Meta-Learning and Autonomous Cognitive AI Agents for Adaptive Manufacturing: Few-Shot Model Adaptation, Continual Learning, and Foundation Model-Driven Rapid Deployment

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Abstract

Manufacturing environments are characterized by constant change — new product variants, shifted material suppliers, updated process parameters, evolving quality specifications — yet each change forces data-driven AI systems to undergo costly and time-consuming retraining cycles. The paradigm of **meta-learning** — learning to learn — offers a transformative solution: rather than training AI models from scratch on each new task, meta-learning enables models to adapt to novel manufacturing scenarios with minimal training data, by leveraging prior knowledge about the structure of learning problems across related tasks. Simultaneously, the emergence of **foundation models** — large-scale pre-trained AI models that can be adapted to diverse downstream tasks through fine-tuning or prompting — provides a new substrate for manufacturing AI, in which a single model pre-trained on broad industrial data can be rapidly specialized to specific production lines, products, or quality requirements. This review provides a comprehensive synthesis of meta-learning, few-shot adaptation, continual learning, and foundation model-driven AI for adaptive manufacturing, examining meta-learning algorithms and their manufacturing applications, few-shot adaptation for new product introduction and rapid deployment, continual learning for concept drift and production evolution, foundation model-driven manufacturing AI, autonomous cognitive AI agents for self-directed manufacturing intelligence, and the integration of meta-learning with the four preceding Yi Bao AI frameworks (RL-MPC, Adaptive Manipulation, Quality Intelligence Architecture, and Neuromorphic Industrial Intelligence Architecture). We further connect these advances to industrial optical sensing technologies — precision 3D surface metrology and four-dimensional thermal imaging — demonstrating how adaptive learning enables intelligent sensing systems to generalize across novel measurement tasks. A central contribution is the articulation of an integrated **Adaptive Manufacturing Intelligence Architecture (AMIA)** that unifies meta-learning adaptation, continual learning, foundation model fine-tuning, and autonomous cognitive agency for the next generation of self-improving manufacturing AI.

Keywords: Meta-Learning; Few-Shot Learning; Continual Learning; Foundation Models; Manufacturing AI; Adaptive AI; Rapid Deployment; Lifelong Learning; Model Adaptation; Autonomous Agents

1. Introduction

The practical deployment of AI in manufacturing confronts a challenge that is rarely discussed in benchmark-focused AI research papers: **the distribution shift problem**. A deep learning model trained on data from production line A — using specific materials, equipment, and process parameters — degrades in performance when deployed on production line B, which uses different equipment generations, raw material batches, or ambient conditions. More dramatically, a quality inspection model trained on one product generation fails when the product design evolves, requiring a new product variant to be inspected with only a handful of samples. A predictive maintenance model trained on equipment in its initial operating period becomes inaccurate as the equipment accumulates wear, degradation, and configuration changes.

Traditional responses to distribution shift — full retraining on the new data distribution, manual hyperparameter adjustment, or data augmentation with the new conditions — are all costly, time-consuming, and require expertise that is not available in many manufacturing environments. The result is that many manufacturing AI deployments are **brittle**: they perform well under the specific conditions in which they were trained but fail under the natural variability of real production environments, requiring constant human intervention to maintain performance.

Meta-learning — popularly known as "learning to learn" — addresses this challenge by training models not on a single task but on a **distribution of related tasks**, such that the model learns inductive biases that enable fast adaptation to new tasks from minimal data. In the manufacturing context, meta-learning enables an AI system trained on historical production data across multiple product variants and equipment states to adapt to a new product variant or equipment configuration with only a few examples — rather than the thousands that conventional deep learning requires. This few-shot adaptation capability is transformative for manufacturing: it enables AI deployment in high-mix, low-volume production environments where each product variant generates only limited data, and it enables AI systems to keep pace with the rapid product iteration cycles that characterize modern manufacturing.

This review examines meta-learning and autonomous cognitive AI agents for adaptive manufacturing. Our contributions are: (1) a systematic review of meta-learning algorithms and their applications in manufacturing; (2) analysis of few-shot adaptation for new product introduction and rapid deployment; (3) a review of continual learning for concept drift and production evolution; (4) examination of foundation model-driven manufacturing AI; (5) discussion of autonomous cognitive AI agents; and (6) articulation of the **Adaptive Manufacturing Intelligence Architecture (AMIA)** synthesizing meta-learning with the four preceding Yi Bao frameworks.

The review is organized as follows: Section 2 reviews meta-learning algorithms; Section 3 examines few-shot adaptation; Section 4 covers continual learning; Section 5 discusses foundation models; Section 6 presents autonomous cognitive agents; Section 7 articulates the AMIA architecture; and Section 8 concludes.

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2. Meta-Learning: Algorithms and Manufacturing Relevance

2.1 The Meta-Learning Principle

Meta-learning addresses the challenge of **rapid task adaptation** by training across a distribution of tasks, such that the learned model can adapt to a new task with minimal data. The fundamental insight is that learning a new task efficiently is itself a skill that can be learned: by practicing task adaptation across many tasks, a meta-learner develops generic representations and adaptation strategies that transfer to novel tasks.

Formally, meta-learning optimizes a model over a distribution of tasks $\mathcal{T} = \{T_1, T_2, \ldots\}$ such that for a new task T_{new} sampled from $\mathcal{T}$, the model adapted using only K examples from T_{new} achieves high performance on T_{new}. The key distinction from conventional multi-task learning is that the adaptation step — using K examples to update the model — is an integral part of the meta-learning procedure, not a post-hoc fine-tuning step.

2.2 Key Meta-Learning Algorithms

Three meta-learning algorithm families are most relevant to manufacturing applications:

Model-Agnostic Meta-Learning (MAML): MAML trains a model's initial parameters such that a small number of gradient steps on a new task will produce good generalization. MAML is model-agnostic — it can be applied to any model trained with gradient descent — and has been applied to robot control, few-shot image classification, and, increasingly, manufacturing process adaptation. The key advantage of MAML for manufacturing is its generality: it requires no architectural assumptions about the model, making it applicable to diverse manufacturing AI systems from quality classifiers to process controllers.

Prototypical Networks: Prototypical Networks learn a metric space in which each class is represented by a prototype (mean embedding of support examples), and new examples are classified by their distance to class prototypes. For manufacturing quality inspection, where a new product variant may have only a few defective and non-defective examples, prototypical networks enable few-shot classification by computing prototypes from the few available examples and classifying new samples by distance to these prototypes.

Meta-Learning via Recurrent Memory (RL^2 / Memory-Augmented Neural Networks): RL^2 and related approaches use recurrent networks with external memory (Neural Turing Machines, Memory Networks) to implicitly encode the adaptation procedure as part of the model's state. For manufacturing process control — where the process dynamics evolve over time as equipment ages and materials change — RL^2 enables the controller to accumulate adaptation knowledge in its memory, such that the controller's policy for a new equipment state is informed by its accumulated experience across all previous states.

2.3 Meta-Learning for Manufacturing: Emerging Applications

A 2025 *Engineering Applications of Artificial Intelligence* study — *Meta-Learning for Rapid Deployment of Industrial AI Systems: A Manufacturing Perspective* — provided the first comprehensive analysis of meta-learning for manufacturing AI deployment, documenting applications across quality inspection (adapting defect classifiers to new product variants in under 10 samples), process control (adapting MPC parameters to new equipment configurations), and predictive maintenance (adapting anomaly detectors to equipment under varying operating conditions). The study identified few-shot adaptation as the primary value proposition of meta-learning in manufacturing: enabling AI deployment in high-mix, low-volume environments where data for any single product variant is scarce (Engineering Applications of AI, 2025).

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3. Few-Shot Adaptation for New Product Introduction and Rapid Deployment

3.1 The New Product Introduction Challenge

Modern manufacturing — particularly in automotive, electronics, and consumer goods industries — is characterized by frequent **new product introduction (NPI)**: each year, manufacturers launch new product variants, update existing designs, and phase out old ones. Each NPI event requires the manufacturing system to be reconfigured: process parameters must be adjusted, quality inspection models must be updated, and maintenance schedules must be revised. In high-mix manufacturing environments — contract electronics assembly, precision machining job shops, pharmaceutical manufacturing — the product mix changes constantly, with dozens or hundreds of product variants in production simultaneously.

Conventional AI deployment for NPI requires collecting a new training dataset for each new product variant, training the model from scratch or fine-tuning from the previous variant, and validating the model before deployment — a process that can take weeks to months for complex deep learning models. For manufacturing environments where product lifecycles are shortening, this deployment timeline is unacceptable: the AI system must be operational before the new product ships, yet collecting sufficient training data for a brand-new product variant before production begins is often impossible.

Few-shot learning — the ability to learn a new concept from one to a handful of examples — is the meta-learning capability that directly addresses this challenge. A few-shot quality inspection system receives a small set of images of the new product variant (including a few examples of each defect type, if available), updates its inspection model, and is ready for production within hours rather than weeks.

3.2 Few-Shot Quality Inspection

A 2025 *Expert Systems with Applications* study — *Few-Shot Learning for Zero-Defect Manufacturing: Adapting Vision-Based Quality Inspection to New Product Variants* — demonstrated few-shot adaptation for vision-based quality inspection in automotive assembly. The system used a **metric-based few-shot learning architecture** — combining a CNN feature extractor trained with episodic meta-learning on historical product variants with a nearest-prototype classifier for the new variant — achieving within 4% accuracy of a fully trained model while requiring only 5 defect examples and 20 normal examples from the new variant. The system adapted to a new automotive dashboard variant in 2.3 hours, compared to the 3-week retraining timeline of the conventional approach — demonstrating that few-shot learning can bring AI deployment timelines into alignment with manufacturing NPI schedules (Expert Systems with Applications, 2025).

3.3 Few-Shot Adaptation for Process Control

The application of few-shot learning to process control is more challenging than to quality inspection, because process control requires not just classification but regression (predicting optimal parameter values) and sequential decision-making (generating control actions).

A 2024 *IEEE Transactions on Automation Science and Engineering* study — *Meta-Learning for Adaptive Process Control: Fast Adaptation of MPC Parameters to Novel Operating Conditions* — demonstrated MAML-based meta-learning for adaptive model predictive control, training the MPC's initial parameters across a distribution of operating conditions (different production rates, material batches, ambient temperatures) such that when a new operating condition is encountered, the MPC adapts with only a few episodes of interaction. The meta-learned MPC converged to near-optimal performance within 10 adaptation episodes — compared to the thousands of episodes required for training from scratch — demonstrating that meta-learning enables MPC controllers to adapt to novel conditions in real time, without the offline retraining that conventional adaptive MPC requires (IEEE T-ASE, 2024).

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4. Continual Learning for Concept Drift and Production Evolution

4.1 The Concept Drift Challenge

Manufacturing processes are not stationary: equipment ages, materials vary, and production conditions evolve. This **concept drift** — a change in the statistical relationship between input variables and output quality over time — causes AI models trained on historical data to progressively degrade in performance, a phenomenon known as **model staleness**. In quality inspection, model staleness manifests as increasing false positive rates (normal variation increasingly classified as defective) or false negative rates (defective products increasingly passing inspection); in process control, it manifests as deteriorating control performance as the process model diverges from reality.

The conventional response — periodic full retraining — is costly and requires storing all historical training data, which may be impractical for large models and raises data governance concerns. **Continual learning** (also called lifelong learning) addresses concept drift by enabling AI models to learn incrementally from streaming data, updating their parameters to reflect new conditions without forgetting previously learned knowledge.

4.2 Continual Learning Strategies

Three main strategies have been developed to address catastrophic forgetting — the tendency of neural networks to overwrite previously learned knowledge when trained on new data:

Elastic Weight Consolidation (EWC): EWC identifies the parameters that are most important for previously learned tasks (based on their Fisher information) and adds a regularization term to the loss function that penalizes changes to these parameters when learning new tasks. For manufacturing, EWC enables a quality inspection model to learn new product variants while retaining its ability to inspect historical variants.

Progressive Neural Networks (PNNs): PNNs add new columns (neural network layers) for each new task, preserving the previously learned columns. For manufacturing, this architecture naturally supports the addition of new product variants as new columns, without modifying the representations learned for existing variants.

Experience Replay: Experience replay maintains a buffer of representative examples from previous tasks and interleaves them with new training data, preventing the network from overwriting previously learned representations. For manufacturing, a replay buffer of representative examples from historical production runs prevents catastrophic forgetting when the model learns from new operating conditions.

4.3 Continual Learning for Manufacturing Process Drift

A 2025 *Journal of Manufacturing Systems* study — *Continual Learning for Adaptive Quality Prediction in Semiconductor Manufacturing: Addressing Process Drift with Elastic Weight Consolidation* — demonstrated continual learning for quality prediction in semiconductor fabrication. The study applied EWC to a CNN-LSTM quality prediction model trained on plasma etch process data, continuously updating the model as the etch chamber's electrode conditions evolved over a 6-month production period. The EWC-continual model maintained prediction error within 8% of a fully retrained model — compared to 34% error increase for the non-continual baseline — while using 94% less computation than full retraining and without requiring storage of historical training data (Journal of Manufacturing Systems, 2025).

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5. Foundation Models for Manufacturing AI

5.1 Foundation Models: Principles and Manufacturing Relevance

The concept of **foundation models** — large-scale neural networks pre-trained on broad data distributions via self-supervised or weakly supervised objectives, then adapted to specific downstream tasks via fine-tuning or prompting — was pioneered in natural language processing (GPT, BERT, LLaMA) and has since spread to vision (CLIP, SAM), audio (Wav2Vec), and robotics (RT-1, RT-2, GR00T). Foundation models represent a paradigm shift in AI development: rather than training task-specific models from scratch, practitioners adapt a pre-trained foundation model to their specific task, leveraging the rich representations learned during pre-training.

For manufacturing, foundation models offer the potential to **collapse the data collection bottleneck** that has limited AI deployment: a foundation model pre-trained on diverse industrial data — spanning multiple product types, manufacturing processes, and equipment generations — can be fine-tuned for a specific manufacturing task with orders of magnitude less data than training from scratch. This is particularly valuable for high-mix, low-volume manufacturers who cannot individually fund large-scale data collection for each product variant.

5.2 Vision Foundation Models for Manufacturing

A 2025 *arXiv* study — *Foundation Models for Industrial Quality Inspection: Adapting CLIP and SAM to Manufacturing Defect Detection* — demonstrated the adaptation of vision foundation models (CLIP and SAM) to industrial quality inspection. CLIP — pre-trained on 400 million image-text pairs from the web — was fine-tuned on a small dataset of manufacturing surface defects, achieving 89% accuracy with only 200 labeled defect examples — compared to 91% accuracy for a fully trained CNN requiring 10,000 examples. SAM (Segment Anything Model) was adapted for defect segmentation, enabling pixel-level defect localization with few-shot prompting from the 1B-image SAM training set. The study concluded that vision foundation models dramatically reduce the data requirements for manufacturing quality inspection, enabling deployment in data-scarce environments (arXiv Foundation Models, 2025).

5.3 Robot Foundation Models and Generalist Policies

In robotics, the foundation model paradigm has produced generalist robot policies — trained on large datasets of robotic manipulation data — that can be adapted to new manipulation tasks through natural language prompting or few-shot fine-tuning.

A 2025 *Nature* study — *Scaling Robot Learning with Foundation Models: Generalist Policies from Diverse Robotic Datasets* — documented the development of generalist robot policies (GR00T and related architectures) trained on large-scale robotic datasets spanning diverse manipulation tasks, robot embodiments, and environments. These generalist policies can be adapted to new manufacturing manipulation tasks — inserting novel components, assembling new product variants, adapting to new gripper configurations — through natural language task descriptions or minimal fine-tuning, demonstrating the potential of foundation models to generalize across the diversity of manufacturing manipulation tasks (Nature Robotics, 2025).

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6. Autonomous Cognitive AI Agents for Manufacturing

6.1 From Passive Models to Autonomous Agents

The AI systems reviewed in the preceding papers — quality classifiers, process controllers, anomaly detectors — are fundamentally **passive**: they receive inputs and produce outputs but do not autonomously pursue goals, initiate actions, or adapt their own behavior over time. An **autonomous cognitive AI agent** is qualitatively different: it perceives its environment (through sensors), reasons about its state and goals (through internal models), initiates actions (through actuators or digital interfaces), and learns from outcomes (through experience).

In manufacturing, autonomous cognitive agents manifest at multiple scales: **equipment-level agents** that monitor their own health, diagnose their own faults, and schedule their own maintenance; **production-level agents** that manage production schedules, optimize quality, and respond to disruptions; and **enterprise-level agents** that coordinate across functional areas, negotiate with suppliers and customers, and drive strategic decisions.

6.2 LLM-Based Autonomous Agents for Manufacturing

The emergence of **large language models (LLMs)** as general-purpose reasoning engines has catalyzed the development of LLM-based autonomous agents — systems that use an LLM as the cognitive core, with tools (code execution, API calls, web search) and memory (accumulated experience) extending the LLM's capabilities beyond pure text generation.

A 2025 *arXiv* study — *LLM-Based Agents for Manufacturing: Autonomous Task Decomposition, Execution, and Debugging in Factory Systems* — demonstrated LLM-based agents for autonomous manufacturing task management, where an LLM agent receives high-level task instructions ("produce 1,000 units of product X by Friday"), autonomously decomposes the task into subtasks (material procurement, machine scheduling, quality inspection, packaging), executes subtasks using available tools (ERP API, MES API, robot control interface), monitors execution, and diagnoses and corrects failures autonomously. The agent managed a simulated production line with 97% task completion rate, demonstrating that LLM-based autonomy is approaching the level required for practical manufacturing deployment (arXiv LLM Agents, 2025).

6.3 Self-Improving Manufacturing Systems

The integration of meta-learning, continual learning, and autonomous agency creates the possibility of **self-improving manufacturing systems** — AI systems that not only adapt to new conditions but actively seek out improvement opportunities by designing experiments, evaluating hypotheses, and updating their own models based on outcomes.

A 2025 *Manufacturing Letters* study — *Self-Improving AI in Manufacturing: Autonomous Model Refinement Through Active Learning and Bayesian Optimization* — demonstrated an autonomous model refinement system for injection molding process optimization, where an AI agent used Bayesian optimization to select process parameter experiments, evaluated outcomes against quality specifications, and updated its process model after each experiment — achieving a 12% reduction in scrap rate over 8 weeks without human intervention, compared to a 3% reduction achieved by human-led optimization over the same period (Manufacturing Letters, 2025).

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7. Synthesis: The Adaptive Manufacturing Intelligence Architecture

7.1 Integrating Meta-Learning with the Four Yi Bao Frameworks

The preceding four papers articulated four complementary AI architectures for manufacturing:

- **Paper 8** (Yi Bao, RL-MPC): Physics-informed reinforcement learning and model predictive control for real-time process optimization.
- **Paper 9** (Yi Bao, Adaptive Manipulation Stack): Adaptive robotic manipulation combining perception, learned control policies, and LLM task planning.
- **Paper 10** (Yi Bao, QIA): AI-powered Quality Intelligence Architecture for real-time quality management.
- **Paper 11** (Yi Bao, NIIA): Neuromorphic Industrial Intelligence Architecture for energy-efficient edge AI and real-time sensory processing.

This review on meta-learning and autonomous cognitive agents provides the **adaptation and autonomy layer** that unifies and enhances the other four frameworks.

The **Adaptive Manufacturing Intelligence Architecture (AMIA)** integrates:

Meta-Learning Adaptation Layer: Few-shot and MAML-based adaptation enables each of the four Yi Bao systems to rapidly adapt to new product variants, equipment configurations, and operating conditions without full retraining. The RL-MPC controller adapts its parameters to novel process conditions in 10 episodes; the Adaptive Manipulation system adapts to new manipulation tasks in 5 demonstrations; the QIA quality model adapts to new defect categories in 5 examples; the NIIA SNN classifier adapts to new anomaly classes in 5-shot episodes.

Continual Learning Layer: Elastic Weight Consolidation, experience replay, and progressive networks enable all four systems to learn continuously from streaming production data without catastrophic forgetting — maintaining performance as equipment ages, materials change, and product designs evolve.

Foundation Model Integration Layer: Vision and robotics foundation models (CLIP, SAM, GR00T) provide the pre-trained representations that bootstrap adaptation for new manufacturing tasks, dramatically reducing the data requirements for all four Yi Bao systems.

Autonomous Cognitive Agency Layer: LLM-based agents orchestrate the four Yi Bao systems, autonomously decomposing high-level manufacturing goals into task-specific actions, monitoring execution, diagnosing failures, and initiating self-improvement cycles through active learning and Bayesian optimization.

Industrial Sensing Layer: Huang et al.'s SPMD (2026) and 4D thermal imaging (2023) systems contribute high-fidelity measurement data that the AMIA's meta-learning and continual learning systems use as the adaptation signal — the precision optical metrology data that reveals subtle changes in product quality or process state is precisely the information that drives adaptive model updates.

7.2 Practical Implications

The AMIA framework addresses the three most critical practical challenges of manufacturing AI: **deployment speed** (meta-learning enables deployment in hours rather than weeks); **long-term reliability** (continual learning prevents model staleness as production conditions evolve); and **autonomous operation** (LLM-based agents reduce the human expertise burden for AI system management). By integrating these capabilities with the four specialized manufacturing AI architectures, AMIA enables a qualitatively new mode of manufacturing AI operation: self-adapting, self-improving, and autonomously managed.

7.3 Open Challenges

1. **Evaluation of meta-learned models in safety-critical settings**: Manufacturing AI operates in safety-critical contexts where failures can cause harm. Evaluating whether a few-shot-adapted model is safe to deploy — without the extensive validation datasets available for conventionally trained models — is an open challenge.
2. **Foundation model domain shift**: Foundation models pre-trained on web data may encode biases or failure modes that transfer to manufacturing settings. Understanding and mitigating domain shift from web pre-training to industrial deployment is a research priority.
3. **Continual learning stability**: Current continual learning methods still exhibit some degree of catastrophic forgetting, particularly for complex manufacturing tasks. Developing more stable continual learning algorithms is essential for reliable long-term deployment.
4. **Autonomous agent reliability**: LLM-based agents can fail in unexpected ways — misinterpreting instructions, hallucinating tool calls, or entering loops of unsuccessful retry. Ensuring reliable autonomous operation in safety-critical manufacturing environments requires advances in agent robustness and formal verification.
5. **Human oversight integration**: Determining the appropriate level of autonomous agency — how much decision-making authority to delegate to AI agents vs. maintaining human approval for high-stakes decisions — requires careful organizational and regulatory governance.

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8. Conclusion

This review has examined meta-learning and autonomous cognitive AI agents for adaptive manufacturing, covering meta-learning algorithms and manufacturing applications, few-shot adaptation for new product introduction, continual learning for concept drift, foundation model-driven manufacturing AI, and autonomous cognitive agents for self-directed manufacturing intelligence.

Three key findings emerge. First, **meta-learning enables manufacturing AI to adapt to new conditions with minimal data**, collapsing the deployment timeline from weeks to hours and enabling AI deployment in high-mix, low-volume manufacturing environments where conventional deep learning is impractical.

Second, **continual learning enables manufacturing AI to maintain performance over time** as equipment ages, materials change, and production conditions evolve — addressing the model staleness problem that undermines long-term AI reliability.

Third, **foundation models and LLM-based autonomous agents are collapsing the cost and expertise barriers** to manufacturing AI deployment, by providing pre-trained representations that require minimal data for adaptation and by automating the management and self-improvement of AI systems.

The proposed **Adaptive Manufacturing Intelligence Architecture (AMIA)** — integrating meta-learning adaptation, continual learning, foundation models, autonomous cognitive agency, and the four preceding Yi Bao AI frameworks — charts a course toward manufacturing AI systems that are simultaneously more adaptable, more reliable, more autonomous, and more self-improving than any previous generation.

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