

Reducing the Number of Quality Defects in a Packaging Film Manufacturing Process using IoT Sensor Data

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Abstract— The use of IoT sensor data in a manufacturing process helps gain deep insights from the real time data generated from the machine. This paper explores the use of exploratory data analysis on 5 parameters in a machine to reduce the number of quality defects, thus reducing the losses suffered by the manufacturer.

Keywords — Data analysis, Productivity, Quality

I. INTRODUCTION

IoT is a network of physical devices which can talk to each other and share data. The concept of Industrial IoT is just an expansion to IoT concept in which data from industrial machines is pushed to the cloud and further data analysis is carried out.

A huge amount of data is generated when we are analysing real time data. This creates a challenge as to where all the data should be stored. That is why the data is stored onto a cloud which is scalable and much more flexible to work analytics on it.

II. DATA COLLECTION

The objective of the work carried out was to reduce the number of quality defects arising due to change in values of key parameters in the machine. The data generated was from a machine which cuts a big roll into a smaller roll based on the requirements.

A. Machine Details

The machine in focus had rewinding arms on each side of the machine which the operator adjusted to produce varying sized output cut rolls.

The process begins with the feeding of a big roll onto the machine. Then it is cut by knives which are positioned at various widths based on customer requirements.

The below images show a block diagram on the stationary state (1) and working state (2) of the machine. The red line is the film which is fed onto the machine.

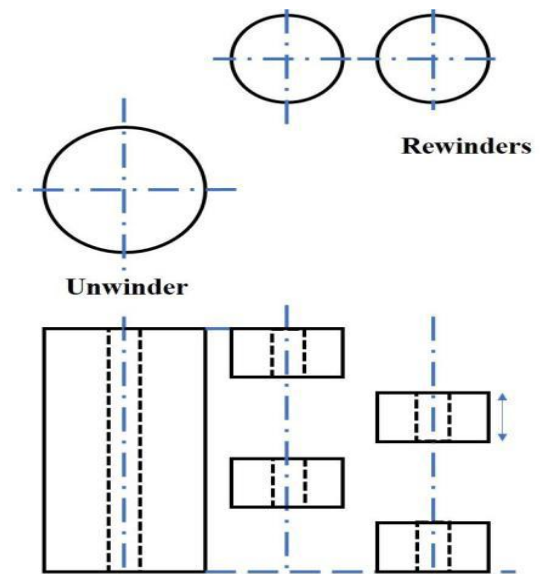


Fig. 1 Machine at Stationary State

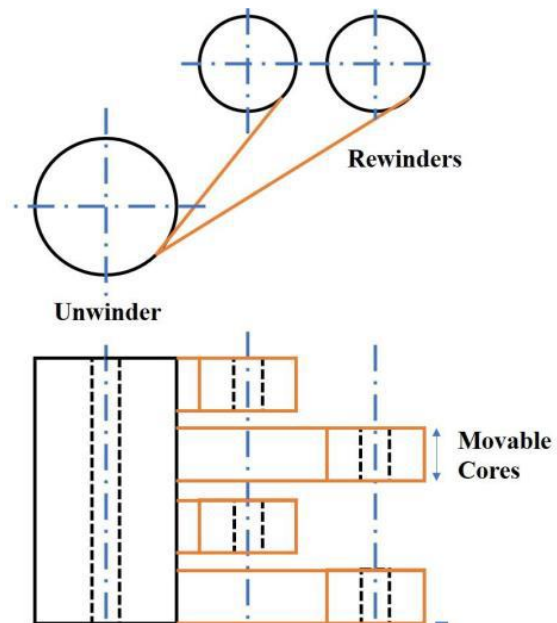


Fig. 2 Machine at Working State

III. PROBLEM APPROACH

The approach consisted of studying the data pattern, the standard cycle parameter trends and then isolating the good rolls vs the bad rolls.

A. Exploratory Data Analysis

A data dump of around 2 months was taken for the analysis. There were 5 critical parameters taken in the analysis. The below figures represent standard cycle trends for Parameter 1 and Parameter 2.

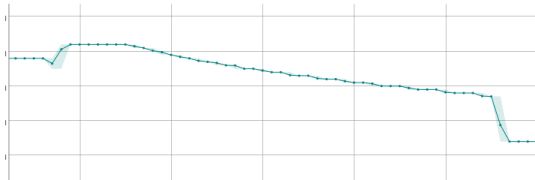


Fig. 3 Standard trend for Parameter 1

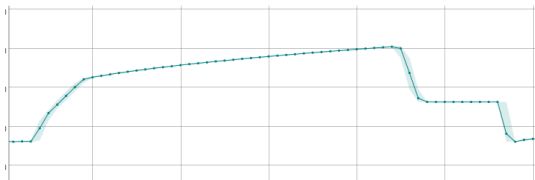


Fig. 4 Standard trend for Parameter 2

The values of these two parameters are pre-set based on the roll width and diameter. If the operator sees that the roll is being degraded, he manually adjusts Parameter 1 and Parameter 2 values based on his experience. Then the operator marks the roll as a defective roll with a fault code. This is then stored into a database onto which analysis is done. Whenever there is no such defect, these rolls are considered as good rolls.

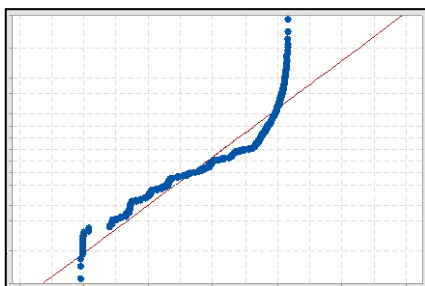


Fig. 5 Parameter 1 Normality Test Result

Normality test was carried out on the standard cycle data and it was found that the Normality Test failed concluding that the data was not a normal distribution. Since the normality test failed, Parameter 1 and Parameter 2 medians were used in the analysis.

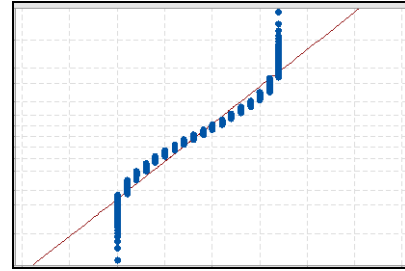


Fig. 6 Parameter 2 Normality Test Result

B. Data Visualizing

After getting the defective marked rolls and the good rolls, a quadrant chart which shows good rolls vs bad rolls based on Parameter 1 and Parameter 2 median values is plotted.

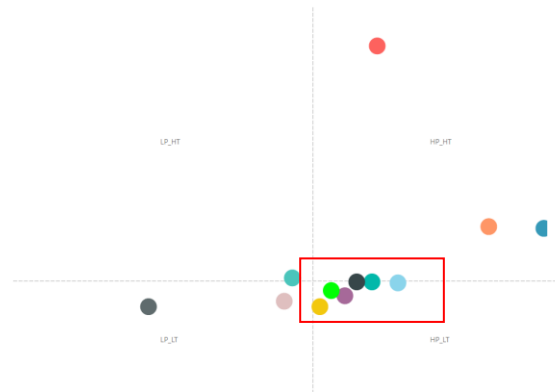


Fig. 7 Quadrant chart showing good rolls (Green) Vs other defects

The above figure clearly shows a varying pattern of defects compared to the Good rolls. This means that the defects in the red box which have median values closer to the good batch may not be the result of Parameter 1 and Parameter 2 and thus we can check for other parameters for these defects.

But for the other defects which have a much bigger variation from the good batch we can say that Parameter 1 and/or Parameter 2 have a huge impact on the degradation of the rolls.

IV. GOOD VS BAD COMPARISON

The below table represents a few defects arising in the machine with their Parameter 1 and Parameter 2 values. Adjacent to those values, there are Parameter 1 and Parameter 2 values for the good batches.

The team was told to use these values of Parameter 1 and Parameter 2 for their upcoming cycles

| Defects | Parameter 1 Median | Parameter 2 Median | Parameter 1 Median (Good) | Parameter 2 Median (Good) |
|---------|--------------------|--------------------|---------------------------|---------------------------|
| A | 1013 | 153 | 1043 | 136 |
| B | 1296 | 148 | 1246 | 147 |
| C | 1712 | 215 | 1235 | 150 |
| D | 984 | 125 | 1067 | 147 |
| E | 1316 | 434 | 2027 | 314 |
| F | 1242 | 148 | 1252 | 141 |
| G | 1112 | 118 | 1098 | 120 |
| H | 1200 | 131 | 1130 | 124 |

Table.1 Comparison of Good Vs Bad Parameter 1 and Parameter 2 values

V. RESULTS

We observed a great reduction in the number of defects. In a period of 2 months, there were 664 defects in total consisting of 36 distinct defects.

After giving them values based on data we have reduced the number of defects from 664 to 568 defects in a period of 2 months having 26 distinct defects.

VI. FUTURE SCOPE

We are getting into the acceleration and deceleration of the parameters which will give rate of change in turn telling whether the rate of change is normal as compared to a good batch of product.

ACKNOWLEDGMENT

We would like to thank all people who directly or indirectly contributed in the research work.

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