DETECTING EQUIPMENT SERVICE PATTERNS IN THE HEALTHCARE SERVICE INDUSTRY

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ABSTRACT

Healthcare equipment service companies confront the challenge of how to identify equipment showing repeated patterns of service events in order to minimize cost to the supplier, downtime for the customer and significant delay in the treatment of patients. Current methodologies employ sensors to detect large variations and alert the service provider before failure or break down. Since time is of the essence, the engineers scramble to make a quick break fix without looking at a holistic view of the problem and the history of the machine. This results in prolonged repair cycles, causing excessive stress to both the service provider and customer; and impacting the reputation of the company. Using modern visualization tools like SAS® Visual Analytics and JMP®, we are able to apply meaningful visualizations to analyze large volumes of service event data. This has enabled us to create a useful index which effectively measures the customer experience over time, and apply regression techniques in tools like SAS® Enterprise Guide® to quickly identify these patterns, thus saving many hours of downtime and unproductive labor.

INTRODUCTION

The goal of this paper is to present a solution to the problem of detecting equipment service patterns in the healthcare industry in order to minimize the costs associated with servicing the machines. We will present the proposed methodology and the results obtained.

NEED FOR DETECTION

According to papers published in the journal The Lancet, the United States spends $9,237 per person on health care. This is the highest among all the 184 countries surveyed and is 18% higher than the next highest spender Switzerland. However, this does not translate to best health outcomes. US is ranked 12th in life expectancy among the 12 wealthiest industrialized countries according to Kaiser Family Foundation, a non-profit organization focusing on health issues. This means that there is a lot of potential to improve efficiencies within the healthcare system as a whole in the US and everybody has their fair role to play in this endeavor.

With tighter federal regulations and uncertain insurance payout changes, hospitals are preparing to face the unknown by slashing their annual budgets especially on medical devices and their services. The value of service can be improved by decreasing the number of service events and thereby decreasing the downtime of the machine. The cost of servicing a machine goes up as the number of service events increases thereby decreasing the overall profitability of the service. If we were to decrease the number of times a machine breaks down and keep the costs low, we may be able to pass on the savings to the hospitals.

In general, when a technician detects a machine is not working he or she calls the hotline number. If, upon clarification of the problem, it is determined an on-site visit is required the service provider dispatches a service engineer to fix the machine as soon as possible. As we studied the history of service events for similar equipment types, we found that in certain situations, patterns of repeated failures are apparent. Repairs for these cases seem to provide only short term relief to the customer. The repeated on site visit by a service engineer, parts replacement and testing costs a significant amount of money to the service provider and an increase in the downtime to the customer. When the machine is down, the customer also loses money as the tests/scans get rerouted to other hospitals. In order to understand the performance of our entire fleet of equipment, we needed to identify what normal looked like and identify the equipment that are away from the normal behavior of that particular group of machine.

To calculate the health of a machine at a given time and hence the distress level of the customer, we designed an index called Distress Index (DI). A higher value corresponds to a higher distress level for the customer. The calculation averages service events over the past 30 days and multiplies this by the count of service event tasks (each touch-point in resolving an issue) plus a weighted sum of on-site visits.

One of the key attributes of this index is that it acts as a running average, i.e., the value not only indicates the status of the machine on a single day but takes into account the activities performed on the machine over the past 30 days. When we graph these daily values we are already getting a smoothed interpretation of the equipment's performance from a service perspective.

DETECTION ALGORITHM

Now that we have defined the DI metric we can graph the scores over history to get a trend. We see the trend of a machine exhibiting repeated service events vs a one-off issue, respectively in Figures 1 and 2.

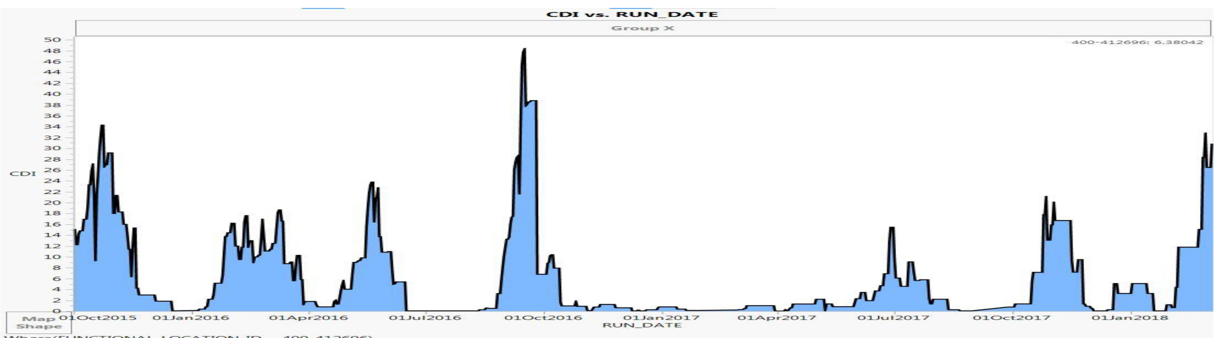

Figure 1. Distress Index over two years for 'Repeated Failures'

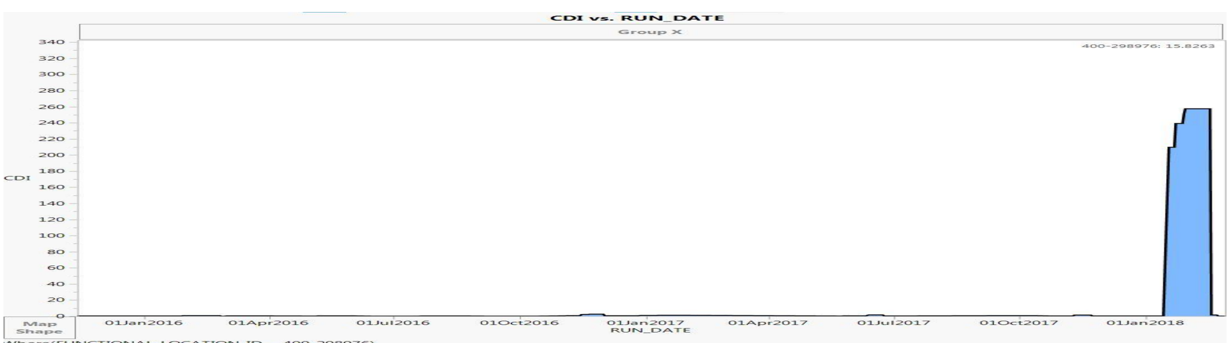

Figure 2. Distress Index over two years for 'One-off' Issue

Additionally, we need to consider an example where most of the peaks do not rise above a pre-set threshold. In these cases, the severity of the service event does not warrant it to be marked as a peak. Luckily, the distress index has been used in the business for several years and the engineers for each business unit have developed thresholds for their machines. In Figure C, we see an example where the peaks do not exceed the threshold except for once. To exclude these peaks we only count peaks which have a magnitude greater than the threshold.

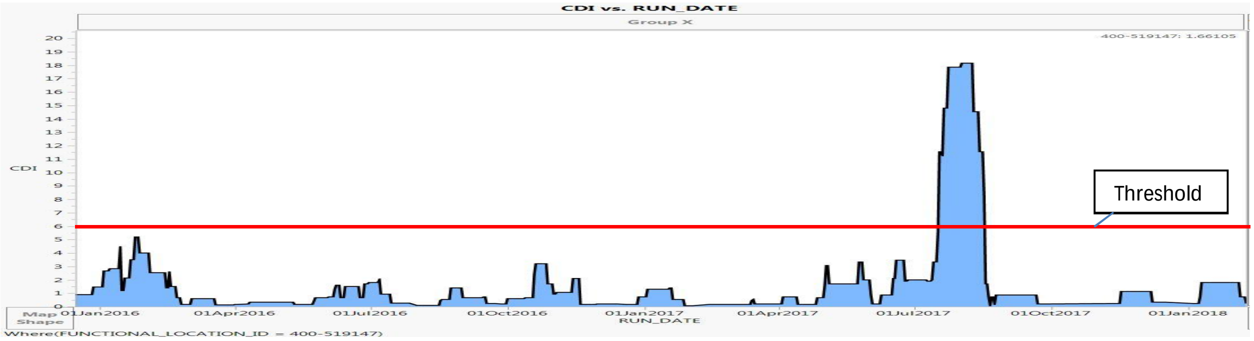

Figure C. Distress Index over two years for equipment where most scores do not exceed the pre-set threshold.

Now we need to develop a method to identify and count the peaks. After researching and testing methods, including polynomial regression, we landed on using finite difference methods. These methods estimate the derivative, or slope of the curve, by calculating the difference in the limit equation for the derivative,

$$f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

This is called a One-sided, or Left-sided, finite difference scheme. In our example, *h = 1 day*. So, we can approximate the slope of the equation by the following formula,

$$slope_{Day\ i} = DI_{day\ i} - DI_{day\ i-1}$$

where $DI_{day\ i}$ is the distress index on the day we are calculating and $DI_{day\ i-1}$ is the distress index on the previous day. Obviously, if the distress index increases from day to day we will get a positive value (slope) and if the index decreases from day to day we get a negative value (slope). We can then count peaks by identifying steps where the slope goes from positive to negative.

The one-sided scheme does produce results, however, since it is only considering two points immediately following each other it captures every peak, even, e.g., if it a minor blip on the way up to a higher peak. In order to 'smooth out' this approximation we used a Central Difference Formula.

$$slope_{Day\ i} = \frac{DI_{day\ i+1} - DI_{day\ i-1}}{2}$$

This method greatly reduces the number of peaks the algorithm is counting. E.g. the equipment in Figure A (400-412696) counted 431 peaks using the one-sided method and 58 peaks using the central difference method. Additionally, if we only count peaks above the threshold this number reduces to 30.

RESULTS

We are able to identify repeated failure patterns and provide engineers with the following:

1. List of machines experiencing this pattern provided to engineers and field managers so that appropriate action can be taken when one of these machines breaks down.
2. Mark equipment in dashboard with indicators which flag repeated failures so the engineer can quickly identify if the equipment has a history of issues.

Cost Comparison

The cost to repair the machines which were identified by the detection algorithm is significantly higher than the average cost per machine in the business unit. In fact, the cost of servicing the top 61 machines identified by the algorithm is over 3 times as high as the average for the entire Business Unit. As you can see these machines place a higher burden on cost of service. This is, in fact, the reason for this project. The business has understood that it is more cost efficient to replace equipment in these situations then to continually send out an engineer to fix them. Until now, however, there was not a process for identifying these machines in the field.

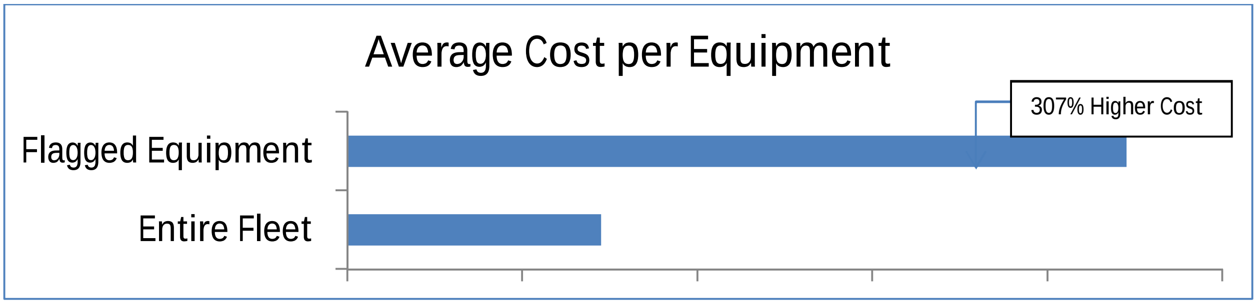

Figure D. The average cost on the equipment flagged by the algorithm cost 307% more than the average cost for the entire fleet.

CONCLUSION

In conclusion, in order to control costs healthcare companies need to use all the information they have to save money. This includes machine data and service data. When this information is used in clever ways it becomes even more powerful. The authors were able to provide actionable information on equipment to engineers and decision makers about the history of the equipment, thus, making it easier to decide the appropriate course for affective resolution.

REFERENCES

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