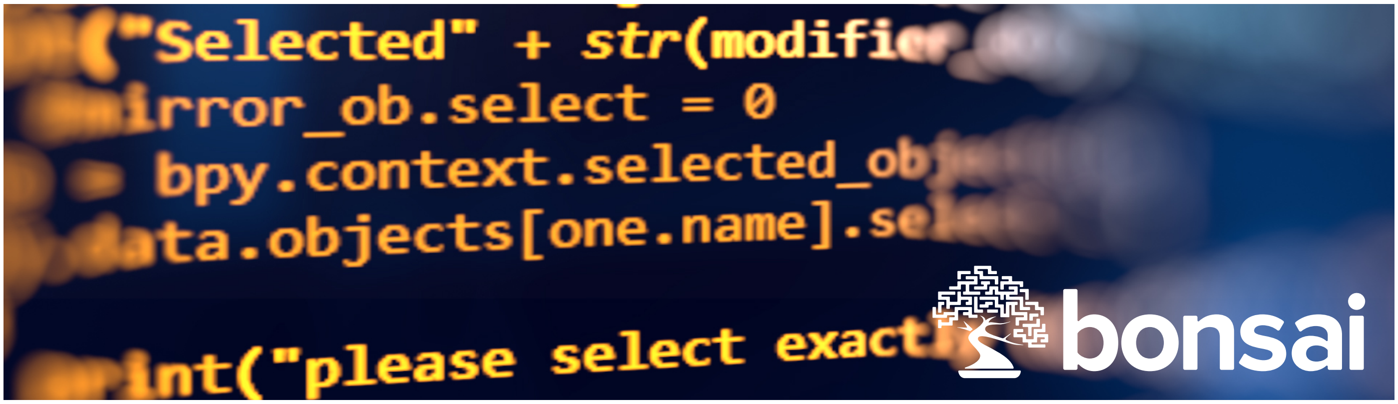

Solution brief

Siemens uses Bonsai AI to automate machine tool calibration

Siemens engineer with no AI expertise trains CNC mill to auto-calibrate more than 30x faster

Industry

Manufacturing

Partner

Siemens Digital Factory Motion Control

Solution

Using Bonsai's AI Platform, Siemens subject matter experts trained an AI model to auto-calibrate a Computer Numerical Control (CNC) machine 39x faster than an expert human operator.

Benefits

- Combining the best of human and machine intelligence
- Algorithm agnostic
- No complex data infrastructure required
- No specialist AI or advanced coding skills required
- Generalization
- Flexible
- Efficient and fast

Challenge

Lathes, grinders and mills are types of Computer Numerical Control (CNC) machine tools, which computers, rather than humans, operate. When first introduced in the late 1940s, their motors ran by reading instructions from punch cards. Present day CNC machines are programmed with sophisticated computer-aided manufacturing (CAM) software, making them capable of highly complex tasks and 'teamwork' through machine-to-machine communication.

Since their inception, CNC machines have revolutionized manufacturing across industrial machinery, automotive, aviation, healthcare, electronics and other sectors. Despite its long history, the CNC market still grows at a steady clip. According to Allied Market Research: "The CNC market is expected to garner $18,293 million by 2022, registering a CAGR of 5.5% during the forecast period 2016 - 2022."

One challenge for users of CNC machines is the changing characteristic of machine components. A typical CNC machine like a mill has three to six axes that execute different functions such as milling, tapping and drilling. For those machines to perform well, meet quality standards, and comply with regulations, they should be periodically re-calibrated. Even minor frictions can lead to errors that result in costly manufacturing imperfections.

Today when CNC machines need to be recalibrated, manufacturers often fly in specialist engineers to do the job. The recalibration procedure typically takes hours and several iterations to reach an acceptably low error value. Since few engineers are skilled enough to accurately tune compensation parameters using few iterations, results can be inconsistent.

While the CNC machines are decommissioned for maintenance, downtime costs can run up to several thousand dollars. Costs run especially high when errors are discovered outside the regular maintenance schedule. This not only results in unplanned downtime, but often also wasted parts and having to fly in a specialist at the last minute.

Looking for innovative solutions, Siemens is investigating new approaches to automate the calibration process for its CNC machines. The company had explored various techniques, with varying results.

Solution

Siemens tasked its innovation team with seeking new, disruptive ways to help automate the calibration process. During this search, Siemens discovered Berkeley-based startup Bonsai, which had pioneered a game-changing new approach to building AI based on deep reinforcement learning. Referred to as 'Machine Teaching', Bonsai's method enables subject matter experts to efficiently teach machines complex tasks by decomposing them into smaller parts, combined with classic machine learning. Here is how it works:

1. **Work with the domain experts to define the overall problem.**
   The Bonsai team worked closely with Siemens' domain expert, an engineer with decades of expertise in CNC machines, and in building complex simulations. The defined problem was a proof-of-concept to automate the calibration process of a five-axis CNC machine. The goal was to tune the compensation parameters to match that of a highly skilled human operator using as few iterations as possible (a precision tolerance below two microns).

2. **Create a 'concept network' by decomposing the problem into a set of simpler sub-tasks, or concepts.**
   Just as it is easier for humans to learn step-by-step, so it is for machines. In a typical production environment, a problem would be broken down into a set of subtasks, called 'concepts'. This accelerates the machine learning process. Siemens' pilot project was simpler, so only one concept needed to be trained.

3. **Design the 'lessons' to teach the machine using a simple scripting language.**
   A key part of this is defining and coding the 'rewards,' or goals the machine should achieve during each lesson. Using Siemens' expertise, the team formulated and coded the 'lesson plans' using Bonsai's Inkling scripting language, which is as easy to use as Python or SQL. These included information about the CNC machine's states, terminal conditions, and actions. To define the rewards, the team leveraged multiple parameters that characterize the degree to which a machine is out of calibration.

4. **Send the compiled code to Bonsai's BRAIN (Basic Recurrent Artificial Intelligence Network) server and then train each BRAIN.**
   The BRAIN Server contains implementations of many learning algorithms, includes logic for picking learning algorithms and guiding training for each concept, and is built with an infrastructure that supports streaming predictions to the target application.

   In total, Siemens worked with Bonsai to create five BRAINs and then trained them using cutting-edge deep reinforcement learning algorithms such as Trust Region Policy Optimization (TRPO) and Deep Deterministic Policy Gradients (DDPG). Unlike the prescriptive controller-driven solution Siemens tried out before, the BRAIN automatically selects the best control scheme. It works its way through the lessons step-by-step until it reaches a defined number of rewards.

   During the training phase, Bonsai and Siemens' subject matter expert used the software to modify reward functions where necessary, assess the training status, refine and iterate training and also introduce variations of the simulation model.

   The five BRAINs were trained and prepared with Bonsai's AI Engine, in a MATLAB/ Simulink simulation environment resembling the physical behavior of the machine used in the PoC designed by Siemens experts.

5. **Deploy the BRAIN and begin streaming predictions.**
   After a BRAIN learns a task with satisfactory results in a simulation environment, it is connected to and transfers all knowledge to the machine via Rest APIs or other interfaces. The BRAIN is also able to control the machine even if the conditions of the real-world machine vary from the simulation. This procedure is tested across all trained BRAINs.

Benefits of This Approach

- **Combining the best of human and machine intelligence.**
  Subject matter experts, who understand variables, behaviors and constraints that make a system run efficiently, can now spend their valuable time training powerful algorithms and libraries that help systems learn faster and work with better precision.

- **Algorithm agnostic.**
  Detaching each concept from the overall problem, and the other concepts, makes the platform algorithm agnostic. This means it can use the best-fitting training method for each concept. For example, existing classical control algorithms and inverse kinematics can be re-used for the learning process. Similarly, more advanced techniques like deep neural networks can be applied to more complex concepts.

- **No complex data infrastructure required.**
  The teaching process doesn't require advanced data pipelines and complex data infrastructures that are, for example, common in supervised machine learning scenarios, but uses a simulator or simulation software instead. Existing machine simulation environments and more complex digital twins can be fine-tuned to meet the teaching requirements.

- **No specialist AI or advanced coding skills required.**
  Bonsai's programming language Inkling can be used with basic coding skills (SQL/ Python level) which most domain experts already have or can learn easily.

- **Generalization.**
  In a simulation, a BRAIN can easily learn about different variations and scenarios across different machines of varying sizes. In Siemens' case, the BRAINs were only trained and prepared in simulation for one axis of the CNC machine. But the BRAINs were then also tested on the remaining different axes, delivering comparable results.

- **Flexible.**
  Concepts can be reused for other Machine Teaching scenarios, accelerating digital transformation programs. Existing

concepts (e.g. controller algorithms) can be easily embedded. This approach is far easier to adapt to the many different production conditions than with traditional control schemes.

- **Efficient and fast.**
  By decomposing the problem in concepts, reusing existing concepts, and training multiple simulations in parallel, the training time can be reduced significantly. However, as with humans, the more time the machine is learning, the better the results (fewer iterations and fewer errors).

Michal Skubacz, Siemens' Vice President and Head of Industry Software at Siemens Motion Control cites several reasons for choosing Bonsai: "Rather than just a toolkit or a bunch of algorithms, Bonsai offers a platform and novel approach that guides us through the whole process. Bonsai automatically selects the best class of neural network algorithms for the type of problem that we want to solve. We don't get locked into one algorithm, or machine learning toolkit, so we can easily change. Bonsai even gives us the option to create hybrid approaches from different algorithm types."

Ultimately Siemens wanted to be able to use the Bonsai Platform and enable its subject matter experts "to apply AI to the machines without themselves having to become deep experts in AI technology."

Results

Only six months in, the project is a success. The team deployed the five BRAINs via REST APIs to communicate directly to a real-world CNC machine in a test environment in the Commonwealth Center for Advanced Manufacturing (CCAM) in Virginia. CCAM confirmed that the two most successful BRAINs ran more than 30x faster in the test environment than the human operators, achieving an error rate of less than two microns in one to four iterations. This result far exceeded the goal set out in the proof of concept (PoC).

Matthew Stremler, Research Manager, CCAM, said: "At CCAM we work with industry and academia to solve challenging manufacturing problems. A big buzzword for us is "adaptive automation" which is all about how to adapt an existing process to improve its productivity, cost and quality. The breakthrough we achieved here using Bonsai demonstrates that organisations can deploy the latest AI technologies in a noisy real-world system."

Siemens is pleased with the results of this PoC, which are a first step to improve significantly the productivity, cost and quality of the CNC machine calibration process. Instead of having to fly in specialists, calibration could be performed as proactively, with consistent results and without incurring high downtime costs. This can free specialists to spend more time on high value projects, delegating repetitive tasks to the machines.

Michal Skubacz, Siemens' Vice President and Head of Industry Software at Siemens Motion Control concluded, "The solution we developed in this proof-of-concept with Bonsai does not aim to replace our human operators, but will augment and support their work. Instead of having operators carry out the same work over and over again, they can focus on training the machines to perform better."