

Research on Adaptive Control Strategy of New Energy Engineering Robots in Advanced Manufacturing Environment

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Abstract: High-voltage connectors for new energy applications are simultaneously affected by sealing resistance, secondary locking, and the traction of thick wire harnesses during assembly. Even small positional deviations can translate into lateral loads, further increasing terminal stress. To address this issue, this paper proposes an adaptive admittance control method for contact risk constraints and constructs a high-voltage connector characteristic model in Gazebo, incorporating CPA, HVIL, and elastic terminals. The method learns short-term risks from real connector trajectories, identifies contact parameters using successful, stalled, and retraction trajectories, and then corrects the local model within the distribution through projection recursion estimation. The controller uses the risk to tighten the predicted lateral force constraints, optimizing only the propulsion speed and lateral stiffness, with damping determined by a fixed damping ratio. Results show that the risk model has an AUROC of 0.79. Under combined perturbations, the constraint violation rate is reduced to 18.5%, and the median peak lateral force is reduced to 6.74 N; the complete success rate of the Gazebo characteristic case is 74.0%. This method can improve contact constraints, but further validation is needed for physical high-voltage connectors.

1 Introduction

Robot assembly studies have shown that contact modeling, state perception, compliant control and learning strategies jointly affect the accuracy and adaptability of complex assembly [1]. Battery packs, high-voltage distribution boxes, and electric drive controllers typically use connectors with seals, interlocks, and secondary locking mechanisms. These connectors have high insertion force, and thick wiring harnesses can continuously pull on the ends. When the plug is misaligned, even if the robot pushes the part to the target depth, the terminal may be pulled back, the locking may not be in place or the HVIL may not close. The test of the charging connector also found that the force characteristics of the alignment, contact and pressing stages are not the same, and the fixed trajectory is difficult to take into account all states [2]. Multi-variety and small-batch production

further amplifies this contradiction. Once the connector model is changed, the original control parameters often cannot be directly used.

Existing research mainly addresses the above problems from three directions: end-effector structure, state recognition, and compliant control. Compliant end-effectors and tactile sensing can absorb small-range positioning errors, but dedicated structures are more sensitive to product changes [3]. Data-driven methods can identify abnormal contacts from historical trajectories, but the cross-connector capability of the model is still affected by geometric differences and action phases [4]. Variable impedance control can change compliance online, but some methods directly convert risk into speed or stiffness, and the control boundary is not clear enough [5]. Real data are usually collected from the original strategy. After the new controller starts to decelerate or retreat, the contact dynamics and input distribution will change. Therefore, how the risk output enters the physical control boundary and how the real trajectory supports the new strategy closed loop are still two problems that need to be solved in this paper.

This paper avoids allowing the risk model to directly generate control variables; instead, it uses risk to tighten predictive force constraints. Projective recursive estimation is responsible for online correction of local contact parameters, giving "adaptive" a clear update target and boundary. The controller also handles risk and OOD state separately: high-risk conditions within the distribution enter constraint adjustment, while out-of-distribution conditions freeze the model and transition to backoff. The Gazebo high-voltage connector characteristic model is only used to test the response capability under new structures and does not represent a physical test bench. Based on this research boundary, this paper focuses on answering three questions: can weak action-level labels form stable short-term risks? Can online models and risk constraints improve contact performance? Can a small number of replacement trajectories support the deployment of new objects under acceptable downtime?

2 Research Methods

2.1 Data, Connector Modeling, and Force/Torque Coordinate Transformations

The risk model uses Ethernet, USB, waterproof connectors, BNC, and D-SUB insertion records from REASSEMBLE. Closed-loop development uses a publicly available waterproof connector model, while external testing uses a high-voltage connector characteristic model. This model includes a resilient seal, 2.2 mm CPA locking travel, HVIL closed contacts, and equivalent harness lateral loads, but does not correspond to a specific commercial model. The entire characteristic model was built in Gazebo, and the study only used it to test the response of the control method to the new structure. Physical high-voltage connector verification is outside the scope of this paper. Raw failure records are categorized as friction stall, attitude deviation, rotational locking, clamping slip, and timeout. Admittance control primarily handles friction stall and small-range attitude deviations; the remaining states are used to define the stop and repositioning boundaries.

The sensor coordinate system is denoted as $\{S\}$, and the connector local coordinate system is denoted as $\{C\}$. The superscript S or C indicates the coordinate system to which the variable belongs, and TCS indicates the homogeneous transformation from the sensor coordinate system to the connector coordinate system. The six-dimensional force perception is transformed according to equation (1):

$$\mathbf{w}_t^C = \text{Ad}_{\text{TCS}}^{-T} \mathbf{w}_t^S \quad (1)$$

The resultant lateral force, resultant lateral bending moment, and insertion progress are calculated according to equations (2) and (3):

$$F_{xy,t} = \sqrt{F_{x,t}^2 + F_{y,t}^2}, \quad T_{xy,t} = \sqrt{T_{x,t}^2 + T_{y,t}^2} \quad (2)$$

$$p_t = \frac{(\mathbf{p}_t^c - \mathbf{p}_0^c)^T \mathbf{e}_z}{L_z} \quad (3)$$

Unified coordinates can reduce spurious correlations caused by task board attitude and sensor mounting orientation [6]. The system synchronizes all signals at 200 Hz. Force data are filtered by a 25 Hz fourth-order causal Butterworth filter, and the derivative is obtained by backward difference. The system uses data from 0.20 s before contact to estimate force bias. Data partitioning considers episode, connector type and acquisition batch to prevent the same task segment from entering different sets. After auditing, the study retained 326 trajectories, of which 260 were successful and 66 were unsuccessful; the training set, validation set and test set contained 196, 65 and 65 trajectories, respectively. All standardized statistics were calculated only from the training set.

2.2 Weakly Supervised Short-Term Risk Learning and Risk-OOD Partitioning

Action-level failure labels cannot be directly copied to each time window. This paper extracts 9 causal windows at the 10%-90% progress position after contact, with each window having a length of 0.30 s. If the failure trajectory does not reach the subsequent progress, the system uses the most recent valid state to complete it and adds a mask synchronously. The model input includes axial force, lateral resultant force, lateral resultant bending moment and its rate of change, while retaining axial velocity, lateral velocity, insertion progress and skill stage. The two-layer temporal convolutional network outputs conditional risk h . The number of network channels is 32 and 48, the number of convolutional kernels is 3, and the dropout is 0.1. The action failure probability under fixed nodes is given by equation (4):

$$\hat{y}_i = 1 - \prod_{m=1}^9 (1 - h_{im}) \quad (4)$$

Closed-loop control uses the six most recent windows to form short-term risks, without accumulating the historical probability of the entire action.

$$R_k = 1 - \prod_{j=k-5}^k (1 - h_j) \quad (5)$$

After the old window leaves the observation range, the risk can decrease again, so the controller can resume progress after the pullback. The validation set determines the temperature parameters only on the three prefixes of 30%, 50% and 70%, so that the predicted probability is closer to the actual failure frequency [7]. Five-fold grouped cross-validation is used within the training set. The window length is searched in the range of 0.20-0.40 s, the channel combination is 16/32, 32/48 or 32/64, and the learning rate is sampled on a logarithmic scale in the range of 10^{-4} - 3×10^{-3} . The search evaluates a maximum of 30 configurations, and each configuration is run with 3 random seeds. The parameter selection takes into account AUPRC, Macro-F1 and Brier scores at the same time to avoid the model only pursuing ranking performance.

Online decision-making uses both short-term risk R and standardized Mahalanobis distance d . The standardized distance is equal to the ratio of the current Mahalanobis distance to the 99th percentile of the development set. Nominal parameters are used for low-risk states within the distribution, and force constraints are tightened for high-risk states within the distribution; low-risk states outside the distribution are converted to low-speed fixed admittance, and rollback or cessation is performed for high-risk states outside the distribution. Model updates are frozen for both types of OOD states. Such partitioning separates "known high-risk" and "unknown states", which also conforms to the basic processing principle of online anomaly detection [8].

2.3 Contact parameter identification and cross-motion verification

Contact parameter identification cannot rely solely on successful advance segments. This paper extracts samples stratified from three types of trajectories: successful advance, frictional stagnation, and manual retraction, and simultaneously identifies static friction, dynamic friction, normal stiffness, and contact damping. The objective function simultaneously constrains axial force, lateral force, and insertion progress. Each error is first normalized to the standard deviation of the training trajectory, and then assigned weights of 0.40, 0.35, and 0.25 respectively to prevent large-dimensional force signals from completely dominating the search.

$$\theta_{\text{opt}} = \underset{\theta}{\operatorname{argmin}} \sum_t \left[w_a (F_{z,t}^{\text{sim}} - F_{z,t}^{\text{obs}})^2 + w_l (F_{xy,t}^{\text{sim}} - F_{xy,t}^{\text{obs}})^2 + w_p (p_t^{\text{sim}} - p_t^{\text{obs}})^2 \right] \quad (6)$$

The search first generated 128 sets of Latin hypercube samples, and then ran CMA-ES from 30 independent initial values. The search ranges for static friction, dynamic friction, stiffness and damping were 0.15-0.50, 0.10-0.40, 4×10^4 - 1.5×10^5 N/m and 40-150 N·s/m, respectively. The study used 500 trajectory bootstraps to estimate the parameter range and checked for ambiguity by profile loss. All parameters were determined only on the training trajectory. The verification phase reported the errors of successful, stalled and retreated trajectories respectively, so as to observe whether the same set of parameters could cover different contact actions [9]. High pressure characteristic conditions were not included in the identification.

During closed-loop operation, the local contact prediction model uses features $\varphi = [F_{xy}, v_z, K_{xy}, \delta_{xy}, 1]$. Parameter θ is updated using projection recursive least squares according to equation (7). The forgetting factor is set to 0.995, and the projection set restricts the sign and magnitude of the parameters. The system only updates parameters when they are within the distribution, have not triggered a hard threshold, and the insertion progress continues to increase; the rollback, stop, and OOD states are all frozen. This rule can absorb velocity changes and small-scale contact deviations, while avoiding unknown collisions from contaminating the recursive parameters:

$$K_k = \frac{P_k \phi_k}{\lambda + \phi_k^T P_k \phi_k}, \quad \hat{\theta}_{k+1} = \Pi_{\Omega} [\hat{\theta}_k + K_k (F_{xy,k+1} - \phi_k^T \hat{\theta}_k)] \quad (7)$$

2.4 Risk-Constrained Adaptive Admittance Control

After obtaining the results from the risk model, the controller needs to transform the risk into executable safety adjustments. This paper does not directly change the velocity and stiffness, but instead solves a bounded quadratic programming problem in each outer loop cycle. Decision variables include only axial velocity, lateral stiffness, and non-negative relaxation variables. All variables are normalized to nominal scales before solving, with weights w_v of 1.0, $0.35 w_{\xi}$, w_K and 50.0, respectively. The objective function balances nominal tick time with parameter smoothing, and sets a higher cost for relaxing the predictive force constraint.

$$\min_{v_{z,k}, K_{xy,k}, \xi_k} w_v (v_{z,k} - v_{z,0})^2 + w_K (K_{xy,k} - K_{xy,0})^2 + w_{\xi} \xi_k^2 \quad (8)$$

Predicting lateral force, velocity, stiffness, and their rate of change requires satisfying the constraint of equation (9):

$$\begin{aligned} \hat{F}_{xy,k}(\theta_k, v_{z,k}, K_{xy,k}) &\leq F_{\text{lim}} - \eta R_k + \xi_k, \quad \xi_k \geq 0, \\ v_{z,\min} &\leq v_{z,k} \leq v_{z,\max}, \quad K_{\min} \leq K_{xy,k} \leq K_{\max}, \\ |\Delta v_{z,k}| &\leq \dot{v}_{\max} \Delta t, \quad |\Delta K_{xy,k}| \leq \dot{K}_{\max} \Delta t. \end{aligned} \quad (9)$$

The short-term risk R is tightened by the safety margin ηR to tighten the upper limit of the lateral force. The relationship between the “risk bin-sub-cycle over-limit rate” in the validation set is used to determine the axial velocity range of 3-12 mm/s and the lateral stiffness range of 250-900 N/m; the upper limits of the velocity and stiffness change rates are 30 mm/s² and 1200 N/(m·s), respectively. Relaxation variables are only allowed to relax the predictive force constraint, while the other boundaries are always kept as hard constraints. If the OSQP times out or does not return the optimal solution, the controller first holds the previous feasible command for one cycle and then switches to low-speed fixed admittance. The energy tank is used to limit the energy added by the adaptive layer [10], while the change rate boundary is used to mitigate command mutations in position control [11].

The robot's outer loop adopts the task space admittance model shown in equation (10):

$$\mathbf{M}_d \ddot{\mathbf{x}}_c + \mathbf{D}_d(k) \dot{\mathbf{x}}_c + \mathbf{K}_d(k)(\mathbf{x}_c - \mathbf{x}_d) = \mathbf{F}_e \quad (10)$$

The quadratic programming approach does not treat damping as an independent decision variable. After the controller obtains K_{xy} , it calculates the damping on the lateral x and y axes according to $D_x = 2\zeta_x \sqrt{M_x K_{xy}}$ and $D_y = 2\zeta_y \sqrt{M_y K_{xy}}$, respectively, with ζ_x and ζ_y both set to 1.0. This approach maintains a fixed relationship between damping and stiffness and reduces the dimensionality of the online solution. The outer admittance model converts contact force into pose correction, and the inner position controller executes the corrected reference trajectory. The energy tank further limits the added stiffness and reference trajectory energy of the adaptive layer.

$$G_k = \frac{1}{2} \mathbf{e}_k^\top (\mathbf{K}_k^{\text{cmd}} - \mathbf{K}_k) \mathbf{e}_k + \mathbf{F}_{e,k}^\top \Delta \mathbf{x}_{d,k}^{\text{ad}} \quad (11)$$

$$E_{\text{req},k} = \max(0, G_k) \quad (12)$$

$$\rho_k = \begin{cases} 1, & E_{\text{req},k} = 0, \\ \min\left(1, \frac{E_k - E_{\min}}{E_{\text{req},k} + \varepsilon}\right), & E_{\text{req},k} > 0, \end{cases} \quad \varepsilon = 10^{-8} \text{ J} \quad (13)$$

$$E_{k+1} = \text{clip}[E_k + \Delta t \dot{\mathbf{e}}_k^\top \mathbf{D}_k \dot{\mathbf{e}}_k - \rho_k E_{\text{req},k}, E_{\min}, E_{\max}] \quad (14)$$

Equation (11) calculates the additional energy generated by the adaptive update, and Equation (12) only retains the positive energy requirement. If $G_k \leq 0$, then $E_{\text{req},k} = 0$ the current update does not need to draw energy from the energy tank, ρ_k and takes 1 according to Equation (13). The system does not directly recover negative energy to avoid repeated calculations with damping dissipation. If $G_k > 0$, ρ_k it will scale continuously according to the remaining energy. Equation (14) restricts the energy state to $[E_{\min}, E_{\max}]$, where $E_{\min} = 0.05 \text{ J}$, $E_{\max} = 0.50 \text{ J}$, $E_0 = 0.25 \text{ J}$. This mechanism only constrains the adaptive outer layer and cannot replace the overall stability proof of the robot's inner loop and the environment.

2.5 Simulation Setup, Baseline Comparisons, and Changeover Evaluation

The experimental platform included Ubuntu 20.04, ROS Noetic, Gazebo Classic 11, and OSQP 0.6.3. The REASSEMBLE base repository was fixed at commit 432cc15ce3e028edc2f98a786f28bf6baf31ac6f. The physical simulation step size was 1 ms, the admittance outer loop frequency was 200 Hz, and the risk update frequency was 50 Hz. The study setup included fixed position B1, fixed admittance B2, instantaneous force adjustment B3, rule-based state machine B4, and the proposed method. B4 used the same pullback, hard threshold, and energy tank as the proposed method, but replaced the learned risk with an artificial force-moment-progress rule. The soft limits for axial force, lateral force, and lateral bending moment were 14 N, 8

N, and 0.9 N·m, respectively; the system stopped immediately when the axial force reached 18 N or the lateral force reached 11 N.

Table 1 lists the development distribution, combined disturbance and Gazebo high voltage connector characteristic conditions. Characteristic conditions increase sealing friction and insertion force, reduce mating clearance and add lateral loads from the thick wire harness. Previous studies have shown that the joint operation of connector and wire harness can cause traction and path constraints to interact [12]. This paper determines CPA locking by the slider displacement reaching 2.2 mm and lasting for 20 ms, HVIL closure by contact state and relative pose, and terminal displacement by elastic pair deformation. These three items are only used for simulation result evaluation, not as risk model input, and do not represent physical electrical testing. The task also requires an insertion depth of 15 mm and no hard stop triggered throughout the process. Each experiment contains 5 random seeds, and each random seed sets 40 paired scenarios. The constraint violation rate is the primary endpoint and the success rate is the secondary endpoint. Bootstrap uses random seeds as the first layer and scenarios as the second layer, combined with precise McNemar test and Holm correction.

This paper limits advanced manufacturing evaluation to algorithm changeover and process traceability within the same assembly unit. New objects are updated with 5, 10, or 20 trajectories to update temperature parameters and initial values of the online model. Object model, software version, risk peak, OOD status, number of pullbacks, and lockout results constitute candidate traceability fields. Equation (15) is used to calculate the changeover downtime percentage, where T_{cal} is the calibration time, T_{cyc} is the single-piece cycle, and N is the production batch size after the changeover. This indicator only reflects the downtime burden caused by data collection and parameter updates, and does not include tooling changes, program downloads, and first article inspections, nor can it be equated with OEE.

$$L_{chg}(N) = \frac{60T_{cal}}{60T_{cal} + NT_{cyc}} \quad (15)$$

Table 1. Gazebo Closed-Loop Operating Conditions and Characteristics of New Energy Connectors

parameter	Normal operating conditions	Combined disturbance conditions	Gazebo high voltage connector characteristic operating conditions
Position/Attitude Error	±0.4 mm / ±0.5°	±0.8 mm / ±1.5°	±1.0 mm / ±2.0°
static/dynamic friction coefficient	0.27/0.21	0.27—0.40 / 0.21—0.33	0.46/0.37
Equivalent fit clearance	0.35 mm	0.25—0.45 mm	0.15 mm
Steady-state axial insertion force	8.2 N	8.2—9.8 N	11.0 N
lateral load of wire harness	0	0—1.0 N	1.8 N
Control delay	0	10 ms	10 ms
Additional criteria	Depth, Limitation	Force Depth, Limitation	Force CPA, HVIL, terminal displacement

3. Research Results

3.1 Risk Model Evaluation and Contact Parameter Identification Results

Table 2 presents the main results of the risk model. The model's AUROC, AUPRC, Macro-F1, and ECE are 0.79, 0.55, 0.67, and 0.047, respectively. Temperature scaling reduced the Brier score from 0.188 to 0.165 but did not change the AUROC. The leave-one-connector-out AUROC is 0.69. This result indicates that local coordinate and schedule alignment can mitigate object discrepancies but cannot eliminate cross-structure degradation. The median lead time for short-term risks relative to the end of actions is 0.19 s, with an interquartile range of 0.10–0.31 s. The false alarm rate for sustained high risks is 18.8%. From a practical control perspective, this lead time is only sufficient to support short-term deceleration or reversal and cannot accommodate replanning of longer paths.

Table 2 also lists the contact parameter identification results. All 30 multi-starting-point searches entered the same low-loss region. The static friction, dynamic friction, stiffness, and damping were 0.27 [0.23, 0.31], 0.21 [0.18, 0.25], $8.4 [7.3, 9.6] \times 10^4$ N/m, and 86 [72, 101] N·s/m, respectively. The maximum correlation coefficient between friction and stiffness was 0.71, indicating that there is still a certain compensatory relationship between the two. The axial force RMSE of successful, stalled, and retraction trajectories was 0.82, 1.26, and 1.09 N, respectively. When the parameters varied within $\pm 10\%$, the change in peak lateral force did not exceed 4.8%, and the change in constraint violation rate did not exceed 3.0 percentage points.

Table 2. Results of Risk Identification and Exposure Parameter Identification

category	index	result	Scope of verification
Risk Model	AUROC/AUPRC/Macro-F1/ECE	0.79/0.55/0.67/0.047	Grouped test set
cross object	Leave-one-connector-out AUROC	0.69	Connector type held out from training
Static/Dynamic Friction	Point estimate [95% interval]	0.27[0.23,0.31]/0.21 [0.18,0.25]	500 Bootstraps
Stiffness/Damping	Point estimate [95% interval]	$8.4[7.3,9.6] \times 10^4$ N/m; 86[72,101] N·s/m	Multi-starting point identification
Cross-action error	Success/Stagnation/Drawdown RMSE	0.82/1.26/1.09 N	Independent verification trajectory

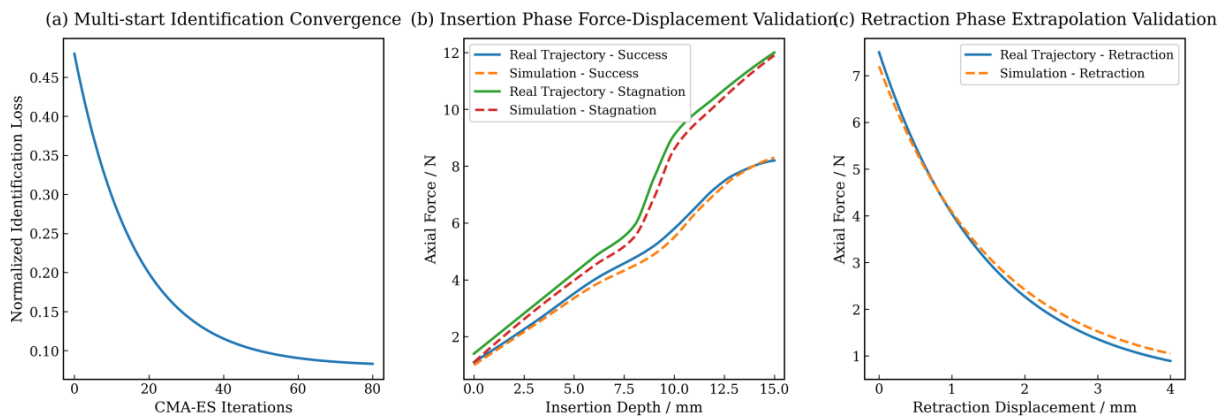


Figure 1. Contact parameter identification and cross-action verification.

(a) The blue solid line represents the representative CMA-ES normalized loss; (b) The blue and green solid lines represent the actual successful trajectory and the actual stalled trajectory, respectively, and the orange and red dashed lines represent the corresponding simulated trajectories; (c) The blue solid line and the orange dashed line represent the axial force of the actual pullback segment and the simulated pullback segment, respectively.

Figure 1 supplements the dynamic information that Table 2 cannot directly present. Figure 1(a) shows that the loss stabilizes after approximately 60 iterations. Figure 1(b) shows that the identification model can reproduce the different force-displacement changes between successful propulsion and frictional stagnation. The pullback segment in Figure 1(c) still has a small error, but the actual curve and the simulated curve have similar decay trends. It can be seen that the model can support relative comparisons between control methods, but it still cannot replace the dynamic verification of solid materials, locking structures, and terminal deformation.

3.2 Closed-Loop Insertion Control Performance and High-Voltage Feature Case Validation

Table 3(a) presents the results of the closed-loop master experiment. Under combined perturbations, the success rates of B1–B4 and the proposed method were 64.5%, 72.5%, 77.0%, 80.0%, and 83.0%, respectively. The difference in success rate between the proposed method and B4 was not statistically significant ($p=0.377$). In contrast, the constraint violation rate decreased from 24.0% to 18.5%, with a 95% confidence interval of 0.5–10.5 percentage points, and a Holm correction $p=0.031$; the median peak lateral force decreased from 7.18 N to 6.74 N, with a paired difference interval of 0.18–0.70 N, $p=0.006$. The task time increased from 1.64 s to 1.71 s, $p=0.004$. The results indicate that the controller more directly improves continuous mechanical constraints, rather than all discrete failure states.

The results for the Gazebo high-voltage characteristic operating condition are also listed in Table 3(a). The overall success rate of the proposed method is 74.0%, and that of B4 is 71.5%; the pass rates for CPA, HVIL, and terminal displacement constraints are 87.0%, 85.5%, and 91.0%, respectively. High-risk scenarios within the distribution account for 21.5%, and adaptive control mainly operates in this region. Low-risk and high-risk scenarios outside the distribution account for 5.0% and 2.0%, respectively; both types of states freeze model updates, with the latter directly entering a rollback or stopping phase. Since this operating condition only uses a parametric structural model, the above results are only used to observe the closed-loop degradation of the method in the face of structural changes.

Table 3 Closed-loop control and few-sample model change evaluation

(a) Closed-loop control master experiment					
method	Combination success rate / %	constraint violation rate / %	Peak lateral force / N	Task time/s	Gazebo high- pressure feature success rate /%
B1	64.5	47.0	9.21	1.50	57.5
B2	72.5	35.5	8.15	1.61	65.5
B3	77.0	29.5	7.59	1.60	69.0
B4	80.0	24.0	7.18	1.64	71.5
The proposed method	83.0	18.5	6.74	1.71	74.0

(b) Small sample size for transformation evaluation

Calibration Track Number	Replacement success rate / %	OOD trigger rate / %	Changeover time/min	Downtime percentage for batches of 500 pieces / %	Log overhead/ms
5	76.0	14.0	3.1	17.9	0.14
10	79.0	9.5	5.6	28.2	0.14
20	81.0	6.0	10.4	42.2	0.14

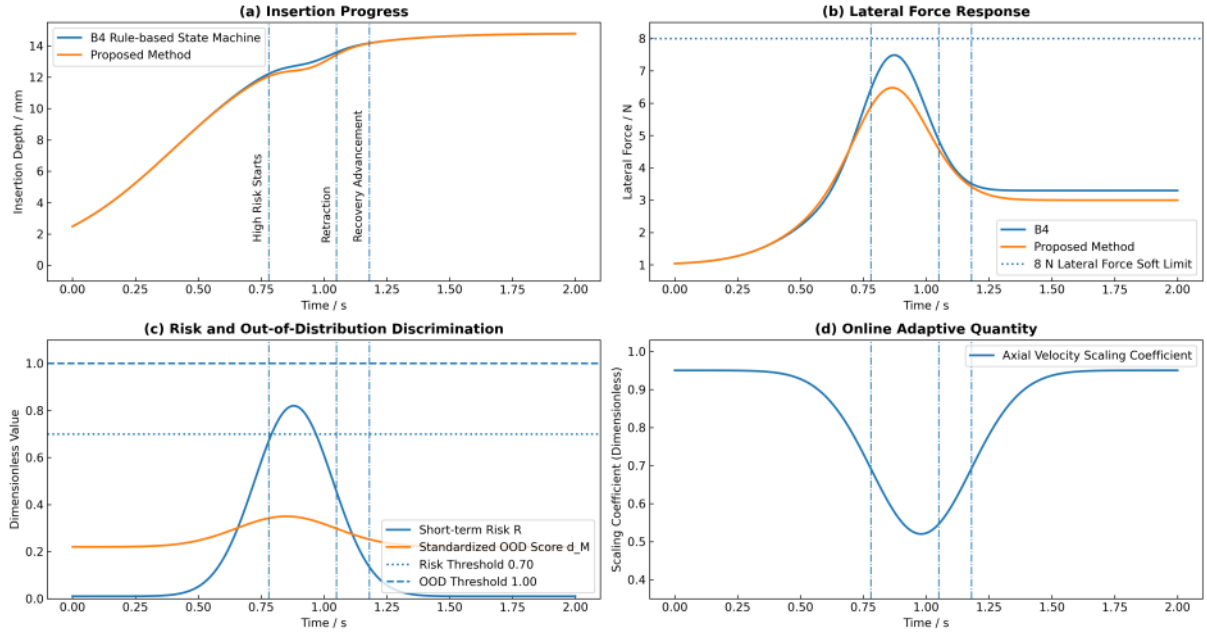


Figure 2. Representative closed-loop trajectories of B4 and the proposed method under combined perturbations.

(a) The blue solid line represents B4, and the orange solid line represents the proposed method. The vertical axis represents the insertion depth in mm. (b) The curve of the same color represents the lateral resultant force, and the blue dotted line represents the 8 N soft limit. (c) The blue solid line represents the short-term risk R , and the orange solid line represents the standardized OOD score d_M . The dotted and dashed lines represent the 0.70 and 1.00 thresholds, respectively. (d) The blue solid line represents the axial velocity scaling factor. The vertical dotted and dashed lines indicate the start of high risk, pullback, and recovery advance in sequence. R , d , and the velocity scaling factor are all dimensionless.

Figure 2 unfolds the overall differences in Table 3(a) into a specific closed-loop trajectory. After the high risk occurs, the proposed method temporarily reduces the advancement speed, and the peak value of the lateral force subsequently falls below B4. At this point, the OOD score has not exceeded the threshold, and the secondary programming can still be adjusted. After the pullback ends, the short-term risk gradually decreases, and the speed scaling factor also begins to recover. This process illustrates that risk tightening first acts on continuous constraints such as lateral force, while task time bears the corresponding cost.

3.3 Few-Shot Changeover Evaluation, Ablation Study, and Failure Mode Analysis

Table 3(b) presents the results of a small sample size change. After using 5, 10, and 20

trajectories for the new object, the success rate increased from 76.0% to 81.0%, the OOD trigger rate decreased from 14.0% to 6.0%, and the changeover time increased from 3.1 min to 10.4 min. Based on a single-piece cycle of 1.71 s and a batch size of 500 pieces, the changeover downtime rates were 17.9%, 28.2%, and 42.2%, respectively. The average, p99, and maximum solution times for quadratic programming were 0.86, 1.74, and 3.18 ms, respectively, all lower than the 5 ms control cycle; the log writing overhead was 0.14 ms. These results suggest that using 10 trajectories represents a more realistic trade-off between performance gain and changeover burden.

The ablation results further illustrate the roles of each module. Upon disabling online parameter updates or risk tightening, the constraint violation rates rose to 22.5% and 23.0%, respectively; when the drawdown constraint was removed, the success rate dropped to 79.5%. If the controller uses cumulative action risk, the old window before pullback will continuously increase the risk, increasing the task time by 0.11 s. After removing the energy tank, the proportion of non-zero relaxation variables and the peak value of stiffness changes both increased, but the success rate changed only slightly. Severe attitude errors, clamping slippage, and rotational locking still require repositioning or manual intervention; local admittance adjustment cannot cover these states.

4. Discussion

Contact assembly encompasses both continuous mechanical states and discrete task outcomes, and the responses of these two types of targets to local admittance adjustment differ. Propulsion velocity, lateral stiffness, and predicted force boundaries can directly alter edge contact loads but cannot correct large attitude errors, clamping slippage, or locking structure mismatches. Therefore, risk information is more suitable for tightening physical constraints than for direct mapping to control parameters. Constraint-based adjustment preserves variable range, solution feasibility, and energy budget, while also maintaining a clear separation between the learning module and traditional safety controls. Even if risk estimation is flawed, hard boundaries, relaxation penalties, and backoff rules still preserve minimum control constraints.

Online adaptation also requires in-distribution evidence. Cross-action identification and projection updates can absorb small-scale changes within the distribution, but once the contact pattern exceeds the development scope, continued updates may write unknown collisions into the model. At this point, the controller freezes parameters and enters a low-speed backoff, essentially reducing control authority. Existing identification still suffers from friction and stiffness compensation, and Gazebo cannot fully describe the hysteresis of sealing materials, plastic deformation of terminals, and viscoelasticity of wiring harnesses. Secondary programming and energy tanks can only constrain outer-layer instructions and cannot replace proof of overall stability.

This paper only discusses advanced manufacturing environments from the perspective of assembly unit-level changeover and process traceability. A small number of trajectories can reduce the proportion of unknown states, but calibration time will also occupy production line cycle time, especially affecting small batch orders. The operation log can serve as a candidate data source for the quality traceability system, but this paper does not verify tooling change, program switching, first article confirmation, and production line scheduling. Equation (15) only reflects the proportion of algorithm calibration time in a batch and cannot represent the complete changeover time or OEE. Subsequent reproduction still needs to supplement the physical CPA, HVIL, terminal damage, and actual total changeover time.

5. Conclusion

This paper proposes an adaptive admittance control method for contact risk in the characteristic assembly task of high-voltage connectors for new energy applications, and establishes a research

chain from real trajectory learning, cross-action parameter identification, online updating within the distribution, to simulation closed-loop control. The study yields two generalizable insights: risk information should be prioritized for tightening interpretable physical constraints, rather than directly generating velocity or impedance; online adaptation should only be performed when there is sufficient in-distribution evidence, and out-of-distribution states require frozen learning and restricted backoff. Current results are still based on simulation characteristic models; further experimental verification is needed for physical high-voltage connectors, complete changeover processes, and quality inspection.

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