Real Time Predictive Maintenance on Plant Equipment and IoT Devices

Heidi Fehr, Tiffany Meeks, and Sandra Ponce

This Photo by Unknown Author is licensed under CC BY-SA-NC

>Background

>>Method/Testing

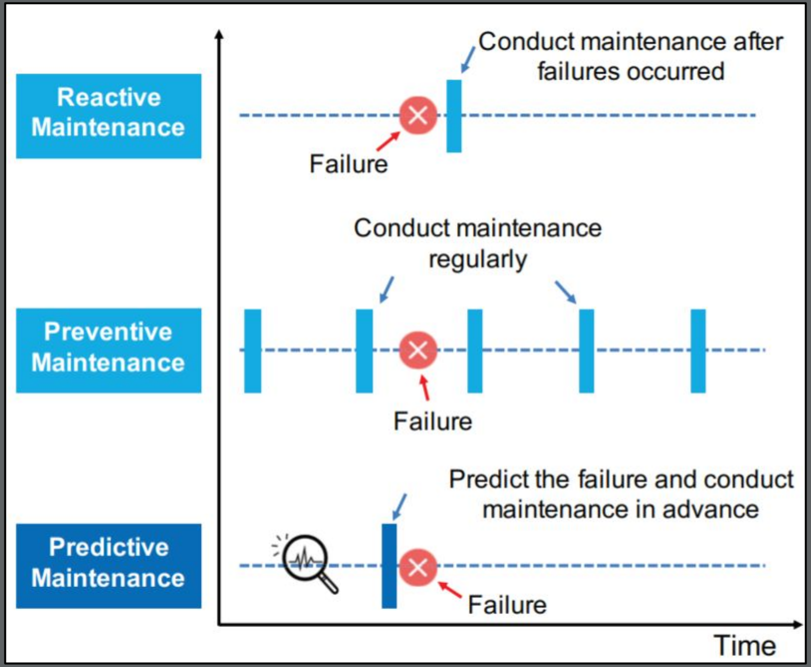
>>>Results

>>>>Conclusions

- Degradation Models
  - Experienced-Based Approaches
  - Model-Based Approaches
    - Physics-Based Approaches
    - Statistical Approaches
    - Empirical Approaches
    - Hybrid Intelligence Models
  - Knowledge-Based Approaches
  - Data Driven Approaches

- What is predictive maintenance?

- Advantages:
  - Maximizes the usage and lifespan of equipment
  - Decreases downtime and resource costs
  - Increases safety and reliability



Machine Learning Models used in PdM

- Artificial Neural Network
- Long Short-Term Memory
- Support Vector Machine
- Decision Tree Regression
- Random Forest Regression
- Linear Regression

Python is an **easy, fast, and flexible** programming language

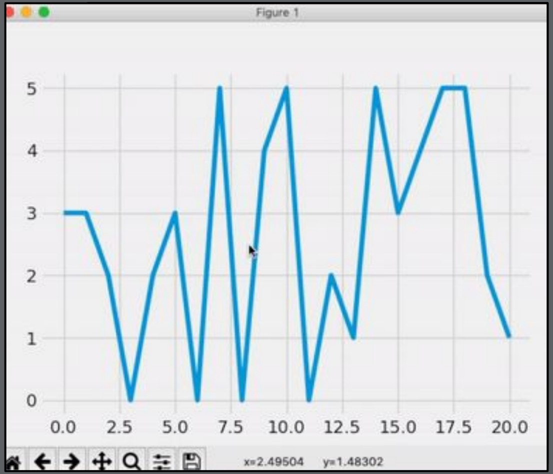
- Classical way of time series forecasting models:
  - Autoregression (AR)
  - Autoregressive Moving Average (ARMA)
  - Autoregressive Integrated Moving Average (ARIMA)
- Machine Learning way of time series forecasting models:
  - Random Forests Regression
  - Support Vector Machine
  - Gradient Boosting Regression
  - K-Nearest Neighbor
  - Decision Tree Regression

What data is being analyzed?

- Time Series
- Pipeline thickness

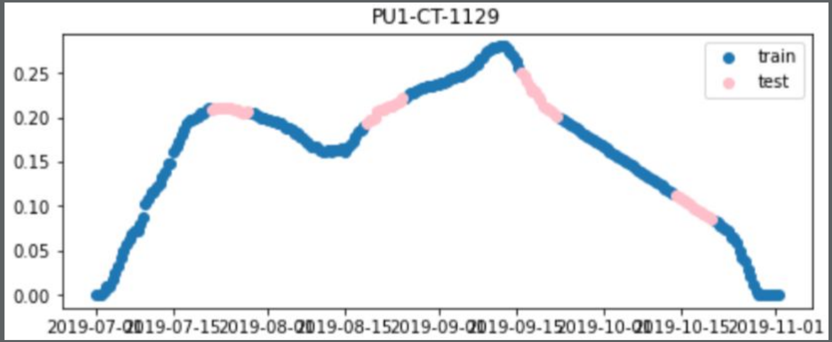
Our Focus on the Time Series Data Provided

- Corrosion Rate Tags
- Integrated Operating Window (IOW) tags

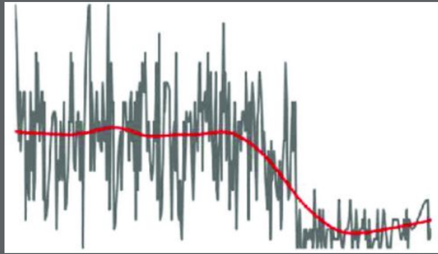


Data Preparation and Cleaning:

1. Read in data from excel worksheet
2. Parsed the dates and index columns
3. Selected a corrosion group (CG) from file
4. Converted the values in the dataset file to numeric values
5. Separated Corrosion Rate (CR) tags from the Integrity operating Window (IOW) tags
6. Selected a tag
7. Dropped the null values in the tag and select a time frame
8. Split data into train and test sets



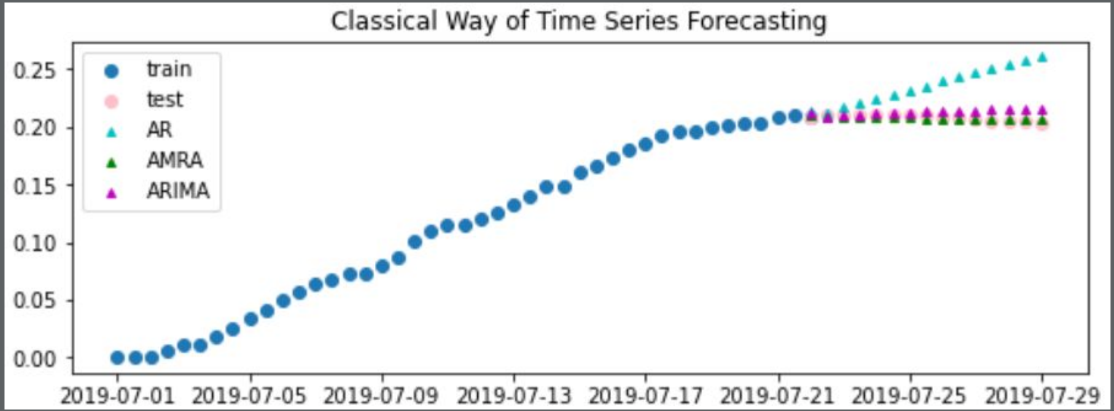
Stationary Time Series

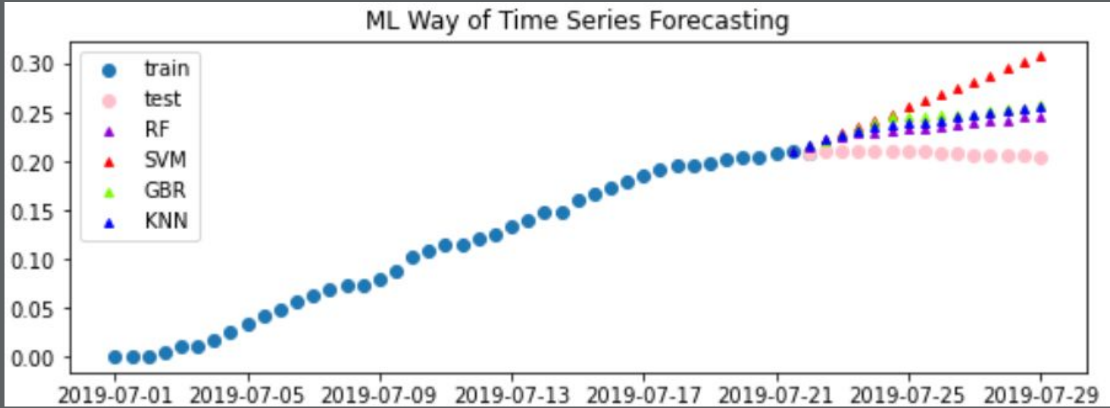


Non-stationary Time Series

PU1-CT-1129

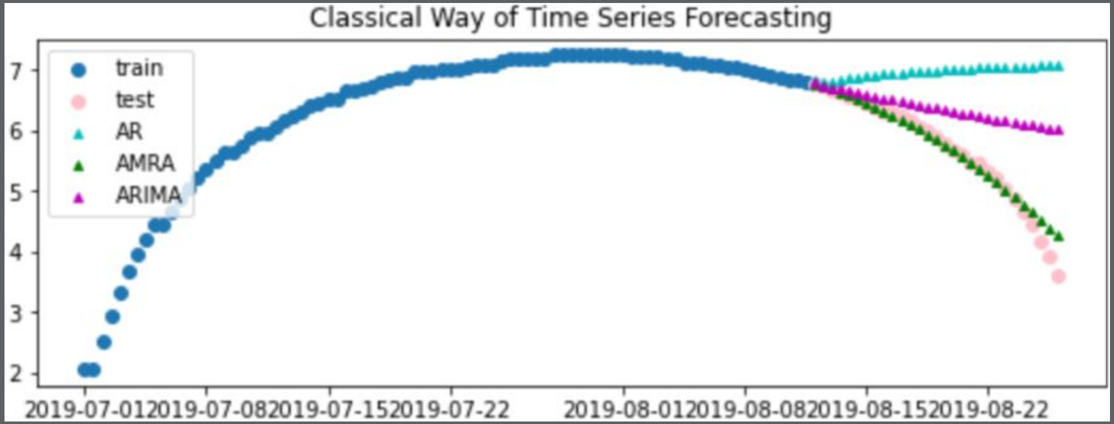
- 3 training weeks, 1 testing week
- ARMA
  - MAPE error: 0.0083
- RF
  - MAPE error: 0.1065

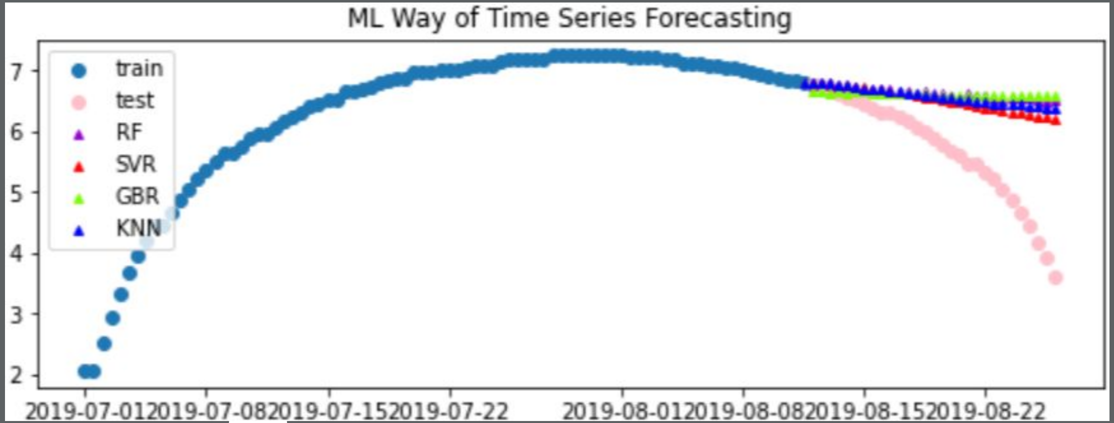




PU1-CT-1162

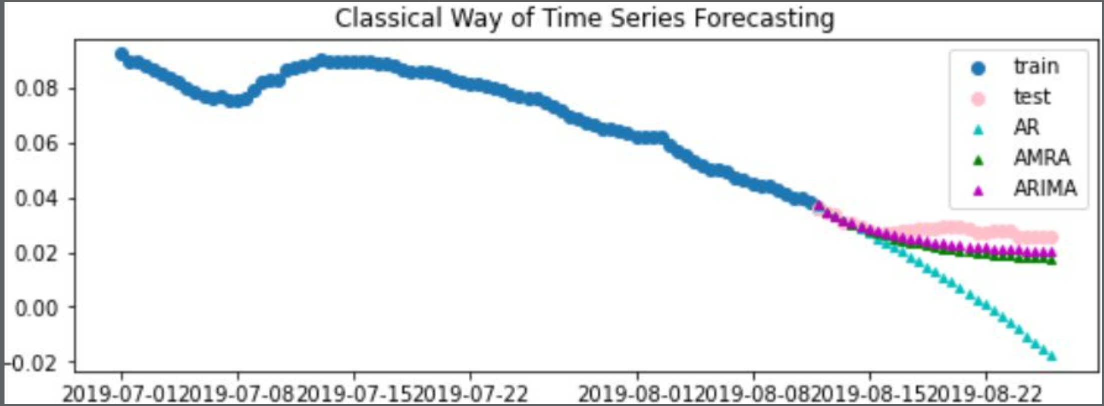
- 6 training weeks, 2 testing weeks
- ARMA
  - MAPE error: 0.0193
- SVM
  - MAPE error: 0.1320

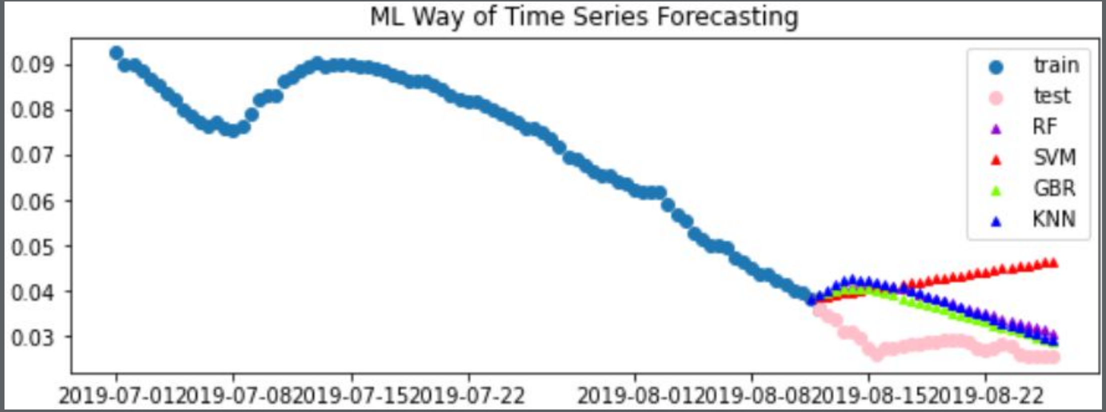




PU1-CT-1188

- 6 training weeks, 2 testing weeks
- ARIMA
  - MAPE error: 0.1633
- GBR
  - MAPE error: 0.1982





Model Accuracy:

Classical Methods
- ARIMA: 43.75%
- ARMA: 37.50%
- AR: 18.75%

ML Methods
- RF: 31.25%
- SVM: 25%
- KNN: 25%
- GBR: 18.75%

All Methods
- ARIMA: 37.50%
- ARMA: 37.50%
- AR: 12.5%
- RF: 6.25%
- KNN: 6.25%

Comparison of Data Using Mean Absolute Percentage Errors

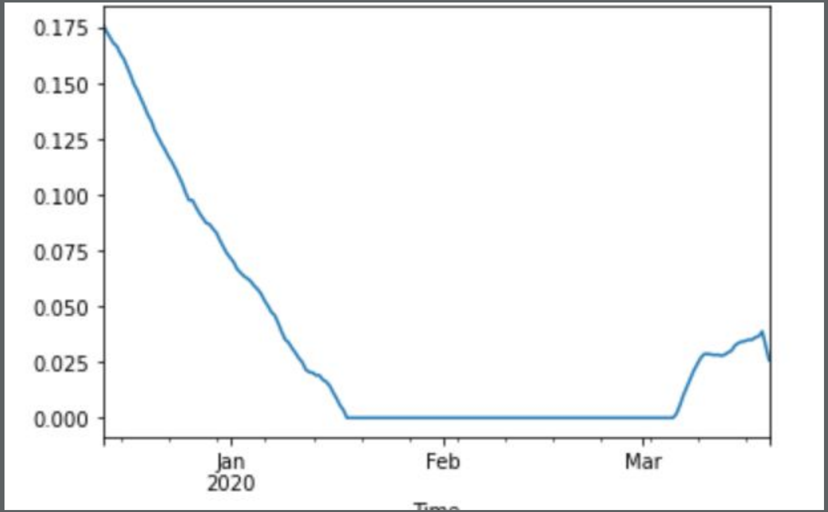
	AR	ARMA	ARIMA	RF	SVM	GBR	KNN
PU1-CT-1101	0.0176	0.0180	0.0654	0.0379	0.1099	0.0708	0.0388
PU1-CT-1103	0.1756	0.1370	0.0114	0.1676	0.2391	0.2067	0.1717
PU1-CT-1105	0.0546	0.0187	0.0367	0.0369	0.0326	0.0371	0.0347
PU1-CT-1129	0.4391	0.3631	0.2510	0.5999	0.5602	0.5850	0.4951
PU1-CT-1129.1	0.1118	0.0083	0.0230	0.1065	0.1946	0.1383	0.1298
PU1-CT-1129.2	0.1004	0.0742	0.0160	0.0405	0.0638	0.0380	0.0377
PU1-CT-1129.3	0.1246	0.1093	0.0634	0.2349	0.1159	0.1937	0.2033
PU1-CT-1129.4	5.43E-08	0.1393	0.1330	6.15E-08	1.94E-07	5.81E-08	8.62E-08
PU1-CT-1161	0.1940	0.0138	0.0626	0.1351	0.1603	0.1679	0.1557
PU1-CT-1162	0.1821	0.0193	0.1109	0.1434	0.1320	0.1420	0.1378
PU1-CT-1173	0.0011	0.0370	3.44E-05	1.18E-07	2.61E-08	1.20E-07	2.03E-07
PU1-CT-1179	0.0808	0.0921	0.0198	0.0566	0.0497	0.0421	0.0622
PU1-CT-1180	1.3494	0.8670	1.9274	17.2086	1.4595	2.1814	3.3926
PU1-CT-1188.1	3.7579	0.2554	0.1633	0.2327	0.3256	0.1982	0.2281
PU1-CT-1188.2	0.1284	0.4034	0.2688	0.2830	0.2752	0.3098	0.1279
PU1-CT-1189	0.0681	0.0542	0.0703	0.0683	0.0659	0.0576	0.0564

Percentage Error of each Model

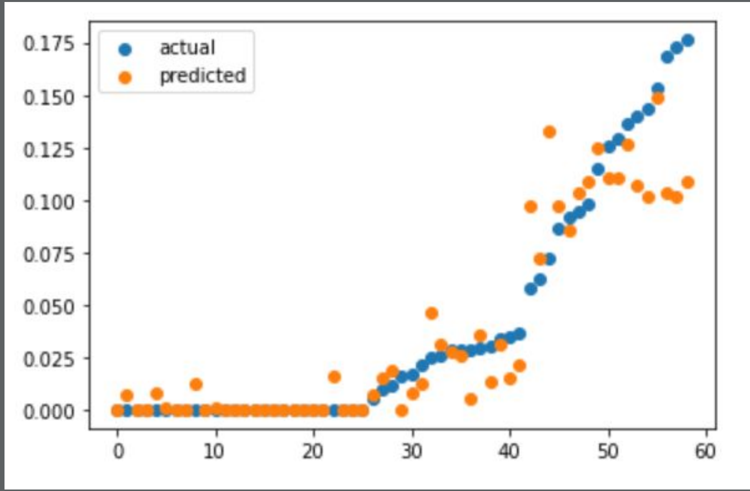
	Percentage Error
LR	2.243627
DT	1.143244
RF	0.997076
GBR	1.334363
KNN	1.061953

PU3-CT-1010

- used IOW data to predict corrosion rates



Random Forest Model



1. ARIMA & ARMA had the highest success rate on the corrosion tags we tested.
2. IOW tags didn't have sufficient data to create low error models.
3. Some next steps to continue this research would be to gather more data (especially IOW tags), test more feature engineering, and test ML models with more hyperparameter tuning
4. These findings will help future research find a better model(s) for the data, which could allow oil refineries to predict the optimal time along the corrosion rate of a pipeline for repairs.

Acknowledgements

- National Science Foundation (NSF)
- North Dakota State University College of Engineering
- University of Nevada – Las Vegas College of Engineering
- Texas A&M College of Engineering
- University Teknologi Petronas College of Engineering

- Dr. Jafreezal Jaafar
- Dr. Om Yadav
- Dr. Hilmi Hasan
- Dr. Bimal Nepal
- Ms. Hajar Razip
- Mr. Abdulsalam Alqarni
- Mr. Luqman Hanif

This work is supported by the National Science Foundation Grant (Grant #: OISE 1952493) Collaborative Research: IRES Track 1: International Research Experience for Students in Big Data Applications in Energy and Related Infrastructure. Any opinions, findings, conclusions, or recommendations presented are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

[1] J. Brownlee. "11 Classical Time Series Forecasting Methods in Python (Cheat Sheet)." Machinelearningmastery.com. Accessed July 20, 2021. [Online]. Available: https://machinelearningmastery.com/time-series-forecasting-methods-in-python-cheat-sheet/

[2] S. Glen. "Mean Absolute Percentage Error (MAPE)." Statisticshowto.com. Accessed June 28, 2021. [Online]. Available: https://www.statisticshowto.com/mean-absolute-percentage-error-mape/

[3] N. Gorjian, L. Ma, M. Mittinity, P. Yarlagadda, and Y. Sun. "A Review on Degradation Models in Reliability Analysis." Proceedings of the 4th World Congress on Engineering Asset Management (WCEAM 2009), 369-384, 2009.

[4] Peng, S., Zhang, Z., Liu, W., and Qiao, W., "A New Hybrid Algorithm Model for Prediction of Internal Corrosion Rate of Multiphase Pipeline," *Journal of Natural Gas Science and Engineering 85,* 2021.

Q & A Time