

Embedded AI framework for adaptive control in automated manufacturing systems

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Keywords: Embedded Artificial Intelligence, Adaptive Control, Automated Manufacturing Systems, Edge Computing, Real-Time Control

Abstract. The growing need of intelligent and adaptable manufacturing systems requires the design of adaptive control strategies that can work in the dynamism and uncertainties. Conventional forms of control such as fixed-gain PID controllers may not be effective to provide optimal control in a system that incorporates process variations, tool wear and external disturbances. The paper introduces a built-in artificial intelligence (AI) framework to adaptive control of automated manufacturing systems, which allows making decisions in real-time at the edge level. The proposed architecture will integrate sensor-driven data acquisition with a mini-AI unit to execute on an embedded system to dynamically adjust control points. The hybrid control method is developed and an introduction of AI-based corrective actions to the baseline controller target are to minimize the tracking error and increase the stability of the system. The framework is applicable to a representative manufacturing system, and the performance of the system is compared with the traditional control methods. Experimentally it has been demonstrated to possess superior response time, reduced steady-state error and high robustness to various operating conditions. The proposed solution offers a computationally efficient and scalable solution to intelligent manufacturing systems of the next generation.

Introduction

The problem of automated manufacturing systems in modern world is growing to be capable of functioning in dynamic and uncertain settings due to variation in materials, tool wear and tear, changing load conditions and environmental disturbances [1-4]. One of the most important issues that cannot be dealt with through the traditional measures to control is the stability of performance and quality of the products in such environments. The traditional types of fixed-gain proportional-



integral-derivative (PID) controllers are designed around a nominal system model and are not well-behaved with nonlinearities and time-varying disturbances[5-7].

However, advancements in recent years in artificial intelligence (AI) and embedded systems have enabled the development of intelligent control systems that can evolve on the fly [8-10]. Edge-level embedded AI allows processing and making decisions on data in a few milliseconds without requiring a centralized computing platform. The ability is especially beneficial in the manufacturing sector where quick reaction and reliability of the system are essential.

One possible solution is to address this issue with adaptive control techniques complemented by AI models, which enable the system control parameters to be constantly modified based on real time behavior. Through sensor data, such as vibration, temperature and force, AI models can familiarize themselves with the dynamics of the system and predict corrective control actions to deal with uncertainties [11-13].

This paper introduces a built-in AI system. The suggested solution is a combination of a baseline controller and an AI-based correction scheme to increase the stability of the system, decrease tracking error, and increase the overall efficiency of the system. The framework is practical-implementation-oriented, making it compatible with the current manufacturing infrastructure and edge devices.

Proposed Embedded AI-Based Control Framework

The proposed adaptive control framework with embedded AI will provide an opportunity to monitor and make smart decisions in real-time in automated manufacturing systems. The architecture combines several sensing units, an embedded processing unit, an AI-based inference engine, and a control actuation layer to attain adaptive operations across different operating conditions. Sensors like vibration, temperature, and force are continuously obtained and sent to the embedded controller where they undergo preprocessing and feature extraction before being sent to AI-based prediction.

The general design of the proposed system is shown in Figure 1, which indicates the communication between sensing, computation, and control units. The embedded controller is the central processing unit, which guarantees low-latency implementation of AI algorithms and fast updates of control signals. The AI module compares real-time sensor data with the baseline controller output and obtains corrective signals which it combines with the baseline controller output to produce adaptive behavior. Proper system monitoring and proper control largely depends on the choice of sensors and system parameters. Tool wear and dynamic instability are detected by the use of vibration signals, thermal variations influencing machining accuracy are measured by temperature sensors and the load variations during operation can be estimated with the help of force sensing. These parameters are obtained with a high enough sampling rate to make the control system responsive in real-time.

The major sensors and the operating parameters utilized in the proposed framework are summarized using Table 1 and the details of the measurement range and functional relevance within the control loop are presented.

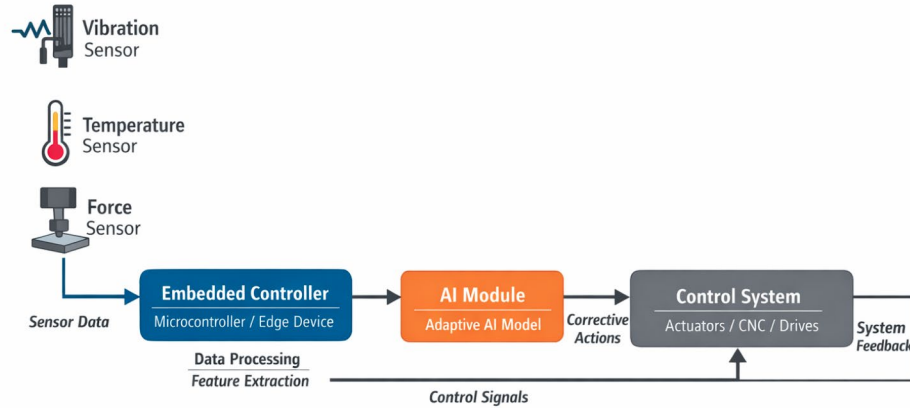


Figure 1: Architecture of Embedded AI-Based Adaptive Control Framework

Table 1: Sensors and System Parameters Used in the Framework

Parameter	Sensor Type	Measurement Range	Accuracy	Purpose
Vibration	Accelerometer	±16 g	±0.02 g	Tool wear and chatter detection
Temperature	Thermocouple (K)	0–300 °C	±1 °C	Thermal variation monitoring
Force	Load Cell	0–500 N	±0.5 N	Cutting force estimation
Sampling Frequency	—	1000 Hz	—	Real-time data acquisition
Signal Resolution	ADC (12-bit)	0–4096 levels	—	Precise signal digitization

The combined functioning of sensing, embedded intelligence and control actuation allows the system to react dynamically to disturbances and uncertainties.

Control Strategy and Formulation

The adaptive control strategy that will be applied in this project is based on the improvement of the traditional feedback controller with an AI-based correction system that will help address nonlinearities of the system and external interference. The manufacturing system can be modeled as a nonlinear dynamic system in discrete time, the state of which changes with the current state and control input. The overall system dynamics can be stated as:

$$x_{k+1} = f(x_k, u_k, d_k)$$

where x_k is the system state at time step k , u_k is the control input, and d_k is external disturbances and uncertainties about system behavior.

With the traditional methods of control, the control input is produced by a fixed-gain controller like PID, which may not be adequate to achieve optimal performance under different conditions. To eliminate this constraint, an adaptive control law is developed by introducing an AI-based correction term into the control input.

The altered control input is given as:

$$u_k = u_{base} + \Delta u_{AI}$$

where u_{base} represents the response of the baseline controller, and u_{AI} is the corrective action of the embedded AI model. It is a correction term that is dynamically estimated on the basis of real-time sensor measurements and system conditions, so that the controller can correct modeling inaccuracies and disturbances.

The control strategy aims at reducing the tracking error between the desired reference signal and the actual system output. The error of tracking can be determined as:

$$e_k = r_k - y_k$$

where r_k is the reference input and y_k is the system output at time step k . The AI module is trained to generate corrective actions that reduce this error while maintaining system stability and responsiveness.

The addition of AI to the control loop makes it possible to continually adapt without explicit reconfiguring of the controller parameters. This leads to better resilience to uncertainties and better performance in dynamic manufacturing conditions. The formulation makes sure that the computational complexity is low enough to be implemented in an embedded system and still provide real-time adaptive control.

Embedded AI Model Design

The success of the suggested adaptive control framework will be heavily reliant on the architecture of a lightweight and computationally efficient AI model that can be deployed in an embedded system. In this paper, the artificial neural network model is used to predict the corrective control action, which is a compact ANN model, depending on the real-time behavior of the system. The model is developed to run with limited memory, processing power, and latency constraints, compatibility with edge-level embedded platforms. The AI model input includes features of sensor signals, such as vibration amplitude, temperature change and force signals, and the system states (tracking error and prior control input). All these inputs show a dynamic state of the manufacturing process. Raw sensor data is first normalised and filtered before model inference in order to minimise noise and enhance the prediction accuracy.

The control correction term is equivalent to the output of the AI model and it is combined with the baseline controller to form adaptive control. The model is also trained in a supervised learning style where historical data of the system is utilized to identify which features of inputs to the system are best corrected by a particular action. The training is done offline to reduce the computational load on the embedded system and the trained model is deployed to the embedded system to perform real time inferences. In order to make the ANN architecture scale to high performance, the architecture is kept shallow, usually one or two hidden layers with a small number of neurons. The choice of activation functions is to balance nonlinearity representation with computational efficiency. The model parameters are optimized to provide a trade-off between accuracy of prediction and speed of inference that is essential to continuing performance of real-time control. Some adaptation to gradual changes of the system with time can be provided along with off-line training as well. This enables the model to further improve its predictions using recent data, which enhances the robustness further. The fact that the AI model is lightweight, energy-efficient and can potentially provide good performance under the constraints of embedded manufacturing systems is made possible by the overall architecture.

Experimental Design and execution

An emulated version of the proposed system is put in place in a representative automated manufacturing system to test the functionality of the proposed system in real-time and its feasibility. The system will consist of a processing unit fitted with a number of sensors, that enable the continuous acquisition of operational information such as vibration, temperature, and force. The embedded controller implements the AI model and control algorithm in a closed-loop system

configuration and guarantees the timely response of control inputs to system behavior. The control system combines an old-fashioned PID controller with an AI-based error correction unit to promote flexibility. Initial control action is provided by the baseline controller, and a corrective signal is produced by the AI module, depending on real-time sensor-based interferences and learnt system dynamics. Such a hybrid control approach allows the compensation of nonlinearities and disturbances that are hard to model analytically. The general control approach can be depicted as the block diagram in Figure 2, which shows the interrelation of the reference input, the baseline controller, AI correction module, and the manufacturing system. The feedback loop maintains the system up to date and the AI model can dynamically optimize the control actions.

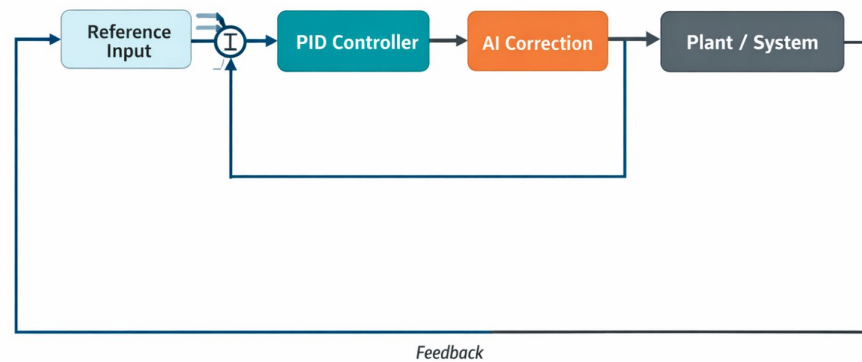


Figure 2: Control Block Diagram of Embedded AI-Based Adaptive Control System

This is implemented on a small embedded platform that can run lightweight AI models with low latency. The sensors and the controller also use the standard protocol such as I2C and serial interfaces that ensure the reliability in data transmission. The control loop is high enough in rate to ensure responsiveness and stability of the system as it is running. The description of the hardware implementation and configuration, including specifics of the embedded platform and AI model, and communication interfaces of the system is presented in Table 2.

Table 2: Experimental Setup and Hardware Configuration

Component	Specification
Embedded Platform	Raspberry Pi 4 / Arduino Mega
Processor Speed	1.4 GHz (Raspberry Pi)
RAM	2–4 GB
AI Model Type	Lightweight ANN (1 Hidden Layer)
Number of Neurons	8–10
Communication Protocol	I2C / SPI / UART
Control Loop Delay	30–50 ms
Power Consumption	< 10 W
Programming Environment	Python / Embedded C

The integrated system is a feedback loop that includes data acquisition, AI inference, control signal generation, and feedback correction. The present on-the-fly application demonstrates the possibilities of real-time implementation of an embedded AI-based adaptive control in the actual factory environment, where the responsiveness and efficiency are ensured.

Results and Analysis

The effectiveness of the suggested embedded AI-powered adaptive control framework is measured against a traditional PID control strategy in different operating conditions. The performance indicators that are evaluated include tracking error, response time, system stability and energy

efficiency. The experimental results show that the implementation of the AI-based correction has an important positive effect on the control performance, especially when the disturbances and nonlinear behavior of the system are involved. Figure 3 demonstrates the difference in the performance of the traditional and AI-based control strategies, and it depicts the change in the system output over time. One can note that, the AI-based adaptive control will converge to the reference signal faster with fewer oscillations, compared to the conventional PID controller, which has a higher overshoot and longer settling time. This is enhanced by the fact that the AI module is in a position to dynamically correct the system uncertainties with respect to time. Additional quantitative results indicate that the error of tracking is significantly less when the proposed framework is used. The controller is an AI-based controller that keeps modifying the control input according to real-time feedback and leads to enhanced accuracy and stability. Moreover, there is faster adaptation and shorter response time as well as greater robustness to changes in operating conditions like loads and thermal effects.

The comparison of the performance parameters in detail is provided in Table 3, where the progress of the proposed approach as compared to the traditional control methods can be observed. The tracking error and power consumption are greatly reduced and the stability of the system is augmented.

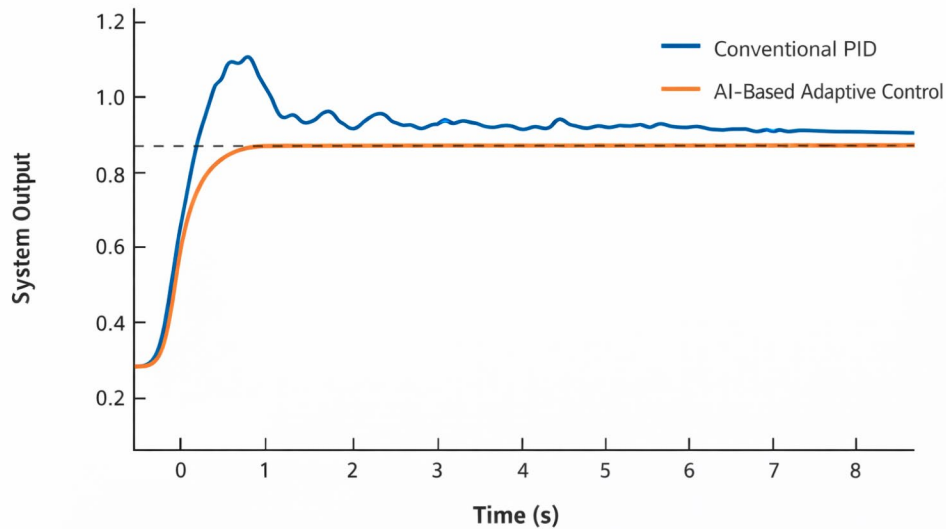


Figure 3: Performance Comparison Between Conventional PID and AI-Based Adaptive Control

Table 3: Performance Comparison of Control Strategies

Metric	PID Control	AI-Based Control	Improvement (%)
Tracking Error (RMSE)	0.085	0.048	43.5%
Settling Time (s)	2.4	1.6	33.3%
Overshoot (%)	12.5	5.8	53.6%
Response Time (s)	1.2	0.85	29.2%
Energy Consumption (J)	120	98	18.3%
Stability Margin	Moderate	High	Improved

The outcomes show clearly that, by integrating embedded AI into the control loop, one can achieve better performance without the excessive burden of computations. The framework is well-balanced in accuracy and efficiency and can be applied to the real-time industrial process. The attained improvements justify the efficiency of the suggested method in overcoming the constraints of the conventional control systems in automated manufacturing setting.

Conclusion

In this paper, an integrated AI-based adaptive control model of automated manufacturing systems has been introduced and discussed, overcoming the drawbacks of the traditional control approaches in dynamic and uncertain operating conditions. The suggested solution combines sensor data in real-time with a low-weight AI model running on an embedded system to produce corrective control measures to support ongoing adjustment of the control input.

The hybrid control approach, which incorporates a baseline controller and AI-based correction, showed considerable enhancement of the system performance. Results of the experiments showed less tracking error, faster response, increased stability and better robustness to disturbances like load variations and thermal effects. These advances were realized in the framework with low computational complexity, allowing the framework to be implemented in real-time on embedded system platforms with resource constraints. The pilot project proves the applicability of the idea of implementing embedded AI to provide intelligent control in the manufacturing plants without significant changes in the existing infrastructure. The suggested system is consistent with the aims of smart manufacturing and Industry 4.0 as it allows low-latency edge-level decentralized decision-making. Future directions could be to expand the framework to multi-machine conditions, add online learning functionality, and connect with digital twin-based platforms to have predictive and self-optimizing manufacturing systems.

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