Predictive Maintenance of High-Velocity Oxy-Fuel Machine Using Convolution Neural Network

* Khairulniza Bin Ibrahim[1], Maslin Binti Masrom[2]

Universiti Teknologi Malaysia
Razak Faculty of Technology and Informatics

khairulniza.ibrahim@gmail.com[1], maslin.kl@utm.my[2]

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*Corresponding author
khairulniza.ibrahim@gmail.com

Abstract

Maintenance activities and programs have reached a critical factor for competitive advantage in the manufacturing world. This is due to the increasing complexity of the interactions between different production activities and increasing extended manufacturing environment along with the increasing cost of maintenance. Existing practices namely preventive maintenance (PvM) which scheduled maintenance is no longer feasible. With the advancement in the machine and artificial intelligence (AI) technology, predictive maintenance (PdM) is the future. In the predictive maintenance, Prognostic and Health Management (PHM) emerged as a technique that is widely used in order to anticipate machine breakdown through Remaining Useful Life (RUL) determination. The aim of this study is to apply machine learning technique in order to predict the Remaining Useful Life (RUL) of the High-Velocity Oxyfuel machine (HVOF) machine. As proposed by many researchers, convolutional neural network (CNN), which primarily used in image processing has been adopted to predict the RUL due to the characteristics and its ability to achieve some level of acceptable functionality and precision using few parameters as input. High-Velocity Oxyfuel machine's data are input to the convolutional neural network (CNN) algorithm to predict breakdown as an output. Historical data as in maintenance reporting system (MRS) from the existing preventive maintenance (PvM) program is also used to understand the time-since-breakdown of the machine. The expected outcome of this study is to study the feasibility to predict HVOF machine breakdown using CNN.

Keywords: *Predictive maintenance, remaining useful life, machine learning, convolution neural network, deep learning.*

1. Introduction

Machining is a very important aspect in the manufacturing world as its capability to produce a product that is diverse and complex in term of geometry (Nee, 2015). With the important role that a machine tool holds, the technology concerning it has also evolved over the years in parallel to the industrial revolution. With the development of the latest machine tool technology, predictive maintenance (PdM) becoming more practicable as a new method to conduct machine maintenance. When compared to the early stage of machine tool in the era machine tool 3.0 (MT 3.0), now a day, most of the machine is equipped with numbers and variety of sensors. This is simply because of the advancement of sensing technology and researches pertaining to it (Fujishima *et al.*, 2016). 83% of the companies are

** Corresponding author. khairulniza.ibrahim@gmail.com*

already using or looking forward toward the PdM platform in their maintenance plan (Milojevic, 2018).

Erosion on compressor blades of the turbine engine is an inevitable phenomenon. In order to overcome erosion, overlay coating (plasma coating) is sprayed onto the concave surface of compressor blades through a process known as High-Velocity Oxy-Fuel (HVOF) to improve its wear resistance. In order to avoid unplanned breakdown, all machines or systems need to be maintained to ensure machine at an acceptable health state.

The HVOF machine, like other new advance machine, is equipped with new technology enabling data extraction for advanced maintenance program. Maintenance program activities have reached its critical factor for competitive advantage for a manufacturing company. This is due to the increasing complexity of the interactions between different production activities and the increasing extended manufacturing environment (Sezer *et al.*, 2018). The prime challenge for a successful machine maintenance program is not the significant autocorrelation between the inter-breakdown times, but the inter-breakdown occurrences that are not exponentially distributed (Pan, 2017).

Different companies adopt different philosophies to maintain their machines for their maintenance program. Therefore, maintenance program can be divided into 4 categories based on their complexity and efficiency to execute it (Susto *et al.*, 2012).

a. Run-to-Fail (R2F) maintenance or corrective maintenance (cm) (Cachada *et al.*, 2018).
a. Preventive maintenance (PvM).
b. Conditional-Based Maintenance (CBM).
c. Predictive Maintenance (PdM).

All the four philosophies are categorized into three as according to their nature of either reactive or preventive (Khazraei and Deuse, 2011):

a. Avoidance-based Maintenance (ABM) where failure avoidance is in focused rather than detection of it.
b. Condition-based Maintenance (CBM) which relies on the fact that most failures do not occur instantaneously, and they can be predicted by condition monitoring.
c. Detective-based maintenance (DBM) which maintenance is undertaken because of condition monitoring done only by the human senses

Operation Dependent Environment Changes (ODEC) which sources of breakdown are due to inherent to machine operation (eg: tools wear and tear) is the effective method to perform PdM of machine (Pan, 2017) and using CBM as a method to conduct the prediction through the understanding of Remaining Useful Life (RUL) for making maintenance decision (Vogl et al., 2019). RUL is defined as time remaining for a component to perform its function before its fails (Okoh *et al.*, 2014)(Chen *et al.*, 2011). Useful life can be divided into 4 stages: healthy, caution, repair and failure (Okoh *et al.*, 2014).

Estimating RUL can be break into 3 techniques that refers to the extent of a machine's life value (Qiao *et al.*, 2015):

a. Unknown life value evaluation (ULVE)
   i. Based on life consumption
   ii. Based on pseudo-life evaluation
b. Known life value evaluation (KLVE)
c. Known life distribution parameters (KLDP)

ULVE is further segmented into another two categories based on the assumption model. The two are i) estimation based on life consumption and ii) estimation based on pseudo-life evaluation (Qiao *et al.*, 2015).

Along with complexity of interaction increases and advancement in machine learning it is deemed impractical to analyze data using the conventional technique (Patrick Jahnke, 2015). Machine learning technique namely supervised learning is mostly deployed in the PdM. Frequently and commonly used algorithms are the *neural network* (NN), *support vector machine* (SVM), *Gaussian process regression* (GP), *Bayesian network*s (BN), *Naïve-Bayes* (NB) and *Hidden Markov model* (HMM) (Sutharssan *et al.*, 2015) and *Convolutional Neural Network* (CNN) (Remadna *et al.*, 2018).

CNN has been successfully deployed in gearbox fault classification (Zeng *et al.*, 2016) and in bearing remaining useful life problem (Ren *et al.*, 2018). Both found that, CNN does not need a complex procedure on feature extraction, and it uses fewer parameters to achieve the highest precision. Two major reasons: CNN does not need human "*handcrafted*" features and the algorithm abilities to learn the features representation from raw data by itself (Babu *et al.*, 2016).

CNN is a multilayer artificial neural network that consists of input layer, alternating convolution and pooling layers that fully connected and output layer (Zeng *et al.*, 2016).

Convolution layers: Feature map from previous layers are convolve using convolution kernels (algorithm will self-learn during the training process). The result output is added by a bias and activation function is used to compute the feature map and passed the result to the next layers.

$$x_j^l = f\left(\sum_{i \in Mj} x_i^{l-1} * k_{ij}^l + b_j^l\right)$$

Where *l* is number of layers, *Mj* is selection of input maps, *k* is weight matrix of the convolution kernel and *b* is the bias.

Pooling layers: The input features will be subsampled by a factor. The objective is to reduce the feature map in order to increase the invariance of features.

Fully connected layers and output layers: Represent all discrete components of features output from the last pooling layers into vector (feature vector) that is fully connected to output layer as shown in figure 1. Where C1 and C3 are convolution layers, while S2 and S4 are the pooling layers.

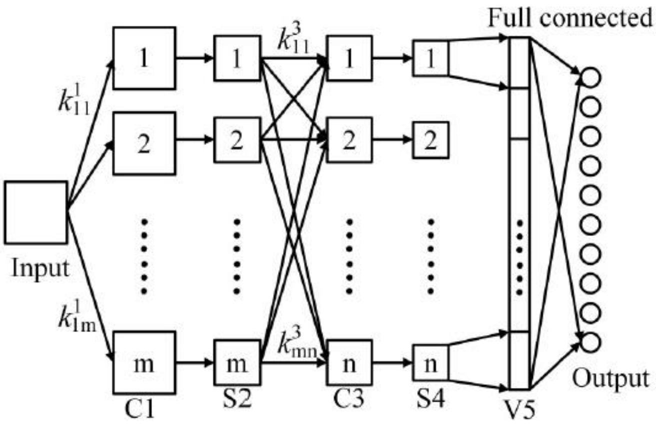


Figure 1. CNN architecture

CNN will transform the raw data into actionable insight that leads to informed decisions and considered as one of the key components for smart manufacturing in the industrial revolution 4.0 (Anon, n.d.). CNN will enable the maintenance management technique with objective to maximize the mean time between repair and minimize the associated costs of unscheduled downtime due to machine failure. This become the motivation as HVOF process is critical and unplanned breakdown causing an increase to operation and repair cost, delaying the on-time delivery and affects the quality of part.

The next two sections, Methodology and Discussions, of this paper will discuss how these three objectives of the experiment are being realized.

2. Methodology

Based on the literature review, CNN is identified as the machine learning algorithm for machine's predictive maintenance (Remadna *et al.*, 2018)

Since human safety is not a critical factor, data will be collected and used off-line to predict the RUL (Sutharssan *et al.*, 2015). Data-driven RUL estimation that using CNN is summarize as below (Ren *et al.*, 2018):

a. Data acquisition: Phase where digital data is collected and save by using the compatible sensors and suitable transducers.
b. Data processing: Step where acquired data is extracted and dimensions of the data is reduced by selecting only relevant features.
c. Condition assessment: Data will be processed, and the current health condition of the machine will be quantified as the basis for failure detection.

d. Diagnostic: Step where detection, isolations and identifications of each cause of degradation.
e. Prognostic: Step where anticipation of failure and RUL before it occurs.
f. Decision support: This is the main step, where recommendation of maintenance will be given.

Data from 2 sources are analyzed and undergo 4 phases of process namely data acquisition, pre-processing, model construction and RUL prediction. The operational framework of this study is described in figure 1.

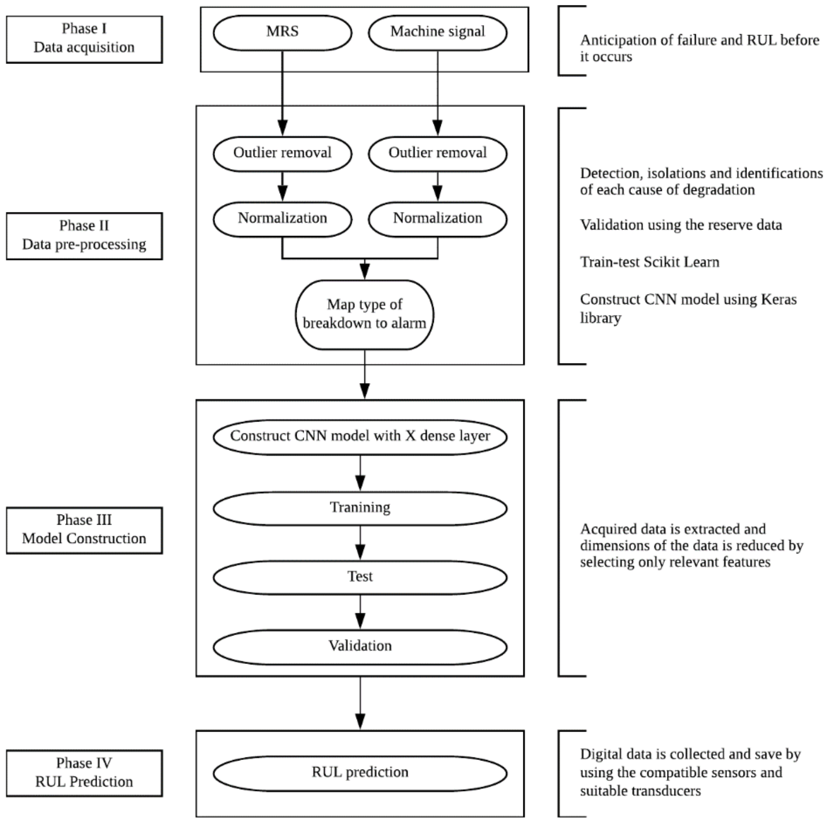


Figure 2. Operational framework

2.1. Importing Data

Data acquisition from MRS: Historical data of HVOF 1 and 2 will be extracted from the MRS. Data from 2013 to 2018 was extracted for further processing and analysis.

Data acquisition from datalogger: Data from the machine that focuses on voltage and temperature as a function of time will be collected. By collecting this data, it will capture fluctuation anomaly in the operation.

At this stage, only data in the MRS is available since the data logger is under installation that expected to be completed in November 2019.

Dataset info		Variables types	
Number of variables	48	Numeric	7
Number of observations	9775	Categorical	30
Total Missing (%)	45.0%	Boolean	3
		Date	1

Figure 3: Data info

2.2. Data Preprocessing

Out of the 51 attributes found in the MRS data, 13 of them were deemed useable to be used to understand the breakdown in sight. This insight unveiled the frequency of breakdowns, a machine that is prone to breakdown, understand the possible root cause of the breakdown and real root cause of the breakdown. What was observed, the 13 attributes with more than 95% missing value and some of them with high cardinality as summarized in table 1. The data consist of 9,775 instances of breakdown reporting over the 5 years (2013 to 2018).

```
Out[6]: ID TAG Request                 2614
        Year                              0
        Date issued                       0
        Merged                            0
        Machines Name                     4
        Issue By                          8
        Location                          3
        Division                       3608
        Description Of problem           14
        Status Of machine                24
        Date & Time Attand                9
        Attand By                        14
        Detail of Problem                32
        Corrective action                85
        Remark by technician           9165
        Date & Time start repair       2695
        Date & Time Finish             2711
        Possible Root Cause             644
        Total breakdown time           9736
        Completed By                    105
        Current Status                 7880
        Priority                       1729
        Item Code                      9165
        Item Detail                    9775
        Issue Out                      9774
        Status                            3
        Repair Category                  83
        Optional                          0
        Optional 2                        0
        Optional 3                     2614
        Optional 4                     2614
        Background & Machine Event     9715
        Root Couse                     9719
        Impact                         9718
        Action Taken                   9771
        Who                            9724
        When                           9723
        Status Action                  9722
        Results                        9723
        Preventive Action              9722
        Containment Action             9732
        Coach                          9715
        Leader                         9713
        Spareparts will taken from store?  6419
        Report Completed?                 0
        Escalated date                 9738
        Indicate Status                1319
        Avaibility Status              9775
        followUp                          0
        ID TAG Number                  7161
        ID TAG Number1                 7161
        dtype: int64
```

Figure 4: Data summary

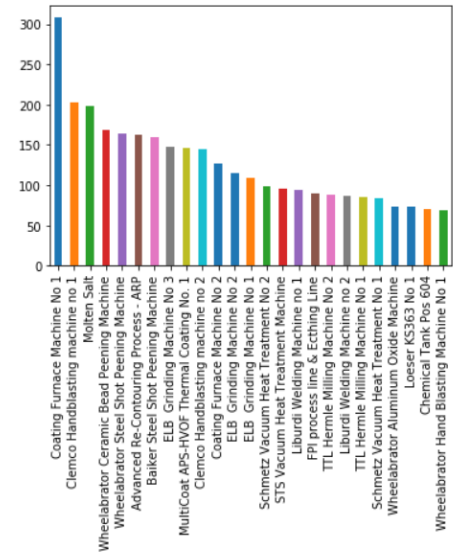
Table 1. Attribute issues

Attribute	Issues
Action Taken	Has 9771/100% missing values
Attend By	High cardinality: 121 distinct value
Availability Status	Has 9771/100% missing values
Background and Machine Event	Has 9715/99.4 missing has a high cardinality: 57 distinct value
Containment Action	9732/99.6% missing value has a high cardinality: 7789 distinct value
Date and time attended	high cardinality: 7797 distinct values
Description Of problem	high cardinality: 6970 distinct values
Detail of Problem	high cardinality: 7405 distinct values
Impact	9718/99.4% missing values
Machine Name	high cardinality: 509 distinct values
Possible Root Cause	644/6.6% missing values
Preventive Action	9722/99.5 missing values

Root Cause	9719/99.4% missing values

Count of breakdown for each machine is visualized as per figure 5, it was noticed that 146 HVOF machine breakdown occurrences since 2013. Most of the breakdown as expected due to wear and tear.

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f33439a9a58>
```




```
Wear & Tear                  3576
Electrical Defect            1926
Fatigue                      1672
Operation Error               833
Misshandling                  437
Dust                          313
Design Error                  263
Maintenanace Error            107
Documentation Error             1
Maintenance Error               1
Main    tenanace Error          1
Electrical Defect,fatigue       1
Name: Possible Root Cause, dtype: int64
```

Figure 5: Machine breakdown occurrences and possible root causes

Other than this data, no further extraction can be made due to missing data and generic description that unable to be deciphered. Further explanation as explained in the discussion and conclusion.

3. Discussion

From the data processing, there are few finding that needs to be clarified with the domain expert. This clarification is deemed critical in order to map the breakdown and machine signal analysis. Before that, the understanding will help in the outlier removal and normalization stage. Summary of items that need to be clarified are as follows:

a. Clarification of breakdown reasons
b. Identification of keyword for the breakdown as there is no standardization of the data input.
c. Mapping of breakdown reasons to machine prompt message.

4. Result

As CNN is extremely useful in the domain of image recognition, there are few researches found successfully using the CNN to solve problem other than image recognition; namely predicting future breakdown of mechanical systems. Therefore, CNN is deemed appropriate for the prediction especially when we have high dimensional data and feature selections is critical. Even though prediction of machine breakdown using CNN requires less human interaction, but all the basic data processing is needed before data can be processed using the CNN.

At this level, there is no result able to be generated due to the issue as described in discussion, additionally more than 95% of instances on critical attributes was found missing. Preprocessing using method dropping the instances will lead to no further analysis can be carried out. Out of the attributes, only 13 are deemed significant for problem understanding.

5. Conclusion

5 years of historical data to understand the useful life of a spare part is not useable. Therefore, the assumption of spare parts lifespan needs to be derived as described in para 1. Automatic data logger needs to be installed for automatic data logging and acquisitions purposes for comprehensive analysis.

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