Using Machine Learning to Identify Machining Parameters in CNC Milling

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Background

- Manufacturing is a 2 trillion-dollar industry (Keller)
- Vital for manufactures to have confidence in consistency of parts
- In-situ quality certification would reduce QA cost and turnaround times
  - Robust classification of a known tool path can identify problems
    - Wrong/defective material
    - Excessive tool ware
    - Incorrect parameters

Purpose of Research

- Harness built-in sensors in CNC milling machine to characterize “aggressiveness” of a cut with machine learning
  - Act as automatic double check in operator inputs
    - Lower barrier to entry for CNC milling
    - Increase confidence in manufacturing faculty
  - Built-in sensors keep complexity and cost low
    - Spindle power, x, y, and z load

Methodology: General Experiment Setup

- Machine: EMCO E350 CNC mill with Siemens 828D controller
- Tool: Accupro 0.25” diameter, 0.75” LOC, 2.5” OAL, four flute, solid carbide square end mill with AlTiN finish
  - Regularly replace tool so wear is not a factor
- Material: 4”x 2.5” 6061 aluminum bar

Methodology: Defining Cutting Aggressiveness

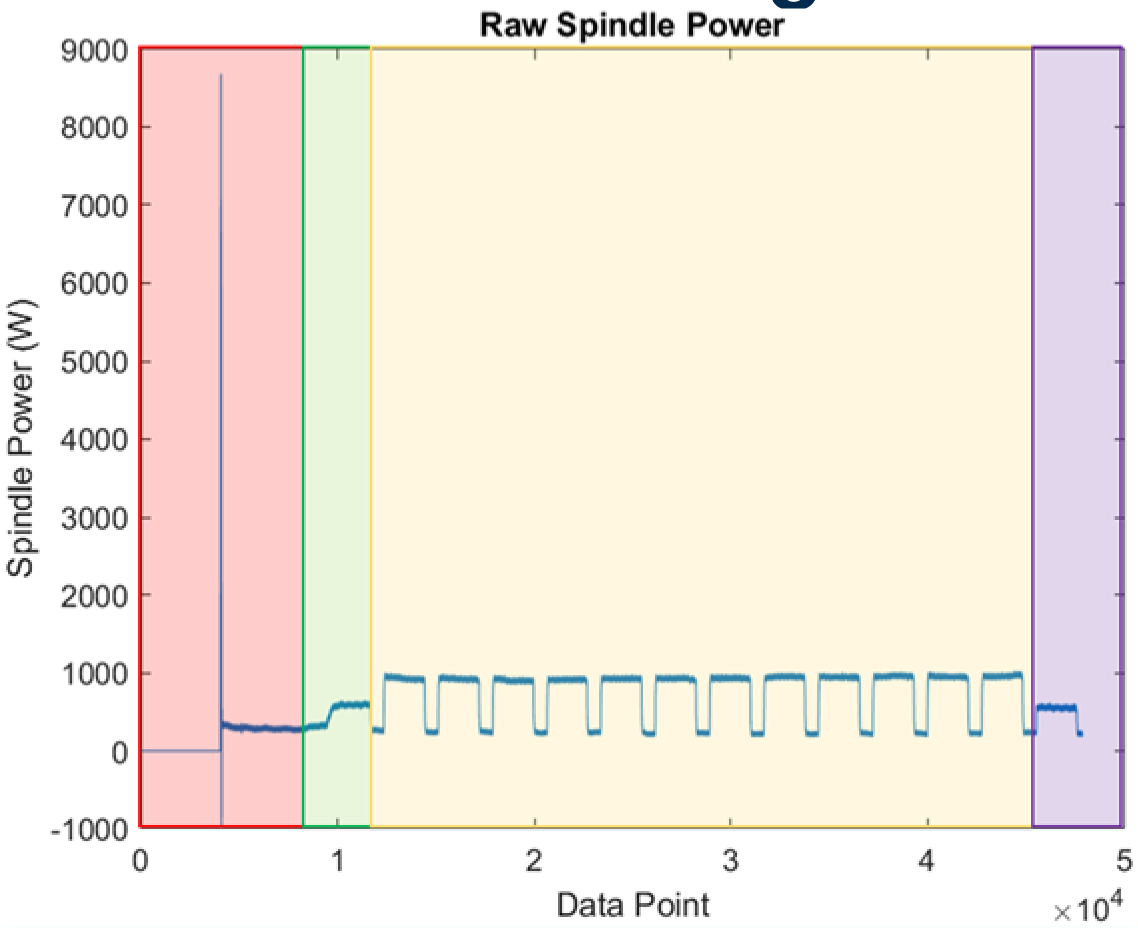
- Commonly used software used to set machining parameters: spindle speed, feed-rate, depth of cut, and width of cut
  - Accounts for machine, tooling, material, and cutting parameters
    - Provides “aggressiveness” as a value from 1 to 100 on a slide bar
      - Adjusting aggressiveness changes feed-rate
- For this work “conservative cut” between 1 and 33, “optimal” between 33 and 66, “aggressive” between 66 and 100
  - Feed-rate swept during cutting to reach full range
  - Can be defined differently for future applications

Methodology: Data Collection

- 828 D controller tracks variables internal to machine
- Trace function can select variables and export them to USB drive as xml file
  - Collects spindle power (Watts), x, y, and z axis drive load (Newtons) at 166 Hz

Methodology: Data Pre-Processing

- Remove any data not indicative of toolpath
  - Start-up/shut-down or section with unwanted different parameters
- Obtain additional features from Continuous Wavelet Transform
  - Total of 630 Features

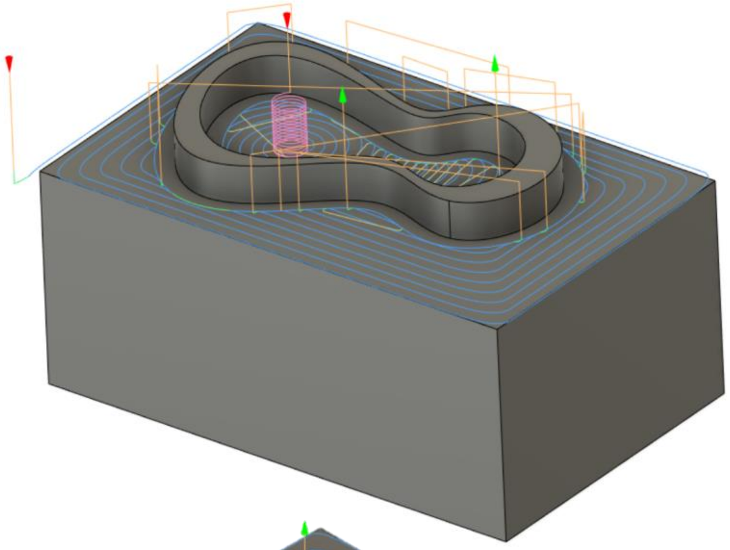


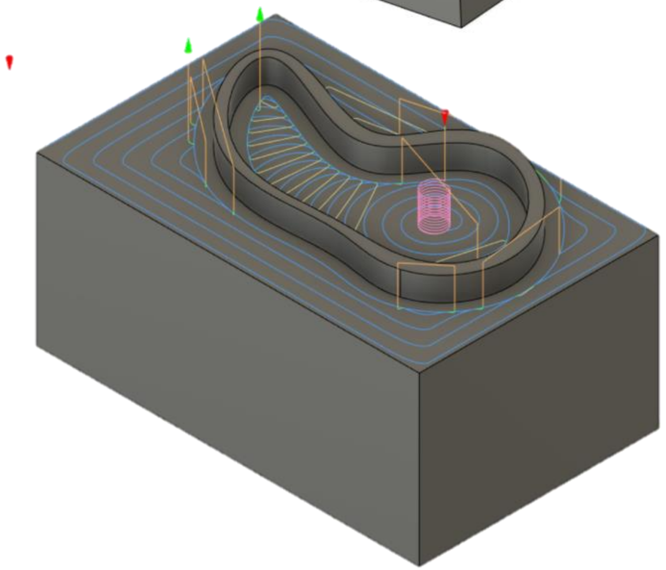
Methodology: Training Machine Learning Algorithms

- Remove redundant features (Pearson Correlation score > 0.85)
- Remove features not important for classification (MI score < 0.4)
  - 12 Remaining Features
- Machine learning algorithms: MLP classifier, Random Forest, Discission Tree, Neural Network, and K Nearest Neighbors
  - Find hyperparameters
  - Generate ROC curve

Training Set Experiment

- Geometry contains lines and curves in several directions along with picking up and reengaging the part
  - 0.25 depth of cut, 0.15 width of cut
  - Preformed 3 times for each “aggressiveness range”
    - Conservative feed-rate range: 22.7 to 37.5 ipm
    - Optimal feed-rate range: 37.5 to 52.3 ipm
    - Aggressive feed-rate range: 52.3 to 67.1 ipm
- Out of experiment cut uses different geometry to test ML





Out of Experiment Cut

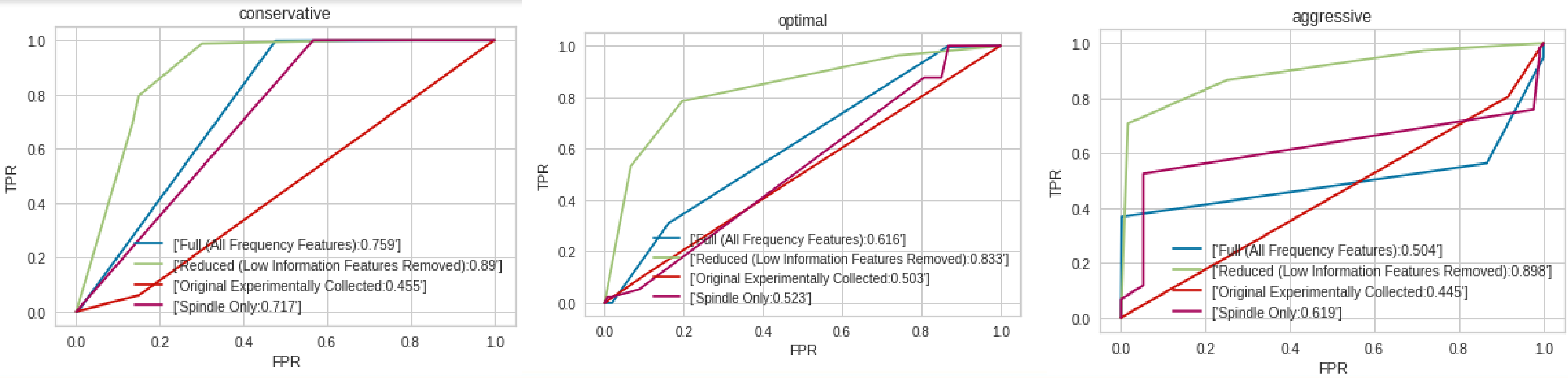
Results

- Decision Tree and Random Forest provide best results
- Best results are for conservative and aggressive regions
  - Bodes well for future use as those would be of the most interest

	Logistic Regression	K Nearest Neighbors	Decision Tree	Random Forest	MLP Neural Network	Best Score
Conservative AUC	0.414126	0.850442	0.889549	0.884815	0.5	Decision Tree
Optimal AUC	0.042879	0.634266	0.833047	0.822814	0.5	Decision Tree
Aggressive AUC	0.898223	0.870091	0.898353	0.900762	0.5	Random Forest

Results

- Decision Tree Results
  - Significantly improved by frequency
    - However, simple model where a single feature producing poor results is unsurprising



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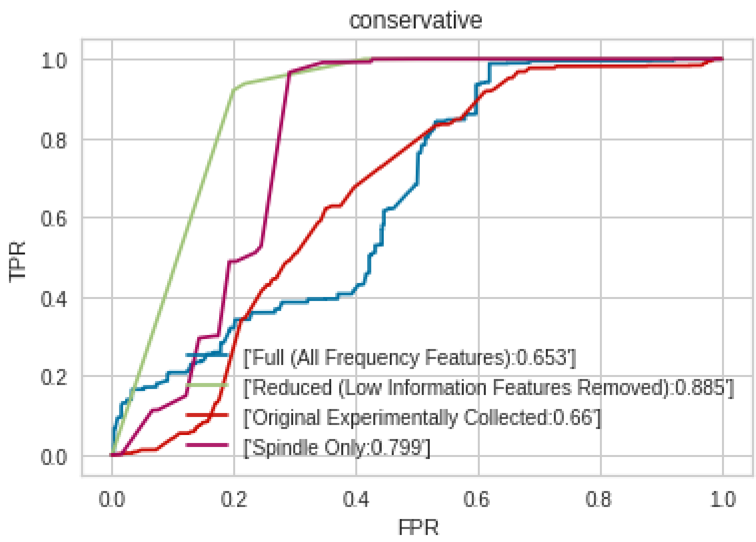
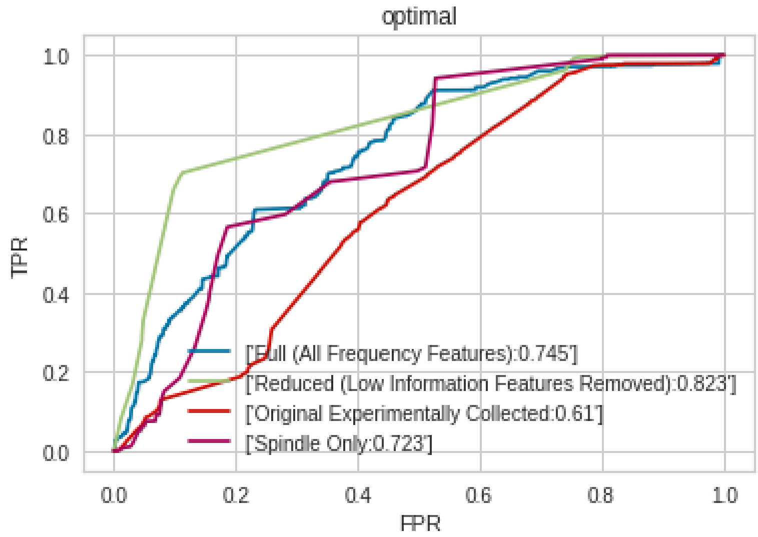
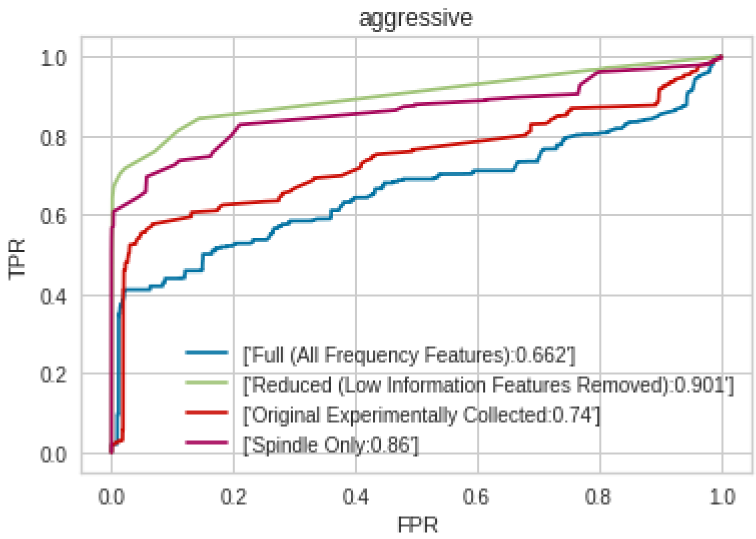
Results

- Random Forrest Feature Space Comparison: more robust
  - Spindle power provides good results
    - Frequency features tangibly improve model performance







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Future Work

- Increase variability by adding different width and depth of cut experiments
  - More applicable to diverse real-world manufacturing

	Width of Cut (in)	Depth of Cut (in)
Data Set 1	0.05	0.45
Data Set 2	0.1	0.3
Data Set 3	0.15	0.15

Conclusion

- Quality assurance vital for manufacturing
  - Real time “aggressiveness” classification good first step
- Random Forest and Decision Tree perform best
- Frequency features tangibly improve classification results
  - Feature augmentation workflow can expand existing manufacturing datasets
    - Improve existing in-situ QA model performance

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References

Keller, Ralph. “What's the Future of U.S. Manufacturing?” Industry Week, vol. 258, no. 10, 2009, p. 10.

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