

CASE STUDY · MANUFACTURING | ARM INSTITUTE, SIEMENS, MAGNA INTERNATIONAL

Adaptive Insertion of Deformable Objects

One model, many parts.

Rather than training a separate model for each part, ThoughtForge uses a single Active Inference controller that adapts to whatever it is given, fusing camera vision with force and torque feedback to guide each insertion in real time. Demonstrated on four automotive part families in live production.

~97%

INSERTION SUCCESS RATE

5.03 sec

CYCLE TIME PER INSERTION

< 5 ms

SENSOR-TO-ADJUSTMENT LATENCY

1 SUMMARY

ThoughtForge, with partners Siemens and Magna International, built a multi-modal AI system for the ARM Institute and its members. A single model handles many parts: rather than training and tuning a separate model for every part number, one controller adapts to whatever part it is given. It also adapts during the insertion itself, correcting for misalignment and part deformation the way a skilled human operator does. The system combines RGB-D vision and wrist force/torque sensing with ThoughtForge's Active Inference control, deployed on a modular Siemens Industrial Edge architecture and demonstrated on four automotive part families in live production.

In a final demonstration at Magna's production facility, the system inserted four automotive part families at roughly first-attempt **97% reliability and a 5.03-second cycle time**, meeting the project requirements outlined below.

2 PROBLEM

Deformable part insertion stays manual because parts vary even within a SKU, and because a plant runs too many part numbers to train a model for each.

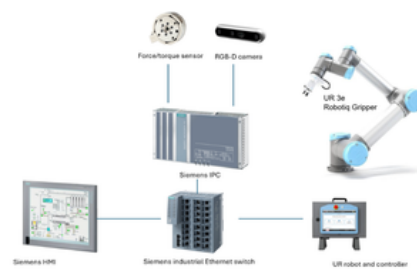
- Deterministic robots fail when parts are deformed, misaligned, or partly occluded in confined spaces.
- Machine learning approaches need large training sets and are brittle outside their training conditions.
- Automotive lines carry repetitive strain injuries, inconsistent seating, and warranty cost from incomplete insertions.
- Aerospace and defense assembly demands tight tolerances, certification traceability, and low tolerance for rework.

3 REQUIREMENTS

- At least 95 percent successful insertions across representative part types.
- Cycle time of 5 seconds or less per insertion.
- Setup time under 24 hours for a new part family; worker touch time under 60 minutes.
- Sufficient throughput to operate within a live facility.
- Rapid re-tasking across part families without long reprogramming cycles.

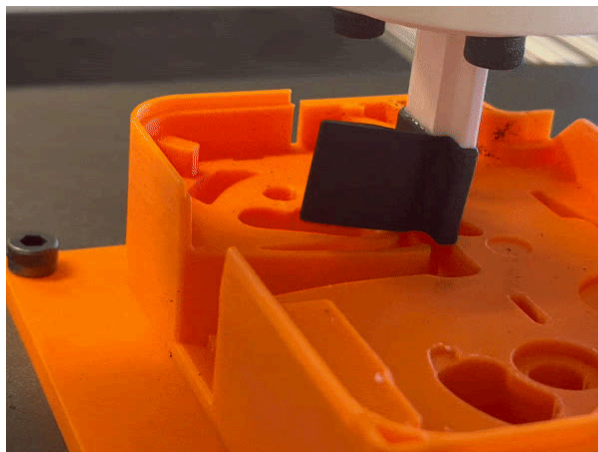
4 APPROACH

Hardware. A UR5e collaborative robot with a Robotiq Hand-E gripper, a wrist-mounted force/torque sensor sampled at 500 Hz, and two RGB-D cameras: an Intel RealSense D455 for wide-area housing localization and a wrist-mounted Framos D415e for part picking. One set of fingertips for all parts, not custom fingers per part. Four iterations produced a tapered, rigidly mounted geometry: narrow enough for the smallest parts and tightest housings, rigid enough not to deflect under grip load.



Hardware Setup | System Design

Perception. A YOLOv11 model, trained on a mix of real and synthetic Blender-generated images, segments the housing in RGB; the matched depth data is registered against CAD models using Iterative Closest Point to recover 3D pose. For part picking, Siemens first evaluated its CAD-based SmartGrasp bin-picking system, but the parts were too small for reliable segmentation, giving 1.5 cm grasp error against a 0.4 cm requirement. The team substituted an ArUco-tagged tray, which held 0.8 mm positional calibration error and can be replaced by commercial CAD-based picking in production.



Control Model Training: Blind Insertion using ThoughtForge Adaptive Torque Control to account for camera localization error

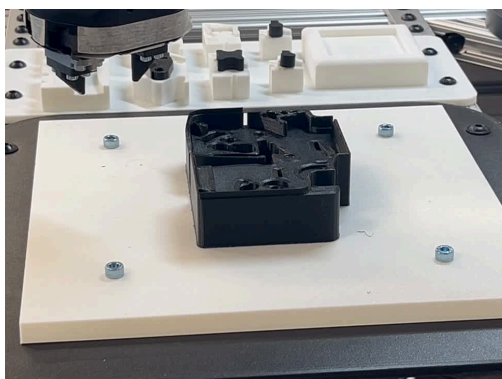
Control. ThoughtForge Active Inference treats insertion as a probabilistic process, continuously updating its model of the task from live sensor data rather than following a fixed trajectory. Sensor-to-adjustment latency under 2ms let the robot feel resistance and correct mid-insertion, which accounted for 68 percent of successful misalignment recoveries.

Orchestration. Siemens Industrial Edge supplied a container-based layer where each capability runs as a swappable, MQTT-connected application. The robot driver, ArUco picking, and orchestrator modules were validated on Edge. The NetAIF insertion module was validated standalone but hit latency issues during Edge onboarding, so it ran outside the Edge stack for the final demonstration; Siemens is testing asynchronous communication methods to resolve this.

5 RESULTS

METRIC	TARGET	ACHIEVED
Insertion success rate	At least 95%	~97% in final demonstration; 91–96% by part type in tests
Cycle time	5 sec or less	5.03 sec in final demonstration; 4.8–6.5 sec by part type
Setup time (new part family)	Under 24 hrs	~21 hrs: ~2 hrs control reconfiguration plus 18–20 hrs vision model training
Worker touch time	Under 60 min	Under 30 min
Throughput	Sufficient for facility operation	12 parts/min on one robot; matching manual line rate needs multi-robot operation
Acquisition cost	Comparable to high-end robotics	\$48,000 to \$52,000 per system
Sustaining cost	Comparable to high-end robotics	~\$15,000/yr, about 30% of system cost
Return on investment	At least 8x	6x projected

PERFORMANCE BY PART TYPE



Four-part, pick through to insertion (not full speed)

The four Magna parts spanned the realistic difficulty range. The rigid **S-Cam** was most reliable at 96 percent and 4.8 seconds, with most failures occurring at grasp rather than insertion. The flexible **T-Bumper** also reached 96 percent at 5.2 seconds despite deforming under grip force.

The **X-Bumper**, the most compliant and the most sensitive to housing movement, reached 92 percent at 6.5 seconds. The **P-Bumper**, only a few millimeters across and at the edge of what the vision system could resolve at 1.2 mm localization error, reached 91 percent at 5.6 seconds.

PROJECTED ECONOMIC IMPACT

The figures below are modeled from demonstration performance, not measured deployment savings. Modeled ROI ranges from 4x in defense sustainment to 8x in automotive, with aerospace near 6x. In automotive, cutting insertion error from 5 percent to 1 percent would save roughly \$800,000 per year at a plant running 10 million insertions, with further savings from reduced repetitive strain injury. In aerospace, verifiable force/torque logs support both rework reduction and the digital audit trail that certification requires.

8x

MODELED ROI, AUTOMOTIVE

6x

MODELED ROI, AEROSPACE

\$800K/yr

SAVED AT 10M INSERTIONS

WHAT THIS MEANS FOR THE INDUSTRY AND OUR CUSTOMERS

Insertion becomes automatable.

Tasks held back by part variation and deformation can now be run by a robot that corrects as it goes, rather than one that needs the world held still.

Re-tasking is measured in hours.

A new part family took about 21 hours end to end and under 30 minutes of worker touch time, so a line can change over without a reprogramming project.

Modular by design.

Each capability runs as a swappable application on Siemens Industrial Edge, so vision, picking, and control can be upgraded independently as production hardware matures.

ABOUT THOUGHTFORGE

ThoughtForge is a robot control system for both simple and complex tasks. Using our patented AI, ThoughtForge-powered robots easily adapts in real time to new parts, dynamic changes, and varying environments, planning motion and paths on-the-fly with unmatched accuracy and robustness.