

AI-AIDED EXPANDER MACHINE PARAMETER OPTIMZATION

TE AMT

- The Automation Manufacturing Technology (AMT) team aims to automate parameter adjustments for a medical manufacturing machine using a closedloop system, with assistance from a machine learning model.
- The project automates parameter adjustments for a medical manufacturing machine using a closed-loop system and a machine learning model.
- The current method for machine tuning in our process generates approximately 20% scrap material, primarily due to the initial setup required to achieve the correct Outer and Inner diameters within needed specification.

Expander Line Machine

- The expander line is a complex machine with a dozen parameters. i.e Air Pressure, Outer Diameter, Water Pressure, etc.
- Operators rely on their experience & intuition to setup and run the machine parameters.
- Using ML model that can predict setup parameters will save hours and additional costs.
- Adding a process control algorithm will also help monitor product quality which required human oversight.



Total Fuel Trim #2	•	Check Mode	Ŀ
0.500		OFF	
0.500 - 0.500	•	0.000 - 0.000	
	-		
0.000 %		Complete	
0.000 - 0.000		0.000 - 0.000	
O2 LR Bank 2 Sensor 1	•	Heated Catalyst Monitor	
0.000 ms		Complete	
0.000 - 0.000		0.000 - 0.000	

Emulator Features

Tubing enters the expander machine, where temperature and pressure are regulated to ensure uniform expansion. The machine adjusts speed and monitors dimensions to meet quality standards. After processing, the tubing is ready for further use.





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- Preprocess data by eliminating redundant entries and conducting exploratory analysis on essential parameters.
- Create an AI model with a baseline accuracy of at least 70%, capable of iterative accuracy enhancement.
- Validate the model using the Cpk metric, ensuring it meets a threshold of 1.3. Integrate realtime prediction deployment into a website for dynamic user interaction.



Missing Data

Models Prediction

The low MSE and MAE indicate precise predictions. The high R-squared shows the model explains much of the data's variance. This makes the model effective for predictive and analytical tasks in complex data environments.





ADVISERS: PABLO PLASCENCIA, MULANG SONG, JOSEPH PALMER, ALEXANDER V. MAMISHEV, MEGHA CHANDRA NANDYALA **SPONSOR:** TE CONNECTIVITY

Machine Learning Approach

Methodology Use Streamlit, a Python library, to connect backend ML processing with frontend presentation. This allows users to interact with ML models directly through a web browser. Data for ML models is stored in MySQL for efficient storage and retrieval.

- Expand data collection to ensu comprehensive coverage and representation.
- Use advanced preprocessing techniques and feature scaling improve dataset quality.
- Explore ensemble methods an deep learning for greater accur and stronger model robustness
- Evaluate model performance v statistical methods under varie conditions.

Website Deployment

Features

- Model Selection
- Real Time Predicted Results
- Calculates CPK, a statistical measure that evaluates how well a process meets predefined specifications.

Future Work, References, and Acknowledgments

ure	•	Enhance the website UI to improve user comprehension and interaction.
gto		References [1] Scikit-learn. (2020). "Scikit-learn: Machine Learning in Python." Retrieved from https://scikit- learn.org/stable/index.html [2] Streamlit. (2020). "Streamlit: The fastest way to build custom ML tools." Retrieved from https://www.streamlit.io/
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