RIT | Golisano Institute for Sustainability

Linton Crystal Technologies looks to improve process quality and yield through machine learning

Company	Sector	Size	Location
Linton Crystal Technologies	Monocrystalline-ingot production for the semiconductor, machined part, and solar industries	25 employees	Rochester, New York

At a glance

- Linton Crystal Technologies (Linton) is an equipment manufacturer that specializes in designing and manufacturing furnaces for growing crystals—cylindrical silicon ingots—based on a method known as the Czochralski process. The crystal ingots are critical components in semiconductors used in electronic devices.
- Significant time and energy is required to produce an ingot using the Czochralski method: Growing a single crystal calls for adjusting more than 400 parameters for a process that lasts over 60 hours and demands a temperature reaching 1,425 degrees Fahrenheit.
- The failure to grow just one crystal ingot represents a major loss of time, energy, and labor for silicon-ingot manufacturers. And the risk will only increase as market demand for digital devices continues to flourish.
- After conducting an Industry 4.0 assessment, engineers from RIT identified **machine learning** as a potential solution for improving the yield and quality of the ingot growth process. This offers significant potential to increase the value of the Linton product with their customers.
- The RIT team analyzed a dataset of successful and failed production runs to develop two types of data-driven models to predict errors during crystal formation before they happen: an LSTM (long short-term memory) model of process time-series data, and an image-based model.
- The LSTM model showed some promise, but not over long periods of time. The team lacked the volume of production data they needed to fully train the model and validate its accuracy over the length of an entire run.
- Results from the image-based model proved more promising; it used images captured by a vision system already onboard Linton's equipment. A neural network was trained to detect unique features of the ingot's curved surface that are considered indicators of good runs.

Company

Linton Crystal Technologies designs, develops, and manufactures furnaces for producing monocrystalline ingots for the semiconductor, machined-part, and solar industries based on the Czochralski process. The company specializes in silicon and also produces equipment for materials such as germanium, gallium arsenide, and indium antimonide (InSb).

Business challenge

Linton's furnaces are used to grow crystals in order to obtain single cylindrical silicon ingots by employing a method known as the Czochralski process. The ingots are used in the electronics industry to make semiconductor devices like integrated circuits. For a crystal growth to be successful, the Czochralski process means maintaining a very high temperature for more than 60 hours and appropriately setting over 400 process parameters.

When a company uses one of Linton's furnaces, a team of experts continually monitors and controls each crystal growth at regular intervals. However, despite their careful observation, flaws in a crystal's structure may still go unnoticed until many hours into the process. Even small quality defects can mean abandoning a run, which, in the end, represents significant losses in terms of time, energy use, and labor.

The Industry 4.0 solution: Machine learning

Machine learning combines several technologies, which, when applied to manufacturing, allow software and machines to sense, understand, act, and learn on their own or augment human activities. Industry 4.0-enabled manufacturers generate a vast amount of data using an array of sensors across their production systems. They increasingly rely on machine learning to quickly analyze and interpret that data to produce valuable insights.

Linton partnered with RIT to learn how—if at all—process data generated by its silicon-growing equipment could be leveraged to improve overall efficiency and operational costs for its customers. Machine learning presented the best strategy for achieving this goal; the RIT team explored the potential for developing a predictive model based on data provided by Linton. Such models rely on algorithms that are trained with large amounts of data, a process called "deep learning." At the core of a model is the neural network, which is made up of node layers that are designed to behave like biological neurons in the human brain.

Why machine learning?

- **Synchronized, intelligent automation:** Machine learning can leverage existing digitalization technologies—such as data-collection hardware, industrial networks, and enterprise software systems—to generate new insights, maximizing the return on Industry 4.0 investments.
- **Optimal efficiency:** Putting machine learning to work in the factory can open entirely new business opportunities for realizing new levels of efficiency and productivity throughout an enterprise.
- **Less surprises, less downtime, less waste:** Machine learning can power predictive maintenance to monitor equipment performance in real time and catch unexpected events coming down the road that might otherwise set businesses back in terms of costs and resources.
- **Continual quality control:** Product and process quality can become nearly constant using machine learning to significantly increase the consistency of overall output.
- **Safer work environment:** Machine learning and related artificial intelligence (AI) technologies—coupled with automation and robotics—can reduce the need for humans to be directly engaged in dangerous and dirty manufacturing tasks.

Approach

Engineers from RIT's Center of Excellence in Advanced and Sustainable Manufacturing (COE-ASM) set out to learn if a relationship could be identified between Linton's controllable process parameters and the resulting quality of a crystal ingot. If so, they would then demonstrate a real-time prediction system to anticipate failures before they happen and, subsequently, minimize wasted resources and energy. By doing so, the RIT team aimed to not only improve Linton's operating efficiency, but also the material impact of both the semiconductor industry and other industries where the Czochralski process is used to "crystalize" metals like silver, palladium, and platinum.

Solution

After considering Linton's goals, the RIT team created two types of models over the course of the project. These were based on a general dataset that consisted of a historical log of process data based on more than 400 parameters and a store of in-process images captured by a camera within Linton's furnace. The dataset captured a number of successful and failed production runs.

Two parallel approaches were taken for modeling the dataset:

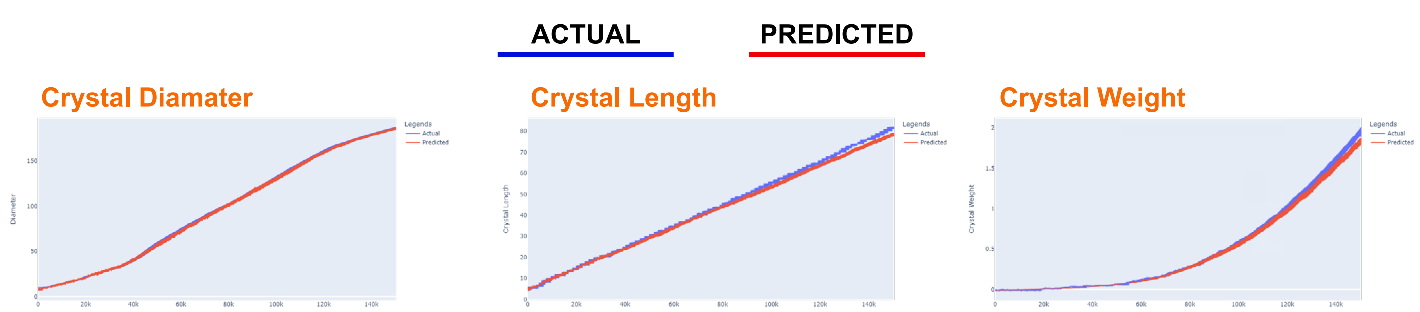
1. The first was a long short-term memory (LSTM) time series model designed to predict future growth trends based on past parameter data. To create this, the RIT team analyzed over 400 parameters tracked in the historical log data. Their goal was to identify those that would deliver essential and unique data points in a model, removing any that were redundant or irrelevant. The parameters included initial process settings and crystal-quality metrics like length and weight. In the end, they selected less than 30 parameters on which to train the real-time prediction system. The time-series parameter signals were converted from a measure of time to band frequencies in order to extract further underlying patterns correlating to either successful or failed runs.

2. The second model used image data captured by Linton's machinery to train a neural network. This model focused on the visual detection of unique geometrical characteristics of growing crystals which are early signals of a good production run.

Results and next steps

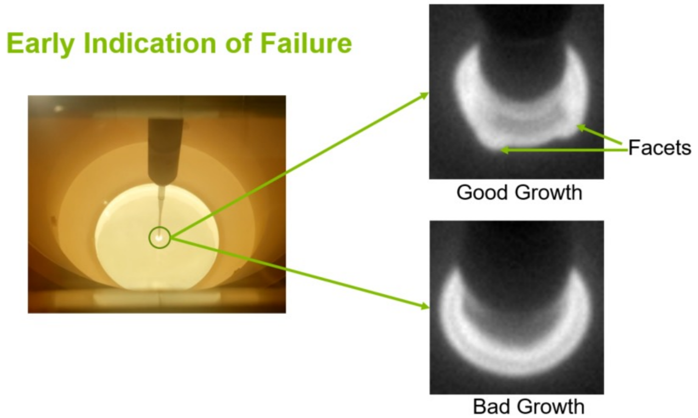
The solution RIT developed for Linton is an example of how machine learning can enhance the value of Industry 4.0. Namely, the project explored a way in which a data-driven model can be used to provide manufacturers with advanced perception and decision-making capabilities.

The time-series-data model revealed that it is possible to roughly predict how a crystal will grow within Linton's furnace within a short future time frame. However, RIT's engineers found that the prediction deviated considerably from the results of an actual process as the model's time horizon is increased. The model's discrepancy, they found, was caused by insufficient training and testing data. Given enough samples of data representing good and bad runs, this forecasting method could still be used to detect impending failures; however, that data was not readily available at the time of the project.



Comparison of predicted crystal development to actual for critical characteristics

The image-based model showed very promising results. Using laboratory data, the engineers concluded that it is feasible to detect geometric features that are consistent with a good quality end-product very early on in the crystal-growing process. The machine-learning models were deployed on production equipment in the Linton Crystal laboratory and demonstrated that the technology can successfully detect the quality precursors in real-time operation.



Examples of image-based facet identification

To achieve full benefit of the system, the model has to be trained with more data that encompasses a greater range of quality variation within the production environment and process parameters of Linton's equipment. Additionally, it needs a usability interface that would allow Linton's customers to adjust the model, such as stop and restart it or tweak parameters. An operator should also be able to override the model's decisions in order to train it for new circumstances that may not have been encountered during training.

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