insertion in a closed loop [7]. Touhid et al. have studied how to synchronise the digital twin of the robot assembly system using computer vision and have determined the deviation

between virtual and actual states, as well as corrected errors in the model [8]. Xin Li and others have built a robot digital twin system that supports task replanning and human-machine cooperation in dynamic environments and altered tasks [9]. Yuchao Li and others used visual-tactile feedback and reinforcement learning strategies in terminal assembly to verify the adaptive value of multimodal perception for uncertain contact assembly [10]. In short, the research frontier has moved from single-sensor and single-trajectory control to multimodal perception, skill strategy and virtual-real collaboration, but quality gating and process traceability for battery module production still need to be systematically designed.

Module assembly is not a simple carrying operation but an integrated process of mechanical, electrical, material and data connection. The front end is for polarity recognition, flexible gripping and geometric consistency; the middle end provides continuous adhesive application and press-fit contact and terminal protection; and the back end is based on feedback from the fastening or welding process and electrical testing. Robot functions need to meet the quality requirements and should not merely be a one-to-one mapping of work stations.

3 Problem Statement: Key Constraints in Intelligent Assembly of Battery Modules

3.1 Position Uncertainty Caused by Reflective Surfaces and Tolerance Accumulation

Square aluminium-cased battery cells and metal busbars have specular reflections, and traditional two-dimensional edge or template matching is easily affected by light, oil stains and batch colour differences. The incoming pallet, conveying mechanism and fixtures also have positioning errors. If the robot only grasps according to off-line calibrated coordinates, these errors will accumulate during cell stacking, placement of heat insulation sheets and busbar positioning. To obtain the six-degree-of-freedom pose of the workpiece in the robot's base coordinate system, multi-view or RGB-D observation can be converted into a reprojection error minimisation problem:

$$\hat{\xi} = \arg \min_{\xi} \sum_{i=1}^n \|u_i - \pi(T(\xi)P_i)\|_2^2 \quad (1)$$

As shown in equation (1), ξ is the pose parameter we wish to estimate; the image feature point and its corresponding 3D feature point form a matching pair, the pose transformation matrix is used to map the 3D points to the camera coordinate system, the projection function performs 2D imaging, and n is the number of effective matches. This model needs to manage the system's camera intrinsic parameters, hand-eye relationship and tool coordinates simultaneously, and decide whether to allow the robot to enter the grasping or pressing stage based on a confidence threshold.

3.2 Risks of a Fixed Trajectory in Complex Processes

Cell sideplate pressing, terminal insertion, bolt initiation and busbar positioning are all contact-type operations. In open space, dimensional or positional errors of only a few micrometres have no practical consequence, but once contact occurs with a constraint hole, guide groove or terminal surface, these errors rapidly generate lateral forces and torques. Pure position control may cause casing scratches, terminal bending or insulation damage, and fixture overload; a single fixed-force threshold will likely mistake normal friction for a fault. Therefore, the world geometry obtained by vision and the local contact information obtained by force perception need to be fused.

$$\hat{x}_k = W_{v,k}x_{v,k} + W_{f,k}x_{f,k}, \quad W_{v,k} + W_{f,k} = I \quad (2)$$

The two state vectors in equation (2) are the visual state and the force contact state at time k , respectively. The two weight matrices are different at different times, and the identity matrix

ensures that the sum of the two weights is 1. When the confidence level is low due to visual obstruction or reflection, increase the force-contact-weight of the system. When there is no contact with the workpiece, the visual state is used as the main basis, and thus the distortion of a single sensor is not directly transmitted to the control layer.

3.3 Lack of Closed-Loop Judgment and Cross-Process Traceability in Process Quality

Traditional automation generally considers "robot action completion" to be the end of a process, but a successful action may not meet quality requirements. For example, a bolt reaches the target angle but does not have sufficient clamping force; the welding trajectory is completed, but the penetration depth and resistance are not met; and cell stacking is finished, but there are still gaps or the total length exceeds the allowed tolerance. If only Boolean completion signals are transmitted by the controller, test equipment and manufacturing execution systems will be unable to track anomalies and parameter drift subsequently. A high-quality closed-loop should record visual measurements, force-displacement curves, torque-angle curves, welding power and speed, inspection results, material identification, etc., and build an auditable digital thread for each module.

3.4 Multi-Model Mixed-Flow Switching and Equipment Disturbances Cause Cycle Time Mismatch

Battery platform iterations have changed cell size, series and parallel connection quantities, terminal types, and side plate structures. Fixed-station cycle times cannot be adjusted for different motion lengths and inspection times of various models, and camera recalibration, tool changes, consumable replenishment and equipment failures can also cause congestion or starvation. If only the first-come, first-served rule is used at the PLC level, the robot may be idle, work-in-progress will accumulate, and high-priority orders may be delayed. Therefore, it is necessary to synchronise the equipment, workpiece, tool and quality status in real time in the digital twin and dynamically select process routes and task priorities.

4 Intelligent Robot Collaboration Strategies for Problem Solving

4.1 Overall Architecture of "Perception-Planning-Execution-Detection-Traceability"

This paper proposes a five-layer collaborative architecture. The perception layer includes a 3D camera, a 2D precision camera, a six-dimensional force/torque sensor, a displacement sensor and an electrical tester; the planning layer stores product formulas, gripping points, assembly constraints, collision models and skill state machines; the execution layer contains a six-axis robot, linear modules, flexible grippers, an automatic tool changer and fastening, gluing or welding tools; the detection layer implements in-process gating for geometry, mechanics, electrical connections and insulation performance; and the traceability layer links robot trajectories, process curves, equipment alarms and quality results to cell and module serial numbers and transmits them back to the MES and digital twin.

As shown in Table 2, the system has the characteristics of "separation of precise positioning and strong execution, and hierarchical integration of real-time control and information optimisation". Cameras and force sensors are responsible for state observation; the robot controller and PLC ensure deterministic actions and safety interlocks; the MES and digital twin handle recipe management, traceability and scheduling. Standard industrial communication interfaces will be selected to avoid limiting the quality data to a single machine and to support the expansion of the production line.

Table 2: Hardware and Software Configuration of the Intelligent Robot Assembly System

Layer	Component	Main function	Key interface	Recommended specification
Perception	RGB-D camera	Coarse pose and obstacle sensing	GigE or EtherCAT	Depth error ≤ 0.5 mm at work range
Perception	2D industrial camera	Terminal and polarity inspection	GigE Vision	Resolution ≥ 5 MP
Sensing	Six-axis F/T sensor	Contact state and collision limiting	EtherCAT	Force resolution ≤ 0.2 N
Execution	Six-axis robot	Handling and process motion	PROFINET or EtherCAT	Payload 20–50 kg, repeatability ≤ 0.05 mm
Tooling	Quick-change end effector	Gripping, pressing, fastening	Digital I/O and pneumatic	Tool ID and lock verification
Control	PLC and robot controller	Sequence, safety and interlock	OPC UA	Deterministic cycle and safe stop
Information	MES and digital twin	Recipe, traceability, rescheduling	OPC UA or MQTT	Timestamp synchronization ≤ 100 ms

4.2 Hierarchical Visual Positioning and Online Calibration

The three links of the vision system are coarse positioning, fine positioning and process verification. An RGB-D camera at the conveyor entrance obtains the coarse pose of the tray and battery cells. A 2D camera at the wrist or above the workstation of the robot can achieve sub-millimeter positioning of poles, holes and busbar edges. After an operation is carried out, another image is taken to confirm that the polarity, gap and position are correct. To prevent glare, polarised light, dome-diffused light and multi-exposure fusion can be employed. To correct for calibration drift, traceable standards are placed on the tool, and after each shift or tool change, hand-eye and tool-centre-point verification is automatically carried out. If the reprojection error or point cloud residual exceeds the set limit, or the recognition confidence falls below the set threshold, assembly will not proceed; instead, the system will reshoot the image, clean the optical surface, or request a manual inspection.

4.3 Vision-Mechanism Fusion and Variable Impedance Control

The robot has a relatively high positional stiffness in free space to meet the cycle time requirements, and then switches to a low-stiffness search mode near terminals, guide slots, or the side of the battery cell. As shown in Equation (3), the controller sets the direction and deviation of contact, and then generates a compliant response according to a Cartesian impedance model as follows:

$$M_d \ddot{e} + D_d \dot{e} + K_d e = F_{\text{ext}} \quad (3)$$

As shown in equation (3), the error vector is the difference between the desired pose and the actual pose of the end-effector. The three parameter matrices are the desired inertia, damping and stiffness matrices. The right side of the equation is the external force and torque at the end-effector. A relatively high stiffness can be selected for the assembly direction to maintain good positioning, and a low stiffness can be used laterally to accommodate deviations. When the force-displacement

curve shows a sudden change in slope, a continuous lateral force occurs or the measured force exceeds the preset limit; at this time, the robot will immediately retract and switch to secondary positioning instead of maintaining rigid propulsion.

Cell grippers should be selected to maximise the contact area, offer adjustable clamping force and a pressure-retaining structure, and integrate pressure or displacement feedback. Busbars and insulators are equipped with a combination of vacuum and mechanical grippers to detect the presence of a vacuum and components. The tool needs to be able to display a torque-angle curve for bolt tightening and detect stripped threads, floating locks or repeated tightening. For laser welding, the robot path should be linked to weld seam tracking, power monitoring, shielding gas and fume treatment. Different tools are mechanically, electrically and/or pneumatically connected to an automatic tool changer, and tool identification codes prevent incorrect recipe selection.

4.4 In-process Quality Gate Control and Process Capability Control

All necessary links have a 'measurement-judgment-handling' quality gate. Stacking is carried out first, and then the total length, end-face parallelism and cell gap are measured; after tightening, the peak torque, final angle and curve window are observed; after welding, visual inspection, process signals and resistance tests are conducted for judgment; finally, insulation, voltage and communication tests are performed. In stable mass production, the process capability index can be used to determine how far the quality characteristics are from the specification limits.

$$C_{pk} = \min\left(\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right) \quad (4)$$

USL and LSL in equation (4) are the upper and lower bounds of the specification, respectively, and μ and σ are the process mean and standard deviation, respectively. For the above characteristics of torque, stack length and terminal position, a process capability index of 1.33 or higher can be used as the routine release goal; if the capability declines but has not exceeded the specification, then a digital twin can be employed for preventive maintenance or parameter compensation before non-conforming products are produced at the line.

4.5 Digital Twin-Driven Task Scheduling and Virtual-Real-time Synchronization

A digital twin is an integrated-state model of robots, work centres, tools, product recipes and work-in-progress. The physical production line will send location, programme number, alarm, cycle time and quality status via OPC UA or message middleware, and the virtual model will predict task completion time, collision risk and buffer usage according to equipment capabilities and process constraints. Model switching, tool failure and rework will all be subject to rescheduling. The aim may be as follows:

$$\min J = w_1 C_{\max} + w_2 \sum_{j=1}^m T_j + w_3 E + w_4 N_c \quad (5)$$

As shown in equation (5), the first term is the maximum completion time; the second term is the sum of all task delays; the third term is energy consumption or idle travel cost; and the fourth term is the number of tool changes and replacements. The four weights are set according to the order of priority and operational objectives. The actual solution should meet the requirements for process sequence, robot load, tool availability, buffer capacity and safety interlocks. Digital twins are not to replace real-time PLC control but to provide predictable recipe verification, task rescheduling and maintenance decisions at a higher level.

5 Engineering Application Verification Framework and Scenario Analysis

5.1 Design Scenario for a Twelve-Cell Square Module

To ensure the verifiability of the solution, this paper establishes a parameterised scenario for a twelve-cell square module: the cells enter the workstation via a pallet, and the robot sequentially performs polarity verification, gripping, placement of heat insulation sheets, stacking, side panel pressing, busbar positioning, pre-fastening or welding positioning, and electrical checks. This is not a real production line of any specific enterprise; rather, it is used to set the design scope for the pilot production line. The rated load of the robot should cover the full-load fixture and a dynamic margin; the vision system needs to be verified under actual working distance, glare and occlusion conditions, and all safety thresholds must be finally confirmed based on the cell supplier's allowable load and process testing.

Table 3: Design Objectives and Acceptance Criteria for a Twelve-Cell Square Module Scenario

Metric	Design target	Measurement method	Acceptance criterion	Data status
Cell pose error	≤ 0.50 mm	Calibrated reference artefact	95th percentile within limit	Engineering target
Angular error	$\leq 0.30^\circ$	Vision and CMM sampling	95th percentile within limit	Engineering target
Lateral contact force	≤ 60 N	Six-axis F/T logging	No sustained over-limit event	Provisional safety limit
Torque process capability	$C_{pk} \geq 1.33$	Torque-angle data analysis	Stable batch meets threshold	Quality target
Nominal cycle time	≤ 45 s/module	PLC timestamp	Average under stable recipe	Scenario assumption
Traceability coverage	100%	MES record audit	No missing critical field	Mandatory requirement
Recipe changeover	≤ 15 min	Start-to-first-good timing	First article passes all gates	Engineering target

Note: The values are the proposed design targets for scenario validation and not measured factory results.

Together, the indicators cover geometric accuracy, contact safety, process capability, cycle time, changeover capability and data integrity, and do not substitute for robot repeatability accuracy in system quality. Force limits and cycle time are the initial design constraints; they need to be verified after prototype and equipment trials, and traceability coverage must be mandatory, otherwise there will be no process records for anomaly analysis or accountability.

5.2 Phased Validation Method

The three stages of the validation will be offline, single-station and full-line. Off-line, the accessibility of robots, single-robot arrangements, tool interference and cycle time are assessed in a digital twin, and Monte Carlo tolerance analysis is performed on typical and limit-size models. The single-station phase needs to meet the camera repeatability and reproducibility test requirements, gripping force calibration, impedance parameter step response, tooling capability analysis and safe-stop test. Full-line phase continuously cycles for throughput verification, first-pass yield, alarm recovery time, data loss rate and changeover time; faults such as visual misidentification, vacuum leakage, tool

locking failure, excessive force and test failures are injected to confirm that the system can safely retract, isolate non-conforming products and keep complete records.

Based on the given scenario cycle time, if the theoretical cycle time is 45 seconds, the ideal output is 80 units/hour. Assuming equipment availability of 0.92, performance rate of 0.95, and quality rate of 0.995, the product of these three is approximately 0.869, and thus the scenario output is around 69 qualified modules/hour. Only the cumulative effect of equipment downtime, speed reduction and quality loss on production capacity is shown in this result; it does not reflect actual production performance. Formal acceptance should be based on the timestamps and quality records of at least one representative production shift, and separately report the average value, 95th percentile and anomaly recovery time.

5.3 Expected Benefits, Applicable Scope and Implementation Risks

Compared with fixed fixtures and pure teach-and-play automation, the proposed solution is expected to have the following advantages: First, multi-level vision reduces the demand for tooling accuracy, and the same workstation can be adapted to different cells and modules based on formulations; second, vision-force fusion and variable-impedance control can reduce the risk of damage during the initial stages of press-fitting, insertion and fastening; third, quality gating moves inspection upstream in the process to prevent the accumulation of defects later on; and fourth, digital twins support offline verification, disturbance rescheduling and process capability-based maintenance. The above advantages should be quantified through controlled experiments by setting up ablation scenarios, such as disabling force feedback, disabling online vision correction, disabling variable-stiffness control, and disabling dynamic scheduling.

The proposed solution also has limitations. Visual models may be affected by data drift due to new reflective materials, stains or aging light sources; force thresholds may be too conservative or too loose if not combined with cell structure tests; digital twins require unified timestamps and reliable interfaces, and data delays can reduce synchronization reliability; laser welding and insulation tests are also subject to special equipment and regulatory standards. The implementation should adhere to the principle of "independent safety functions and degradable intelligent functions": even if the sensing or optimisation module fails, safety PLCs, mechanical limits, emergency stops and energy isolation must remain effective, and the production line can degrade to a low-speed confirmation mode rather than operating in an uncontrolled (runaway) manner.

6 Conclusion

Given the high-cycle, multi-model and high-safety-responsibility assembly requirements of new energy vehicle battery modules, this paper proposes an intelligent robot application framework that integrates visual positioning, visual-force state fusion, Cartesian impedance control, in-process quality gating and digital twin scheduling. According to the above public data, the scale of new-energy vehicle battery production continues to grow, and the automotive and electronics industries remain core application domains for industrial robots. Therefore, the production line of battery modules should balance load and cycle time, precision and compliance, automation and traceability. This paper introduces five adjustable models to present the mathematical foundation of pose estimation, sensor fusion, compliant response, process capability and task scheduling, and specifies the design goals, acceptance criteria and staged verification methods for a twelve-cell square module.

Robots need to have repeatability in their engineering applications; however, this is not enough, and unified acceptance tests should also cover factors such as the contact force envelope, torque or welding process capability, first-pass yield, fault recovery and traceability integrity. The scenario

calculations in this paper are only for method demonstration and have not used long-term production data from a real production line. Future work should include cross-device verification under conditions involving cells from multiple suppliers, different module structures and severe disturbances. Future research will focus on self-supervised learning-based reflective surface sensing, provably safe learning-based compliant strategies, and digital twin model drift detection to improve the system's transferability and reliability over an extended period.

References

- [1] International Energy Agency. *Global EV Outlook 2026: Moving towards increased affordability*. Paris: IEA, 2026. Available at: <https://doi.org/10.1787/a9e65774-en>.
- [2] International Federation of Robotics. *World Robotics 2024: Industrial Robots*. Frankfurt am Main: IFR, 2024. Available at: <https://ifr.org/ifr-press-releases/news/record-4-million-robots-work-in-factories-around-the-globe>.
- [3] Kaarlela T, Villagrossi E, Rastegarpanah A, et al. Robotized disassembly of electric vehicle batteries: A systematic literature review. *Journal of Manufacturing Systems*, 2024, 74: 901-921. DOI: 10.1016/j.jmsy.2024.05.013.
- [4] Zang Y, Qu M, Pham DT, et al. Robotic disassembly of electric vehicle batteries: Technologies and opportunities. *Computers & Industrial Engineering*, 2024, 198: 110727. DOI: 10.1016/j.cie.2024.110727.
- [5] Liang C, Parnada A, Gbadebo A, et al. An experimental robotic cell for the disassembly of electric vehicle battery modules. *Journal of Remanufacturing*, 2025, 15: 381-410. DOI: 10.1007/s13243-025-00156-9.
- [6] Wang B, Zhang J, Wu D. Force-vision fusion fuzzy control for robotic batch precision assembly of flexibly absorbed pegs. *Robotics and Computer-Integrated Manufacturing*, 2025, 92: 102861. DOI: 10.1016/j.rcim.2024.102861.
- [7] Ota K, Jha DK, Jain S, et al. Autonomous robotic assembly: From part singulation to precise assembly. In: *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems*. Abu Dhabi: IEEE, 2024: 13525-13532. DOI: 10.1109/IROS58592.2024.10802423.
- [8] Touhid MTB, Zhu E, Ehteshamfar MV, et al. Synchronization evaluation of digital twin for a robotic assembly system using computer vision. *Manufacturing Letters*, 2024, 41: 1257-1263. DOI: 10.1016/j.mfglet.2024.09.152.
- [9] Li X, He B, Wang Z, et al. A digital twin system for task-replanning and human-robot control of robot manipulation. *Advanced Engineering Informatics*, 2024, 62: 102570. DOI: 10.1016/j.aei.2024.102570.
- [10] Li Y, Jin Z, Liu J, et al. Visuo-tactile feedback policies for terminal assembly facilitated by reinforcement learning. *Frontiers in Robotics and AI*, 2025, 12: 1660244. DOI: 10.3389/frobt.2025.1660244.