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BESPOKE MARINE MACHINE LEARNING ALGORITHM FOR ENHANCED OPERATIONAL EFFICIENCY

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Abstract*:* The maintenance of marine equipment/system follows a tight laid down regime of Condition Based Predictive Maintenance (CBPM) maintenance schedule wherein the marine equipment/system are subjected to maintenance based on running hours/condition of the machinery. The Authors et al. suggest that implementation of Machine learning algorithm coupled with the existing CBPM practices can lead to enhanced operational hours of the equipment/system, major cost savings and better predictability of the upcoming failure on any marine machinery. Exhaustive practical study cum analysis has been undertaken by the Authors et.al to design a Marine Machine Learning (MML) algorithm which is as mentioned in this paper.
Key Words - Marine, CBPM, Predictive Analytics

Current Scenario of Maintenance Philosophy in Marine Sector

In the Marine Sector (Merchant and Armed Forces) across the world, Condition Based Predictive Maintenance (CBPM) practices are followed as specified by the Original Equipment Manufacturer (OEM) towards maintenance of any equipment/system which is the heartbeat of any machinery. There are many maintenance routines as part of CBPM, such as Daily Routines, Weekly Routines, Monthly Routines, Three Monthly Routines, Six Monthly Routines and so on that are undertaken to keep the equipment in a seaworthy condition. These maintenance routines result in layoff the equipment/system for considerable time depending on the maintenance routine which also add up to environment pollution / depletion of essential marine stock. Situations also arise wherein many-a-time the marine equipment/systems are opened for maintenance routines and the maintainer discovers that the maintenance is really not required.

Proposal

The Authors suggest a cost-effective prognostic criterion for augmenting the predictive analytical techniques using bespoke Marine Machine Learning (MML) algorithm which shall augment the existing CBPM procedure(s) for upcoming maintenance of marine equipment/system.

Practical Applicability

The proposed bespoke MML algorithm has been extensively tried out for over one operational cycle on Engine Driven Sea Water Pump of fishing boat(s)/trawlers and medium sized vessels viz RORO (Roll On-Roll Off) vessels based out of Kochi and the results are highly positive.

Problems on equipment/systems that the proposed ML Algorithm can solve

Residual Useful Life (RUL) : Predicting the RUL gives the maintainer/user of the equipment/system about the residual useful remaining life of the machinery giving an indication as to when will the equipment/system will fail so that the maintenance can be planned in advance.

Irregular behavior of equipment/system : Experience has stated that any equipment/system generally fails whenever there is any anomaly in the same. Prediction by way of anomaly detection can help the maintainer/user of the anomaly detection through time series analysis which shall pre warn the user/maintainer of irregular behavior of equipment/system which otherwise shall hamper the maritime operation

Deciding on when CBPM maintenance routines needs to be carried : The CBPM routines are carried out by the ships staff as per the instructions laid down in the Maintenance Manual. Accurate predictions can help the user/maintainer of the equipment/system to do away with maintenance routines that would otherwise warrant an equipment/system to be opened up resulting in lay off of the equipment and usage of (consumable) spares.

Target Equipment/System used for study

For the purpose of the current work, the Authors et al. have used the Engine driven sea water pump that is Engine mounted and draws in sea water and is used to cool for jacket cooling fresh water that in-turn cools the piston liner of the engine.

Usage of MML in predictive Maintenance

The concept of predictive maintenance is a purely mathematical technique for solving any problem. However, towards carrying out predictive analytics on any equipment/system, the following steps were undertaken:

a) Data collection and data cleaning

b) Statistical modelling using R
c) Optimization using ML algorithm
d) Training and testing the dataset
e) Data visualization using BOKEH

Since the running parameters of any marine equipment/system is continuously monitored by the equipment watchkeeper, usage of BOKEH plots is resorted to by the Authors et al., as the results obtained using BOKEH plots are highly accurate for real time data. This paper also suggests integration of ML algorithm for predictive maintenance using the following steps:

a) Capture of raw data using SCADA (Supervisory control and Data Acquisition) which is a control system architecture for high level supervisory management.
b) Feeding the MML algorithm with running data of machinery
c) Drawing output from MML algorithm which indicates to the Engineer Officer (E.O),Senior Engineer Officer (SEO), Section in charge and Equipment Watchkeeper of upcoming maintenance requirements.

The above system would help the system to detect anomalies and test correlations while searching for patterns across the various data feed.

Prediction on Upcoming Maintenance

In order to predict the upcoming maintenance due, the data that is needed is the running data, maintenance data and historic data. The Authors et al. has done work on storing the historic data on cloud using MongoDB, and extraction of this data using PYTHON. Snippet of code for extracting old and historic data relevant to the equipment from MongoDB is as under:

```
import pymongo

from pymongo import MongoClient

#connect to database
conneciton=MongoClient('localhost',27017)
db=connection.mydb

#handle to old and historic database
data=db.olddata
```

Multi class classification techniques (MCCT) was found to be most effective to calculate the RUL of a marine equipment/system as the same has been found to be the best fit model for the same. MCCT was deployed under two scenarios for the case under discussion to predict the upcoming CBPM schedules:

- Predict future outcomes – This enabled the ships staff to watch for symptoms on upcoming failures and plan maintenance schedules.
- Root Cause Analysis (RCA) of a given failure – Predict the exact failures based on RCA alongwith the tools/spares required to liquidate the failure.

The plot obtained on real time using regression technique for predicting the RUL of the Engine Driven Sea Water pump is as under:

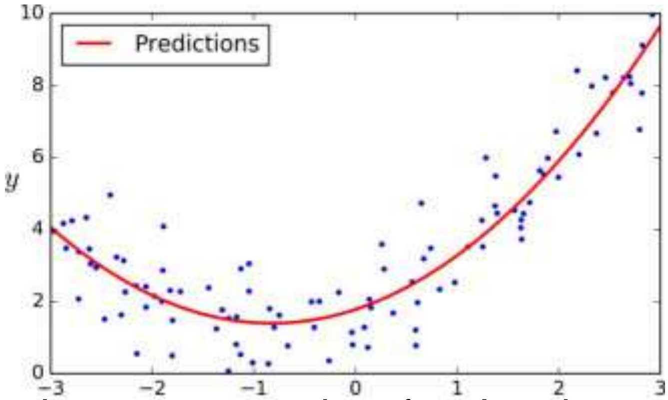

Fig 2 : Plot obtained on real time using regression technique for predicting the RUL of the Engine Driven Sea Water pump

Workflow for algorithm development

The diagram shown as under shows the workflow for MML algorithm development :

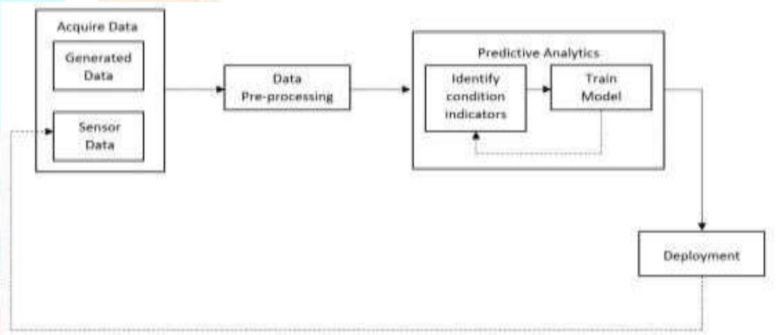

Fig 3 : Workflow for MML algorithm development

Algorithm used for predicting failure within a given time window

In the marine sector, the most important issue that effects the operational efficiency of any sea going vessel is predicting the failure of any equipment/system. The Authors et al. had taken a test case of maintenance an engine driven sea water pump as a case and predicted the failure using classification model which is as depicted in the figure as under:

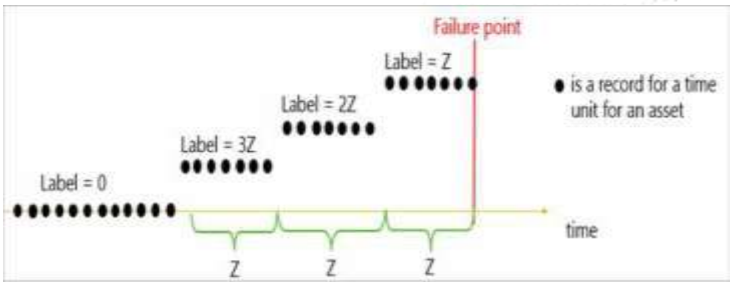

Fig 4 : Figure depicting failure using Classification Model of E/D Sea Water Pump

The task of classification for usage in marine sector can be viewed as a three-step process:

(a) Train Model: The training set of data is used and a training model is created.

(b). Evaluation model: The above trained model is evaluated using certain set of metrics

(c). Model usage: the model post training and evaluation is put into use

Python code for MML

PYTHON code dealing with missing values in raw data collected to predict the RUL of engine driven sea water pump

```
# Find columns with Null values
nullcols = []
for col in dfX.columns:
    nbnull = (dfX[col].isnull()*1).sum()
    if ( nbnull > 0 ):
        tp = type(dfX[dfX[col].notnull()][col].iat[0]) # type of first
        nullcols.append([col, tp])
        print(col, nbnull, t)
```

PYTHON code for predicting RUL

```
# select columns that have "few" unique values
cramer_cols = [col for col in df.columns.values if (len(df[col].uniq

for col in cramer_cols:
    try:
        cm = pd.crosstab(df[col], df['status_group']).values # conti
        cv1 = cramers_corrected_stat(cm)
        if (cv1>=0.20):
            print(col, int(cv1*100))
    except:
        None
```

Fig 5 : Patch PYTHON Code for MML

Indicator of Maintenance Efficiency

When we know form the equipment exploitation history the mean times when the maintenance of any marine equipment has been carried out then we can easily identify any of the maintenance efficiency indicators. Finally, the maintainer efficiency also has a big say in the nex maintenance of any marine machinery. The following indicators have been considered by the Authors et al. for prediction of Maintenance Efficiency :

The average availability: A=M[T 1] / M[T 0]

The average total downtime stated mathematically as :
M[TDT]= T{ M[T 0] - M[T 1]} / M[T 0]

Optimal number of predictive checks:

In the hostile marine environment wherein the equipment/systems are operating, a fine line was drawn post exhaustive study on the optima number of predictive checks that needs to be carried out by the Ships Staff (N opt) which is dependent on the selected optimization criteria.

It has been adduced that the maximum number of predictive checks (Nopt) can be found out by solving the optimization problem as under:

N opt => max A(N)

However, if the maintainer/user opts for minimum average downtime cost per unit time of any equipment/system, the same can be expressed as
N opt => min M[C(N)]

$$N_{opt} => \max_{N} A(N)$$

$$N_{opt} => \min_{N} M[C(N)]$$

Conclusion

This paper attempts to augment the existing CBPM practices followed in marine sector with MML algorithm for effective CBPM practices. New equations has been drawn for optimal number of predictive checks, indicator of maintainer efficiency (which plays a major role in the equipmen upkeep of any marine equipment/system)

It has been found that the MML results in :

[1] Reduction in frequency of maintenance

[2] Minimization of time spent on maintenance of any marine equipment/system, thereby ensuring higher operational availability of any equipment/system

[3] Higher savings

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