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Online Monitoring and Analysis of Lube Oil Degradation for Gas Turbine Engine using Recurrent Neural Network (RNN)

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Abstract – Lubrication is one of the important aspects of the engine that will impact the overall performance of the gas turbine engine. Degradation of oil is usually known by offline analysis that use oil sample to check some properties and contaminant. The offline analysis will take a longer time, as needed to collect the sample, send it to the laboratory, analyze the sample and create the report. The purpose of this research is to analyze oil parameters in real-time so can predict oil degradation. Sensors and transducers installed on the lube oil system can read some parameters of the oil then transmit easily to the server. The method that will use in this paper is Recurrent Neural Network (RNN) with multi-step Long Short Term Memory (LSTM). The result of this paper will predict oil degradation on the future operation of gas turbine engine.

Keywords – lubrication, oil, gas turbine, IoT, condition monitoring

I. INTRODUCTION

A gas turbine engine is equipment that uses gas as fluid to rotate the turbine with internal combustion. It converts kinetic energy to mechanical energy [1]. This engine consists of two main components, there are stator and rotor. The rotor supports by some bearings when it is rotating. The bearings and other parts such as gears must be lubricated prior, during, and post-operation to reduce the heat produced by friction to keep bearing at design working temperature [2].

Healthiness lubrication systems need to monitor continuously to ensure the safe operation of the turbine and prevent catastrophic failure [3]. Lubrication systems contain some equipment, piping, and oil itself. This paper focuses on oil that flows through the system. New oil is used for the first time of engine operation. During normal operation, the quality of oil will degrade over time. Degradation of the oil will affect the performance of lubrication itself. Level of degradation does not easy and fast to know as need to perform offline lube analysis that take several weeks from taking sampling, shipping to laboratory, reading each properties, analysis and generate report.

There were several previous papers related lube oil system analysis that can divide by three topics, first is fault finding [4], second is condition-based maintenance [5] and third is online machine health monitoring [6]. Lube oil parameters used to find fault equipment on the lube oil system [4], while other research [5], it used for predicting maintenance plan of equipment. Measuring multiple oil properties as online health monitoring tried to replace some of offline sampling parameters [6].

In this research will focus to analyze the historical parameters of the oil to predict oil degradation on the future operation of gas turbine engine. The method that will be used is Recurrent Neural Network to solve the problem that uses time-series data [7] while other research uses a combination of Rough Set and Feed-forward Neural Network for fault diagnostic and condition-based maintenance of lubrication system.

II. RESEARCH METHODOLOGY

This research will be performed using the historical log of the gas turbine engine from Company XYZ. Historical log contains all parameters of gas turbine engine includes lube oil system which recorded every hour from November 2019 to November 2020. Based on the type of dataset that will be used, RNN is one of the best deep learning methods to predict future state of time series data. RNN use their internal state memory for processing sequences. So, it usually used for time series forecasting, audio analysis, handwriting recognition and other application [8]. However, there is limitation of memory for simple RNN, so LSTM variant used to handle this issue as it can save information for longer time than simple RNN [9].

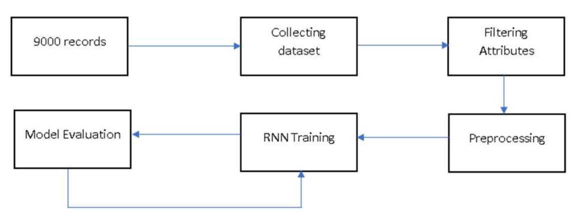


Figure 1 Oil degradation prediction step

A. *Dataset collecting*

Research starts from collecting a dataset of the engine from server. Raw data set will filter for lubrication system attributes and engine load then export to csv file. There are seven attributes that will be used for training. Parameters that will be used in this research consist of time, engine running hour, lube oil header pressure and temperature, bearing drain temperature, delta bearing drain temperature, and total kW (kilowatt).

B. *Preprocessing step*

Preprocessing step is used for preparing the dataset so it can be ready to process to the next step which is the training step. This step consists of data split and normalization. The data split that is used for training is 70 % of first 1000 data.

Table 1 Dataset sample from engine historical log

TIME	RH	LO_PRESS	LO_TEMP	BRG_DRN	DELTA_BRG_DRN	kW
11/6/2019 0:00	10740	2.82	60.94	105.78	44.83	8322
11/6/2019 1:00	10741	2.81	62.11	106.44	44.33	8645.5
11/6/2019 2:00	10742	2.81	61.5	105.58	44.08	8238
11/6/2019 3:00	10743	2.81	60.17	104.5	44.33	7801.5
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
11/21/2020 8:00	20210	2.95	61.39	90.22	28.83	2023.96
11/21/2020 9:00	20211	2.96	63.33	91.5	28.17	1998.18
11/21/2020 10:00	20212	2.96	64.56	92.5	27.94	2027.13

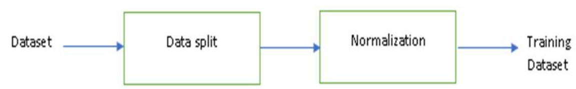


Figure 2 Pre-processing step

Normalization will transform the numeric value become 0 to 1 value.

C. *Training step*

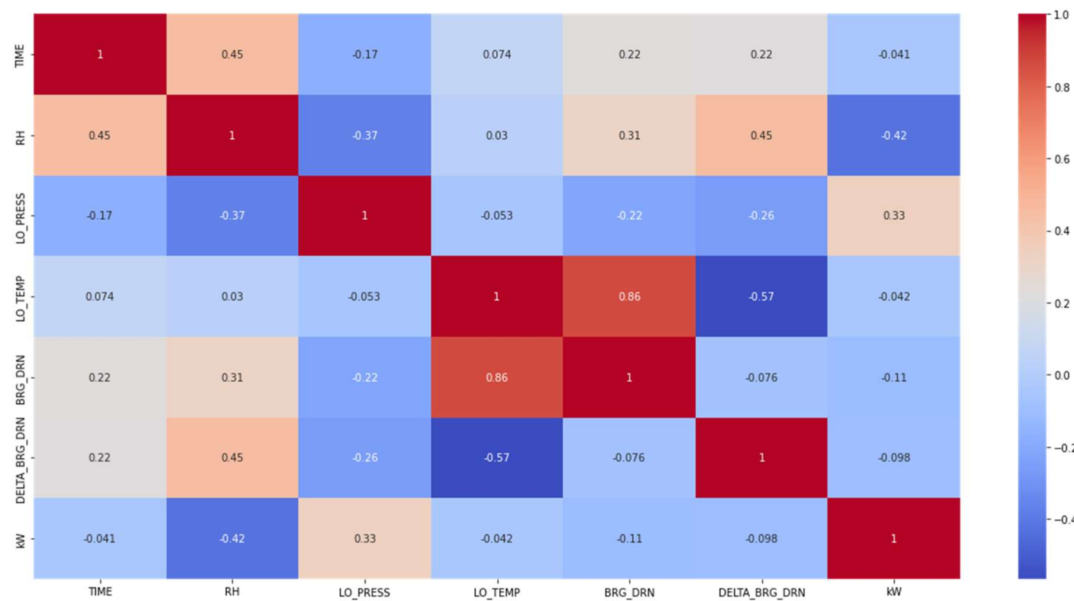
In this training step, data set will split in two parts which consist of train data and test data. Base on empirical studies, it showed that using 70-80% train data and 20-30% test data will get best result [10]. In this research will use 80:20 ratio between train data and test data. Training method that will be used is one of best accuracy methods, so it will compare all methods to get the best one.

III. RESULTS AND DISCUSSION

A. *Correlation Matrix*

All labels on dataset will analyze to get correlation between them [11]. In this paper will focus on DELTA_BRG_DRN (delta between lube oil temperature header) and LO_TEMP (lube oil bearing drain temperature) feature to see degradation of lube oil. Increasing delta temperature means performance of absorbing heat from bearing by lube oil is decreasing. Thus, will decreasing the load (kW) of gas turbine engine to maintain bearing drain temperature below alarm set point.

Table 2 Correlation Matrix



There are many factors that affecting of increasing delta bearing drain temperature, based on correlation matrix on table 2, it shows that BRG_DRN, LO_TEMP and RH (running hour) are top three of importance label that have more correlation with delta bearing drain temperature.

B. *Insight of data*

Comparison of parameters with many combinations can get some insight of dataset. Load expected of the engine is above 9000 kW. Filtering applied for kW that only show above 8000 kw data as this is minimum load requirement. Optimum delta bearing temperature at load above 9000 kW is between 42-48 deg C as shown on Figure 3. Engine load is decreasing by increasing running hour as delta bearing drain temperature increase, shown on Figure 4. Based on Figure 5 delta bearing temperature increasing linear around 8 deg C for 4,000 running hours period. After replacing the lube oil, delta drain bearing temperature back to normal then slightly increasing linear with running hour.

C. *Prediction*

Using RNN-LSTM, data set will train and create the model, from the model it can predict future data using Tensorflow module [12] with multi-step prediction [13]. Based on prediction, control system can send alarm at 24 hours prior to reach high set point so engine operator can act to prevent unplanned shutdown. Figure 7 shows prediction for next hour based on 24 hours last reading.

For predict to next 24-hour show on Figure 8. MAE used for evaluation as it is better than MSE (Mean Squared Error) [14]. It got MAE (Mean absolute error) higher than one step prediction.

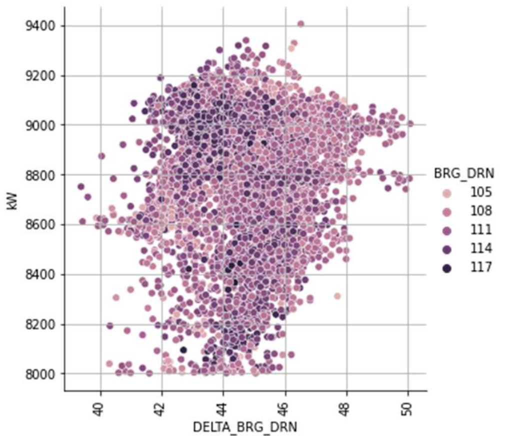


Figure 3 Delta bearing drain vs. kW with bearing drain

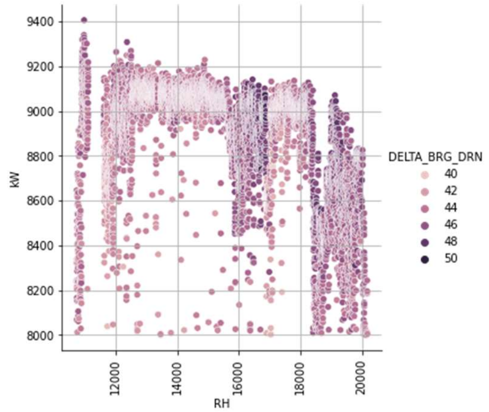


Figure 4 RH and kW with Delta bearing drain

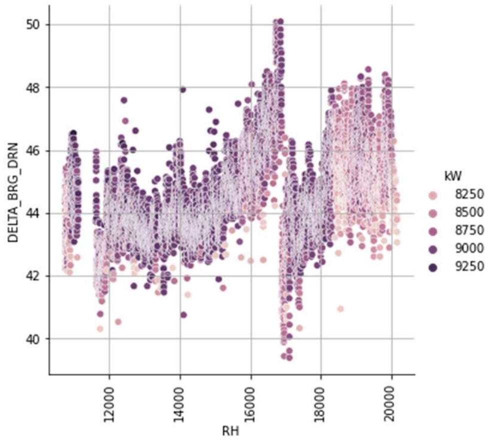


Figure 5 RH vs. delta bearing drain with kW

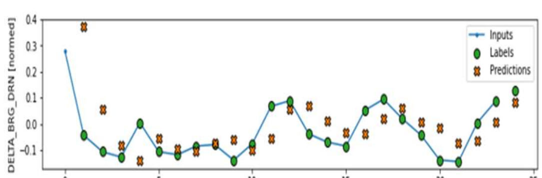


Figure 6 Prediction single-step next an hour

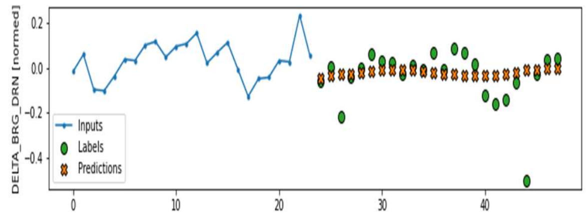


Figure 7 Multi-step model using RNN-LSTM to predict next 24h

Table 3 Model performance

Step	Loss	MAE (Mean Absolute Error)
Single	0.086	0.1292
Multi	0.7654	0.4701

IV. CONCLUSION

Future prediction of lube oil degradation for next 24 hours give useful insight that will be used as decision to treat and or to replace the lube oil. This project is initial concept to add analysis feature on the HMI and or Server. Based on results from prediction, it needs more work to get better method than current research by combination of method and or modify layer of the method. Beside on the lube oil temperature prediction, next research should consider also to add other oil properties measurement system such as LOAC (Lab-On-A-Chip) [15] for more accurate analysis. In the future, prediction system will be embedded in to Turbine control and monitoring system as added value of artificial neural network instead only automatic control system.

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