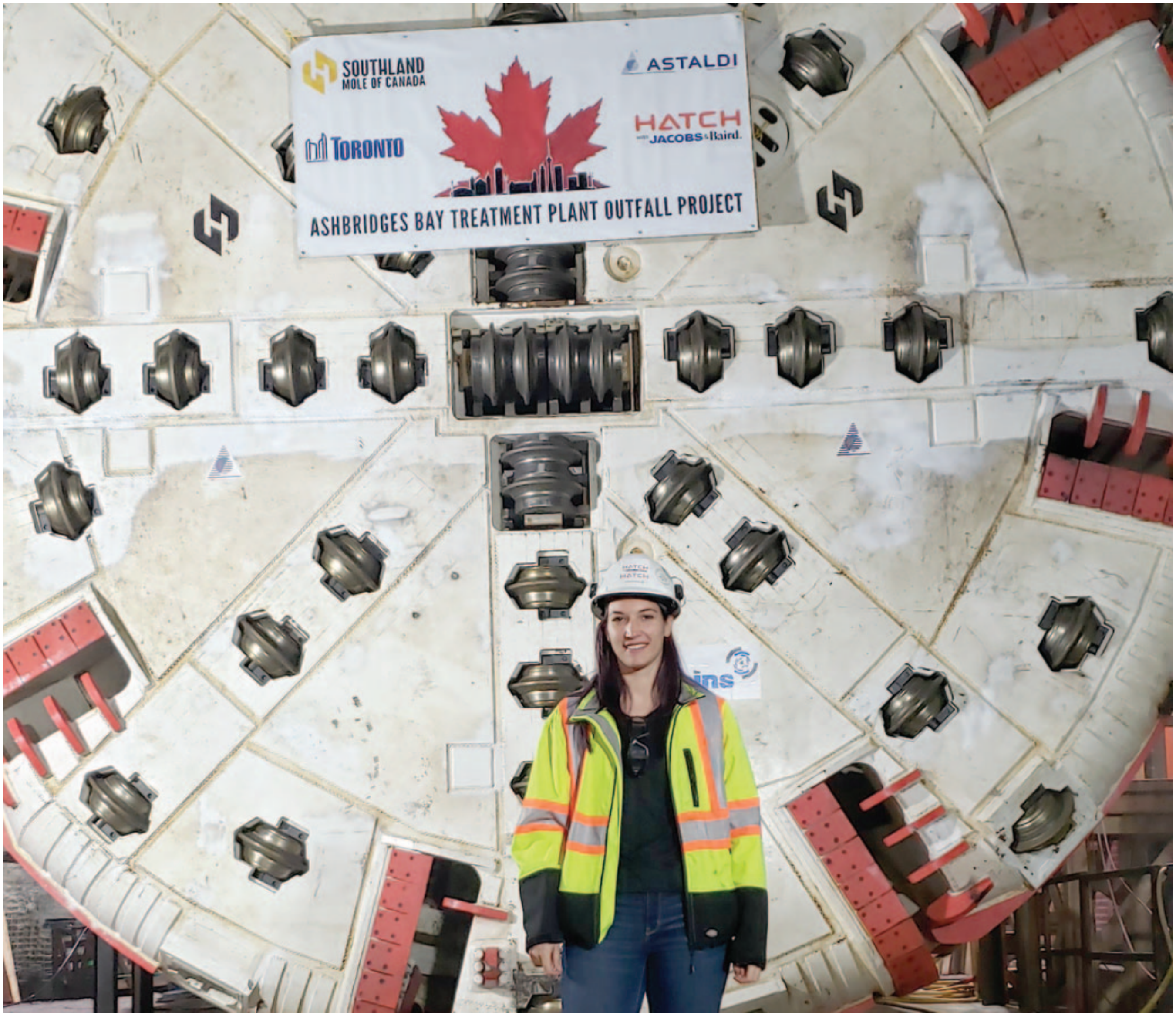
Courtesy of Josephine Morgenroth



Josephine Morgenroth, geotechnical engineer at Hatch, is researching how to forecast underground seismic events with machine learning.

Thinking ahead

As the use of artificial intelligence and machine learning in mining is becoming more commonplace, research is underway to automate every part of a mining operation

By Lynn Greiner

When most people think of artificial intelligence (AI) and machine learning (ML), they think of shiny things like self-driving cars, but the truth is, it has been around in some form for decades. It just was not practical for real-time applications, as computers were not strong enough to run the models in a timely manner.

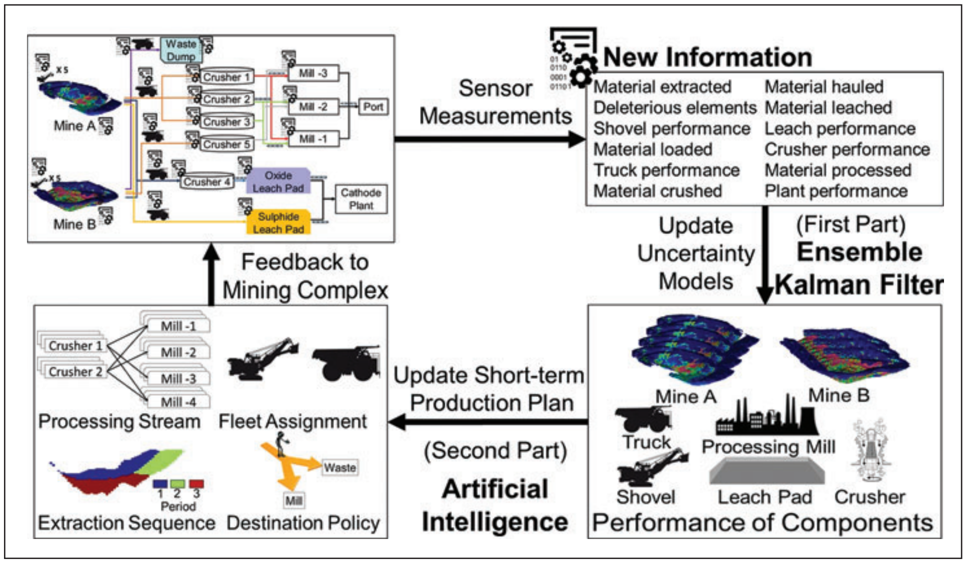
The difference today is that we finally have the computing power to make it viable, and mining companies are now embracing it. UK research firm Global Data predicts that the industry will spend US$218 million annually on AI platforms by 2024, noting, "AI has the potential to deliver tangible benefits across the mining value chain, from discovery through to extraction and maintenance."

The technology can be used from end to end in the mining process, from measuring seismic activity underground, to ensuring productivity in processing plants or even optimizing an entire mining ecosystem from the moment the ore is dug to when it hits the markets.

Optimizing the industrial mining complex

The COSMO Lab, a collaborative mining engineering laboratory based out of McGill University is exploring new ways to optimize that flow.

"We look into what we call industrial mining complexes or mineral value chains," explained COSMO Stochastic Mine Planning Lab director Roussos Dimitrakopoulos. "It means we look at where materials are produced from mineral deposits (and in most cases, you may have more than one location where you extract materials), how the material flows from the mines and mineral deposits to the various components – from stockpiles to blending to crushers to waste dumps and so on – until it goes to the mineral processing plants, and then we link the mineral processing plants and their production to the markets. So, the one source is these deposits and on the other end you have the markets. We look at this as one system."



Courtesy of COSMO Lab

A massive amount of information is being collected for COSMO Lab's work on self-learning mining complexes.

For the past decade, his team has been working on an optimized model for the whole system. The big issue is dealing with high levels of uncertainty, something stochastic models (a technique of presenting data or predicting outcomes that takes into account a certain degree of randomness, or unpredictability) are designed for. There is, he said, uncertainty not only in the material coming out of the ground, but in market demand and pricing. Models quantify the uncertainty, assisting mines in strategic long-term planning. But then that plan needs to be operationalized.

Adding to the complexity is the sheer size of the models; the lab is working on more efficient ways to tame these computational monsters, including the use of reinforcement learning, a technique that makes decisions based on how inputs affect defined goals. According to Dimitrakopoulos, COSMO's self-learning technology is still in the research stage and might require another five to ten years before its put to real use in production.

"On the operational side of things, we have way too much information," added Yassine Yaakoubi, a research fellow at COSMO Lab. "We need to understand the part of information that has the most impact on the short-term production schedule in the mine. And we can only do this by testing different features or providing different information, and then using and analyzing different ways of integrating reinforcement learning, to figure out how to update the short-term plan in order to adjust for this new incoming information."

Keeping excavations stable

While the COSMO Lab team is trying to create a self-learning industrial mining complex, Hatch geotechnical engineer Josephine Morgenroth's focus is underground. She worked in the infrastructure and mining space, looking at the stability of both underground and surface excavations, before returning to academia to pursue a PhD at York University's Lassonde School of Engineering. Her research focus is using machine learning algorithms to forecast the stability of underground excavations in mines.

"That's where all the data is, and where people are willing to push the envelope a little bit," Morgenroth said. "Mines have so many excavations that they're willing to try out new things in each kind of successive development, whereas in infrastructure tunnels, or rails, or those types of things, they have to get it right the first time, so they're not as keen to use new technology."

Her current project is with a mine near Sudbury, Ontario, that has what she calls "a high-stress mining environment that deals with a lot of seismicity and rockburst hazards." She is working on predicting the seismicity around excavations as operations progress, and how stresses redistribute around the excavation as stopes are removed and blasting proceeds.

There are millions of records in the microseismic database, so the mining company calibrates its numerical models to only the large-scale seismic events.

"It's not very efficient," Morgenroth observed. "And it means they can only calibrate those models once a year because it takes so much computational time and also engineering time."

Morgenroth's solution to the problem: she has developed an algorithm using a technique designed for time-series data, fed it the microseismic data, and trained it to predict the big events and the ensuing stress state around the excavation afterwards.

"That's been really successful, working with the mine itself and with the rock engineer and consultant in order to automate the calibration process of those models," she said. "And the next step will be to take that prediction from the machine learning algorithm and to update the numerical model that's being used every time new seismic data is collected, so that they can improve operations and costing and scheduling into the future."

Ultimately, the trained model could be used to speed up the scenario analyses where engineers numerically remove a stope to see how stresses redistribute. However, it is not there yet. Currently, Morgenroth said, "We're at the stage where we're happy with the algorithm and the way that it's been built. And now we're going to take those outputs and put them into the numerical model to see if it mimics their operational standpoint. We're in that changing hands point of the process where the research will actually get implemented. And we'll see what the benefits are that they get."

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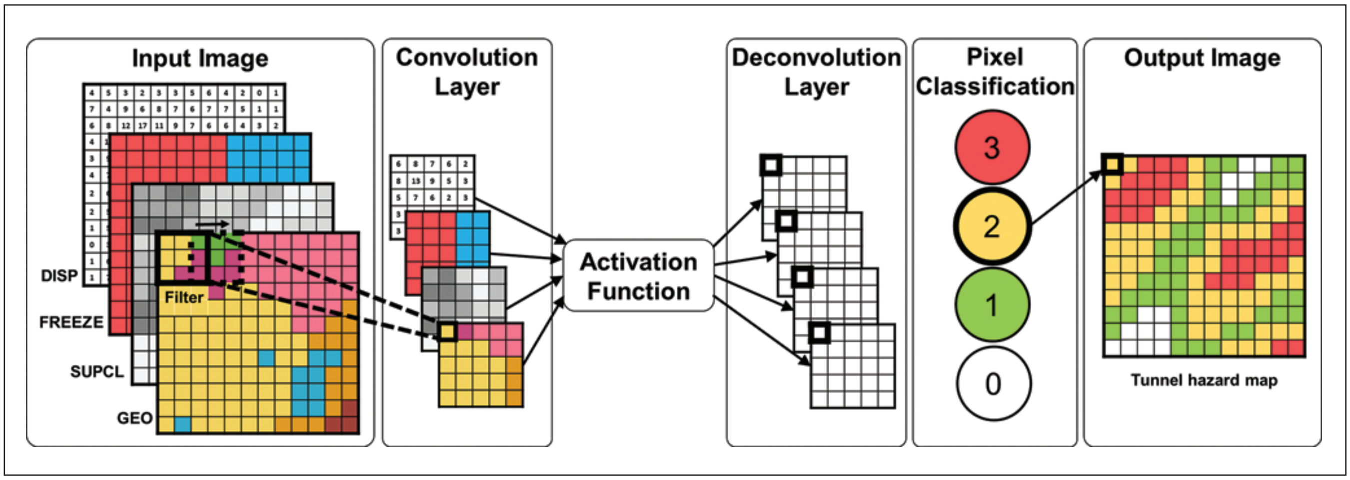

A convolutional neural network is an image processing algorithm that filters over the channels of an image to find relationships between said channels. Here, an input of a tunnel map outputs a hazard class for each location in the tunnel.

The methods are proven in other areas dealing with risk assessment, she added, noting, "We're well beyond the tipping point. I think it might even be [in production in] three to seven years, especially as younger people are entering the workforce, and they can do a bit of programming or a lot of programming depending on where they come from. That, combined with the expert judgment and the experience that's already in the industry, I think we're at a very interesting time point right now, where the time is just right for machine learning to be used as a common engineering tool. And I say, it's not that machine learning is the magic wand that will solve all of our problems, but it is another tool in the engineering toolbox. I think it would be unwise for any mining company to be resistant to it, because it's not 'if' it's 'when' it becomes a common tool."

Processing plants that run themselves

At the other end of the chain, well above ground, applied artificial intelligence company NTWIST focuses on processing plants, and one of the big challenges, said product manager Grayson Ingram, is employing AI safely in the context of autonomous operations for mining.

The company focuses on automating areas that are too complex or time-consuming for traditional techniques, such as feed mill characterization, grinding and recovery. It typically optimizes at a unit operation level, but its vision is to automate the entire plant. Ingram said that it uses a mix of machine learning technologies to train its AI, including traditional supervised and unsupervised learning and advanced techniques such as supervised learning neural nets, reinforcement learning and deep learning-based computer vision.

Initial training uses historical data, usually more than one year's worth to account for seasonal variations. As production proceeds, there is automated assessment of the model's performance, with autonomous retraining when necessary.

One module of the solution analyzes incoming data from each instrument to detect drift or failure and notifies an operator if it sees a problem. Then, rather than grinding to a halt, the model continues to function using remaining data sources, communicating the impact on model confidence to the operator. And if the model determines it has low confidence in its predictions, it can request operator intervention or revert to a predetermined backup or use fall-back logic.

NTWIST offers two types of deployments: closed loop, where the AI runs things on its own, and open loop, where there is also a human involved. In both cases, the system integrates with the existing process control infrastructure.

For example, in a grinding circuit that must reduce rock to a specific particle size, in a manual system, the operator must monitor a lot of parameters to ensure the output is correct.

"The operator uses a mix of intuition, and some heuristics or guiding principles to try to achieve the optimal outcome," Ingram said. "What we do is introduce our technology and that's going to process all of the data sources related to the circuit and build a data-driven model to reflect the physical processes. And with that understanding, we're able to recommend what changes should be made in that circuit to achieve the optimal outcomes. That information can either be implemented in closed loop, or passed on to an operator who can then use it to guide decision making. You turn every operator essentially into your best operator by providing them with the appropriate information to make optimal decisions."

And one key feature that helps instill operator confidence in the system is the integration of explainable AI, which describes why the AI made a particular decision. That makes it auditable. But for Ingram, that's not the most important part.

"I definitely know, from a technology perspective, that we want to be very careful that we understand the impact of the decisions we're making and have appropriate guardrails to avoid outcomes that are going to impact safety," he said. "There are significant safety, financial or other impacts from deploying artificial intelligence and machine learning tools without having appropriate guardrails in place to make sure they function as intended. AI is data driven. And so there's always the opportunity of having negative impacts when you don't consider whether your training data appropriately represents the conditions that you would like to model and understand in the future.

"We want to make sure that we understand what types of situations or operational scenarios are represented by the historical data used to train the machine learning model," Ingram continued. "And we really want to make sure that if there is a situation that hasn't been adequately represented in the historical data, rather than making a prediction or recommendation based on an inadequate data set, we default to some other action that is appropriate for whatever use case we're looking at."

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