Machine learning for predictive maintenance of industrial machines using IoT sensor data

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Machine Learning for Predictive Maintenance of Industrial Machines using IoT Sensor Data

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***Abstract*—The industrial Internet of Things (IIoT) is the use of Internet of Things (IoT) technologies in manufacturing which harnesses the machine data generated by various sensors and applies various analytics on it to gain useful information. The data captured by the machines is usually accompanied by a date time component which proves vital for predictive modelling.**

This paper explores the use of AutoRegressive Integrated Moving Average (ARIMA) forecasting on the time series data collected from various sensors from a Slitting Machine, to predict the possible failures and quality defects, thus improving the overall manufacturing process. The use of Machine Learning thus proves a vital component in IIoT having use cases in quality management and quality control, lowering the cost of maintenance and improving the overall manufacturing process.

***Keywords*—Machine Learning, ARIMA Forecasting, Data Analysis, Predictive maintenance & Productivity.**

I. Introduction

IoT is networking of physical devices and computers which enables them to collect and share data. The collected data is usually aggregated and stored on cloud platforms. IoT allows remote sensing and monitoring of these devices. This internetworking and connectivity is allowing automation in various fields.

One such great example is that of industrial IoT (IIoT). The IoT enabled manufacturing systems enable monitoring of vital machine data and controlling the machine using various signals. This helps to improve the manufacturing process and helps to plan maintenance activities of the machines.

Combining machine-to-machine (M2M) communication, PLC, SCADA, IPC, data analytics and business intelligence, the IIoT is changing the face of manufacturing activities. And as a result, companies in various domains are harnessing its effectiveness in increasing their productivities.

With condition based monitoring setup, we have real time insights of the most critical parameters. The systems currently at use in most manufacturing units have limited capability considering analysis and storage of historic data. Hence, we aggregate this data on cloud and use machine learning to predict failures beforehand to avoid major losses incurred by the firm if the machine stops for any reason and prevent the production of low grade products.

II. Data Collection

The main aim of this work is to provide prognostics for industrial machines to increase productivity and prevent quality failures. We have collected the data from a Slitting machine which is used to rewind and cut packaging films for various customers.

A. Machine Details

The data was generated from a slitting machine with 14 arms (7 on each side) which produce variable sized packaging rolls from a huge wound roll (Figure 1).

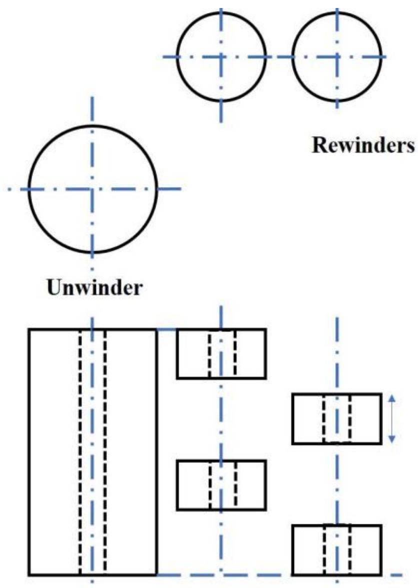

Figure.1. Slitting Machine at Stationary State.

The operation starts with a roll unwinding process from the winding machine which is then straightened up and fed to the slitter to cut into required roll widths. Blades or Knives cut the packaging film depending upon the requirements (Figure 2).

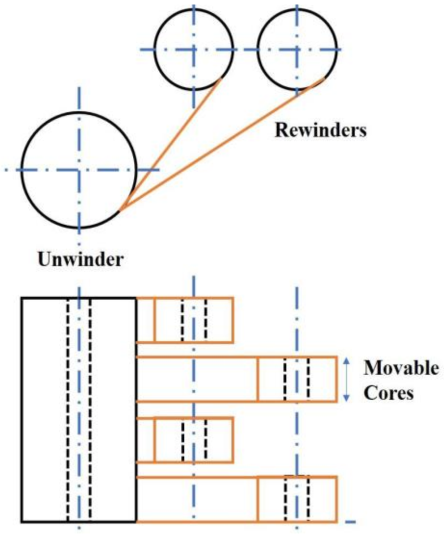

Figure.2. Slitting Machine at Working State.

We studied the process and found that tension and pressure were of higher importance in degradation of the packaging roll. A preset tension and pressure is given to the machine by the operator. This preset tension and pressure is maintained by the machine itself depending upon the roll diameter, roll width and roll length.

As the roll diameter increases, tension needs to be reduced to maintain the preset rate. Similarly, for the pressure values, pressure increases while the cycle is in process. This is done by the programmable logic controller (PLC) on board which sends signals to the required actuators.

B. System Setup

The PLC on the machine stores data for various parameters which need to be monitored. The concept of Daisy Chaining is used to reduce the wiring between the machines and PLCs. Using an RS485 port the data is sent to the adaptor which then converts the data into TCP form which is fed to the Industrial Personal Computer (IPC). The IPC is connected to the internet and pushes the data to the cloud using MQTT protocol in the form of data packets. The figure shows a block diagram for the process of data transmission from the motor (control of slitter rolls) to PLC to the IPC which is connected to the internet for pushing the data to the cloud (Figure 3).

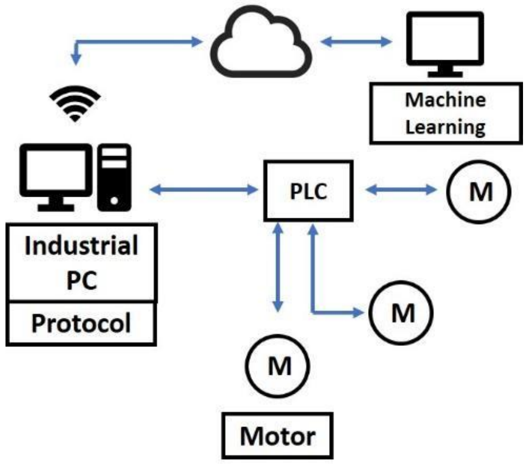

Figure.3. Block diagram of system setup.

C. Data Description

Data generated from the Slitting machine was collected using sensors and pushed to the cloud. This data was sampled per second and collected for a period of one month.

The data is stored as CSV in the system, consisting of 5 columns namely, Time Stamp, Tension, Pressure, Width and Diameter.

III. APPROACH

Our approach consists of two stages. The first incorporates data analysis, clustering and supervised learning methods to gain insights from the data and the second follows the first to add predictive models using ARIMA.

A. Exploratory Data Analysis

The sensors send the data when the machine shows a change in state which usually is sampled per second. Hence, the data received consists of many Null values. The first step towards preprocessing [1] includes replacing the Null values with the sliding mean values. Since, the failure points in the data are less as compared to the data points representing good production cycles, we tried outlier detection using clustering and studied the outliers to gain insights (Figure 4).

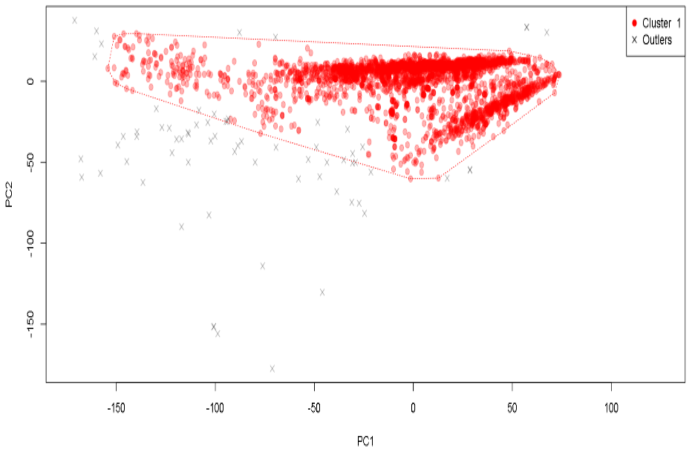

Figure.4. Clustering of parameters to find outliers.

Then a thorough analysis was carried out on the outliers as well as the failure points which were marked in the incoming labelled data to find the differences from the good cycles of production. Deeper analysis was done to understand the effects of the parameters on the product quality. One such example is discussed below.

A quality failure occurs when there is a sudden drop in pressure and it leads to a bad production cycle (Figure 5). Hence, this analysis helped us to map the failures with characteristic changes in the parameter values. The occurrence of such phenomena leads to product quality degradation.

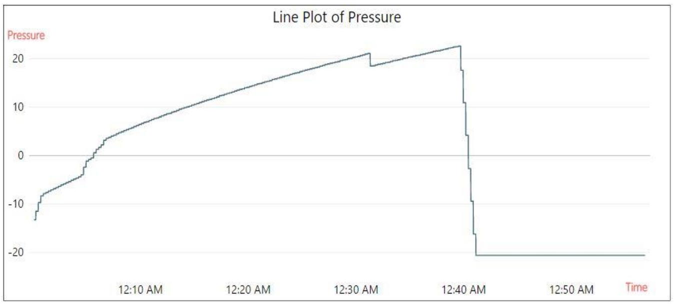

Figure.5. Plot of pressure of a bad production cycle.

Various supervised models [2] like Neural Networks, Support Vector Machines [3], and CART were used on the dataset to train a classifier to detect quality failures in production cycles.

B. Predictive Analysis

The use of predictive analysis proves to be a viable design solution for industrial machine prognostics. We have used Autoregressive Integrated Moving Average (ARIMA) [4] for forecasting the machine parameters to map the future states of the machine.

C. Data Preprocessing

The data received from sensors is essentially a discrete time data sampled per second of time. The decomposition of the time series data revealed an increasing trend (Figure 6) in the residues.

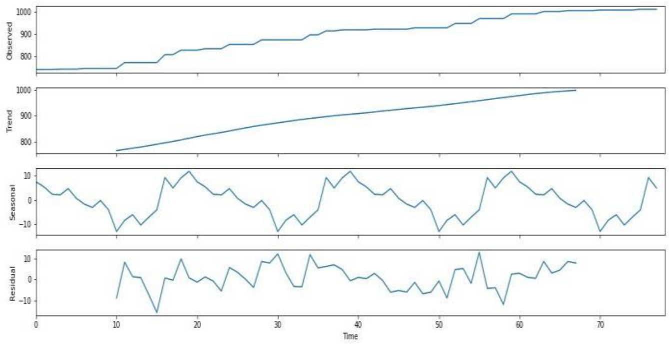

Figure.6. Decomposition of Time Series Data.

Hence, the time series was stationarised using differencing. Logarithmic transformation was used to reduce the variance of the time series data. Differencing removes changes in the level of the time series, and hence, eliminates trends and seasonality. With this, the rolling mean and standard deviation were made independent of time (Figure 7).

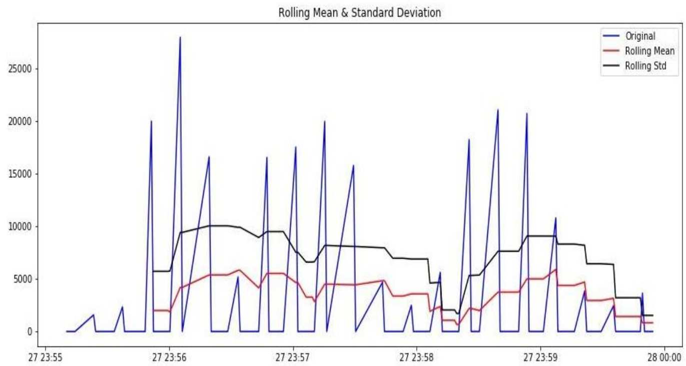

Figure.7. Test of Stationarity.

D. ARIMA

Autoregressive integrated moving average (ARIMA) model was used to predict future points [5] in the data series. Since the data showed non-stationarity, we have used ARIMA. The model is fitted (Figure 8) in the dataset and further points are predicted to find if the future states which might lead to a failure.

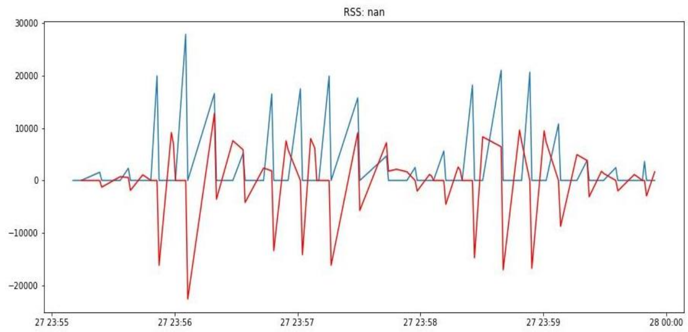

Figure.8. Plot of ARIMA model.

IV. PROPOSED SYSTEM ARCHITECTURE

The supervised models are trained on the historic data while the same dataset is used to train the ARIMA model. This system is then stacked together. For new and unseen production cycles, the ARIMA model predicts the values of the parameters for the rest of the production cycle and these values are fed to the supervised model to classify. If the model predicts the cycle as a bad production cycle, necessary steps must be taken to avoid it from happening.

V. RESULTS

The supervised models which were trained on the dataset divided as 70% training, 10% cross validation and 20% test, showed the following accuracies (Table 1).

TABLE I. COMPARISON OF DIFFERENT SUPERVISED MODELS

Supervised Model	**Prediction Accuracy (%)**
Naive Bayes	96.61
Support Vector Machine	95.52
CART	94.46
Deep Neural Network	98.69

It can be inferred that the deep neural network model was more efficient in modeling the data. However, the occurrences of the bad quality cycles are low as compared to the good quality cycles. Hence, the model keeps on actively learning with the newly arriving data and keeps on updating the weights.

The predictive model is incorporated to help in reducing the low-quality production cycles and help in planning the maintenance activities [6]. The model is used to forecast the values till the end of the production cycle to predict the quality of the job which is produced.

VI. FUTURE SCOPE

The system can be further trained to predict the remaining useful life (RUL) [7] of the machine before it requires maintenance or replacement. The use of stacked architectures [8] of various models can be used to increase the confidence in classification. Furthermore, use of proactive anomaly detection [9] can be used to send signals to the machine controller to control the machine parameters to prevent bad quality production cycles and hence increase the overall productivity.

VII. CONCLUSION

IoT based machine learning will help overcome major limitations in productivity and maintenance costs associated with it. The supervised models can be used to find insights from the data and the subsequent use of prognostics and forecasting will make sure that the production process runs efficiently with minimal costs incurred for maintenance and reduce product quality degradation.

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