September 23, 2019

SERVO MOTOR SHUTDOWN PREDICTION FOR 3DMJF

HP INC

Servo Motor Shutdown Prediction for 3DMJF

Goal for Predictive Maintenance for 3D printing system is to contribute to reduce unplanned downtime and possible failures, helping the customers save money while building trust. Not all failure modes can be captured in internal testing owing to variety of usage environments and usage conditions. For instance, the threshold for specific sensor monitoring might not be applicable with specific usage conditions for customer(s). In this paper, we describe a process based on machine learning to predict the lifespan of servo motors (Z-Motor) in terms of number of layers remaining and generate alarms.

Problem Solved

Servo Motors consists of a motor coupled to a sensor for position feedback, allowing precise control of angular or linear position, velocity and acceleration. It also requires a relatively sophisticated controller, often a dedicated module designed specifically for use with servomotors. For the printer operation, servo motors have an important role for printing and their failure usually means job failures, quality issues, and even potential damage to the device. Some examples of 3D MJF servo motors are: Recoater Motor, Scan Axis, Shaker Motor, Cleaning Roll, Vane Motor and Z-Platform Motor (Z-Motor).

The Build Unit (BU) is part of a printing solution and, together with the Printer, stores and transports a building volume where material layers are spread, and parts are formed. The BU platform (printing bed) moves in the z direction (up/down) in the printing process and the Z-Motor is responsible for this movement. For 3D printing the Z-Motor shutdowns may generate hundreds of system errors, resulting in jobs failures, downtime and unscheduled on-site visits.

A considerable part of the failures happens at an advanced printing stage, causing job failure and downtime for the BUs. The lifespan of this motor varies a lot for different usages, number of parts, press configuration etc., so using a common preventive maintenance strategy presents the risks of failing jobs or having a lot of downtime for short periods of replacements. In this work, a predictive model has been developed to predict Z-motor shutdown in terms of number of jobs that are about to get printed.

The data for this experiment is a combination of multiple data sources from motor traces sampled at high frequency, printed layers by BU and system errors from shutdown events. The motor traces include a snapshot of the motor voltage, the values of actual and reference platform velocity and platform position and the platform movement state.

Description

Our solution consists in creating a model to predict when a Z-Motor shutdown will happen in terms of layers (approx. Five thousand layers per job). This predictive model will help the support team and the customers to:

- Schedule a maintenance of the BU, avoiding unplanned downtime;
- Decrease the number of job failures related to Z-Motor shutdowns;
- Explore the data and recommend improvements on the data collection.

The data for this experiment is a combination of multiple data sources from motor traces sampled at high frequency, printed layers by BU and system errors from shutdown events. The motor traces include a snapshot of the PWM motor voltage, the values of actual and reference platform velocity and platform position and the platform movement state (SLEW, ACCEL, DECEL and HOLD). Currently, the printers just send traces generated by Warming Up and Annealing printing stages and, when a shutdown happens, the last few minutes of traces are stored. For this analysis, only the heating traces are used, since they provide the most homogeneous observations of traces (same number of layers, material weight etc.)

Data Ingestion: The servo traces data is part of a telemetry package from the Big Data repository, sent by the printer and the processing station after a session (a session is a period between two restarts). In order to collect the data needed an ETL process was created (see Figure 1) to extract the traces and printer logs writing back to S3 in parquet format.

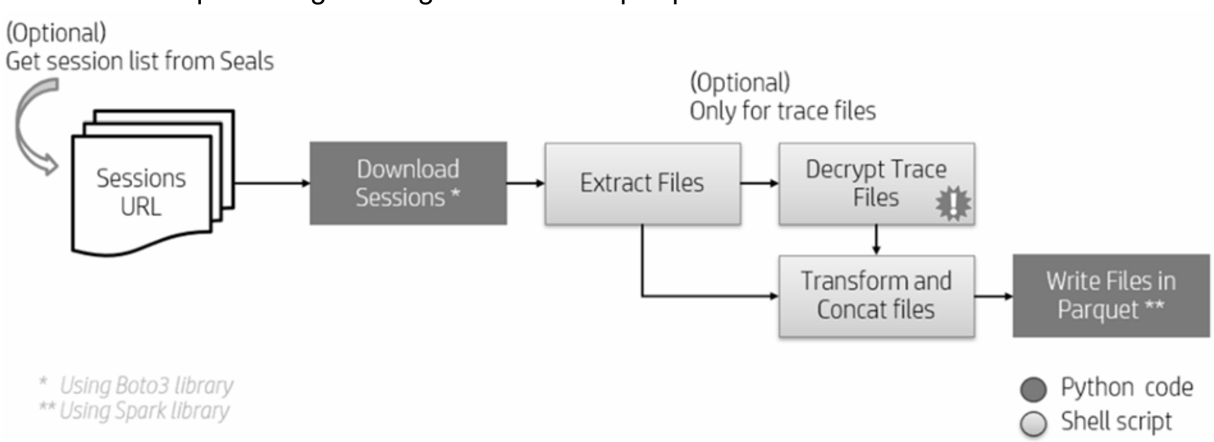

Figure 1 - Data ingestion workflow

The telemetry data for BUs is captured and stored as part of the session of the printer and the processing station. As the trace files are rewritten on every new file generated, we need to analyze the printer logs to know which trolley was responsible for generating the traces and grab its identifier. The counters for printed layers by BU are extracted from a counter that counts all printed layers by BU.

Data Cleaning: The following filters were used:

- Old MB1 Build Units (BU's serial numbers that start by ESXX) are filtered out;
- Trolleys with less than one Warming Up session data prior to a shutdown are not used;
- BUs with improvements are removed.

Feature Engineering: To create the features of the dataset, by each session and for each state and bed movement direction, speed and position from various sub-systems are summarized using the various descriptive statistics. With data analysis and the domain knowledge, it was identified that part of the degraded Z-Motors shows high PWM variation (similar to a noise). To capture this information, an inflection point for PWM was added to the input features. Figure 2 represents example of remaining layer count (target column) for each session which is calculated by the difference in layers over the actual session and the layer count for the next shutdown.

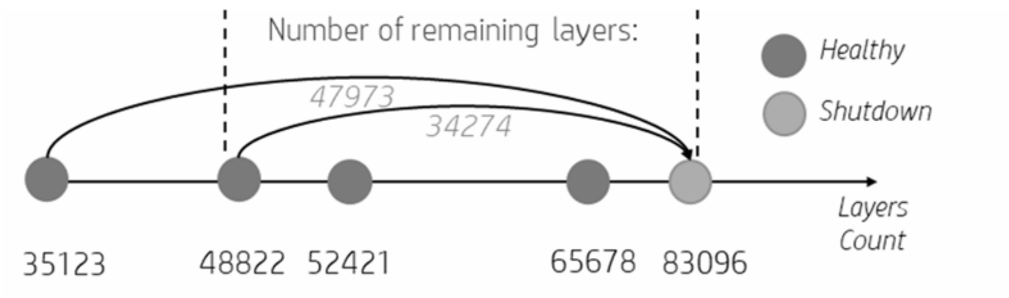

Figure 2 - Calculating the Remaining layer target before a shutdown

Post processing and cleaning the data with business logic filters, the final dataset contains up to hundreds of distinct BU's, from over three hundred print sessions and over hundred shutdown events for a period of 6 months.

Model Training: After the data being processed and filtered, the final dataset has a mix between healthy sessions and sessions with shutdowns from five months of observations (Nov/17 to Mar/18). For the remaining layers prediction, a Random Forest regression model was trained using 10 folds on k-fold cross validation.

Evaluation and Feature Importance: RMSE was used as evaluation metric and the output of the model predictions is transformed to different classes of remaining layers: Low, Medium and High or more layers leading to shut down. Using a 20k layer threshold to separate the regression result into two classes of outputs (close to a shutdown or not), the accuracy and recall were calculated at 88% and 95%, respectively, implying a robust field model deployment.

The model runs on every device connected to cloud and triggers a prediction that combined with an alarm definition goes through predictive maintenance system. This alarm is used to possibly generate a support call and the replacement of the component.

Advantages

- This predictive system for servo motor failures will help avoiding unplanned downtime, which for industrial customers might represent a saving of thousands of dollars.
- By using layers as a measure for remaining life, it allows customers to plan according to their production needs.
- The approache used is leverageable for other printer products

Disclosed by Nailson Boaz Costa Leite, Andre Rabelo, Syed Fahad Allam Shan and Gabriel de la Cal. HP Inc.