

News & Highlights

AI-Driven Robotic Laboratories Show Promise

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Elaborate proof-of-principle experiments in several laboratories around the world have recently offered glimpses of a future in which high-throughput automatic laboratories guided by artificial intelligence (AI) might enhance the process for discovery of new materials, such as those for clean energy technologies. And in chemical engineering, using AI to aid in synthesis planning and performance offers the prospect of scientists needing little more than an idea and an internet connection to generate novel molecules in state-of-the-art, remote laboratories.

Announced in August 2020, International Business Machine Corporation (IBM)'s RoboRXN for Chemistry provides a high-profile example of the potential for combining AI and laboratory automation [1]. The system not only provides chemical recipes to produce organic molecules of interest but can also synthesize those molecules automatically using commercially available hardware—in the case of IBM's demonstrator, a Flex-category automated-synthesis workstation (Fig. 1) manufactured by Chemspeed Technologies (Füllinsdorf, Switzerland).

RoboRXN is best considered in two parts, the synthesizer hardware and its “brain” of AI algorithms trained using experimental procedures for chemical synthesis extracted from approximately a million patents using a machine learning approach based on natural language processing. The process converts even unstructured experimental procedures, written in English, into the structured steps required to conduct those experiments, including directions such as shaking, stirring, and heating [2,3]. The system's AI can also predict the outcomes of complex organic chemistry reactions [4].

Importantly for scientists interested in designing and producing specific novel molecules, the system can suggest retrosynthesis routes. In other words, a user tells it what molecule is required, and the system offers practical recipe options to produce it, focusing on reaction routes that use commercially available ingredients. IBM was already offering this degree of insight freely through its cloud-based application RXN for Chemistry. “The challenge was, can you train models that are capable of predicting how to synthesize a molecule using all the knowledge gathered in the last 200 years and, at the same time, transform that knowledge into instructions that can be executed by commercial automation hardware?” said Teodoro Laino, Manager, Accelerated Discovery at IBM Research Europe in Zurich, Switzerland.



Fig. 1. A snapshot of a live view of IBM's RoboRXN for Chemistry system synthesizing a molecule. On the lower-left quadrant of the picture, some of the automated-synthesis workstation's six reaction chambers are visible. Phials containing ingredients are on the right, with blue caps. Credit: IBM RoboRXN for Chemistry, with permission.

RoboRXN provides proof-of-principle that this, in essence, can be done. It converts its chemical recipes to machine-readable instructions, which can then be carried out by an automated laboratory able to synthesize the desired molecule. How might such a system be used? “A major attraction is for the pharma space, where chemical manufacturing has been extensively outsourced in recent years. The concept of being able to make your own chemicals in-house is gaining traction,” said Laino. “The AI component is taking the place of the chemical experience that scientists must otherwise develop over several decades, and the automation hardware is providing the possibility to scale the execution of the different processes to 24 h per day.”

Another way to approach an AI-powered robotic laboratory is to automate both the research and the instruments. In a demonstration reported in March 2020, a team led by Andrew Cooper, professor of chemistry and director of the Materials Innovation Factory at the University of Liverpool, Liverpool, UK, used a dextrous mobile robot manufactured by Kuka (Augsburg, Germany) to search for novel photocatalysts to produce hydrogen from water (Fig. 2). The robot ran autonomously for eight days and performed 688 experiments, in batches of 16, testing mixtures composed of ten



Fig. 2. The “automated researcher” in action at the Cooper Group laboratory at the University of Liverpool, Liverpool, UK. The KUKA Mobile Robot moves freely and has a reach of 82 cm. It identifies its relative position using a combination of laser scanning and touch feedback for fine positioning. It moves slowly, for safety reasons, but the system’s experimental throughput is rapid compared with a human experimenter because it performs experiments in batches, and “thinks at lightning speed,” said Professor Andrew Cooper. Credit: Andrew Cooper, with permission.

different chemical solutions including a catalyst, two surfactants, and three dyes. Each individual experiment was evaluated with gas chromatography to ascertain its performance [5]. “Before we had the automation, students would do about one experiment a day by hand,” said Cooper. “The robot actually moves slowly for safety reasons, but it is like the Terminator—it just does not stop. It works 24/7, doing 16 experiments at a time.”

The ability to deal with so many variables is where machine learning shows its unique strength, Cooper said. Because the “research space” for this experiment contained nearly 100 million possible combinations of ingredients, the automated system used a Bayesian optimization algorithm to evaluate the results of each experiment—based on hydrogen production—and then decide on which mixtures of ingredients to try in its next batch. When the system found a promising combination, it attempted to optimize that while also continuing to prospect in other areas of the research space. “It is very hard for a human to be optimizing something while simultaneously trying other things. The number of dimensions is way too high for it to even be conceptualized by human brains,” said Cooper. While human chemists prefer to test one variable at a time, he said, this AI method does exactly the reverse—it changes everything all at once, refining its machine learning models with every batch. The experimental run delivered photocatalyst mixtures six times more active than the initial formulations [5].

One big benefit of automating the research is that it becomes easier to add further capabilities to the laboratory space, said Cooper. “Every month we are adding a new station, making it much more complex. We are working on X-ray diffraction now, which is important because it allows you to determine the structure of materials—not just what do they do, but what they are.” Cooper’s 400 m² laboratory now includes two robots, with two more on order, all of which could work together as a team.

Researchers at the University of British Columbia (UBC) in Vancouver, BC, Canada, have developed another AI-powered automated materials-science platform, this one conceived to accelerate the discovery of advanced materials for clean energy [6]. Named Ada, the “self-driving” robotic platform produces and tests novel thin-film materials without human supervision (Fig. 3). Tasked in one experiment with maximizing the carrier mobility of electron-hole transport materials frequently used in perovskite solar cells, Ada fabricated films by creating mixtures of three solutions, including an oxidant and a dopant [7]. The system deposited these mixtures onto glass substrates and then annealed them, with the relative concentration of dopant and the annealing time as the input variables. After annealing, the electrical and optical characteristics of each sample were measured automatically. Each experimental cycle took 20 min, at which point the system used a Bayesian optimization approach to decide for itself which combination of variables to try next. It took 35 cycles (~12 h) for Ada to identify the optimal cobalt concentration and annealing time [7].

As with the robot in Cooper’s laboratory, Ada was successful in combining AI and automation to rapidly navigate a broad experimental space. The Canadian team behind Ada currently has six of these platforms, working on different projects, said Ada Project Manager Amanda Brown, including one designed to develop electrolyzers for carbon dioxide to facilitate direct air capture of carbon. “It is an enormously multidisciplinary effort,” said Curtis Berlinguette, lead principal investigator and UBC professor of chemistry and chemical and biological engineering. “We have mechatronics engineers, mechanical engineers, chemists, material scientists, programmers, and machine learning experts all working together to build out our platforms.”

Though the work shows promise, there remain many limitations for AI-powered robotic laboratories to navigate. “Collectively, the field is starting to tackle more ambitious and harder problems, but I feel we have been stuck in this proof-of-concept stage for quite a while,” said Connor Coley, assistant professor of chemical engineering at the Massachusetts Institute of Technology (MIT) in Cambridge, MA, USA, and part of the Machine Learning for Pharmaceutical Discovery and Synthesis Consortium, an MIT collaboration with the pharmaceutical and biotechnology industries. There are a range of challenges for automation to deal with, said Coley, whose work includes combining AI-powered synthesis planning

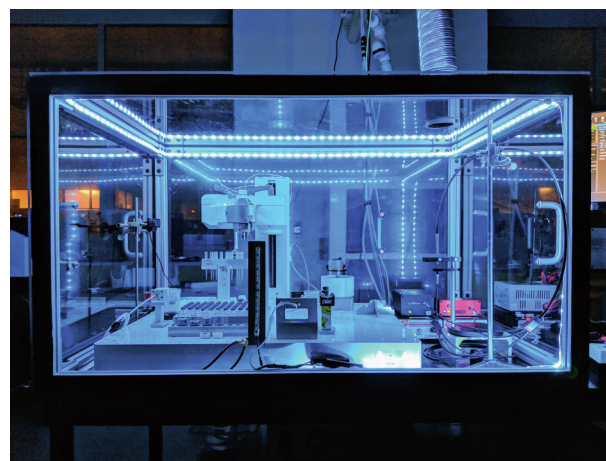


Fig. 3. The University of Columbia’s Ada robotic laboratory platform, a “self-driving” system designed to accelerate the discovery and development of novel, thin-film materials for clean energy technologies. The light-colored column to the left-of-center has an articulated robot arm on top. The black column in front of it is a substrate storage rack, and the light-colored cylinder just right-of center is the spin coater. Credit: UBC, with permission.

with robotic automation to produce medicinal compounds [8]. “If you are not doing things at a very small scale, then exothermic reactions are a problem. And we are still relatively bad, as a community, at dispensing solids robotically. Some reactive solid powders tend to clump, so accurately dispensing those and weighing out precise quantities remains an issue.”

With IBM’s RoboRXN, the hardware currently used by the team cannot perform the sort of purifications often needed in multistep chemical processes. “If you want to purify it, you must take it out of the loop, purify, and then restart the automation process,” Laino said. “This has a big impact on the performance of the entire chemical synthesis.”

Should these challenges, and many others, be overcome in the years ahead, AI-driven robotic laboratories could deliver not only high-throughput chemistry and materials research, but also more adventurous investigations. “I sometimes regret emphasizing the speed of AI-powered robotic research, because it is not really the point,” said Cooper. “The underlying goal was always to look at things we simply could not look at. Because the rate of enhancement is so big with automation, you can afford to do really speculative things and take some chances.”

Laino, however, has a different vision for the future of RoboRXN, based on a combination of remote access and scaling-up. “Imagine a big warehouse, where instead of a big data center full of computers, you have robots doing chemistry-on-demand. Suddenly, you see the potential of bringing this technology into a field like

chemistry. It is a revolution that is going to definitely take some time, but this is going to dramatically change the way we see and do chemistry.”

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