A New Look at Resource Management

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Abstract This paper introduces tree analysis as an application for Business Intelligence in resource management. A dataset of Overall Equipment Effectiveness measures is analyzed using tree analysis to identify variances in production efficiency. The findings provide insight to problem machines, shifts, or time periods where resources are utilized less efficiently.

A New Look at Resource Management

What value could be added to an organization if it was possible to get inside datasets and see, first hand, what was going on? By being "inside the data", it would be possible to identify problems in manufacturing processes and make suggestions for improvements. Data mining techniques, specifically tree-based models, can provide a way look at data from the inside, out.

In this paper, we focused on the implementation of tree-based models using OEE data from a large safety-products manufacturing company. By implementing business intelligence techniques, primarily decision trees, we were able to provide managers with the opportunity to derive more utility from their existing data.

RESOURCE MANAGEMENT

Resource management focuses on maximizing the use of all resources in an organization, everything from managing people and machinery to office supplies. Resource management has several sub-disciplines. These disciplines include human resource management, productions and operations management, process management,

and project management. Each of these disciplines is composed of several sub-processes of their own, one of which is monitoring and controlling production operations. There are several metrics used in industry to monitor production operations, one of which is Overall Equipment Effectiveness, OEE.

OEE

OEE is defined as a key metric in Total Productive Maintenance, TPM, and Lean Manufacturing programs that gives a consistent way to measure the effectiveness of TPM and other initiatives by providing an overall framework for measuring production efficiency (2). Company-wide, TPM is concerned with eliminating all forms of waste (4). OEE shows how well a company is utilizing its resources, which include equipment, labor and the ability to satisfy the customer in terms of delivering quality products (5). OEE is the product of three measures: Availability, Performance, and Quality (2).

*OEE = Availability * Performance Efficiency * Quality*

$$\text{OEE} = \frac{\text{Run Time}}{\text{Run Time} + \text{Down Time}} * \frac{\text{Standard Time}}{\text{Operating Time}} * \frac{\text{Good Parts}}{\text{Good Parts} + \text{Bad Parts}}$$

Consistent improvement or a high OEE shows that a company is successful in driving out waste and improving customer service (4).

DATA MINING IN MANUFACTURING

Although an Advanced Planning and Scheduling (APS) system is capable of keeping a typical manufacturing company's operations under control on a daily basis, it is necessary to go a step further to discover, analyze, and resolve fundamental problems (3).

This is where Business Intelligence and Data Mining tools provide additional insight into manufacturing processes.

Data mining has evolved over the years. In fact, as early as 5-10 years ago, many referred to OLAP analysis as data mining. As the information age continues to evolve, the ability to capture greater amounts of higher quality data impacts the effectiveness that business analysts can derive from this data. Today, business intelligence techniques help managers to find answers to several questions, including but not limited to:

- Are there any statistical relationships between variables?
- How strong are the relationships between variables?
- If certain explanatory variables are manipulated, what corresponding changes can be expected in the response variable?
- What quantitative measures are needed for forecasting?

The term “data mining” is characterized as the technology that incorporates the application of statistical techniques, in conjunction with mathematical formulas that attempt to identify significant relationships between variables in historical data. These results can then be used to forecast business measures, perform sensitivity analysis, or just identify significant relationships that exist in the data at hand. Some of the common methodologies that make up the world of data mining include clustering, segmentation and classification, neural networks, regression, association analysis, etc. Analysts use these tools to let the data tell them what is happening in their businesses rather than test the validity of rigorous theory against samples of data (1).

Versatile tools that graphically represent the segmentation of data are tree-based models, or decision tree models. Decision trees divide data sets into multiple hierarchical groups. These groups provide insight based upon the response variable(s). Decision tree algorithms, in particular, are an application of regression analysis, where the user has the power to analyze the response variable(s) with selected predictor variable(s). *Decision trees can be used in manufacturing operations to understand the variation in input variables, analyze the machine-related differences in production, study the manufacturing phases for defining bottlenecks, and help managers in decision making processes.*

CASE STUDY

We have used the OEE data from a large safety-products manufacturing company. The company has been collecting data on their machines for over two years; the data is currently used to create a number of operational reports to track the progress of manufacturing efforts.

Currently, the manufacturing company has a total of ten machines performing the same basic process; the machines vary by age and brand. Production line workers fill out daily OEE run sheets, that include the machine, type of part being produced, the shift, the date, the quality of the production run, any downtime that occurred during the shift, and any maintenance that has occurred on the machine during the shift. Management estimates 20% of all collected data is flawed. Errors in the data collection process include data timing and poor quality reporting.

Data timing errors focus around when data is recorded into the system. Occasionally, line workers will not record production in the period it is run. This causes

the OEE number for that period to be unusually low. Then, in the next period the line worker will record the previous period's work. This damages the OEE data by making the OEE data of the first period appear lower than it actually was and causes the OEE data of the second period to appear to be larger than it actually was. As a result, it is not uncommon for the second period to have OEE calculations greater than 100%.

Quality reporting is another area that the manufacturer is having problems with. Currently, line workers are reporting the quality of their production runs at 100%. This is contrary to what management believes to be true. It seems that line workers are failing to account for the materials that are sent through to prime a process when there is a set-up change. These materials generally need to be reworked, as the calibrations of the machining process may need to be adjusted. Additionally, some products have been found to be of poor quality later in the production process; these products should be counted against the quality of a production run to gain more accurate insight into true OEE rates of the manufacturing processes.

Contrary to the common belief that if you gather your data poorly, you are destined to failure, tree algorithms may still provide useful insight with flawed data. Decision trees are able to operate without perfect data because of their grouping algorithm. As long as the data collecting process is consistent, the grouping algorithm is capable of predicting meaningful relationships between variables.

VALUE ADDED BY BI TECHINIQUES

In order to determine primary root causes of variation in overall OEE, we performed a tree analysis on the data. In tree-based models, predictor and subgroup

classifications are determined by traditional statistical hypothesis testing techniques including chi-squared and F-tests. One practical feature of tree algorithms is that they provide end-users, who may lack statistical knowledge, the convenience of a visual output.

We used Partitionator® software to build tree algorithms. Partitionator® is built on the statistical foundations of FIRM, Formal Inference Recursive Modeling, with its roots going back to work done in the 1970's and 1980's by Dr. Douglas Hawkins (6). We began our analysis by defining OEE as the response variable and defining the variables, availability, quality, performance efficiency, machine, shift, day, and month, as predictor variables. Figure I is a histogram of the response variable, OEE.

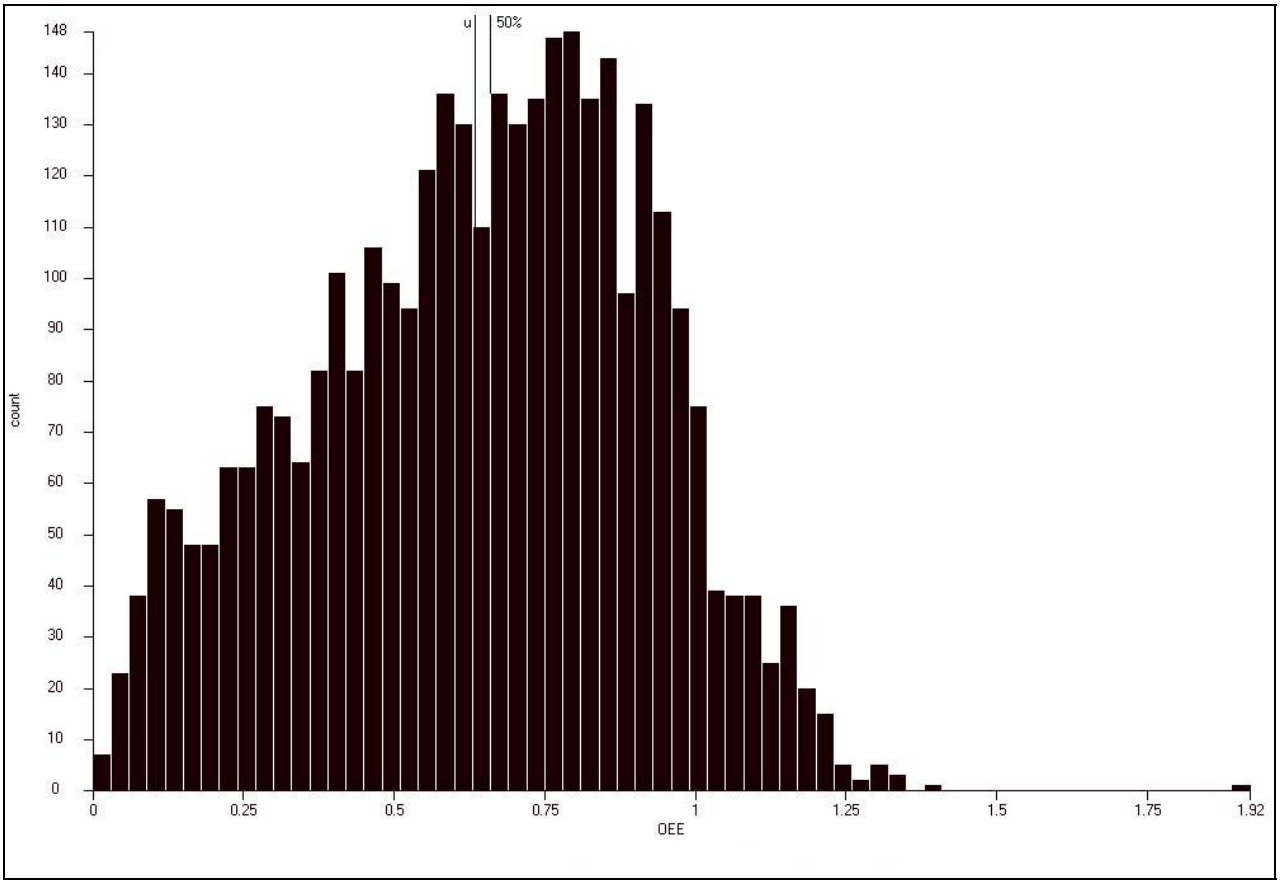

FIGURE I - Histogram of OEE

The errors in the data collection and recording phase can be seen in the histogram; there are OEE rates above 100%, which are not actually possible.

OEE is defined as the response variable, and month, shift, day, and machine are defined as predictor variables. Figure II shows the results of the analysis.

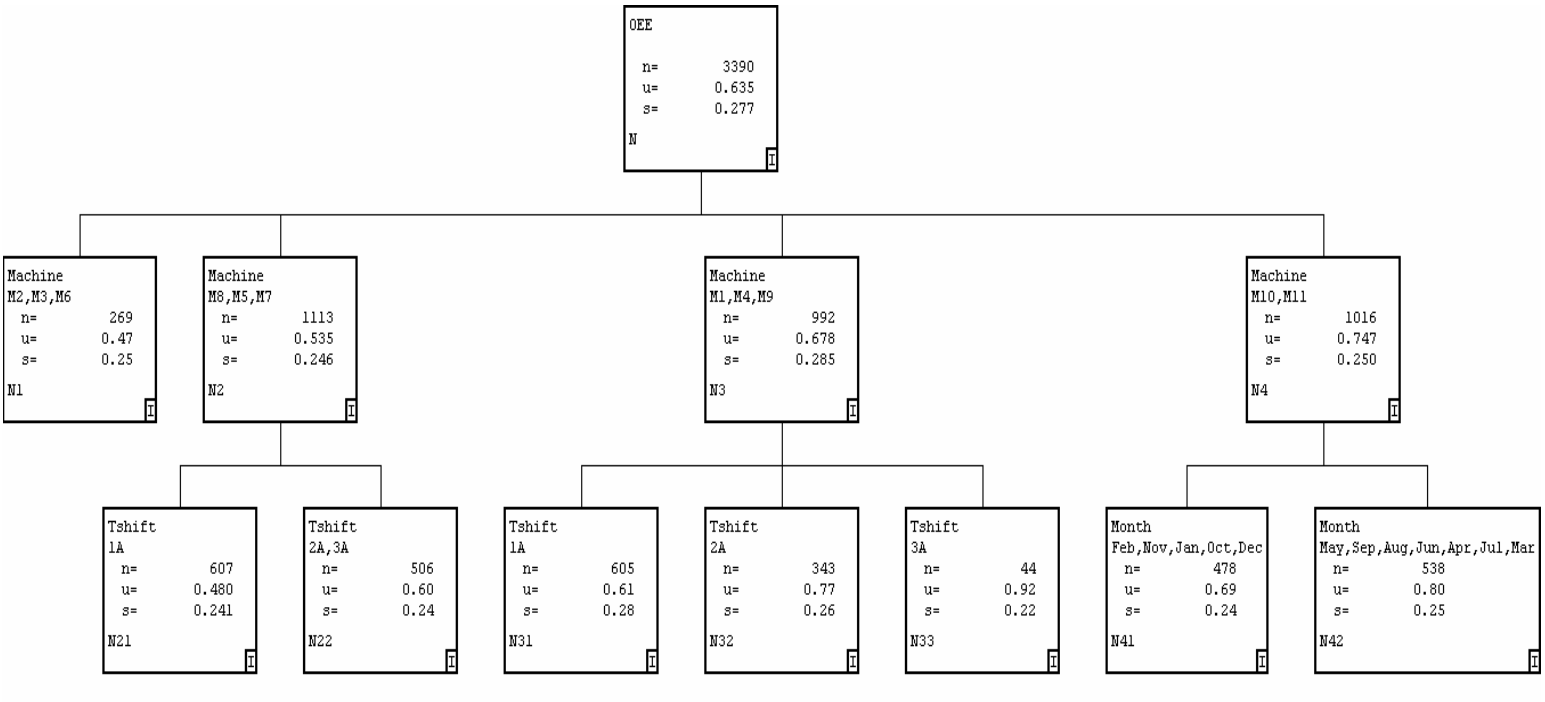

FIGURE II – A Detailed Tree Diagram

The top box, or node, shows the number of observations [n], mean [u] and standard deviation [s] of OEE for the 3,390 observations in the data set. The tree splits from the initial node on the most statistically significant variable, which is Machine. Thus, the variation in OEE is best explained by machine. As the first split shows, M10 and M11 have the highest mean OEE of 0.747. Discussions with plant managers revealed that machines M10 and M11 were the newest machines, possibly explaining their higher efficiency levels. Proceeding to the second-level splits, shift is the second most significant predictor of OEE in the older machines, while month is the best predictor for

M10 and M11. For M10 and M11, the mean OEE is lower during the winter months. The results raise questions about production patterns of the different machines. Are the differences in production caused by production line workers? Or, do seasonal maintenance or temperatures cause them? This highlights the essential need for more detailed data collection. With such a process, managers would be able to explore the root causes of variation in their production.

OEE is a function of Availability, Performance, and Quality. When these particular variables were included in the analysis, Availability was shown to be the most statistically significant predictor. Figure III shows this split.

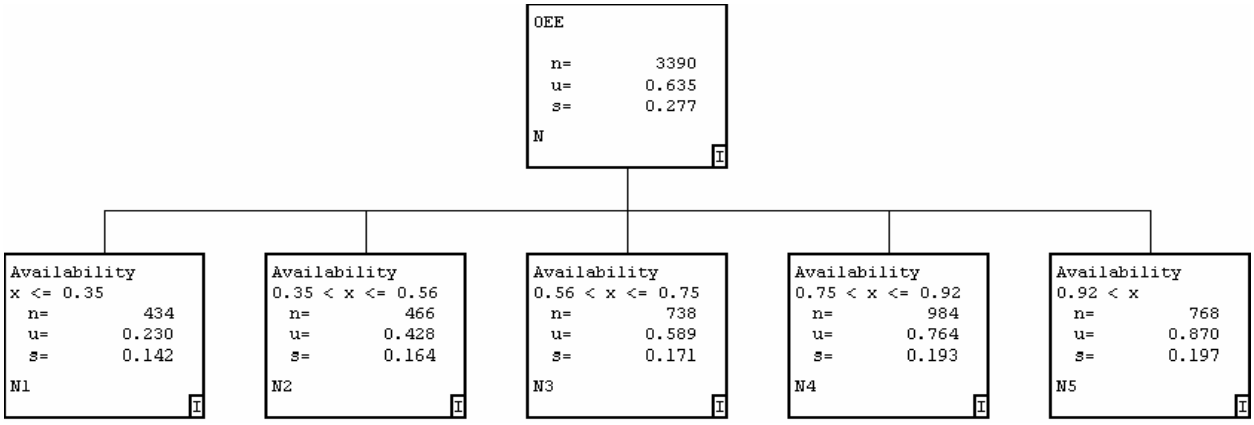

FIGURE III - Split of OEE on Availability

The variance in OEE is best explained by the overall range of Availability. The increase of variance in OEE as Availability increases is also clear in Figure IV.

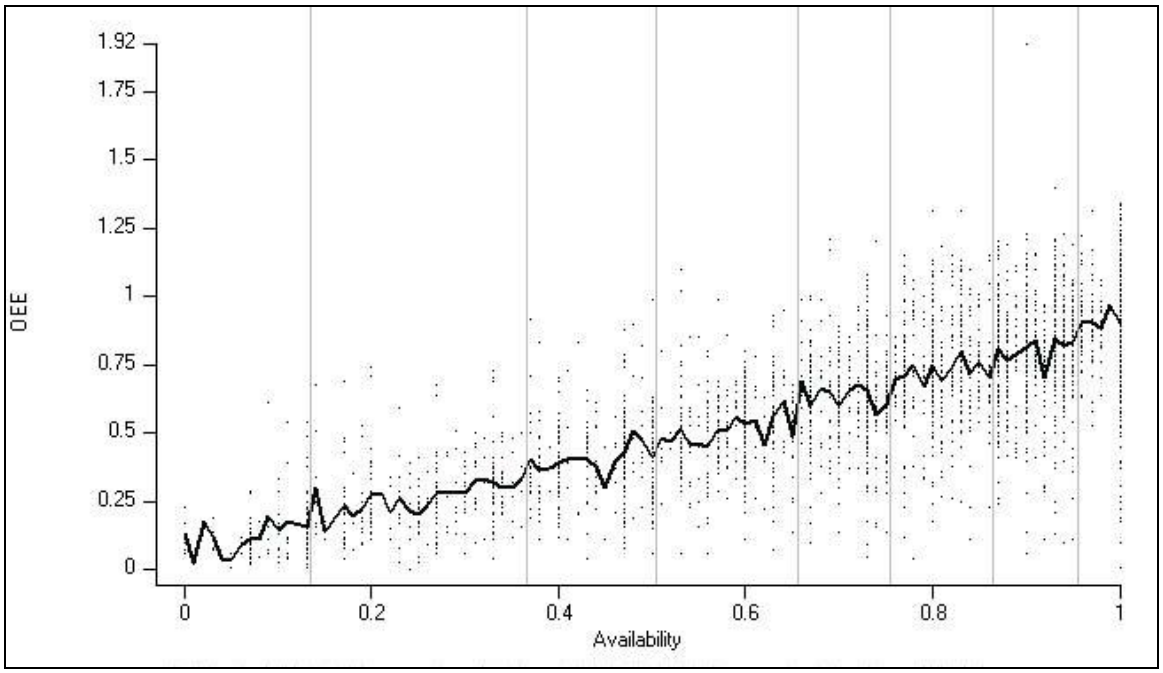

FIGURE IV - OEE vs. Availability

As expected, the dispersion of dots is wider in the right bins of the graph. Another visualization of the affect of availability on OEE can be represented in histograms. In Figure V, each of the five nodes from Figure III is displayed as a histogram.

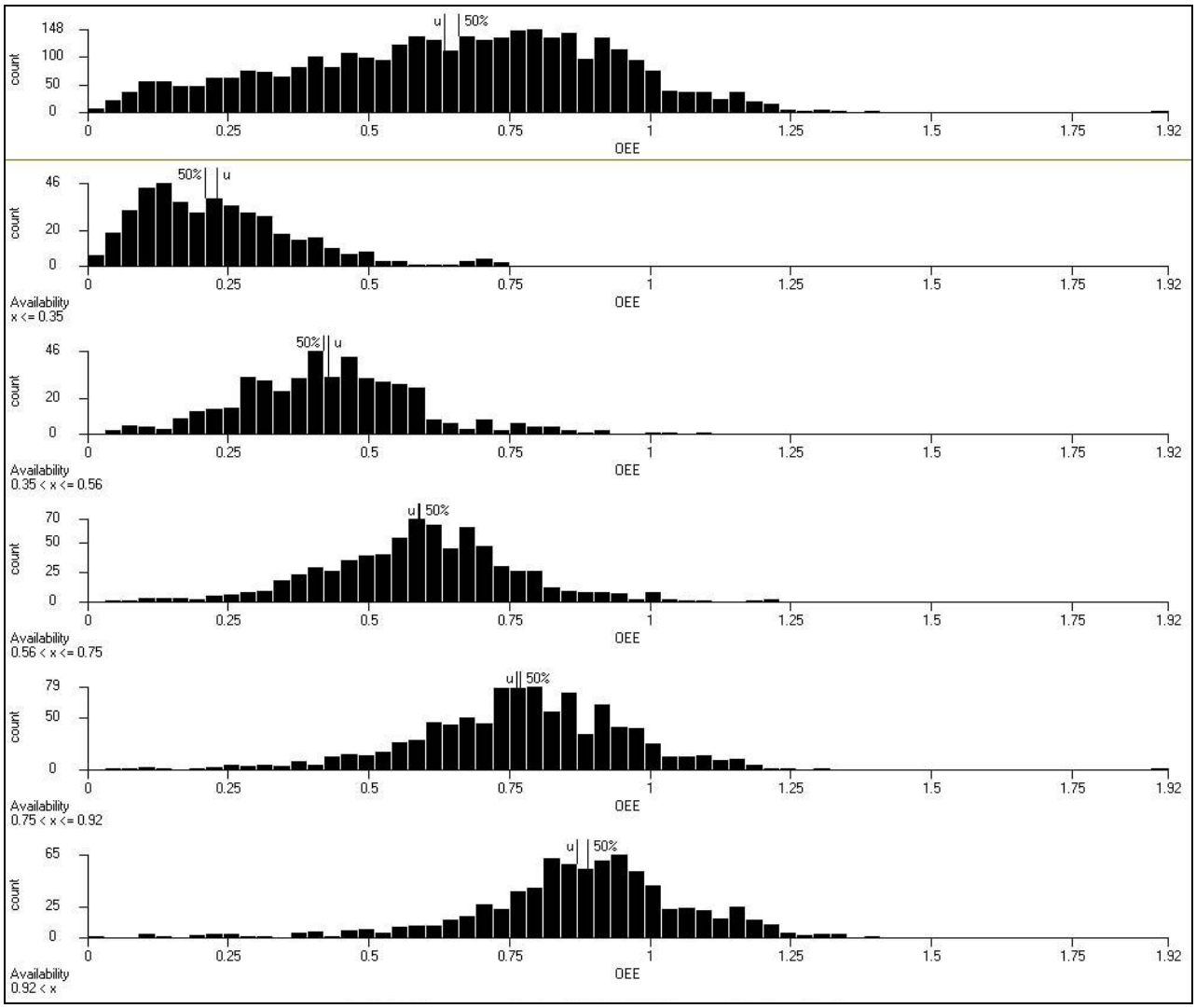

FIGURE V - Histograms of Nodes Presented in Figure III

It is useful to see the shift in mean and the dispersion of OEE for each class represented in Figure III. A manager would be interested in determining the main reasons for inconsistent levels of availability. Figure VI shows the results of a manual split on Availability.

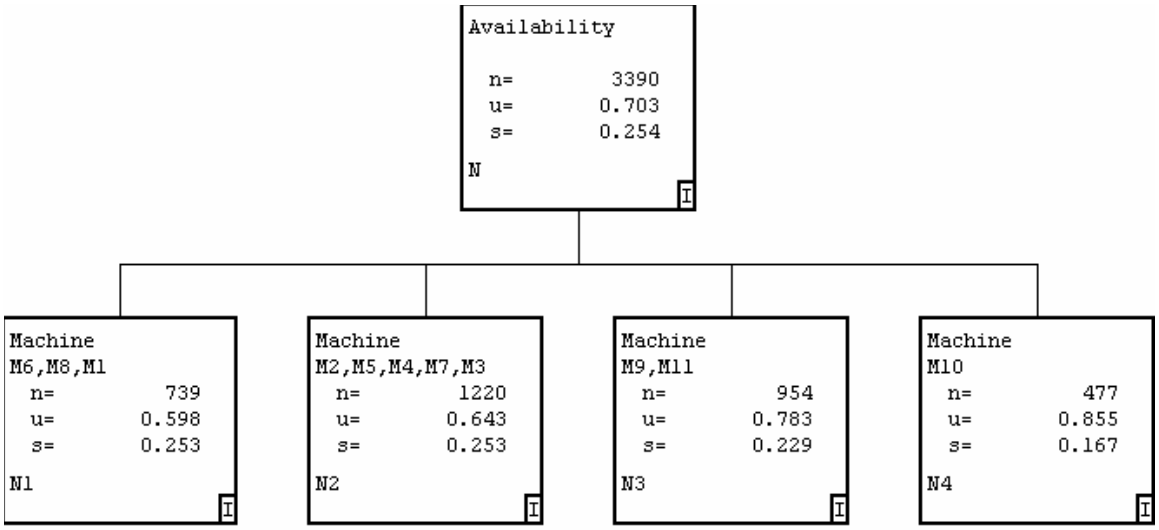

FIGURE VI - Split of Availability on Machine

Machine type best explains the variance in Availability. Since Availability is the ratio of actual operating time to planned operating time, Figure VI shows that M10 is operating much more, with less unscheduled down time, than the other machines. Lower variance in availability is important because it shows that the production conforms to the planned schedule. This is an opportunity for management to investigate the difference between M10 and the rest of the machines.

Since there is a seasonal trend in the mean OEE rates for M10 and M11, we performed a decision tree analysis by using only time variables as predictors. Figure VII shows the results of a manual split on OEE using Month.

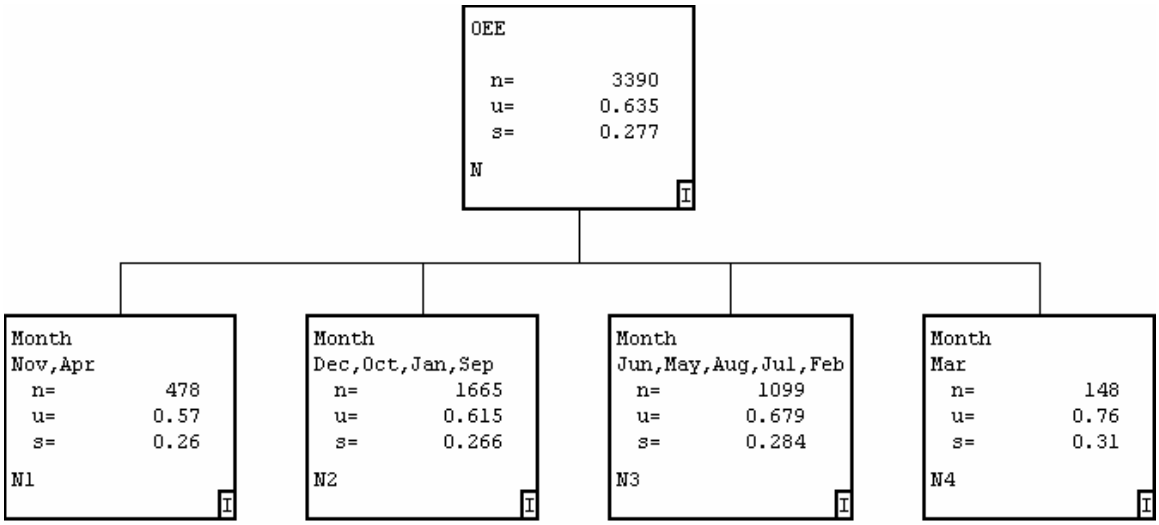

FIGURE VII - Split of OEE on Month

Figure VII suggests that there are no seasonal cycles in machine utilization when we look at all of the machines together. The mean OEE is the highest for the month of March at 0.76 and lowest for November and April at 0.57. Again, management could use these results to investigate why OEE rates are lowest in November and April.

CONCLUSION

Tree-based models are new tools that allow manufacturing operations to automatically select and visualize the most salient and actionable features of their data. The models in this case study helped monitor OEE rates by identifying problem machines, shifts, or time periods where resources were utilized less efficiently. We identified machines M2, M3, and M6 as having the lowest mean OEE rates. A next step to analyze these machines would be to construct cause-and-effect diagrams to determine why these particular machines are less efficient. A more thorough analysis would involve analyzing the reasons for downtime that caused low availability measurements.

This case study is one application of decision trees to a manufacturing process. Decision trees are an ideal fit for analyzing resource management initiatives because information about resource consumption and usage can be collected in a visual format. It should be noted that, the techniques used in this case can provide value for any type of business that collects information for analysis.

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