Estimating Remaining Useful Life for Predictive Maintenance using ML Techniques

Bachelor’s Thesis Project Phase II - CAM 1

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Introduction

- **Industry 4.0** is the fourth industrial revolution
- This revolution focuses on using artificial intelligence to improve and streamline processes.
- Implementation of technology to
    - Monitor asset health
    - Optimize maintenance schedules
    - Real-time alerts to operational risks
    - Lower service costs
    - Maximized uptime
    - Improved production throughput

Figure 1 : Components of Industry 4.0 [1]

Prognostics and Health Management (PHM) in **Industry 4.0**

- Prognostics is an engineering discipline focused on predicting the time at which a system or a component will no longer perform its intended function. The predicted time then becomes the remaining useful life (RUL).

- **Predictive maintenance**
    - Method of preventing asset failure by analyzing production data
    - To identify patterns and predict issues before they happen.

- Predictive analytics is applied to the machine data to
    - Predict conditions of upcoming failure.
    - Repair
    - Replacement of tool

- **Benefits -**
    - Reduced Maintenance Time
    - Increased efficiency

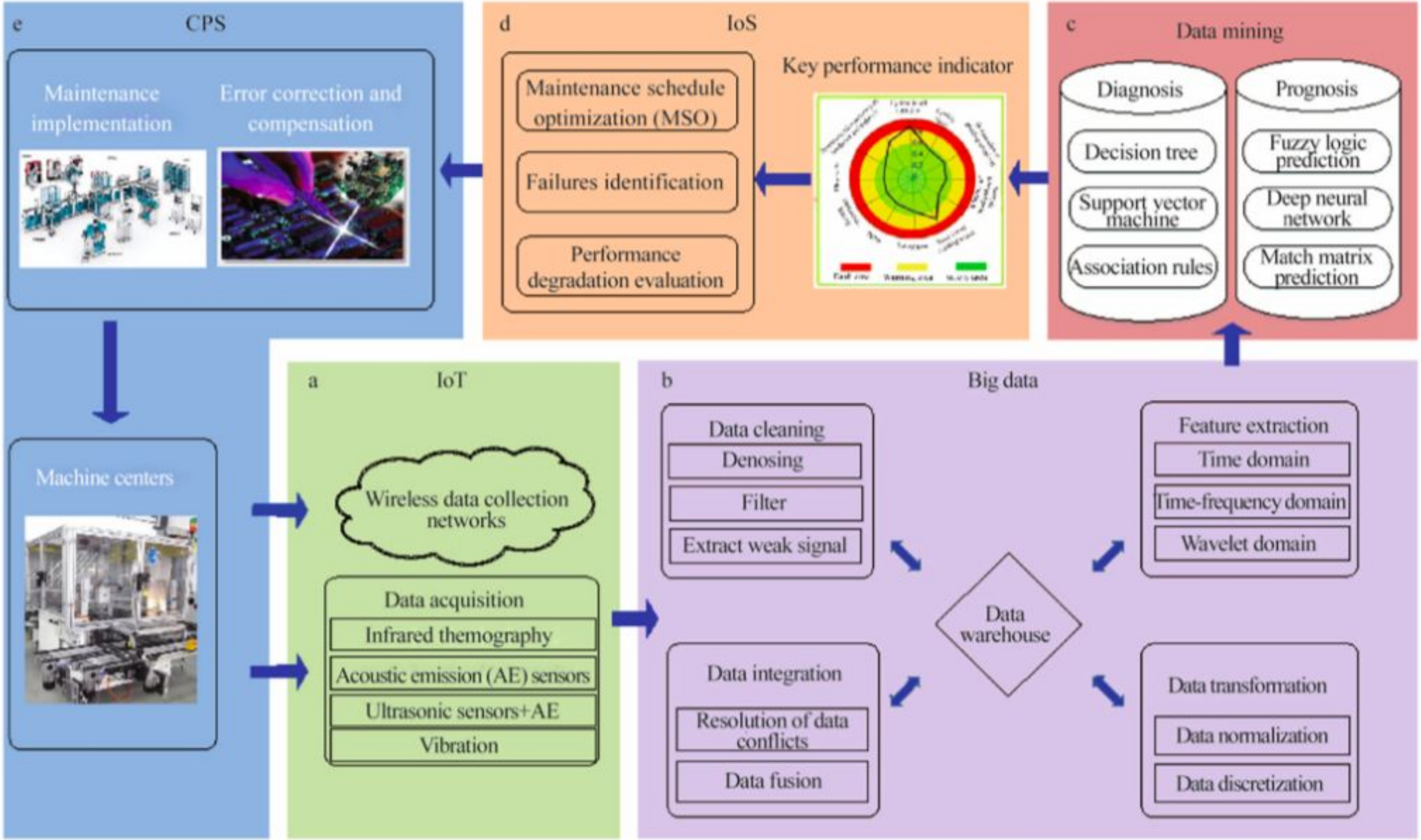

Fig. 2 Framework of fault diagnosis and prognosis in machine centers **a** Sensor selection and data acquisition module, **b** data preprocessing module, **c** data mining module, **d** decision support module, **e** maintenance implementation module [2]

	Predictive Maintenance	**Preventive Maintenance**
Definition	Predictive maintenance (PdM) is work that is scheduled as-needed based on real time conditions of assets.	Preventive maintenance (PM) is work that is scheduled based on calendar time, asset runtime, or some other period of time.
Resources needed	● Condition monitoring software, tools and sensors are required ● Maintenance software for scheduling	● Maintenance software for scheduling ● Maintenance scheduler
Pros	● Reduces labor and material costs as maintenance is performed when needed ● Reduces maximum amount of downtime	● Better than reactive maintenance ● Cheaper monitoring softwares ● Easier to implement
Cons	● Expensive technology needs purchased ● Time-intensive to implement correctly	● Labor intensive (not performed as needed) but needs ● Risk of over-maintaining (e.g. over-lubrication can damage asset)

Limitations in Predictive Maintenance

- Sensors used in Industry typically have a very high sampling rate (over 10000 samples per second).
- A vast array of such sensors across multiple machines results in a stream of data which is difficult to store in an economical manner.
- Machine Learning models can thus only be trained on a batch of stored data.
- As the sensors and operating conditions themselves drift over time, models trained on a batch of data do not accurately model the processes.
- “Catastrophic forgetting” is the tendency of ML models to completely and abruptly forget previously learned information upon learning new information.

Objectives

- Estimating RUL (Remaining Useful Life) using existing ML techniques
- Testing and Validating against benchmark results
- Developing and validating an improved methodology for Dynamic Predictive Maintenance

Methodology

1. Data preprocessing-
   - Remaining Useful Life (RUL) targeting
   - Normalization
   - Feature (sensor) selection

2. Modelling using the following machine learning algorithms -
   - Support Vector Machines [A1]
   - Random Forests [A2]
   - Gradient Boosting Trees [A3]
   - K Nearest Neighbours [A4]
   - Multi Layer Perceptron [A5]

3. Testing and Validating against benchmark results

Data Preprocessing

1. **Feature Selection -**

   Sensors specified in literature are retained, unspecified sensors are removed from the dataset

2. **Normalisation -**

   Normalise the sensor readings to values between 0 and 1

3. **RUL Targeting -**

   The target variable in the dataset is either 0 or 1 (working/failure). We modify the target using its index to make it possible to predict the number of cycles until failure.

RUL using Piecewise Linear Degradation

- For this data-set (Heimes, 2008) [8] has proposed a piece-wise linear degradation model which limits the maximum value of the RUL function

- The maximum value was chosen based on the observations of the data and its numerical value is different for each data-set.

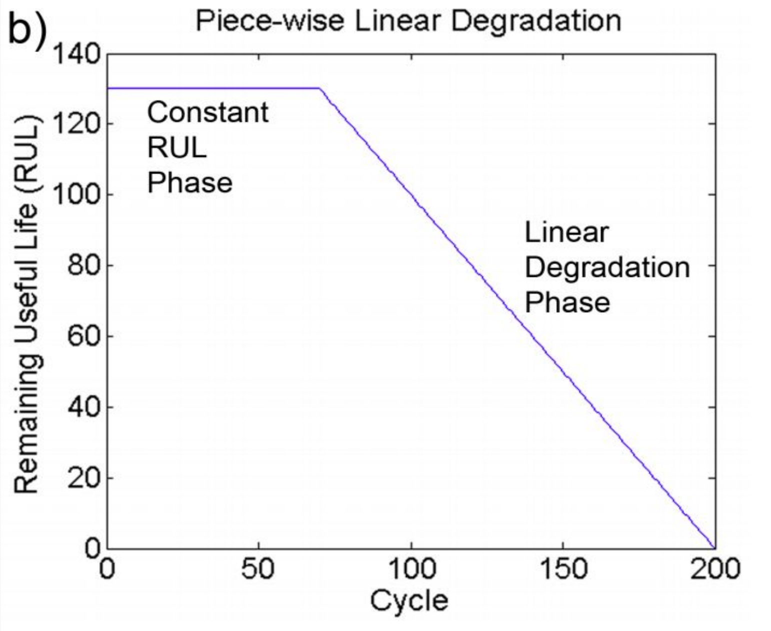

Fig.3 RUL Targeting [6]

Dataset

- Turbofan engine data set is a publicly available dataset provided by the Prognostics CoE at NASA Ames consisting of 4 sets, simulated under different combinations of operational conditions and fault modes.
- Data from 16 sensors is used to predict Remaining Useful Life for 100 engines
- The parameters for each flight are the flight conditions, health indicators, measurement temperatures and pressure measurements.
- Data sets consist of multiple multivariate time series. Each time series is from a different engine i.e., the data can be considered to be from a fleet of engines of the same type
- Data Set: FD001
  - Train trajectories: 100
  - Test trajectories: 100
  - Conditions: ONE (Sea Level)
- RMSE(Root Mean Square Error) error is used as metric, lower is better

Symbol	Description	Units
Parameters available to participants as sensor data		
T2	Total temperature at fan inlet	°R
T24	Total temperature at LPC outlet	°R
T30	Total temperature at HPC outlet	°R
T50	Total temperature at LPT outlet	°R
P2	Pressure at fan inlet	psia
P15	Total pressure in bypass-duct	psia
P30	Total pressure at HPC outlet	psia
Nf	Physical fan speed	rpm
Nc	Physical core speed	rpm
epr	Engine pressure ratio (P50/P2)	--
Ps30	Static pressure at HPC outlet	psia
phi	Ratio of fuel flow to Ps30	pps/psi
NRf	Corrected fan speed	rpm
NRc	Corrected core speed	rpm
BPR	Bypass Ratio	--
farB	Burner fuel-air ratio	--
htBleed	Bleed Enthalpy	--
Nf_dmd	Demanded fan speed	rpm
PCNfR_dmd	Demanded corrected fan speed	rpm
W31	HPT coolant bleed	lbm/s
W32	LPT coolant bleed	lbm/s
Parameters for calculating the Health Index		
T48 (EGT)	Total temperature at HPT outlet	°R
SmFan	Fan stall margin	--
SmLPC	LPC stall margin	--
SmHPC	HPC stall margin	--

Fig.4 Sensor description [5]

Results

ML Techniques	Benchmark RMSE [3]	RMSE obtained
SVM	20.58	20.07
RF	20.23	20.47
GBT	18.80	20.21
KNN	19.73	19.95
MLP	18.48	21.14

Conclusion

- Testing and validation methodology successfully recreates the established benchmark reported by C. Zhang et al. [3]

Work in Progress

JAN — **Preprocessing**

- RUL targeting
- Feature selection
- Normalization for MLP

FEB — **Benchmarking**

- Found benchmark papers
- Reproduced their methodology
- Replicated results

MAR — **Modelling**

- Developing an improved methodology for Dynamic Predictive Maintenance

APR — **Documentation**

- Testing and Validation
- Report writing

References

1. Hackster.io
2. Li, Z., Wang, Y. & Wang, K. Intelligent predictive maintenance for fault diagnosis and prognosis in machine centers: Industry 4.0 scenario. *Adv. Manuf.* 5, 377–387 (2017) https://doi.org/10.1007/s40436-017-0203-8
3. C. Zhang, P. Lim, A. K. Qin and K. C. Tan, "Multiobjective Deep Belief Networks Ensemble for Remaining Useful Life Estimation in Prognostics," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 28, no. 10, pp. 2306-2318, Oct. 2017. doi: 10.1109/TNNLS.2016.2582798
4. Ellefsen, André Listou, Emil Bjørlykhaug, Vilmar Æsøy, Sergey Ushakov and Houxiang Zhang. "Remaining useful life predictions for turbofan engine degradation using semi-supervised deep architecture." *Rel. Eng. & Sys. Safety* 183 (2019): 240-251.
5. A. Saxena, K. Goebel, D. Simon and N. Eklund, "Damage propagation modeling for aircraft engine run-to-failure simulation," *2008 International Conference on Prognostics and Health Management*, Denver, CO, 2008, pp. 1-9.doi: 10.1109/PHM.2008.4711414 (Table 2)
6. Pin, Lim & Goh, Chi-Keong & Tan, K.C. & Dutta, P.. (2014). Estimation of remaining useful life based on switching Kalman Filter neural network ensemble. PHM 2014 - Proceedings of the Annual Conference of the Prognostics and Health Management Society 2014. 2-9.
7. W. Zhang, D. Yang and H. Wang, "Data-Driven Methods for Predictive Maintenance of Industrial Equipment: A Survey," in *IEEE Systems Journal*, vol. 13, no. 3, pp. 2213-2227, Sept. 2019.
8. Heimes, Felix. (2008). Recurrent neural networks for remaining useful life estimation. 1 - 6. 10.1109/PHM.2008.4711422.

Appendix - Support Vector Machine

- Support-vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis.
- Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier.
- An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible.
- New examples are then mapped into that same space and predicted to belong to a category based on the side of the gap on which they fall.

Appendix - Random Forest

- A random forest is a meta estimator that fits a number of classifying decision trees on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting.
- The sub-sample size is always the same as the original input sample size but the samples are drawn with replacement if bootstraping.

Appendix - Gradient Boosting Trees

- Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees.
- It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function.

Appendix - KNR

- Regression based on k-nearest neighbors.
- The target is predicted by local interpolation of the targets associated of the nearest neighbors in the training set.

Appendix - Multi Layer Perceptron

- Multi-layer Perceptron (MLP) is a supervised learning algorithm that learns a function $f(\cdot) : R^m \rightarrow R^o$ by training on a dataset, where is the number of dimensions for input and is the number of dimensions for output.
- Given a set of features $X = x_1, x_2, \ldots, x_m$ and a target Y, it can learn a non-linear function approximator for either classification or regression. It is different from logistic regression, in that between the input and the output layer, there can be one or more non-linear layers, called hidden layers. Figure 1 shows a one hidden layer MLP with scalar output.

Appendix - Cross Validation

- Cross-validation is a resampling procedure used to evaluate machine learning models on a limited data sample.
- The procedure has a single parameter called k that refers to the number of groups that a given data sample is to be split into. As such, the procedure is often called k-fold cross-validation. When a specific value for k is chosen, it may be used in place of k in the reference to the model, such as k=10 becoming 10-fold cross-validation.
- Cross-validation is primarily used in applied machine learning to estimate the skill of a machine learning model on unseen data. That is, to use a limited sample in order to estimate how the model is expected to perform in general when used to make predictions on data not used during the training of the model.