Predictive Maintenance(Remaining Useful Life) Capstone Project

Model and Predict Turbofan Engine Life at NASA

Project Description & Overview

This project takes a more defined look into highly innovative and emerging field-predictive analytics, which exists as a counterpart to preventive maintenance. While quality control methods like Monte Carlo simulations and sampling studies can help remove discrepancies from machines, they still lack the formidable nature to help predict an oncoming breakdown and help technicians interpret more about the remainder of the machine's life. Lack of knowledge about such parameters can cause financial losses, depreciation cuts and even human losses. The dataset has been collected from the engine degradation simulation experiments that were conducted at NASA for a turbofan engine using C-MAPSS. Four different sets are simulated using a mix of different combinations of operational and faulty modes along with the recorded RUL(Remaining Useful Life). The aim of this model is to split up the sensor data into appropriate training and testing fragments and perform exploration tests to better interpret the relationship between normal processing and failure trends for fault evolution. The dataset was obtained from the Prognostics CoE at NASA Ames.

The dataset has been collected into a number of txt files along with the resultant RUL values. These datasets play an important role in assessing the health of the machines and devising solutions for maintenance checks and mitigate changes in time. Model creation from the collected data also helps in reduce the depreciation costs associated with salvaging the machines and formulate better scheduling periods annually for shutting down the machines for the purpose of quality control checks. A more accurate predictive model would help in achieving this, all the while reducing the possibilities of damages incurred by constant use.

Project Requirements

Requirements

- Python 3.0.X version or higher.
- NumPy.
- Scickit.
- Signal Processing Libraries.

Objectives and Purpose

The data set has been split into sections that include the trajectories captured from the turbine's use along with the conditions and fault modes. Each of the datasets is unique due to the variation of these modes and faults. The first dataset consists of a sea level condition with one fault mode(HPC degradation). The second dataset consists of six conditions with the same fault mode. The third dataset is based around one condition and two fault modes(HPC degradation and fan degradation). The final portion of the dataset has four conditions with the same two fault modes mentioned previously.

Each of the records represent a multiple multivariate time series for different engines in a fleet of testing units. One of the key advantages of this dataset is that the engines have different degrees of initial wear and manufacturing variation which is unknown to the user. Three operational settings, left to the user's choice can be implemented. The data is also filled with sensor noise.

Based on the experimental readings, the engines are operating in normal work environments at the start of each time series, but rapidly gains fault readings which increase in size and magnitude until the system breaks. The engine is operating normally at the start of each time series, and develops a fault at some point during the series. In the training set, the fault grows in magnitude until system failure. In the test set, the time series ends some time prior to system failure. The objective of this project is to develop modular interpretation of the relationship between these sensor readings and the resultant remaining useful life by predicting the number of remaining operational cycles before a failure is reported. Column 1 represents the unit number, column 2 represents the time in cycles, columns 3 to 26 are the sensor measurements for all the settings and modes.

Solution Statement

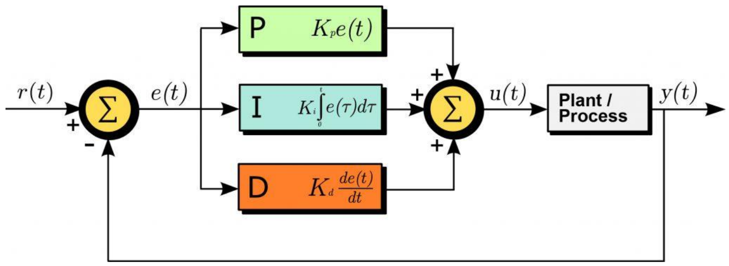
By processing through the signals and building predicting models, the results can assist in creating more augmented controllers that can prevent the destruction of important machinery, save capital and ensure safe working environments. The objectives of this capstone project can be thus summarized in the following points:-

1. Creating models that connect the signalling data to the RUL output and understanding how breakdowns occur.
2. Segmenting data trends and performing signalling analysis to remove trends, means and visualize results in a more uniform manner.
3. Create PCA plots to connect the relationship between parameters and outputs.
4. Generate features if possible from parameters based on timing analysis and sensor information.
5. Building model predictive controllers using neural networks or well-defined logical gates with feedback loops.
6. Additionally, use time series analysis methods like ARIMA, ARMAX and BJ models for the trends.

PID & MPC Controllers

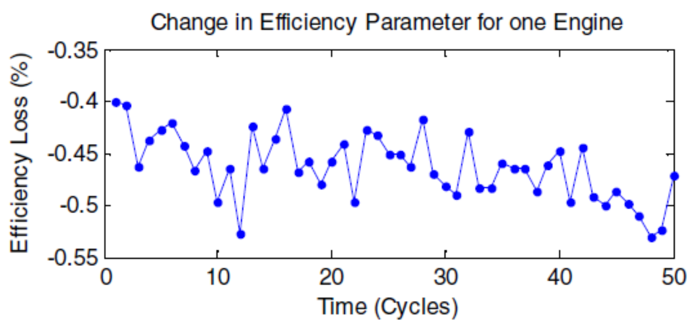
Industries have conventionally used error reduction and prediction based models in PID circuits for reducing the variations between the controlled variables and predicted variables. More advanced model predictive models however can account for unexpected and unwarranted errors which significantly reduce biases, with more uniform connections to the output. One of the objective of this project will be to use the Python framework to create an MPC influenced control system for the sensor information and connect it to the output with the aim to properly pin point when the turbine will undergo damage.

It should be noted that building MPC control systems does require an initial set of weights and biases which can be optimized as the model continues to learn the system and improve its coefficients.

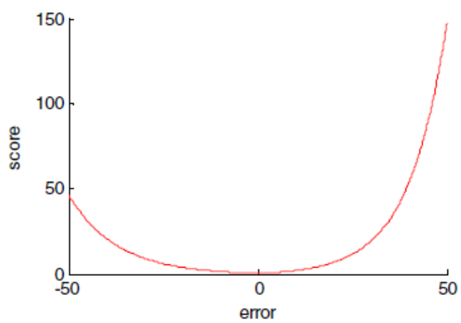


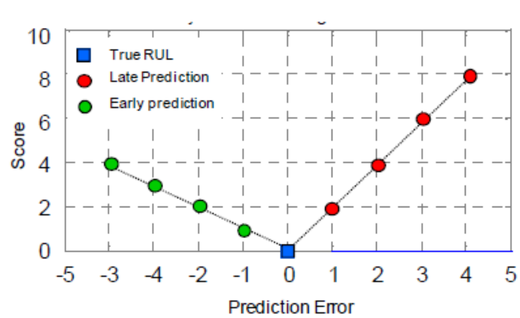
Benchmarking and Solution Comparison

The benchmark solution for RUL prediction is done through PID controls and for the purpose of this project, the model results will be compared against the MPC control systems. Ideally, the project will create a typical PID control unit system and track variations for a small sample of the inputs. While public benchmark models for the turbine are not available, alternatives can be generated through Python and checked for efficiency by comparing the resultant values from literature.



As per the research paper that discusses the turbine's function and components, RUL prediction models were developed by technicians working on the system and certain results for modular accuracies can be compared. As seen from the images below, the predictive threshold for each data point along with the scores(represented as RMSE and MSE), a benchmark comparison can be made through checking how quick it takes for the model to return the system to stability. Theoretically, a PID system is not compatible for building reactive systems, but will be compared for the benchmark tests. Conventional neural network programs use classical regression programs for the models which will be replaced with a host of models including LinearSVC, Xgboost, bagging, boosting, SVM, Naïve Bayes.





Evaluation Metrics

There will be three major evaluation metrics for the models for this project that will cover accuracy, response and adaptability. The project will consider root mean square error, mean square error, response time, accuracy based on training to testing ratios as the major evaluation metrics. These metrics have been influenced partially by the criteria used in the research paper(listed in the references section). The remaining useful life of a turbine is integral to know in order to prevent large mishaps and as a result response to sudden changes and adaptability are important to consider as well. In order to incorporate these metrics, standard difference in response time will be compared against the conventional algorithms mentioned in the paper and compared in terms of adaptability to deal with new data.

Project Design & Flow

The project will first begin by parsing the values to a single file with appropriate labels and columns. Necessary columns for engineered features would be generated and a correlational plot would be generated to study the relationship between them and the RUL. The dataset will be cleaned, scaled, normalized and standardized before being analyzed using a PCA algorithm which will capture as much variance as possible.
The inputs will then be regenerated as time series plots and tested for accuracy using conventional ARIMA, ARMAX, BJ models. These models would test the output RUL against a single column such as sensor reading or mode to mimic realistic testing environments.
The data would then be split into a training and testing set with tests performed using a collection of algorithmic models. These models would compared the resultant metrics and come to a conclusion about which model can best predict the timeframe of a machine breakdown with the fastest response.
Attention will also be put on the number of modes and conditions that each of tests use for model prediction. The final project result will be to ideally create a MPC controller either on MATLAB or Python which can be used by technicians and engineers to test their turbine data and confirm the possibility of a machine breakdown along with more significant statistics like response time and coverage of variations.
The results will be deployed finally through Sagemaker and showcased on a github repo. A blogpost will cover the major findings from the project and also shed light on the best practices for creating the best models for predictive maintenance experiments, with a central focus on large scale electrical appliances.

Resources and Links

Citation Source

A. Saxena and K. Goebel (2008). "Turbofan Engine Degradation Simulation Data Set", NASA Ames Prognostics Data Repository (http://ti.arc.nasa.gov/project/prognostic-data-repository), NASA Ames Research Center, Moffett Field, CA

Additional Links

NASA PCoE Datasets Source