Chapter 06 / Capítulo 06

Next-Generation Industrial Engineering: Artificial Intelligence, Smart Manufacturing, and Sustainable Industrial Engineering
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Integration of Artificial Intelligence and Robotics in Industrial Engineering

Integración de Inteligencia Artificial y Robótica en Ingeniería Industrial

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ABSTRACT

Modern industrial engineering is undergoing a cognitive transformation driven by the integration of artificial intelligence (AI), fuzzy logic, and stream-based control architectures. This chapter presents the design and experimental validation of an intelligent robotic control system that unifies computer vision technologies, AI inference modules, and the Node-RED orchestration environment. The proposed model establishes a closed cognitive control loop — perception, reasoning, and action — operating in real time. Cameras capture object positions, the AI module determines spatial coordinates and orientation, while a fuzzy controller based on the product t-norm computes optimal grasping parameters. Node-RED provides seamless stream-level integration of all subsystems and transmits adaptive commands to industrial robots through standard protocols such as MQTT and Modbus/TCP.

Experimental results obtained from 180 test cycles demonstrated a 45–50 % reduction in positional and angular errors, a 36 % decrease in system response time, a 16 % increase in grasping accuracy, and a 12 % reduction in energy consumption compared with classical PID control. These findings confirm the efficiency of the AI-Fuzzy-Node-RED architecture, which combines interpretability, low-latency execution, and energy efficiency. The developed system ensures transparent synchronization among perception, decision-making, and actuation layers and can be reproduced on standard industrial platforms without modifying PLC code.

The research shows that integrating AI, fuzzy logic, and Node-RED creates a foundation for intelligent, adaptive, and sustainable manufacturing systems aligned with the principles of Industry 4.0 and Industry 5.0. Such systems enable robotic complexes to operate autonomously, collaborate with humans, and optimize production processes dynamically in real-time industrial environments.

Keywords: Industrial Engineering; Artificial Intelligence; Fuzzy Logic; Node-RED; Computer Vision; Intelligent Control; Cognitive Robotics; Industry 4.0; Industry 5.0.

RESUMEN

La ingeniería industrial moderna está experimentando una transformación cognitiva impulsada por la integración de la inteligencia artificial (IA), la lógica difusa y las arquitecturas de control basadas en flujos. Este capítulo presenta el diseño y la validación experimental de un sistema de control robótico inteligente que unifica tecnologías de visión artificial, módulos de inferencia de IA y el entorno de orquestación Node-RED. El modelo propuesto establece un bucle cerrado de control cognitivo (percepción, razonamiento y acción) que opera en tiempo real. Las cámaras capturan la posición de los objetos, el módulo de IA determina las coordenadas espaciales y la orientación, mientras que un controlador difuso basado en la norma t del producto calcula los parámetros óptimos de agarre. Node-RED proporciona una integración fluida a nivel de flujo de todos los subsistemas y transmite comandos adaptativos a los robots industriales mediante protocolos estándar como MQTT y Modbus/TCP.

Los resultados experimentales obtenidos a partir de 180 ciclos de prueba demostraron una reducción del 45-50 % en los errores de posición y angulares, una disminución del 36 % en el tiempo de respuesta del sistema, un aumento del 16 % en la precisión de agarre y una reducción del 12 % en el consumo de energía en comparación con el control PID clásico. Estos hallazgos confirman la eficiencia de la arquitectura AI-Fuzzy-Node-RED, que combina interpretabilidad, ejecución de baja latencia y eficiencia energética. El sistema desarrollado garantiza una sincronización transparente entre las capas de percepción, toma de decisiones y actuación, y puede reproducirse en plataformas industriales estándar sin modificar el código PLC.

La investigación demuestra que la integración de IA, lógica difusa y Node-RED sienta las bases para sistemas de fabricación inteligentes, adaptativos y sostenibles, alineados con los principios de la Industria 4.0 y la Industria 5.0. Estos sistemas permiten que los complejos robóticos operen de forma autónoma, colaboren con humanos y optimicen dinámicamente los procesos de producción en entornos industriales en tiempo real.

Palabras clave: Ingeniería Industrial; Inteligencia Artificial; Lógica Difusa; Node-RED; Visión Artificial; Control Inteligente; Robótica cognitiva; Industria 4.0; Industria 5.0.

INTRODUCTION

Modern industrial engineering is undergoing a profound transformation driven by the intellectualization of manufacturing processes. Traditional automated systems designed to execute rigid, pre-programmed tasks are gradually being replaced by adaptive, self-learning, and interconnected cyber-physical systems. At the heart of this evolution lies the synergy between artificial intelligence (AI) and robotics, which has become a key enabler of the Industry 4.0 paradigm and the foundation for the emerging Industry 5.0 concept.(1)

The integration of AI and robotic systems makes it possible not merely to automate operations but to endow machines with elements of cognitive behavior—the ability to perceive the environment, analyze changes, and make autonomous decisions. While robotics provides the means for physical actuation, AI adds a cognitive layer responsible for perception, prediction, and adaptation. The convergence of these domains defines a new discipline—intelligent industrial engineering—where design, control, and optimization of production systems are based on data-driven methods and machine learning.(2)

One of the most promising directions of this integration is the use of Node-RED platforms, which offer visually oriented tools for designing the logic of interaction between sensors, AI modules, and actuators.[3] Owing to its modular architecture, Node-RED enables flexible interconnection of system components: cameras and sensors transmit data to AI modules, which analyze images and object states and generate control commands subsequently transmitted to robots. This approach is particularly critical in dynamic manufacturing environments, such as conveyor systems, where object position and orientation vary in real time. The interaction among perception, decision-making, and actuation represents a central challenge in modern industrial engineering.[4] Most current robotic solutions still operate under rigid control scripts and lack the capacity for self-adaptation. However, the increasing complexity and variability of manufacturing processes demand new system properties—flexibility, predictability, and autonomy. In this context, AI and Node-RED function as integrative components that facilitate the transition from reactive to proactive process control.

Intelligent industrial robots equipped with computer-vision systems can analyze product quality in real time, detect deviations, verify assembly accuracy, and autonomously adjust their actions. Such capabilities are already being adopted by leading manufacturing corporations—Siemens, ABB, KUKA, and FANUC—which embed machine-learning algorithms into controllers and manipulators to improve positional precision and reduce energy consumption.[5] Moreover, integration with Node-RED and similar environments allows for remote control, diagnostics, and equipment monitoring through unified cloud-based interfaces.

Nevertheless, several scientific and technical challenges still limit large-scale deployment of AI–robotic systems in industrial engineering. These include:

1. Complexity of integrating heterogeneous systems and communication protocols.
2. The need for standardized datasets for neural-network training.
3. Constraints in real-time computational resources.
4. Issues of interpretability and trust in AI-based decisions.
5. Insufficient training of engineers for hybrid AI–robotic infrastructures.[6]

In response, the research community has emphasized the development of unified architectures that ensure scalability, compatibility, and transparency in AI–robotic interaction. One promising solution is the implementation of such architectures using the stream-based visual programming environment Node-RED, capable of integrating machine vision, sensor data, machine learning, and actuator control within a single feedback loop.

The objective of this chapter is to present a conceptual and applied model for integrating artificial intelligence and robotics in industrial engineering through Node-RED. The chapter is structured as follows:

- Theoretical foundations of AI–robotics interaction in cyber-physical production systems.
- Architecture of the proposed control system, including perception, analysis, and decision-making modules.
- Methods for implementing data exchange via Node-RED.
- Results of simulation and real-time experiments on industrial manipulator control.

The developed system employs computer-vision technologies (OpenCV + TensorFlow / YOLO) to identify objects, analyze their position and orientation, and then generate control signals for the robotic manipulator via Node-RED. This ensures adaptive system behavior, allowing the robot to autonomously adjust its grasp trajectory in response to object movement or orientation changes.

Thus, the research builds upon the paradigm of cognitive automation, where the essential characteristic is not merely task execution but the system's ability to perceive, interpret, and learn. The development of such technologies has strategic importance for both national and global economies, as intelligent production systems form the backbone of sustainable smart factories, minimizing human intervention while improving energy efficiency.

The contribution of this work lies in uniting theoretical advancements in AI and robotics with the practical flexibility of Node-RED to create accessible, modular, and cost-effective industrial automation solutions. The presented framework establishes the basis for the subsequent sections of this chapter:

- Methods (system structure and algorithmic implementation).
- Results (simulation and experimental validation).
- Discussion (evaluation of efficiency and limitations).
- Conclusion (forecast of intelligent industrial system development toward 2030).

LITERATURE REVIEW

Integration of AI and Robotics in the Context of Industry 4.0

Modern cyber-physical manufacturing systems demand that robotics provide not only high repeatability but also adaptability—capable of scene perception, uncertainty interpretation, and real-time grasp adjustment. Comprehensive reviews on learning-based robotic grasping emphasize that the transition from rigid programming to AI-based (especially deep-learning) methods significantly enhances robustness to variations in object pose and shape, as well as sensor noise, while increasing demands on data infrastructure and subsystem integration.(7)

Node-RED as a Stream-Oriented Platform for Industrial Integration

In industrial engineering, Node-RED serves as a lightweight, visually oriented "middleware" connecting sensors (cameras, 3D sensors), AI modules (local or cloud-based), and robots/PLCs through standard protocols such as MQTT, Modbus/TCP, and OPC UA. Studies show that Node-RED simplifies interoperability among heterogeneous devices and enables rapid creation of data and control flows for IIoT/SCADA scenarios, digital twins, and edge analytics, which is essential for prototyping and for deploying these flows to industrial edge gateways.(8)

In robotics, Node-RED acts as a visual orchestration layer connecting image sources, preprocessing/detection nodes, and end-effectors. Publications describe both direct control via Modbus/PLC and hybrid Node-RED ↔ ROS architectures, where ROS handles low-level kinematics and motion planning, while Node-RED coordinates dataflows, HMI, and communication with AI services (local or cloud).(9)

Computer Vision for Robotic Grasping: From Classical to Learning-Based Methods

Survey studies indicate a clear trend: from classical feature-based approaches to CNN-based detectors (YOLO, Faster/Mask R-CNN), and further toward reinforcement-learning or imitation-learning-based control policies. This transition increases robustness to background changes, lighting, and occlusions but imposes requirements on labeled datasets, computational resources, and the camera → inference → robot pipeline latency to preserve closed-loop control.(10)

For industrial applications with constrained computational budgets and a need for explainable decision-making, Fuzzy Logic Controllers (FLCs) remain relevant. FLC rules are easily validated by process engineers, while approximations of uncertainties (e.g., fuzzy positions/angles) are handled transparently.(11)

Product t-Norm Fuzzy Rules in Camera-Based Grasping Tasks

Earlier and more recent studies on fuzzy-logic-based grasping demonstrate that the t-norm (product) operator, used as a conjunction in rules such as IF (object detected with confidence μ_1) AND (alignment adequate μ_2) AND (friction sufficient μ_3) THEN (grip force/speed = …) enables smooth transitions of control actions as membership values μ_i vary. This is particularly valuable in conveyor systems where object positions continuously change. Comparative analyses of FLC structures with various membership functions (triangular, Gaussian, etc.) confirm that fuzzy logic improves noise robustness and simplifies parameter tuning, especially in camera → FIS → gripper pipelines.(12)

Meanwhile, hybrid DL + Fuzzy Logic approaches are emerging, where CNN-based perception provides pose or class estimation and prior contact parameters, while FLC modules compute force and/or velocity outputs. These hybrid models maintain interpretability and stability against neural-network overconfidence, improving scene uncertainty resilience in humanoid and collaborative robots.(13)

Integration Pattern "Camera → AI/FIS → Node-RED → Robot"

A consistent engineering pattern has been established:

1. Vision: camera streams (GigE/USB/CSI) are preprocessed (normalization, segmentation); object detection or pose estimation models output coordinates (x,y,θ), confidence (μ_{det}), and physical attributes (class, friction, rigidity).(14)
2. Fuzzy Logic (FIS): membership functions are computed for alignment, distances, and allowed angles; product t-norm rules aggregate these conditions and output control terms (e.g., *soft grasp*, *reorientation*, *retry*), which are then defuzzified (centroid/weighted average) into continuous control commands (forces, speeds, contact times).(15)
3. Node-RED Orchestration: flow nodes receive FIS/vision outputs, form adaptive commands, and publish them via MQTT/REST/Modbus to robot controllers or ROS bridges. Simultaneously, HMIs, logging, and telemetry to edge/cloud layers are implemented for monitoring and digital twins.(16)

Empirical IIoT/SCADA case studies indicate that Node-RED at edge nodes lowers integration barriers across multi-vendor PLCs/sensors and simplifies AI-driven control deployment (with scalability toward the cloud). This allows for precise latency tuning and QoS prioritization, which are critical for closed-loop grasping control.(17)

Research Gaps and Challenges

Despite growing empirical validation, several challenges remain:

1. Formalizing end-to-end latency in hybrid control loops combining edge AI + Node-RED + industrial PLCs.
2. Validating fuzzy-rule sets under real-world pose/friction distributions.
3. Establishing safety and explainability standards for collaborative work cells.
4. Developing hardware-in-the-loop (HIL) testing methods for Node-RED flows prior to deployment.
5. Addressing the shortage of open datasets linking vision-to-grasping tasks comparable to industrial conditions.(18)

METHOD

Methodological Framework

The methodological design of this research follows a multiple-case study approach consistent with Yin's design theory and applied robotics methodology.[18] The purpose is not only to describe single implementations of AI and Node-RED-based robotic integration, but to identify general mechanisms that enable successful convergence of stream-based orchestration, fuzzy-logic inference, and sensor-driven decision modules in industrial environments.[19,20]

The central hypothesis states that the combined architecture AI + Fuzzy Logic + Node-RED significantly increases the accuracy and stability of robotic object grasping under variable shape and position conditions compared to classical PID control ($p < 0,05$).[21] A mixed-methods approach was employed:[22]

- Quantitative analysis — measuring angular deviation (°), grasping force (N), and response delay (ms) in multi-object scenarios.
- Qualitative analysis — expert evaluation of Node-RED flow logic in industrial interoperability and human–machine interface usability.[23]
- Decision modeling — fuzzy-rule sensitivity analysis with respect to input variables such as illumination, conveyor velocity, and object mass.[24]

System Architecture and Data Flow

The architecture comprises four interconnected subsystems:[23]

1. Computer vision (camera + OpenCV / YOLO).
2. AI inference (object identification and pose estimation).
3. Fuzzy Inference System (FIS).
4. Stream orchestration via Node-RED and Modbus/TCP interface to the robotic controller.

The camera provides real-time images at 30 fps. The feature vector of the detected object is defined as:

$$x(t) = [x_c, y_c, \theta, \mu_{\text{det}}],$$

Where x_c, y_c are centroid coordinates, θ is the rotation angle, and μ_{det} is the detection confidence. The vector x(t) is processed by the AI module and passed to the fuzzy logic controller, which computes the adaptive gripping velocity and force.[25]

Mathematical Model of Fuzzy Control

Membership Functions

Each linguistic variable is represented by triangular or Gaussian membership functions.[24] For example, the triangular function is defined as:

$$\mu_A(x) = \begin{cases} 0, & x \le a, \\ \dfrac{x-a}{b-a}, & a < x \le b, \\ \dfrac{c-x}{c-b}, & b < x \le c, \\ 0, & x \ge c. \end{cases}$$

Where (a,b,c) are the boundary points of the fuzzy term (e.g., *small deviation*, *medium*, *large*).

Product t-Norm Fuzzy Rules
To aggregate conditions, a **product t-norm** was applied:[25]

$$\mu_{\mathrm{AND}}(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} \mu_i(x_i).$$

The fuzzy rules are expressed as:

$$R_k : \mathrm{IF}\ (E_\theta = A_i)\ \mathrm{AND}\ (E_d = B_j)\ \mathrm{THEN}\ (U = C_{ij}),$$

Where (E_θ) – angular error, (E_d) – distance error, and (U) – control output (grip speed). The aggregated output membership is computed as:

$$\mu_U(u) = \max_k \left[\mu_{A_i}(E_\theta) \times \mu_{B_j}(E_d) \times \mu_{C_{ij}}(u) \right],$$

And the defuzzified control signal is obtained via the center-of-gravity method:[26]

$$u^* = \frac{\int u \mu_U(u) du}{\int \mu_U(u) du}.$$

Node-RED Integration
In Node-RED, the control logic is implemented as a sequential flow:

1. Input node – receives camera data via MQTT or HTTP;
2. AI node – performs object detection or pose estimation;
3. FIS node – applies fuzzy rules and product t-norm aggregation;
4. Output node – sends adaptive commands to the robot via Modbus/TCP.[19,23]

An example of the FIS node logic is shown below:

- var mu1 = Math.exp(-Math.pow(msg.payload.err_angle/15,2)).
- var mu2 = Math.exp(-Math.pow(msg.payload.err_dist/20,2)).
- var muAND = mu1 * mu2;   // product t-norm
- msg.payload.u = 100 * muAND; // grip speed command
- return msg

This logic guarantees continuous adaptation and real-time response, consistent with industrial latency requirements (<100 ms).[21,23]

Experimental Parameters and Data Analysis
The experiment was conducted on a 6-DOF robotic arm with a pneumatic gripper and a USB camera (resolution 640×480). The principal parameters are summarized in table 1.[22,24]

Table 1. Experimental parameters

Parameter	Symbol	Value	Unit
Frame rate	f_c	30	fps
Processing latency	t_p	65	ms
Mean position error	E_d	1,8	mm
Mean angular error	E_θ	2,3	°
System response time	T_r	0,18	s

The integrated grasping-quality index was defined as:

$$Q=\alpha_1\left(1-\frac{E_d}{E_{d,\max}}\right)+\alpha_2\left(1-\frac{E_\theta}{E_{\theta,\max}}\right)+\alpha_3\left(1-\frac{T_r}{T_{r,\max}}\right),$$

Where:

$$\alpha_1+\alpha_2+\alpha_3=1.$$

Assuming equal weights (α_i=1/3), the system achieved (Q=0,86) with the AI/FIS Node-RED integration and (Q=0,68) with classical PID control, confirming the research hypothesis.[20,21]

Validation and Limitations

System reliability was evaluated using Cohen's κ = 0,83, indicating strong inter-trial consistency. Limitations include: (1) single object type (cube), (2) single-camera setup, (3) controlled illumination conditions. Future work will extend experiments to multi-camera configurations and non-rigid or irregular objects.[24,25,26]

Methodological Novelty

The novelty of this approach lies in the fusion of fuzzy-logic interpretability and Node-RED's industrial interoperability. The mathematical formalization through the product t-norm ensures smooth, continuous adaptation of robotic motion, while Node-RED enables real-time deployment without modifying PLC code.

This hybrid methodology provides a universal foundation for building adaptive, intelligent manufacturing cells aligned with the Industry 4.0 and 5.0 paradigms—bridging perception, cognition, and actuation within a unified, explainable control framework.

RESULTS

Experimental Data Overview

A total of 180 experimental trials were conducted, equally divided between two control configurations: (a) Baseline PID control, and (b) AI-Fuzzy-Node-RED adaptive control.

Each trial involved a robotic arm performing object grasping and placement tasks under variable illumination, object position, and conveyor speed. Performance metrics recorded included:

$$R_k : \text{IF } (E_\theta = A_i) \text{ AND } (E_d = B_j) \text{ THEN } (U = C_{ij}),$$

- Position error Ed (mm).
- Angular alignment error ($E\theta$) (degrees).
- Response time (Tr) (seconds).
- Successful grasp ratio Rg=Ns/Nt, where Ns is the number of successful grasps and Nt the total attempts.
- Overall quality index Q computed as in equation (1).

Mean and standard deviation values for both configurations are summarized in table 2.

Table 2. Comparison of baseline and AI-Fuzzy-Node-RED control

Metric	PID Control (Mean ± SD)	AI-Fuzzy-Node-RED (Mean ± SD)	Improvement (%)
Ed (mm)	3,6 ± 0,7	1,8 ± 0,5	50,0 ↓
E_θ (°)	4,2 ± 1,1	2,3 ± 0,6	45,2 ↓
Tr (s)	0,28 ± 0,05	0,18 ± 0,03	35,7 ↓
Rg	0,82 ± 0,04	0,95 ± 0,02	+15,9 ↑
Q (0-1)	0,68 ± 0,05	0,86 ± 0,03	+26,5 ↑

All improvements were statistically significant ($p < 0{,}01$) according to paired *t*-tests.

Statistical and Analytical Interpretation

The integrated quality index Q (equation 1) served as a composite measure of positional precision, angular alignment, and temporal responsiveness. The average gain in Q was $\Delta Q = 0{,}18$, with a large effect size (Cohen's *d* = 1,42).

Regression analysis revealed strong linear relationships between the system's fuzzy inference performance and the physical accuracy metrics. The simplified regression model is expressed as:

$$Q = \beta_0 + \beta_1 \mu_{\text{det}} + \beta_2 \mu_{\text{AND}} - \beta_3 T_r + \varepsilon,$$

Where:

- μ_{det}— confidence from the vision AI module.
- μ_{AND}— aggregated fuzzy rule activation (product t-norm).
- Tr — system response time.

The estimated coefficients were:

$$\beta_1 = 0.42, \quad \beta_2 = 0.37, \quad \beta_3 = 0.28, \quad R^2 = 0.84,$$

Confirming that both AI confidence and fuzzy activation have positive impacts on grasping quality, while latency degrades performance.

Sensitivity Analysis of Fuzzy Parameters

To evaluate robustness, Gaussian membership widths ((\sigma)) and rule weights ((w_i)) were varied ±20 %.

- Reducing δ (narrower sets) increased sensitivity but caused oscillations in grip velocity.
- Increasing δ provided smoother motion but lowered adaptation speed. An optimal range was found at δ_θ=15°, δ_d=20mm yielding minimal variance in Q.

The product t-norm outperformed other conjunction methods (min-operator, bounded sum) by achieving smoother transitions between rule activations. The mean standard deviation of the control output u^* decreased from 9,4 % to 4,7 % when using the product t-norm.

Response-Time and Communication Latency

Node-RED orchestration added negligible communication overhead. The average end-to-end delay was 65 ms, including data acquisition, AI inference, fuzzy computation, and Modbus command dispatch. Correlation analysis showed a weak dependency between latency and accuracy (r = –0,28, p > 0,05), confirming that network-based streaming control is viable for sub-second closed loops in industrial scenarios.

Energy and Efficiency Metrics

Energy consumption per cycle was indirectly measured via current drawn by servo actuators:

$$E_c = \int_0^{T_c} V(t) I(t) dt$$

Where (V(t)) is supply voltage and (I(t)) current. The adaptive controller reduced transient torque peaks, lowering mean energy use by 12 % compared to PID control. This outcome aligns with literature reporting energy savings through trajectory optimization and soft-motion profiles in AI-enhanced control systems.

Qualitative Observations

Expert assessments (n = 6 industrial robotics specialists) highlighted:

- High transparency of Node-RED logic, simplifying debugging and modification.
- Ease of interoperability with existing PLCs and SCADA systems.
- Improved safety due to smoother transitions and reduced overshoot.
- Enhanced maintainability, as logic blocks can be re-parameterized without rewriting embedded code.

The experts rated the system's practical deployability at 4,6 / 5 on a Likert scale, emphasizing the potential for integration into small and medium-scale manufacturing lines.

Comparative Summary

A comparative index Ip was introduced to quantify overall performance improvement:

$$I_p = \frac{Q_{\text{AI-Fuzzy}} - Q_{\text{PID}}}{Q_{\text{PID}}} \times 100\%.$$

Across all trials, Ip averaged 26,5 %, with variance under 5 %.

The summary of key performance enhancements is given below:

Table 3. Key performance enhancements

Criterion	Indicator	Improvement (%)
Grasp accuracy	Ed, E_θ	45-50
Response time	Tr	36
Success rate	Rg	16
Energy efficiency	Ec	12
Overall quality	Q	27

Discussion of Result Patterns

The results confirm that combining AI-based perception with fuzzy-logic reasoning and Node-RED orchestration creates a robust cognitive control loop suitable for Industry 4.0 environments. The fuzzy inference layer successfully bridges discrete AI detections with continuous robotic motion, ensuring smooth adaptability.

The key insight is that the product t-norm rule base acts as a nonlinear mapping from uncertain perception data to stable control actions, while Node-RED provides modular integration and real-time supervision. Together, they form a flexible, scalable, and interpretable industrial control architecture.

Summary

In summary, the AI-Fuzzy-Node-RED framework demonstrated significant quantitative and qualitative advantages over classical PID control. It improved precision, reduced delays, optimized energy consumption, and enhanced overall process flexibility — thus validating the research hypothesis and contributing a reproducible method for intelligent robotic control within modern industrial engineering.

DISCUSSION

The experimental results clearly demonstrate that integrating artificial intelligence, fuzzy-logic reasoning, and Node-RED orchestration transforms conventional robotic control into a cognitively adaptive system. Compared with PID control, the proposed architecture significantly reduced positional and angular errors, improved responsiveness, and enhanced overall energy efficiency.

The improvement is primarily attributed to the product t-norm fuzzy aggregation, which provides smooth transitions between control states, and to Node-RED's low-latency data orchestration that maintains real-time synchronization between perception, decision, and actuation. This confirms that even lightweight industrial hardware can host intelligent behaviors when modular logic and AI inference are properly coupled.

From an engineering standpoint, the synergy between AI perception and fuzzy interpretability bridges the gap between black-box neural decisions and deterministic industrial standards. The fuzzy controller translates probabilistic AI outputs into explainable control actions, satisfying the transparency requirements of Industry 4.0. The Node-RED layer, in turn, offers interoperability with PLCs, SCADA, and IoT services — enabling scalability toward distributed cyber-physical systems.

Economically and operationally, the observed gains (≈ 25–30 %) in quality and efficiency indicate that intelligent adaptive control can reduce downtime, limit energy waste, and extend actuator lifespan. This aligns with sustainability principles and supports the transition to Industry 5.0, where human-machine collaboration emphasizes safety, efficiency, and adaptability.

Nevertheless, challenges remain: ensuring deterministic timing in large-scale networks, developing standardized fuzzy-AI integration protocols, and securing data integrity across industrial communication layers. Future research should focus on extending the framework to multi-robot collaboration, predictive maintenance, and edge-deployed AI for fault-tolerant industrial automation.

In summary, the AI–Fuzzy–Node-RED model provides a reproducible, transparent, and energy-efficient foundation for intelligent industrial robotics. It exemplifies how explainable AI, modular architecture, and low-cost integration tools can jointly advance the digital transformation of industrial engineering systems.

CONCLUSIONS

This chapter has presented the conceptual design, mathematical modeling, and experimental validation of an intelligent robotic control system that integrates artificial intelligence, fuzzy logic reasoning, and Node-RED orchestration into a unified industrial engineering framework.

The results provide convincing empirical evidence that such integration fundamentally enhances robotic precision, responsiveness, and energy efficiency while preserving interpretability and modularity.

From the theoretical perspective, the study demonstrates that the product t-norm-based fuzzy aggregation acts as an efficient nonlinear mapping between uncertain perception data and continuous actuator commands. This formulation bridges probabilistic AI inference with deterministic industrial logic, enabling smooth decision transitions in the presence of environmental variability. The model also reinforces the cognitive automation paradigm, in which perception, reasoning, and action coexist within a single adaptive loop.

From the methodological viewpoint, the combination of AI modules (for perception), FIS controllers (for reasoning), and Node-RED (for orchestration) constitutes a scalable architecture that can be reproduced in different industrial contexts without altering PLC code. The platform's visual-flow environment shortens development cycles, supports interoperability through standard protocols (MQTT, Modbus/TCP, OPC UA), and facilitates human supervision and explainability—key principles of human-centric automation.

From the experimental standpoint, the proposed system achieved measurable improvements across all performance dimensions:

- Reduction of positional and angular errors by ≈ 45–50 %.
- Decrease of average response time by ≈ 36 %.
- Increase of grasp success rate by ≈ 16 %.
- Reduction of actuator energy consumption by ≈ 12 %.
- Total improvement of the integrated quality index (q) by ≈ 27 %.

These quantitative results confirm the feasibility of deploying AI-enhanced fuzzy controllers through low-latency Node-RED flows even on moderate industrial hardware. The practical implication is the availability of a cost-effective and transparent alternative to proprietary robotic control systems, particularly suitable for small- and medium-scale manufacturing enterprises.

From the strategic and industrial perspective, the research aligns with the global transition from Industry 4.0 to Industry 5.0—a stage emphasizing adaptability, sustainability, and human-machine symbiosis. The AI–Fuzzy–Node-RED model supports this evolution by offering:

1. Cognitive adaptability: robots capable of interpreting sensory uncertainty and autonomously adjusting their behavior.
2. Sustainability: energy-efficient, low-waste operations consistent with ESG and ISO 14001 frameworks.
3. Interoperability: seamless communication between legacy industrial systems and modern digital layers.
4. Explainability: transparent, rule-based reasoning that meets ethical and regulatory standards for AI deployment in safety-critical environments.

The limitations identified—such as single-object testing, ideal illumination, and constrained sample variability—suggest directions for future work. Expanding the framework to multi-object manipulation, multi-camera 3D vision, and collaborative robot swarms will further validate its scalability. Additionally, integrating predictive maintenance modules and reinforcement-learning policies may allow the system to self-optimize in dynamic production lines.

In conclusion, the study contributes a holistic, interpretable, and reproducible framework for intelligent industrial robotics. It confirms that the convergence of AI perception, fuzzy-logic reasoning, and Node-RED orchestration can yield not only technical efficiency but also operational transparency and sustainability.

Looking ahead to 2030, industrial engineering is expected to shift toward cognitive factories, where hybrid AI-driven robots collaborate seamlessly with humans, learn from data, and autonomously manage production ecosystems. The findings of this chapter therefore mark a tangible step toward that vision—demonstrating how intelligence, interpretability, and interconnectivity together redefine the future of industrial automation.

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