Predicting the Lifespan of Industrial Printheads with Survival Analysis

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Maastricht University Canon CANON PRODUCTION PRINTING

Overview

Context

- This research was conducted in collaboration with **Canon Production Printing (CPP)**, which specializes in **industrial-scale printers** used for commercial and production-grade applications.
- A core component of these systems is the **printhead**, responsible for jetting toner or ink.
- Ensuring accurate lifespan prediction of these components is crucial for **maintenance scheduling**, **cost reduction**, and **customer satisfaction**.

Lifespan Prediction

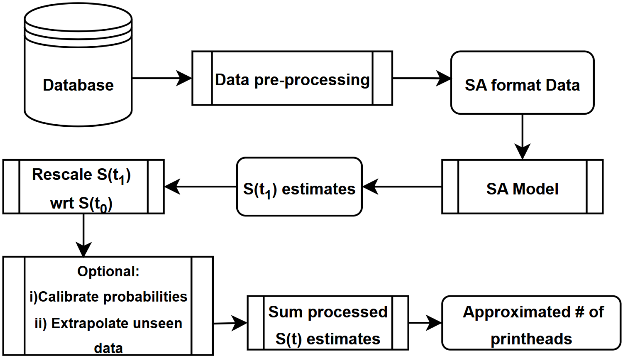
Definition

Lifespan prediction involves estimating the amount of time a component or system will continue to function before it fails.

Why it's challenging:

- Failures may occur unpredictably or after long operational periods.
- Often only **censored** information is available (the unit hasn't failed yet).
- Usage data can be noisy, sparse, or irregular.

Objective



- Improve the accuracy of **printhead lifespan prediction** using modern survival analysis techniques.

Dataset

- Focus on one specific printhead model (older, lots of data).
- **Timeframe:** 2008 - 2024
- Data sources:
  - **Printer metadata**: installation date, position, managed color.
  - **Operational logs**: warm hours (when the printer is on, even if not printing), toner volume.
- Considerations:
  - Heavy **censoring rate: over 70%** of printheads had not failed at time of observation.
  - Missing nozzle-level data due to pre-logging architecture.

Data Cleaning

- **Motivation:** Raw operational data included outliers, inconsistencies, and noise due to diverse printer environments and incomplete logging.
- **Domain knowledge informed cleaning:** Rules and cutoffs were defined in collaboration with Canon Production Printing domain experts.
  - Implausibly high usage statistics
  - Usage $>$ **12 hours/day** (considered abnormal)
  - Devices in storage $>$ **1.5 years** before installation
  - **Dead-on-arrival units** (immediate failures after installation)

Survival Analysis Overview

Goal: Estimate the time until a printhead fails or number of failures.

Each instance i is represented as a triplet (X_i, y_i, δ_i), where:

- X_i: feature vector (e.g., warm hours, toner volume)
- y_i: survival time (T_i)
- δ_i: event indicator ($1 =$ failure, $0 =$ censored)

Survival Function $S(t)$ represents the probability that a printhead survives beyond time t:

$$S(t) = \Pr(T \geq t)$$

To estimate the number of failing printheads, each instance is treated as a Bernoulli variable where p_i is the model-estimated failure probability for unit i:

$$E(X) = \sum_{i=1}^{n} p_i$$

Survival Analysis Methods

Models Implemented:

- Kaplan-Meier (KM)
- Random Survival Forest (RSF)
- Gradient Boosting (CBoost)
- Cox Proportional Hazards (CoxPH)
- Weibull Accelerated Time-Failure Model (ATF)

Purpose: To compare models under consistent preprocessing and evaluation settings.

Non-parametric

$\updownarrow$

Parametric

Evaluation Procedure

Evaluation Setup:

- A prediction window is a specific range of time ($[t_0; t_1]$), where:
  - t_0: maximum date of data logging per printhead (used for training)
  - t_1: future date for which failures are predicted (used for evaluation)
- We extracted six windows, each one year long and spaced six months apart, from:

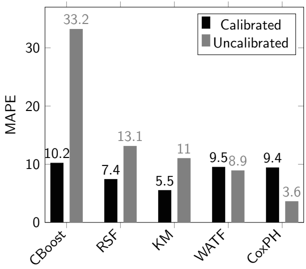
$$[t_0 = \text{May 2021};\ t_1 = \text{May 2022}] \text{ to } [t_0 = \text{Nov 2023};\ t_1 = \text{Nov 2024}]$$

Models were evaluated using:

- Concordance Index (CI)
- Integrated Brier Score (IBS)
- Mean Absolute Percentage Error (MAPE)

Results and Discussion

- **CoxPH (uncalibrated)** had the lowest MAPE: **3.6%**.
- **KM (calibrated)** also performed well: **5.5% MAPE**.
- **Calibration** notably improved CBoost and RSF.
- **MAPE** proved more meaningful for failure prediction than CI or IBS.



Model	CI	IBS
CBoost	**0.818**	**0.077**
RSF	0.807	0.096
ATF	0.79	0.091
CoxPH	0.774	0.094
KM	N/A	0.2
Random Estimator	0.5	0.25

Conclusion and Future Work

Conclusion:

- Survival analysis effectively models printhead lifespan.
- **CoxPH (uncalibrated)** and **KM (calibrated)** gave the most accurate predictions.
- **MAPE** proved more practical than CI or IBS for failure estimation.

Future Work:

- Apply models to additional printheads.
- Integrate richer sensor data (e.g., **nozzle-level logs**).
- Explore deep learning and calibration curves.

Thank You!

Questions or Comments?

This work was conducted in collaboration with Canon Production Printing.