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Research on Energy-Efficient Adaptive Processing Control Method for Industrial Robots Driven by Multi-Source Perception in Complex Working Conditions Toward Green Manufacturing

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Abstract. This paper provides an energy-efficient adaptive processing control algorithm design for robotic systems functioning in intricate grinding conditions. The testing system includes the following elements: ABB IRB 2600 industrial robot, ATI Mini45 six-axis force sensor, Basler acA1920-40gm industrial camera, Yokogawa WT310 power meter, and National Instruments USB-6363 data acquisition unit. Multiple signals – force, vision, electrical, and robotic movement – are acquired simultaneously in equal intervals of time. The robot performs 180-second grinding operations of 36 stainless steel test specimens possessing smooth, bent, and rough surfaces. Filtering is performed for the force and power signals (with frequency of 10 Hz) while images are processed with rate of 20 Hz. Logs of robotic movement are aligned by means of 0.1 seconds. Adaptive adjustment of feed rate, reference contact force, and rotation speed of the tool is implemented by using MATLAB/Simulink and RobotStudio tools. The adaptive algorithm results in reducing energy consumption by 13.8%, on average, compared to the case of constant control parameters (standard deviation of 2.6%, -13.8 ± 2.6%) while peak power decreases by 118.4 W (standard deviation of 24.7 W, -118.4 ± 24.7 W).

Keywords: Industrial robot, multi-source perception, adaptive control, energy efficiency, green manufacturing, processing optimization

1. Introduction

Industrial robots are widely used in grinding, polishing, deburring, and surface finishing because they provide programmable motion, repeatable tool paths, and stable execution under standardized manufacturing tasks [1]. With the rise of green manufacturing, energy consumption has become an important technical indicator in robotic processing, especially when robots operate for long cycles and repeated surface-treatment tasks [2]. In practical production, energy use is affected not only by robot trajectory but also by tool contact, force fluctuation, actuator load, surface geometry, and process disturbance. Fixed processing parameters can maintain simplicity, but they often fail to match changing working conditions.

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In complex grinding environments, the interaction between robot, tool, and workpiece changes continuously. Surface curvature affects tool contact posture. Roughness variation changes local resistance. Tool wear modifies the contact state. Motion disturbance affects trajectory tracking and joint loading. These conditions cause unnecessary energy consumption, unstable contact force, and inconsistent surface quality [3]. Recent robotic grinding and polishing studies show that adaptive parameter optimization, force control, and vision-based sensing can improve processing stability, but many systems still focus on either energy modeling or process quality separately [4, 5].

Multi-source perception provides a direct route for linking working-state recognition with energy-efficient control. Force data describe contact load and force fluctuation. Vision data record edge deviation, processed-zone texture, and surface uniformity. Electrical data reflect actuator demand and instantaneous energy loading. Position and motion logs show trajectory deviation and tracking disturbance [6, 7]. This paper proposes an adaptive processing control framework that integrates these perception channels into online state variables and uses them to update feed rate, reference contact force, and tool rotational speed. The research is implemented on a fixed robot grinding platform and evaluated through energy, process stability, and surface-quality indicators.

2. Literature review

2.1. Energy-efficient processing control of industrial robots

Energy-efficient robot processing research focuses on reducing energy consumption while maintaining task accuracy and productivity. Existing studies have examined robot selection, energy-aware trajectory planning, idle-time reduction, motor-load control, and data-driven energy prediction [1]. Recent work further applies LSTM-based prediction, hybrid model-driven and data-driven identification, and scoping reviews of energy consumption in industrial robotics [8]. These studies show that robot energy use is strongly linked to path execution, actuator load, joint dynamics, and control parameters. In surface processing tasks, energy consumption is also affected by contact state and material removal resistance.

2.2. Multi-source perception in complex manufacturing conditions

Multi-source perception combines heterogeneous sensing channels to describe robot-task-environment interaction during manufacturing. In robotic grinding and polishing, force sensors measure contact stability, vision sensors detect geometric deviation and surface condition, power meters capture electrical loading, and robot motion logs describe path-tracking status. Laser vision and force-related sensing have been applied to robotic weld-seam grinding, curved surface processing, and contact-force control [4-7]. Sensor fusion is important because single-channel feedback cannot fully represent complex processing conditions. Force fluctuation may indicate contact instability, while vision deviation may indicate surface or path error. Electrical signals can further reveal hidden load changes that are not visible from trajectory data alone.

2.3. Adaptive control for green manufacturing

Adaptive control in green manufacturing updates process variables according to feedback signals from the working environment. In robotic grinding and polishing, adaptive schemes commonly adjust feed rate, contact force, impedance parameters, tool posture, or tool speed according to force, position, vision, or energy-related signals [5, 6]. Recent studies on robotic machining and industrial

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robot energy consumption indicate that adaptive control can connect process stability with energy reduction when control parameters are updated during execution rather than fixed offline [8, 9]. However, effective adaptive control requires clearly defined process-state variables, synchronized sensory inputs, fixed update rules, and measurable links between energy indicators and surface-quality outputs [10].

3. Experimental methodology

3.1. Experimental platform and data acquisition configuration

The test bed is made up of an ABB IRB 2600 industrial robot, an ATI Mini45 6-axis force sensor, a Basler acA1920-40gm industrial camera, a Yokogawa WT310 power meter, and a National Instruments USB-6363 data acquisition module. The robot does robotic grinding on stainless steel work pieces that are flat, curved or unevenly rough. The robot path is programmed using the ABB RobotStudio 2024 software and the initial processing parameters are set at feed rate 45 mm/s, reference normal contact force 30 N and tool rotational speed 4200 rpm. The ATI Mini45 sensor is used to measure force data and includes normal force, tangential force, torque components and force fluctuation. Acquisition frequency is synchronized at 100 Hz by using the USB-6363 module. The Basler industrial camera records grayscale images of the part edge and processed zone at 20 fps and the image resolution is fixed at 1920 × 1200 pixels. The Yokogawa WT310 power meter measures voltage, current, active power, and cumulative energy at 100 Hz. Robot movement logs are exported out of RobotStudio with end-effector location, joint speeds, trajectory errors, and tracking errors. All signals are saved per trial ID, workpiece ID, time stamp, sensor channel and processing stage. Unified data set comprises raw sensor streams, filtered signals, extracted features, adaptive control commands, energy indicators, and post-processing surface-quality measurements. Every 180 s trial is subdivided into 0.1 s control cycles and provides 1800 synchronized control samples per workpiece.

3.2. Multi-source feature construction and process state variables

Signal processing is performed in Python 3.11 using NumPy, pandas, OpenCV, SciPy, and scikit-learn. Force signals are filtered with a fourth-order Butterworth low-pass filter using a 10 Hz cutoff frequency. Force-based features include mean normal force, normal force deviation, tangential force magnitude, force variation magnitude, contact force variance, and force peak count within each 0.1 s cycle. Force deviation is calculated relative to the reference normal contact force.

Vision-based features are extracted from cropped processing-region images. OpenCV is used to calculate edge deviation, processed area intensity homogeneity, local texture contrast, processed-zone boundary consistency, and surface extraction stability. Edge deviation is measured as the pixel distance between the detected processed boundary and the nominal tool path projection. Texture contrast is computed from gray-level co-occurrence features within the processed zone. Surface extraction consistency is calculated from frame-to-frame boundary stability.

Electrical features include active power, current magnitude, energy increment per cycle, power variation coefficient, and short-term peak power. Robot motion features include end-effector velocity, joint speed variance, trajectory deviation, position tracking error, and acceleration fluctuation.

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3.3. Adaptive control model and energy optimization rules

The adaptive controller is implemented in MATLAB/Simulink R2024a and linked with ABB RobotStudio through a cycle-level command interface. The controller updates three parameters: feed rate, reference contact force, and tool rotational speed. The control cycle is fixed at 0.1 s. For each cycle, Python computes the four state variables and sends them to MATLAB/Simulink. The controller then generates updated parameter commands and records the command value, triggering condition, and state-variable value.

The integrated process-state vector is calculated as shown in Equation (1):

$$\Psi_t = [\omega_f \frac{|F_n(t)-F_r|}{F_r} + \omega_e \frac{\sigma_F(t)}{\overline{F_n}(t)+\epsilon}]CSI_t + [\omega_s(1-H_f(t)) + \omega_e E_d(t) + \omega_e C_T(t)]SAI_t \quad (1)$$

$$+[\omega_m T_d(t) + \omega_j J_v(t) + \omega_p P_e(t)]MDI_t + [\omega_q \frac{P(t)}{P_{ref}} + \omega_i \frac{I(t)}{I_{ref}} + \omega_M \Delta E_i]ELI_t$$

where CSI_t, SAI_t, MDI_t, and ELI_t denote contact stability, surface adaptability, movement disturbance, and energy loading states. $F_n(t)$ is normal force, F_r is reference force, $\sigma_F(t)$ is short-term force variation, $E_d(t)$ is edge deviation, $C_T(t)$ is texture contrast, $T_d(t)$ is trajectory deviation, $J_v(t)$ is joint speed variance, $P_e(t)$ is position error, $P(t)$ is active power, $I(t)$ is current magnitude, and ΔE_i is energy increment.

The controller reduces feed rate when motion disturbance exceeds 0.65, increases reference force when contact stability falls below 0.50, lowers tool speed when energy loading is high while surface adaptability remains acceptable, and increases tool speed when surface adaptability is low but contact stability remains sufficient.

4. Experimental procedure

4.1. Workpiece preparation, task arrangement, and sensor calibration

The experiment involves working with 36 pieces of stainless steel that are separated into three types of surface condition: 12 pieces with flat surfaces, 12 pieces with curved surfaces, and 12 pieces with uneven rough surfaces. All workpieces are ethanol cleaned prior to processing and have the same nominal grinding path. All workpieces use the same abrasive head, tool mounting angle and starting robot posture. The grinding path length is kept constant at 480 mm and each trial takes 180 s. The force sensor is calibrated with a static load sequence of 5 N, 10 N, 20 N, 30 N, and 40 N. Calibration of cameras is done on a fixed checkerboard template and the conversion factor between pixels and distance is measured prior to image processing. The no-load condition of the robot during stand-by is set to zero power meter.

4.2. Data preprocessing, state recognition, and control execution

Raw force and power signals are synchronized by timestamp and resampled to the 0.1 s control cycle (see in Figure 1). Force and power channels are filtered with a fourth-order Butterworth low-pass filter at 10 Hz. Image frames are cropped to the same processing region, converted to grayscale, and processed with edge detection, texture extraction, and intensity homogeneity calculation. Robot motion logs are exported from RobotStudio and matched to the same 0.1 s interval.

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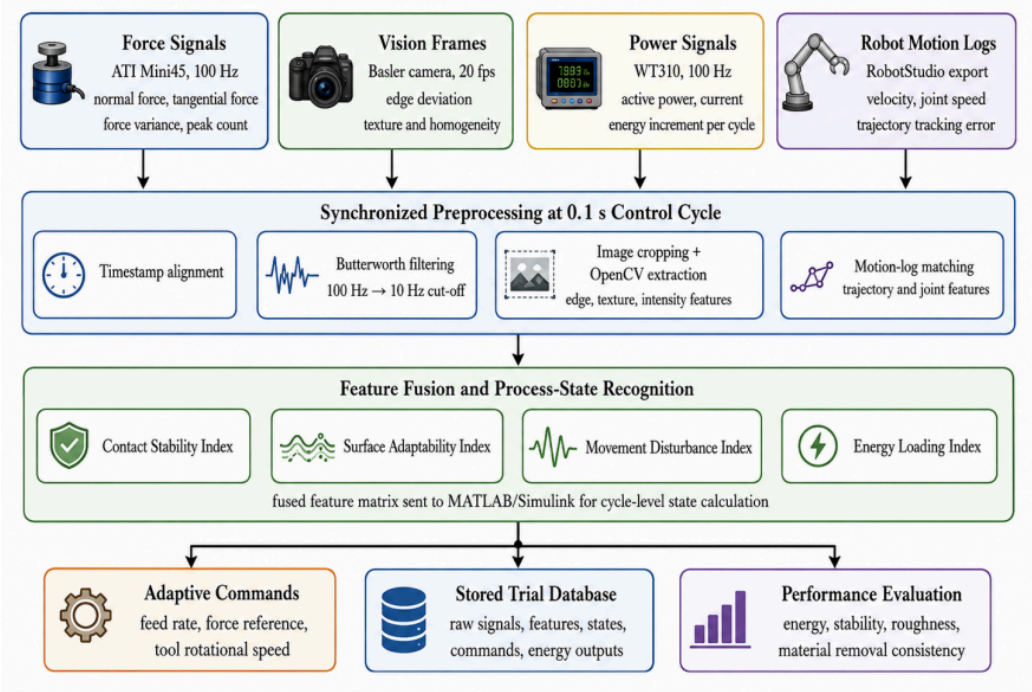


Figure 1. Data preprocessing and state recognition workflow

The fused feature matrix is sent to MATLAB/Simulink for online state calculation. For each cycle, the system computes contact stability index, surface adaptability index, movement disturbance index, and energy loading index. When a threshold condition is satisfied, the corresponding control rule updates feed rate, contact force, or tool rotational speed. All commands are written back to the ABB controller. Raw signals, feature values, state variables, control commands, energy outputs, and surface-quality results are saved into one trial-level database.

4.3. Evaluation protocol and comparative experiment settings

The experiment includes two control groups: baseline fixed-parameter control and multi-source adaptive control. Both groups use the same 36 workpieces, tool type, robot path, processing duration, and initial parameter settings. For each trial, energy indicators include total energy consumption, specific energy consumption, average active power, peak power, and energy increment per cycle. Process stability indicators include normal force deviation, force variance, trajectory deviation, tracking error, and control command frequency. Surface quality is measured after processing using a Mitutoyo SJ-210 roughness tester. Surface indicators include surface roughness Ra, roughness standard deviation, material removal consistency, and processed-zone texture uniformity. Each workpiece is measured at five equally spaced points along the processed path, and the average value is used as the trial result. Statistical comparison is conducted in Python and MATLAB. Paired tests are applied between baseline and adaptive trials under the same surface-condition group.

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5. Experimental results

5.1. Multi-source perception statistics under different working conditions

Multi-source signals varied strongly across surface conditions. Curved surfaces showed higher trajectory deviation at 0.42 ± 0.09 mm, while uneven rough surfaces produced the largest normal force variance at 18.6 ± 3.7 N^2 and the highest power variation coefficient at 0.143 ± 0.026. Flat surfaces remained more stable, with force deviation of 2.8 ± 0.6 N and trajectory deviation of 0.18 ± 0.04 mm (see Table 1). The mechanism pattern indicates that geometric curvature mainly increases motion disturbance, while roughness mainly increases contact and energy loading instability.

Table 1. Multi-source perception statistics under different working conditions

Surface Condition	Normal Force Deviation (N)	Trajectory Deviation (mm)	Power Variation Coefficient	Edge Deviation (pixel)	Energy Loading Index
Flat Surface	2.8 ± 0.6	0.18 ± 0.04	0.071 ± 0.014	4.7 ± 1.2	0.42 ± 0.06
Curved Surface	4.9 ± 0.9**	0.42 ± 0.09***	0.104 ± 0.019**	8.9 ± 1.8***	0.57 ± 0.08**
Uneven Rough Surface	6.3 ± 1.1***	0.35 ± 0.07**	0.143 ± 0.026***	7.6 ± 1.5**	0.68 ± 0.09***

5.2. Comparative results of energy consumption and process stability

Compared with fixed-parameter control, multi-source adaptive control reduced total energy consumption from 142.6 ± 11.8 Wh to 122.9 ± 9.7 Wh**, and specific energy consumption decreased from 3.84 ± 0.41 Wh/cm^2 to 3.29 ± 0.36 Wh/cm^2**. Peak power decreased by −118.4 ± 24.7 W***. Normal force deviation decreased from 5.1 ± 1.0 N to 3.4 ± 0.8 N**, and trajectory deviation decreased from 0.36 ± 0.08 mm to 0.24 ± 0.06 mm**.

5.3. Surface quality and overall performance under adaptive control

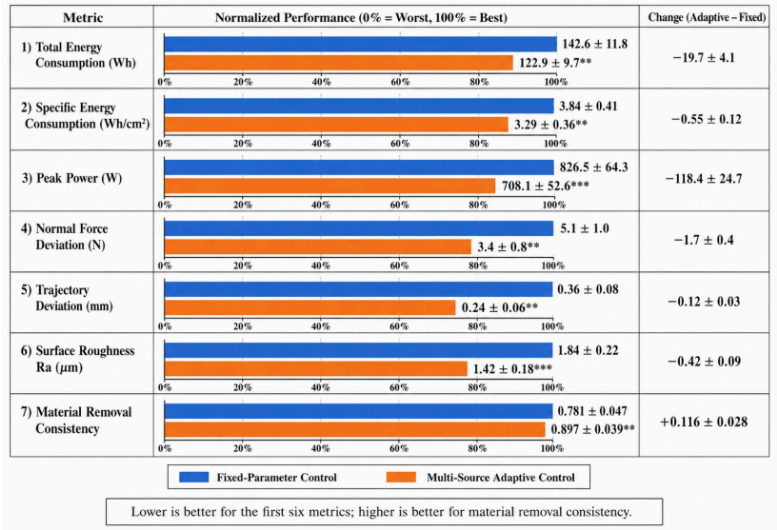


Figure 2. Comparative performance between fixed-parameter and adaptive control

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Adaptive control improved surface quality while reducing energy use. Surface roughness Ra decreased from 1.84 ± 0.22 μm to 1.42 ± 0.18 μm***, and material removal consistency increased by +0.116 ± 0.028** (see Figure 2). The combined mechanism is that force feedback stabilizes contact, vision feedback limits path-surface mismatch, and power feedback suppresses excessive tool speed under high-load conditions. Energy saving therefore does not occur through parameter reduction alone, but through synchronized correction of contact, trajectory, and tool-speed states.

6. Conclusion

The study establishes an energy-efficient adaptive processing control method for industrial robots under complex grinding conditions. The framework integrates force sensing, vision sensing, electrical monitoring, and robot motion feedback into four process-state variables: contact stability, surface adaptability, movement disturbance, and energy loading. The adaptive controller updates feed rate, reference contact force, and tool rotational speed at 0.1 s intervals according to fixed state thresholds and parameter-update rules. Experimental results show that adaptive control reduces energy consumption, suppresses peak power, improves force and trajectory stability, and enhances final surface quality. The mechanism is based on coordinated correction rather than simple parameter reduction. Force perception stabilizes contact, vision perception identifies surface-path mismatch, motion feedback reduces disturbance, and electrical signals prevent unnecessary high-load operation. The results indicate that multi-source perception-driven adaptive control can support green manufacturing by connecting energy reduction with process stability and surface-quality maintenance.

References

[1] Soori, M., Arezoo, B., & Dastres, R. (2023). Optimization of energy consumption in industrial robots, a review. *Cognitive Robotics, 3*, 142–157.
[2] Jiang, P., Wang, Z., Li, X., Wang, X. V., Yang, B., & Zheng, J. (2023). Energy consumption prediction and optimization of industrial robots based on LSTM. *Journal of Manufacturing Systems, 70*, 137–148.
[3] Jiang, P., Zheng, J., Wang, Z., Qin, Y., & Li, X. (2025). Industrial robot energy consumption model identification: A coupling model-driven and data-driven paradigm. *Expert Systems with Applications, 262*, 125604.
[4] Ge, J., Deng, Z., Li, Z., Liu, T., Zhuo, R., & Chen, X. (2023). Adaptive parameter optimization approach for robotic grinding of weld seam based on laser vision sensor. *Robotics and Computer-Integrated Manufacturing, 82*, 102540.
[5] Ke, X., Yu, Y., Li, K., Wang, T., Zhong, B., Wang, Z., Kong, L., Guo, J., Huang, L., Idir, M., Liu, C., & Wang, C. (2023). Review on robot-assisted polishing: Status and future trends. *Robotics and Computer-Integrated Manufacturing, 80*, 102482.
[6] Zhou, H., Ma, S., Wang, G., Deng, Y., & Liu, Z. (2021). A hybrid control strategy for grinding and polishing robot based on adaptive impedance control. *Advances in Mechanical Engineering, 13*(3), 16878140211004034.
[7] Li, J., Guan, Y., Chen, H., Wang, B., Zhang, T., Hong, J., & Wang, D. (2022). Real-time normal contact force control for robotic surface processing of workpieces without a priori geometric model. *The International Journal of Advanced Manufacturing Technology, 119*, 2537–2551.
[8] Muru, J., & Rassõlkin, A. (2025). A scoping review of energy consumption in industrial robotics. *Machines, 13*(7), 542.
[9] Wang, M., Chen, K., Wang, P., Song, Y., & Sun, T. (2024). Teleoperation mode and control strategy for the machining of large casting parts. *Robotics and Computer-Integrated Manufacturing, 86*, 102690.
[10] Chang, Q., Li, L., Li, Y., Huang, Z., & Xu, X. (2024). A data-driven method for predicting and optimizing the energy consumption of industrial robots. *Actuators, 13*(12), 516.