Predictive Maintenance for Airlines

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Introduction

Aircraft maintenance is an integral part of ensuring an aircraft is safe for operations. Poor maintenance planning can lead to devastating financial results for air carriers and keep aircraft grounded, passengers waiting and can even lead to flight cancellations. Additionally, an inaccurate overview of maintenance causes overstocking of surplus aircraft parts, resulting in air carriers losing vast sums of money.

To increase operational reliability and cost saving measures, aircraft operators follow aircraft maintenance programs. There are three well-known types of maintenance: reactive, preventive and predictive. Reactive maintenance refers to a timeline in which a particular part of an aircraft is used to its limits and repairs are only performed after a failure. This method is usually costly and dangerous for operational safety. Therefore, many aircraft operators use preventive aircraft maintenance (PM), also known as planned maintenance, which refers to a determined timeline of checks on certain airplane components.

The obvious challenge for carriers is a focused execution, which produces tangible and demonstrable improvements in cost and reliability. For OEMs accelerating adoption and profitably monetizing investments in predictive maintenance will be a significant challenge.

Another primary concern is data security. Due to the enormous amount of data that needs to be processed, it is critical to guarantee that equipment performance data cannot be accessed by outside parties, and that outside parties are not able to control predictive maintenance systems

Problem Statement

The airport is currently carrying scale increases year by year, the traditional method of airport resource allocation has been unable to adapt to the requirements of the operation of the airport. Dynamic allocation and scheduling of airport terminal passenger service resources are one of the most effective ways to improve passenger service levels and operational efficiency within the terminal, while the relatively accurate passenger traffic forecasting is the prerequisite for dynamic allocation and scheduling.

Solution

In this project, we have developed a model to predict the number of international airline passengers in units of 1000, given a year and a month.

The data ranges from January 1949 to December 1960, or 12 years, with 144 observations. Prediction for next months is computed based on current year and month traffic.

Dataset link:

https://www.kaggle.com/chirag19/air-passengers

RNN and LSTM have been used in the development of the model and we have used Flask to deploy the model as a web application.

Literature Survey

I. Chukwuekwe, Douglas Okafor, et al. "Reliable, robust and resilient systems: Towards development of a predictive maintenance concept within the Industry 4.0 environment." EFNMS Euro maintenance conference. 2016.

Challenges

Integrating techniques into an architectural PHM system or health management platform.

Implemented Approach

- Implementation of fault prediction algorithms, including model-based airplane fault prediction algorithms, databased airplane prediction algorithms, and knowledge-based fault prediction methods.
- Proposed the workflow and dataflow of the PHM system, defining data translation, data sharing, data integration, data processing and maintenance decision making information.
- Proposed the reliability and integration of the PHM system, through the algorithms hosted and the failure analysis of the applied system.

II. Moorman, R. W. "TOOL OF THE FUTURE: PREDICTIVE MAINTENANCE SOLUTIONS ARE NO LONGER A TECHNOLOGICAL NOVELTY BUT ANOTHER HELPFUL TOOL FOR COST-CONSCIOUS AIRLINES." ATW: Air Transport World (2005)

Challenges

Validation of the savings,Maintenance of hubs

Implemented Approach

- The program allows operations to go more smoothly with a "no fault found" function.
- Forward-looking function for spare parts inventory.
- Airbus intends to offer an onboard version to allow cockpit monitoring.
- AIRMAN is now in its third iteration and claims about a $4 per hour cost reduction and a reduction of 10 min.

III. Korvesis, Panagiotis, Stephane Besseau, and Michalis Vazirgiannis. "Predictive maintenance in aviation: Failure prediction from post-flight reports." 2018 IEEE 34th International Conference on Data Engineering (ICDE). IEEE, 2018

Challenges

Predicting future events from event logs in the context of predictive maintenance

Implemented Approach

- Model constitutes a novel combination of state of the art statistical and machine learning techniques and our experimental evaluation shows that it outperforms a common baseline approach.
- A major contribution of this work is the fact that it constitutes the first attempt to perform failure prediction given only post flight reports.

IV. Jhunjhunwala, Pranay, et al. "IMPROVING AIRLINES'ON-TIME PERFORMANCE." Boston Consulting Group. Retrieved August 23 (2016): 2020

Challenges

Scheduling and operations personnel must be in constant communication, since the activities and decisions of one directly affect the other

Implemented Approach

- Airlines have three ways to protect their systems against delays in a cost-effective manner: improving execution, reducing complexity, and creating buffers
- OTP can have serious downstream effects, from which it can take days, or even weeks, to recover.

V. Wang, Fangyuan, et al. "Aircraft auxiliary power unit performance assessment and remaining useful life evaluation for predictive maintenance." Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy 234.6 (2020): 804-816.

Challenges

Implementing the performance baseline model for auxiliary power unit is established using random forest method.

Implemented Approach

- The performance degradation trend is predicted using Bayesian dynamic linear model.
- Computed health index can effectively characterize the auxiliary power units performance degradation and the remaining useful life relative prediction errors are less than 4% when auxiliary power unit enters the rapid degradation stage

Experimental Investigations

- ### Data Collection.
  - Collect the dataset or create the dataset.
- ### Data Preprocessing.
  - Import the libraries
  - Reading the dataset
  - Handling missing values
  - Data Visualization
  - Split the data into train and test
  - Normalize the data
  - Reshape the train and test data
- ### Model Building
  - Import the model building Libraries
  - Initializing the model
  - Adding LSTM Layer
  - Adding Output Layer
  - Configure the Learning Process
  - Training and testing the model
  - Optimize the Model
  - Save the Model
- ### Application Building
  - Build HTML page.
  - Build Python code.

Hardware and Software Specifications

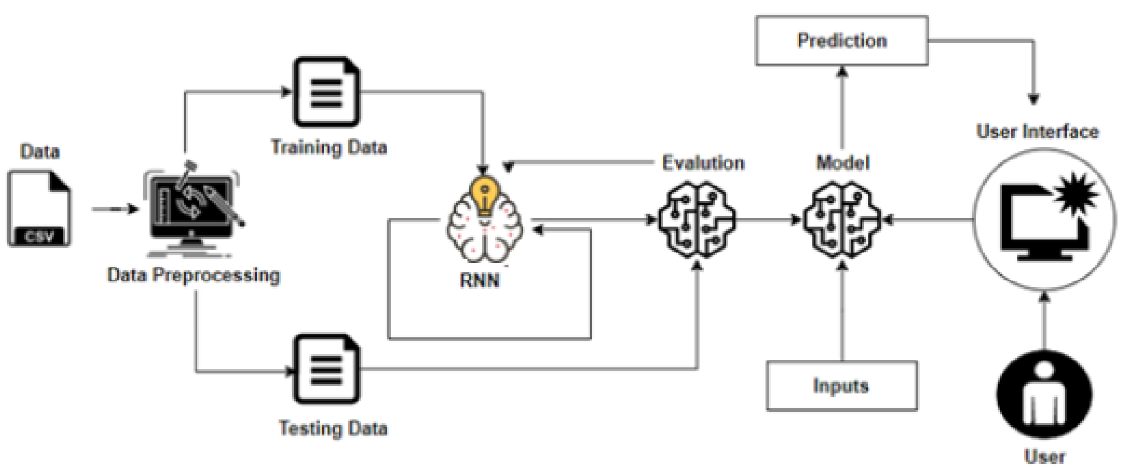
Libraries

- Pandas
- Numpy
- Matplotlib
- Seaborn
- Keras
- Tensorflow
- Sklearn

Software Requirements

- CPU: RAM 4GB
- GPU: Memory 2GB

Flowchart



Conclusion

In this project, we presented an effective RNN based predictive maintenance solution for predictive maintenance of airlines. The model uses LSTM for predicting the number of passengers in the near future. The model created is shown to have very low loss rate and high overall accuracy.

Future Scope

As part of the future work, we would investigate additional data sources, and expand our model to predict a large number of different parameters so that airlines can remain well-maintained.

Bibliography

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https://www.ibm.com/cloud/learn/deep-learning